#IstandwithPutin Meets COVID-19 Conspiracies: A Multi-tiered Hybrid Analysis of Tweets Supporting the War in Ukraine

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1 Introduction

On 24 February 2022, Putin started his war on Ukraine under the false pretext of "liberating the country of Nazism". European leaders swiftly denounced Putin's war and social media users worldwide expressed their shock online (Chen & Ferrara, 2022). While much of the online conversation was rightfully condemning the unwarranted siege on Ukraine, a hashtag in support of Putin's "special military operation" began to emerge and quickly gained traction, even prompting it to become one of the most popular Twitter hashtags on 28 February 2022: #IstandwithPutin.

Researchers specialized in disinformation came forward with a first assessment of the hashtag's amplification patterns, identifying large bot-networks as the main driver behind the spike in engagement (CASM, 2022; Collins & Korecki, 2022; Le Roux, 2022), rather than actual tweeters coming out in droves to support Putin's war. Similarly, Hanley et al.(2022) found that Kremlin-backed disinformation on Nazism running rampant in Ukraine did not resonate within a Western audience and that, rather, social media users in the US and the EU were actively pushing against such propagandistic advances, countering them *en masse* (Chen & Ferrara, 2022; Ciuriak, 2022). This predominantly positive view on social media's role in shaping the conversation on Russia's invasion of Ukraine marks a departure from more negative assessments ever since the successful Brexit campaign and Trump's victorious election campaign in 2016 (Bradshaw & Howard, 2017; Howard & Kollanyi, 2016), reviving, instead, conceptualizations reminiscent of the techno-democratic optimism that unfolded when social media first arose (Bruns, 2015; Chadwick & Howard, 2009).

Other findings, however, point out that shunning the popularity of #IstandwithPutin as solely bot-driven falls short of critically engaging with the Twitter conversation and the user base employing the hashtag. Jarynowski (2022) for example, found that online support for Putin came largely from German accounts that were formerly engaged in amplifying conspiratorial anti-vax content. This appeared to be part of a larger EU-wide dynamic with multiple COVID-related conspiracy theories quickly being applied to this new context by European users situated in various online echo chambers of COVID conspiracists (EDMO, 2022; Kayali & Scott, 2022). However, at the time of writing, the few articles on both sides of the argument rely either on quantitative or qualitative tools, failing to demonstrate a combination of methods that is customarily advocated for in researching social media's effect on society to generate more holistic findings (Wardle & Derakhshan, 2017).

This controversy and the lack of methodological richness raises some questions on whether social media are indeed on the precipices of redeeming themselves, rekindling the techno-democratic optimism seen during their advent. Or whether the online conversation on Putin's war perhaps just sees a continuation of conspiratorial themes established during the pandemic and the promulgation of conspiratorial motifs in some echo chambers but that then appealed to an EU-mainstream (Bruns, Harrington, & Hurcombe, 2021). In light of these considerations, this thesis sets out to provide answers to the following research questions:

RQ1: To what extent do EU tweeters supporting Putin's war in Ukraine repurpose conspiratorial COVID motifs?
RQ2: How are tweeters applying such motifs connected to other (pro-Putin) users on Twitter?

