Analyzing the Role of Ukrainian and Russian Diaspora in Disinformation Campaigns

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Abstract: Recent digital technological developments facilitate the translation, empowerment, and extension of expressing individualand collective ideas, beliefs, and attitudes towards specific concepts and events through different social platforms. In this complex arena, social media manipulation campaigns and corresponding mechanisms like disinformation and misinformation are used through techniques like deep fakes and fake news for, e.g., altering existing information and spreading manufactured information to {targeted, diverse} audiences or producing polarization among communities and users. Nevertheless, academic and practitioner efforts to capture, control, and limit social manipulation techniques exist in the form of strategies and policies based on human intelligence, Artificial Intelligence, or a combination thereof. However, such mechanisms and consonant techniques advance in adaptivity and complexity and can reach and impact broader communities. On this behalf, and especially in conjunction with the ongoing events surrounding the ongoing war in Ukraine, increased attention and dedication is shown to both current and recent events surrounding this conflict, e.g., Crimea's annexation and the MH17 crash in 2014. Such events characterize old battles of ongoing conflicts that could teach important lessons on understanding the role and involvement of Russian and Ukrainian diaspora communities in corresponding social manipulation discourses in social platforms like Twitter and Facebook. To tackle this, multidisciplinary research is conducted using the Design Science Research methodology following the Data Science approach building a series of Machine Learning models. Accordingly, this research aims to build and bring social awareness and resilience to both users and social media policy decision-makers on the role, involvement, and implications of diaspora digital communities in conflicts.

Keywords: information operations, cyber operations, diaspora, social manipulation, disinformation, machine learning.

1. Introduction

"The signal is the truth. The noise is what distracts us from truth." (Nate Silver)

As an ability, mobility characterizes life-based entities such as humans along with non-life-based entities like cars, airplanes, and particularly, more complex constructions like information which travels at incredible high speeds through different ICT-based environments. Remaining in the ICT-based arena and acknowledging its role and involvement for decades in both peace and war related settings and activities (Brinkerhoff, 2006), and going deeper to focusing on one such environment - social media - it is important to acknowledge the projection of human perspectives, beliefs, and activities herein: these play roles like initiator, propagator, amplifier, or receiver in different social media discourses. In these lines, different opinions and experiences were shared and continue to be shared in conflicts like the ones in Afghanistan, Syria, and Ukraine (Dodge, Elgert & Paul, 2022) inside the countries, their corresponding diaspora, and globally (Carter, 2005; Kozachenko, 2018; Minora et al., 2022; Slobozhan, Brik & Sharma, 2022). Specifically, the scale and intensity of discourses and narratives regarding Ukraine significantly increased since the Euromaidan, annexation of Crimea, MH17 flight crash, and ongoing conflict. While these activities are labelled as gray zone conflicts, new frozen conflicts, or parts of ongoing hybrid warfare strategies (Fitton, 2016; Maathuis, Pieters, van den berg, 2018a), they actively involve nationals and diaspora communities showing a traceable emergence through both hesitation and direct involvement (Kozachenko, 2018). Coupling these aspects with the ongoing advancements of social manipulation mechanisms like disinformation and misinformation for intentionally or unintentionally fabricating or altering information by users and dedicated organizations like specialized cyber troops following complex strategies (Bradshaw & Howard, 2018), implies (in)direct exposure to real facts and noise that can influence one's beliefs and behavior at both individual and collective levels. While these issues occupy an important role in scientific and practitioner agendas and efforts, limited attention is dedicated to understanding the role and interaction between diaspora communities and social media manipulation. To tackle this issue, this research aims to investigate the role that diaspora has in relation to disinformation propagation, specifically focusing on Ukrainian and Russian diaspora. To achieve this aim, multidisciplinary research is conducted merging studies and techniques from social media manipulation, digital diaspora and diaspora studies, international relations, and AI domains following a Design Science Research methodological approach (Peffers et al., 2007; Peffers, Tuunanen & Niehaves, 2018. Through this approach, two datasets are constructed with data from 2014-2015, and a series

of Machine Learning models are built aiming to answering the main research question: What is the interaction between diaspora users and disinformation campaigns on Twitter surrounding the initial phase of the ongoing Russian-Ukraine conflict? Hence, the main contributions of this research are defined as follows:

- To the scientific community by encouraging further multidisciplinary research relying on data and Albased models further complemented by multi-domain expert knowledge for properly understanding the dynamics and interaction inside and between diaspora and social manipulation in conflict time.
- To different social media platforms and relevant organizations which have the power to release publicly
 available datasets and further contribute to open science efforts for tackling/countering social media
 manipulation mechanisms in relation to former, ongoing, or anticipated conflicts.

The outline of this article is assembled as follows. Section 2 sets the context and tackles related studied considering the multidisciplinary nature of this research. Section 3 presents the methodological approach taken for achieving the aim of this research. Section 4 addresses the data collection process for building the underlying AI models of this research. Section 5 discusses the implementation of the models proposed together with the results obtained. Section 6 reflects on the findings of this research and future research lines.

2. Disinformation and Diaspora Related Research

As a concept, diaspora implies a population that leaves the homeland to a new land being surrounded in its space by its (collective) memory and myths about the homeland, in some situations even an idealization of the home notion, a continuous connection or a (fragmented) return to the homeland, ethnic group consciousness over time, in some cases a troubled relationship with host societies, a sense of co-responsibility to host societies and co-ethnics, and the possibility of an improved life (Cohen, 2008). Diaspora implies living diasporic experiences through both incompleteness and extension of oneself. Being able to experience these inside and through digital realms like social media enhances one's needs for representation, communication, and exchange of information with others (Georgiou, 2013; Kurbalija, 2013): this facilitated the creation of a recently introduced concept: digital diaspora. Nevertheless, social media is a part of cyberspace which is a dynamic, complex, and uncertain domain (Maathuis, 2022d), implying that its users are directly exposed to malicious agents and their manipulation mechanisms through actions like purposeful and systematic information falsification or alteration that could influence users' beliefs and behaviours (Brangetto & Veenendaal, 2016; Maathuis & Chockalingam, 2022a). Moreover, social manipulation or influence operations like discrediting, destabilizing, undermining, or promoting specific maliciously intended groups, improving one's attitude towards an aggressor, or generating tension and/or conflict among (members of) a society use mechanisms like disinformation or misinformation; shortly: disinformation implies fabricating and using intentionally altered or false information while misinformation implies unintentionally building and using altered or false information (Wardle & Derakhshan, 2017; Mazarr et al., 2019).

Once the background of this research is introduced, further are analyzed relevant studies for understanding the dimensions of this research taking a multidisciplinary stance, i.e., starting with studies that set the context and going to the last ones that reflect on existing datasets and AI techniques used in this domain. Accordingly, Bhandari (2021) conducts a review for conceptualizing diaspora and cultural identity of immigrants categorizing four phases/groups in this process: (i) the forced migration of immigrants including Jewish, Africans, and Armenian communities, (ii) historical, cultural, and social diversities of people, (iii) deconstruction of the bipolar perspective of home versus host country through appreciation of inconsistencies and fluidities of immigrants' identity, and (iv) relevance of the origin and historical exploitation of people from poor countries. One the first studies in this direction is conducted by (Brinkerhoff, 2006) which analyzed the influence of digital diaspora in Egyptian Copt community focusing on the role of the U.S. Copt Association for supporting a more democratic government in Egypt. Ajder (2018) conducts a pilot survey for understanding how Romanian diaspora Facebook groups build the public sphere where public opinion is formed, how they can shape political subjectivity, and what is the impact of their administrators as community organizers. Zhang & Zhao (2020) analyzes the unique role of Chinese diaspora vloggers during the Covid-19 pandemic through manual keyword search and chance sampling following platform recommendations on YouTube. The results obtained show that vloggers have universal feelings like fears and culturally specific ones like mask-wearing related while inviting their viewers to construct their emotional experience revealing a new form of migrant identity and its role in delivering healthrelated information in this crisis. Moreover, Heyd (2016) defines an important notion for understanding digital diaspora: narratives of belonging. The author argues that this concept brings together two evocative notions: storytelling "as a fundamental human activity and linguistic act of identity" and belonging "as a category that is