To answer these research questions, I start my literature review by grounding the current view on social media's role in shaping the conversation on Russia's invasion of Ukraine in the wider debate on the effects of social media on society. Section 2.2 starts off with a short definition of conspiracy theories generally and is then followed by a review of the literature on specific COVID tropes, which is needed to identify COVID motifs in the first place. To compensate for the current lack of multi-methodological approaches, this thesis proposes a multi-tiered hybrid method that overcomes challenges to data access, and draws on a large dataset generated through accessing the official Twitter API directly and blends together qualitative and quantitative methods in section 3. This section is divided into three sub-sections, corresponding to the three tiers that this method consists of. First, to capture the wider pro-Putin debate, a Python script is devised to collect all tweets featuring the hashtags #IstandwithPutin, #NaziUkraine, #AbolishNAto, and #IstandwithRussia between 20 March 2022 and 4 April 2022. The retrieved dataset is then cleaned and the location of users is qualitatively assessed to rid the dataset of non-EU users. In the second step, a hybrid content analysis, consisting of topic modelling and content analysis is conducted to assess the extent to which EU tweeters supporting Putin's war in Ukraine repurpose conspiratorial COVID motifs. The last tier of this method then sees the application of social network analysis to shine light on the second research question regarding how tweeters repurposing COVID motifs are connected to the wider Twitter network. By employing this method in section 4, I sketch a more conclusive picture of the pro-Putin conversation on Twitter and to what extent this conversation is heavy on references to COVID conspiracy theories and elucidate the network dynamics of the EU tweeters in the data set. In the conclusion, I summarize these findings, outline limitations, and describe how this thesis, especially method-wise, contributes to closing the current research gap.

The generated findings via the multi-tiered hybrid method provide little support for the claim that COVID conspiracies have been retrofitted by EU tweeters to support the invasion of Ukraine, with only 111 tweets by 60 users identified to do so. Rather than COVID motifs, four distinctive narratives dominated the tweet collection, namely Anti-NATO narratives, Nazi disinformation, vows of loyalty to Putin, and accusations of a Russophobic bias in the Western media apparatus. Further, the small user set employing such motifs is found to be largely irrelevant for the wider conversation, with little linkages to the wider network and only connected to other users repurposing such content.

2 Social Media and (COVID) Conspiracy Theories

This literature review first describes how academia's perception of social media's effect(s) on society, specifically those of the social sciences and humanities, has gone through various stages. The section on this narrational evolution grounds this thesis' research subject in the wider debate on how social media (negatively) affect democracy, delimits relevant concepts, focuses on the nascent conversation on Putin's war potentially altering these readings, and already alludes to the role that (COVID) conspiracies have played in fermenting negative impressions. Section 2.2 first defines conspiracy theories conceptually and then outlines the most impactful conspiracy tropes perpetuated online in connection with the COVID-19 pandemic. Establishing common themes allows to then assess the extent to which these motifs are repurposed in the context of the war in Ukraine in the empirical chapter. Special attention is paid here to the methodology of publications on COVID conspiracy theories, demonstrating that the broad selection of disciplines working on COVID-19 conspiracy theories brought with them a multi-methodological richness. The nascent scholarly debate on social media's role in the ongoing war currently lacks such richness, illustrating the second gap that this thesis undertakes to contribute in respect of.

2.1 Social Media's Effect on Society: An Ever-changing Narrative

The dominant perspective of the social sciences and humanities on social media has changed throughout the years and with it, came the rise and demise of various concepts. Early scholarly notions toward social media were reminiscent of the techno-democratic optimism that emerged with the mainstreaming of the internet (Bimber, 2000; Dahlberg, 2001). Just as with the internet before but further compounded now, a strong emphasis was placed upon social media's ability to connect individuals across borders and their capacity to break apart informational monopolies by transforming users from exclusive receivers of information into "prosumers" operating in many-to-many-networks (Bruns, 2015; Jensen & Helles, 2011; Loader & Mercea, 2011). Scholars argued that this challenge to traditional media presented unprecedented opportunities for grassroots mobilization (Chadwick & Howard, 2009; Cogburn & Espinoza-Vasquez, 2011). This primarily positive view was accompanied by concepts emblematic of the predominant overenthusiasm of the time, such as "liberation technology" (Diamond, 2010) or "e-Democracy" (Kersting, 2012), and reached its climax with the so-called "Arab Spring". Deemed a social media revolution, the academy almost unanimously stylized Twitter, Facebook, and YouTube as the facilitators of the Arab world's collective uprising (Kassam, 2013) and framed the fall of these regimes as indicative of social media's democracy-serving function which would eventually usher in the end of authoritarianism worldwide (Howard et al., 2011; Howard & Husain, 2013). Democratic reforms failed to materialize in most of the Arab world (Khondker, 2019), however, and, subsequently, the fanfare of social media's power for democratic emancipation was superseded by more nuanced analysis (Loader & Mercea, 2011; Lynch, 2011).