relevant to all explorations to all human experience in societies marked by globalization and mobility". For this notion, Heyd (2016) identifies four criteria when analyzing diaspora text: personal narratives, i.e., reflecting an episode that is personalized and related to a lived individual experience, account of events, reference to components embedded in the notion of belonging, and evaluation through, e.g., critical positioning towards narrated events. Kozachenko (2018) analyzes the role of global Ukrainian diaspora in supporting democratic changes in Ukraine as representatives of Ukrainian national identity that promotes visions about Ukraine's past and future through re-inventing and re-imagining the national belonging. At the same time, Hartmann, Golovchenko & Augenstein (2019) investigates the circulation of disinformation related to the MH17 plane crash analyzing pro-Ukrainian and pro-Russian perspective on Twitter datasets. Furthermore, Korzh, Kovalchuk & Marshall (2022) analyze the motivation behind the movement created by Ukrainian diaspora to support Euromaidan based on symbolic and psychological causes outside and through social media platforms like Facebook and Twitter, while Slobozhan, Brik & Sharma (2022) investigate a new Facebook dataset for analyzing the Euromaidan protest between November 2013 to February 2014 focusing on linguistic aspects. While the authors stress the need for more studies on the dynamics of online protests, among the results found is the fact that while both Ukrainian and Russian languages are used, among the protesters Russian language was used for maximizing outreach.

These studies show the relevance of using different AI techniques for both descriptive and predictive purposes. Additionally, Choras et al., (2021), Kapantai et al., (2021), and Rani, Das & Bhardwaj (2022) review and discuss valuable AI solutions and results obtained when detecting social mechanisms like disinformation and misinformation. Along these lines, Mridha et al., (2021) perform a comprehensive literature review on deep learning techniques successfully used for fake news detection. Moreover, Mullah & Zainon (2021) conduct a review on ML techniques for hate speech detection in social media reflecting on using different techniques like decision trees, SVM (Support Vector Machine), random forests plus BoW (Bag of Words) and N-grans for feature extraction, and evaluation criteria such as F1-score, precision, and recall. Next to these research studies, societal and governmental initiatives exist for strengthening diasporic communities through a global approach to consolidate efforts on diaspora engagement for development proposed by the European Commission that built the EU Global Diaspora Facility (EUDiF) (European Commission, 2020). Another relevant platform is iDiaspora which is sustained by the United Nations for global engagement as a knowledge exchange hub for sharing opinions, ideas, experiences, and best practices for building sustainable positive change and maximizing diaspora's impact (United Nations, 2022).

Based on the comprehensive review conducted in this research it can be concluded that while different dimensions of the ongoing conflict between Russia and Ukraine are tackled through different studies, e.g., annexation of Crimea, Euromaidan, and current events, still limited studies are dedicated to understanding diaspora's role in relation to disinformation propagation in social media. Consequently, this represents the knowledge gap that this research tackles implementing ML models that have already shown good results in different social media analytics and social manipulation detection solutions.

3. Research Methodology

To accomplish the aim of this research, i.e., to investigate the role of diaspora in relation to disinformation propagation in social media, multidisciplinary research is conducted in social media manipulation, diaspora studies, international relations, and AI domains. Hence, the following research question is formulated: What is the interaction between diaspora users and disinformation campaigns on Twitter surrounding the ongoing Russian-Ukraine conflict? To find an answer to this question while considering the societal role and impact of this research, the Design Science Research methodology (Peffers et al., 2007; Peffers, Tuunanen & Niehaves, 2018) is used in a Data Science approach. Accordingly, the following research activities are taken:

- Solution objective: the goal of this research is split into four smaller objectives: (i) to gather relevant
 disinformation campaigns surrounding the ongoing Russian-Ukraine conflict from 2014-2015, (i) to
 collect insights about user communities interacting with the identified disinformation campaigns, (iii)
 to select ML techniques and build corresponding ML models for analysing diaspora membership, and
 (iv) to capture and understand the relationship between the communities found and diaspora
 members.
- Design and development: to achieve these goals, relevant datasets are searched and further constructed so that ML models can be built and evaluated.