This moment of more measured appraisal was followed by a move toward more negative conceptions, with publications beginning to problematize attempts by governments – wary of social media-driven regime change –to enforce control over platforms or actively abusing social media's affordances to effectively suppress domestic dissent (Nocettii, 2015; Shirky, 2011). In 2016, Brexit and Trump's successful bid for the US presidency demarcate the beginning of a more radical shift in academic and societal discourse. Social media manipulation by foreign governments, namely, the inauthentic and coordinated amplification of counterfactual content through bots and sock puppets, was depicted as decisive for the success of both campaigns and prompted many scholars to drastically redirect their research (Bradshaw & Howard, 2017; Howard & Kollanyi, 2016). From 2016 onwards, pessimistic projections of social media's effect on society were put in the limelight. With Brexit and Trump's presidency often serving as a starting point, these projections largely centered around questions on how social media and the revolution of the information space that came therewith endangers democracies, harms institutions, and provides ample opportunity for authoritarian leaders to compound their position (Bradshaw & Howard, 2019; Fuchs, 2018; Persily, 2017).

These gloomy framings engendered attention from across the academy, with an increasingly eclectic set of scholars gravitating to this research subject. Although interrogating different aspects and arguing from different angles, these researchers have been more often than not united in their call for interdisciplinarity in studying the harmful effects of social media on society (Wardle & Derakhshan, 2017). Such interdisciplinarity was deemed necessary, as the manifold challenges arising with social media abuses, ranging from being technical, legal, or psychological in nature, may only be successfully mitigated if disciplines like law, computer science, psychology, and journalism are brought together (Bhattacharjee et al., 2020). A growing number of publications and new-found initiatives have delivered such profound interdisciplinary work since, incorporating and synthesizing concept and especially methods from various relevant disciplines (Hoffmann, Taylor, & Bradshaw, 2019; Schreiber, Picus, Fischinger, & Boyer, 2021; Starbird, 2018).

This broad scholarly interest came with the re-popularization of old concepts like "information warfare" (Lin & Kerr, 2019), "fake news" (Horne & Adali, 2017), and "disinformation" (Jowett & O'Donnell, 2018), the updating of concepts to a new digitalized context, such as “computational propaganda” (Woolley & Howard, 2016) and “Populism 2.0” (Moffitt, 2018), or the coining of new terms like “Information disorder” (Wardle & Derakhshan, 2017), “anti-social social media” (Vaidhyanathan, 2018) or “surveillance capitalism” (Zuboff, 2019). Compared to the other outlined concepts, the latter three are less concerned with questions on who, why, and how social media are *abused,* but emphasis is placed on the platforms *themselves.* Namely*,* how the design of platforms and the platform dynamics underpinning them *systemically* provide malign actors, foreign or domestic, a platform to disseminate their content successfully in the first place (Faris et al., 2017; Just & Latzer, 2017). In these discussions*,* much attention is paid to how social media contribute to and facilitates isolated thinking. Two concepts commonly invoked in this context are Pariser’s “filter bubble” (2011) and Sunstein’s (2001) “echo chamber”. Filter bubbles refer to the algorithmically-based creation of social media feeds, while echo chambers are used to describe informational cocoons of one’s own making by selective engaging with bias-confirming continent (Möller, 2021). Online echo chambers, as they perpetually reinforce a user’s (increasingly) hyper-partisan thinking (Flaxman, Goel, & Rao, 2016), are ascribed great importance for the formation of conspiratorial beliefs (Bruder & Kunert, 2022; Luzsa & Mayr, 2021).