- Demonstration: for the first goal, two new Twitter datasets are created containing messages interacting
 with disinformation campaigns; for the second goal, by applying community detection algorithms, user
 communities are identified; for the third goal, diaspora membership is computed as a ML classification
 problem resulting in Ukrainian, Russian, or non/other; for the fourth goal, a mapping is created
 between the second and third goals so that possible relationships between user communities and
 diaspora can be found. Accordingly, these processes are built in C# using the .NET framework and
 Python.
- Evaluation and Communication: the evaluation is conducted using specific evaluation metrics and the
 results are transparently discussed. Moreover, the results are communicated through this article and
 corresponding scientific presentations.

4. Data Collection

To understand the dynamics involved and achieve the aim defined, social media information gathering is performed (Maybaum & Ziolkowski, 2013) focusing on the first stage of the Russian-Ukraine conflict since February 2014 starting with Crimea's annexation and continuing with the conflict in Donbas until end of 2015. This process is carried out in two phases: first, by using the StopFake checker which focuses on the Russian-Ukrainian conflict (Stopfake, 2021) from where a set of articles is selected (see Figure 1), and second, by continuing with Twitter search based on extracted keywords in the first phase (see Figure 2).

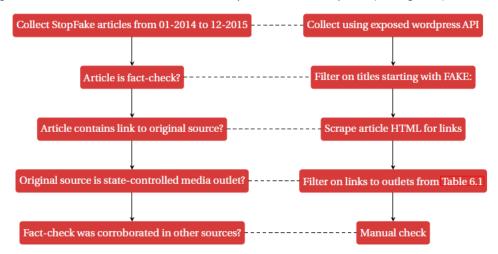


Figure 1. Data collection first phase

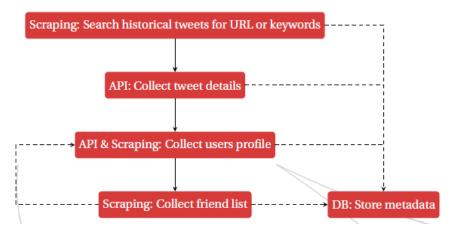


Figure 2. Data collection second phase entity relation diagram

Hence, two datasets are built as follows:

• Dataset 1 contains all messages with content about the Donbas region in English language which means 155444 tweets, 22068 users, 83142 user mentions, 9993 hashtags and 66565 linked URLs.

Dataset 2 contains disinformation messages about the MH17 crash (Hartmann, Golovchenko & Augenstein, 2019; Torenvlied et al., 2015) limited to one month before and one month after the flight was shut down, i.e., between 17.07.2014 and 31.09.2014 which means 3961 tweets, 3074 users, 1229 user mentions, 369 hashtags and 1701 linked URLs.

5. Models Implementation and Results

Considering the analysis conducted in the related studies to this research and the results obtained through the application of different AI techniques and technologies for tackling different social media aspects and issues, to achieve the next three objectives of this research, a combination of baseline ML algorithms, social network analysis, and NLP (Natural Language Processing) techniques are considered and discussed.

To gather insights about user communities interacting with the identified disinformation communities, a network analysis is conducted using mention networks considering the approach taken by Helmus (2018) followed by text analysis in the communities identified. Accordingly, the mention network is built as a directed graph of user-to-user mentions where each user (u) is represented as a vertex, mention relationship is represented through a directed edge, and the wight assigned to each edge indicates the number of mentions between users, as depicted in Figure 3. Furthermore, the visualization is done using the force-directed layout algorithm proposed by Jacomy et al. (2014) which minimizes the number of overlapping edges while retaining an equal edge length for each edge. By applying noise reduction for the first dataset to reduce the number of overall relationships and get a better understanding of the well-connected vertices, i.e., removing vertices with an in or out degree less than 5 or more than 1020, results in 1727 vertices and 12195 edges (from 18093 vertices and 49454 edges without noise reduction), as depicted in Figure 4 left. For the second dataset the second mention is smaller and through size reduction contains 690 vertices and 733 edges (from 1236 vertices and 1095 edges) as captured in Figure 4 right.

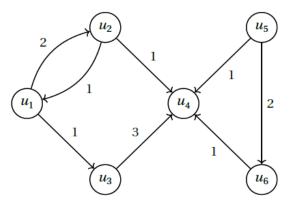


Figure 3. Simplified mention network

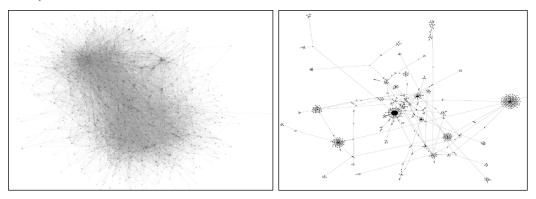


Figure 4. Mention networks: simplified (left) and full (right)

Furthermore, the Leiden community detection algorithm developed by Traag, Waltman & Eck (2019) is used for the first dataset for finding groups of vertices within the graph that are more connected internally and less connected to other vertices in the graph. Hence, 16 communities are identified and the largest 6 are selected for additional analysis since they contain more than 100 users and further illustrated in Figure 5 left with their corresponding Gephi visualization captured in Figure 5 right.

Community	Color	Number of users	%	
0	(Magenta)	317	18.36	
1	(Light green)	259	15.00	
2	(Orange)	241	13.95	
3	(Light blue)	188	10.88	
4	(Purple)	152	8.80	
5	(Mustard)	142	8.22	

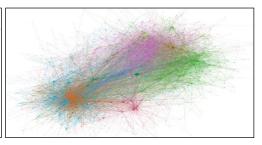


Figure 5. Top six communities based: colours (left), capture (right)

Furthermore, for understanding the topics and keywords used within these communities, the (NLTK) library is used so that the Tweets of the users inside these communities are pre-processed (e.g., tokenization, removal of unnecessary characters like stopwords, lemmatization) and analysed to extract the top 10-word pairs (bigrams) and URL domains for each community using TF-IDF (Term Frequency-Inverse Document Frequency), as captured in Figure 6 and Figure 7 with the corresponding community sentiment captured in Figure 8.

Bigrams	Bigrams
save people	russian troop
ukrainian army	special status
war crime	russian army
kill people	humanitarian aid
child woman	russian soldier
killed child	ukrainian army
child ukrainian	right sector
save child	humanitarian convoy
poroshenko fascist	russian military
ukrainian troop	look like
fascist poroshenko	artillery strike
people killed	conflict zone
sos people	osce mission
woman elderly	minsk agreement
russian military	ukrainian soldier
poroshenko kill	people republic
junta killed	occupied area
fascist junta	putin want
look poroshenko	frozen conflict
people look	martial law

Figure 6. Clusters of topics discussed (selection)