Arguably, the pandemic brought the next gradation of negative perspectives on social media, as the volume, velocity, and variety of online conversations featuring and amplifying false claims, whether deliberate or not, reached new highs. The WHO referred to this unprecedented level of faux information as an “infodemic” (WHO, 2020), a term that subsequently enjoyed wide uptake amongst researchers (Bruns et al., 2021; Leitner et al., 2021). Publications dedicated to this infodemic found that COVID conspiracy theories were widely shared in certain echo chambers and eventually resonated, unlike earlier online conspiracy theories such as “Pizzagate” (Kuo & Marwick, 2021), not only within (far-)right echo chambers but across society (Bruns et al., 2021). At the heart of these conspiracy theories lay arguments on COVID-19 being ‘a vehicle for exerting political control over citizens’ (Griffith et al., 2021, p. 4) or bioengineered to eradicate humanity. Repeatedly, such narratives also portrayed elected governments in the West as mere puppet regimes ruled by sinister secret societies and urged citizens to rise up and overthrow these “pseudo-democracies”, inspiring non-compliance with public health measures and framing these as expressions of a noble civil resistance.

So far, the majority of academic analysis on social media’s role in the ongoing (information) war in Ukraine suggests a break with this perceptual downward trend since 2016, ushering in instead a new phase of perceptions on social media. These accounts articulate that the decentralized nature of social media is a helpful tool in times of war, as an engaged user base 'can help to expose propaganda' (Ciuriak, 2022, p. 2) and ultimately counter it (Chen & Ferrara, 2022). The quantitative sentence-level topic analysis by Hanley, Kumar, and Drurumeric (2022) confirms this positive assessment, finding that the avalanche of Kremlin-sponsored Nazi disinformation targeting Ukraine and attempts to discredit Western media for their lack of reporting on this issue are failing at resonating in the West and are drowned out by EU users empathetic to Ukraine's plight. Similarly, a quantitative social network analysis aimed at grappling with the popularity of #IstandwithPutin - ranking amongst Twitter's top trends on 28 February 2020 with hundreds of thousands of tweets incorporating the hashtag - detects inauthentic coordinated behavior responsible for hashtag-amplification, rather than organic support by actual users (CASM, 2022; Le Roux, 2022), which consequently inspired rigorous account removal by Twitter itself (Collins & Korecki, 2022) and also highlights how such coordinated attempts not seem to be successful.

On the other hand, a minority of publication challenges this refound optimism. Jarynowski's (2022) quantitative research on German user behavior on Twitter shows that users who had been active in anti-vax conversations before are 51 times more likely to come out in support of Putin now than accounts positioning themselves against him, with no indication that these accounts had been automated. Fact-checkers, through qualitative content analysis, also identified a regaining in traction of COVID-conspiracy theories after they had lost momentum with loosening COVID restrictions and an alleged adaption of such theories amongst US and EU-based users in online conversations pertaining to the war (EDMO, 2022; Kayali & Scott, 2022). Such repurposed COVID themes draw on common motifs of population control, or frames of the war being secretly financed by Gates or Soros as another scheme to eradicate humanity. This evidences that support of the invasion might not come from the majority of people but still occurs organically amongst a large number of users holding conspiratorial beliefs instilled during the pandemic.

This thesis contributes to this unsettled debate by interrogating whether COVID-19 conspiracy theories are instrumental in tweets supporting Putin's actions, while employing a multi-tiered method that compensates for the lack of methodological synergies in the existing literature. To do so, the following section defines conspiracy theories more generally before engaging with specific COVID-19 conspiracies.

2.2 COVID Conspiracy Theories: Alternating Culprits – Same Goal(s)

To shine light on the extent to which COVID tropes are applied in Twitter conversations supporting the invasion of Ukraine, this section first starts with a brief definition of conspiracy theories, followed by an elaboration of the most prominent COVID and complemented by findings on their resonance amongst social media networks and geographic differences in the prevalence of conspiratorial thinking in the EU. Special attention is paid to the methodologies of these publications to evidence the wealth of mixed-methods in this research field. As established previously, the emerging conversation on how Putin's war impacts social media and *vice versa* is yet deficient of such holistic approaches, highlighting the gap in the current literature that this thesis contributes to close.