URL	Count	Domain	Count	URL	Count	
www.youtube.com	770	www.youtube.com	785	www.youtube.com	206	
tass.com	357	euromaidanpress.com	632	shar.es	176	
russia-insider.com	355	twitter.com	580	www.facebook.com	157	
sputniknews.com	299	j.mp	559	www.globalresearch.ca	155	
twitter.com	269	fb.me	480	whereisthefuckingplane.com	114	
ln.is	232	liveuamap.com	386	www.businessinsider.com	98	
m.vk.com	139	www.facebook.com	363	www.theguardian.com	82	
shar.es	112	www.unian.info	299	edition.cnn.com	75	
www.facebook.com	102	www.interpretermag.com	246	www.informationng.com	71	
www.rt.com	100	translate.google.com	166	www.bloomberg.com	67	
youtu.be	84	en.censor.net.ua	159	www.infowars.com	60	
novorossia.today	77	24today.net	152	feeds.theguardian.com	55	
fb.me	72	www.kyivpost.com	133	news.google.com	45	
russian.rt.com	60	khpg.org	127	www.rt.com	44	
slavyangrad.org	59	youtu.be	126	goo.gl	40	
fortruss.blogspot.com	55	maidantranslations.com	88	watchinga.com	36	
rt.com	55	postmodernnews.com	88	linkis.com	31	
j.mp	52	www.rferl.org	75	breitbart.com.feedsportal.com	30	
www.kyivpost.com	47	inforesist.org	70	www.presstv.ir	30	
english.pravda.ru	44	www.pravda.com.ua	69	telegraph.feedsportal.com	28	

Figure 7. Clusters of URL domains (selection): first two left from Dataset 1 and third right from Dataset 2

Community	Color	Sentiment					
0	(Magenta)	pro-Western / pro-Ukrainian					
1	(Light green)	pro-Western / pro-Ukrainian					
2	(Orange)	pro-Russian					
3	(Light blue)	pro-Russian					
4	(Purple)	pro-Russian					
5	(Mustard)	pro-Western / pro-Ukrainian					

Figure 8. Community sentiment

Once that communities are detected, diaspora profiling is conducted using ML algorithms to predict if the users belong to Ukrainian, Russian, or Other one(s). On this behalf, data distribution is captured in Figure 8 for reflecting the balance of the data used and the features used are related to, e.g., mentioning belong to one of the countries, having one of the flags associated with, country code, using specific RU/UA characters, friends.

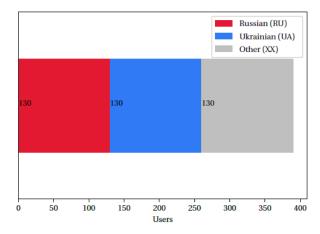


Figure 9. Data distribution

Hence the following ML techniques are implemented: Random Forest, gradient boosted decision tree, Support Vector Machines, logistic regression, Naïve Bayes, K-Nearest Neighbour, and decision tree. In the initial test, Random Forest is the best performing one. To deal with generalization issues like overfitting (i.e., the model performs well on test data and outperforms on unseen data) and increase the effectivity selection of the model, the cross-validation mechanism is applied with 5 folds (Stratified k-fold cross validation) (Alpaydin, 2010) to make sure that parts and representaives of the data are used in both training and evaluation processes. Furthermore, the optimization process is conducted by tunning hyperparameters of the models implemented through (i) random search which takes all possible parameter configurations within the given ranges and randomly selects a predefined number of combinations to train the model with. The results are then compared using a scoring function which conducts to obtaining the best scoring configuration, followed by an (ii) exhaustive grid search to find the best performing congiguration, see Figure 9.

	Precision	Recall	F1-score	Support		Precision	Recall	F1-score	Support		Precision	Recall	F1-score	Support
RU	0.97	0.89	0.93	38	RU	0.97	0.89	0.93	38	RU	0.89	0.87	0.88	38
UA	0.89	0.87	0.88	38	UA	0.82	0.87	0.85	38	UA	0.94	0.82	0.87	38
XX	0.80	0.88	0.84	41	XX	0.79	0.80	0.80	41	XX	0.81	0.93	0.86	41
Macro avg	0.89	0.88	0.88	117	Macro avg	0.86	0.86	0.86	117	Macro avg	0.88	0.87	0.87	117
Weighted avg	0.89	0.88	0.88	117	Weighted avg	0.86	0.85	0.86	117	Weighted avg	0.88	0.87	0.87	117
Accuracy	0.88				Accuracy	0.85				Accuracy	0.87			

Figure 10. Performance metrics for optimized random forests (left), gradient boosted decision tree (middle), SVM (right)

Through cross-validation, the results obtained are shown in Figure 10 where it can be seen that the best performing algorithm is Random Forests.

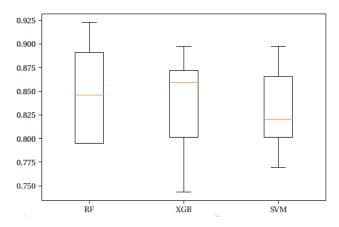


Figure 11. Model performance

Once the communities are identified, and diaspora classification is executed, further meaningful relationships between them is further investigated. Accordingly, for Dataset 1 all user profiles that belong to the top 6 communities are used and the obtained diaspora membership data distribution using Random Forests is captured in Figure 11 left where it can be seen, e.g., that Community 1 has 19% Russian diaspora users, 29% Ukrainian diaspora users, and 52% other. For Dataset 2 the results are different since the topic itself, i.e., MH17 crash has global meaning and implications for other countries like the Netherlands and Malaysia as well, which explains why the Ukrainian and Russian diaspora are represented by 7% (see Figure 11 right).

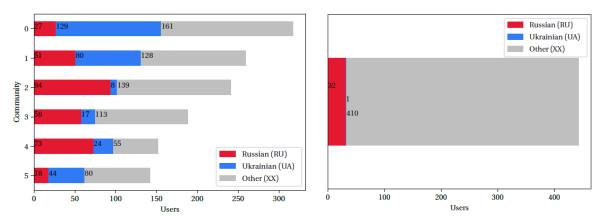


Figure 12. Diaspora membership data distribution for Dataset 1 (left) and Dataset 2 (right)

Based on the results obtained, from Dataset 1 it can be concluded that a general interest is shown to the ongoing conflict between Russia and Ukraine in the period investigated by these communities as well as other global communities, while from Dataset 2 it can be concluded that given the global nature of the topic, the investigated communities are in minority, which implies that these two communities did not play a significant role in spreading disinformation in English language on Twitter.

6. Conclusions

While the ethos of social media is in continuous movement and change due to ongoing societal and technological progress, advancements, and nationally or globally triggered events, its users are (in)directly impacted by (parts of) the cyber/information operations and events either commenced by or propagated to social media discourses and narratives related to actions like behaviour influence and planning disruption as it can be seen for instance in conflicts carried out in the last decade and the ongoing Covid-19 pandemic (Gill & Ziolkowski, 2013; Maathuis, Pieters & an den Berg, 2018b; Yilmaz, 2021; Nakayama, 2022; Chockalingam & Maathuis, 2022). The fact that such discourses and narratives are partially carried out also by diaspora communities (Kozachenko, 2018) in an (un)intentional way through social media manipulation mechanisms like disinformation and misinformation, adds to the complexity, dynamism, and uncertainty surrounding (i) the real goals and target audience of the content, and (ii) understanding the dynamics involved and relations between diaspora communities and social media manipulation mechanisms. Such issues are still open considering the existing academic and practitioner efforts and need to be tackled to be able to build proper, transparent, and accountable intelligent solutions

(Maathuis, 2022b; Maathuis, 2022c) that make users aware and arm them with adaptive means for tackling and/or countering social media manipulation mechanisms. This represents the knowledge gap that this research tackles aiming at investigating the role of diaspora in relation to disinformation propagation in social media. On this behalf, multidisciplinary research is carried out following a Design Science Research methodology in a Data Science approach by building a series of ML models and corresponding datasets with Twitter messages related to the first part of the Russian-Ukraine conflict and corresponding discourses around the situation in Donbas and the MH17 flight crash.

Based on the research conducted, the findings show that diaspora members play a clear role in the general discourses surrounding the Russian-Ukrainian conflict, but based on the existing datasets containing Twitter messages in English an active role in spreading disinformation was not found. Hence, while acknowledging the difficulties of gathering data for research purposes (Walker, S., Mercea, D., & Bastos, 2019), a call for further collecting multi-{domain, source, type} data is made considering other dimensions and events surrounding the investigated conflict for properly grasping the dynamics and role of diaspora members during conflict as a further prerequisite of an intelligent, secure, and safe digital domain.

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