Definitions of "conspiracy theory", although numerous, are almost indistinguishable. Marwick and Lewis define conspiracy theories as 'a belief in the machinations of a powerful group of people who have managed to conceal their role in an event or situation' (2017, p. 18). This definition is illustrative of the key characteristic featured in all definitions of conspiracy theories: an ominous group of societal and/or political elites who – in secrecy – control *everything*. This dichotomy of a public opposed by an enigmatic faction is concocted with the total rejection of official explanations of the causes of a specific event or series of events. This is because any explanation is slammed as a fabrication by said elite to cover up their mysterious, pernicious agenda (Douglas et al., 2019; Sunstein & Vermeule, 2009; Theocharis et al., 2021).

From the onset, the COVID pandemic was accompanied by conspiracy theories. In early 2020, most of these centered around the network standard 5G's assumed role in accelerating the virus' spread (SOMA, 2020) and COVID's alleged biolab origins, with a sub-strain focused on bioweapon claims (Imhoff & Lamberty, 2020). Analyzing about 90,000 Facebook posts via computational timeseries analysis and content-analysis, Bruns et al. find that 5G conspiracies tie in with an amalgamation of long-held conspiracy tropes on mass extermination like 'water fluoridation, chemtrails, genetically modified foods' (2021, p. 232). As such, 5G conspiracy theories resemble a continuation of anti-science sentiments popular in spiritual, alternative-health, evangelical, or (far)right-wing groups. Although biolab stories cannot be as easily dismissed as 5G hoaxes, due to academic deliberation on COVID's origin still being ongoing, claims of the virus being a bioweapon have been refuted (Leitenberg, 2020). This did not stop these allegations from circulating on social media, however. Resonating within similar anti-science echo chambers as 5G narratives, the virus was said to be deliberately manufactured to subjugate or exterminate the world population (Imhoff & Lamberty, 2020). The alleged elitist plotters behind 5G or bioweapon-driven depopulation plans vary according to the constituency, leading to a 'growing array of conspiracy boogeymen [...]: Bill Gates, George Soros, the WHO, the UN, Big Tech' (Bruns et al., 2021, p. 233) that are said to control mainstream media to further brainwash society.

Combining social network analysis and content analysis, Ball and Maxmen observe a convergence of 5G/bioweapon tropes and anti-vax conspiracies in anticipation of a potential vaccine by March 2020. Such increasingly grotesque frames include tales of coronavirus vaccines being ‘a ploy to monitor people through an injected microchip or quantum-dot spy software’ (Ball & Maxmen, 2020, p. 372) commanded via 5G frequencies. In that sense, this narrative weaves persistent anti-science tropes on 5G, biolabs and vaccines together in an effort to further fan the flames of mass extermination rhetoric. Such machination narratives on vaccines being a tool to subjugate or exterminate mankind received a further boost in popularity with the release of the pseudo-documentary “*Plandemic: The Hidden Agenda Behind Covid-19*” in May 2020. The video promotes alternative remedies, downplays the severity of the disease, and – most importantly – intensified speculations on a hidden agenda of US elites and frames mainstream media as a pawn to achieve their ends (Kharazian & Knight, 2020). As the multi-methodological analysis of amplification patterns highlights, the video ranks among the most widely shared pieces of COVID-related conspiratorial content (ibid). Subsequently, Tweets containing conspiratorial lines of thought increasingly featured the hashtag “plandemic” to frame the pandemic as an orchestrated effort and, hence, as a pretext for removing civil liberties, with particular popularity among QAnon[1]-linked accounts (de Smedt & Rupar, 2020).

Content-analysis of Twitter conversations between late 2020 and mid-2021, however, demonstrates that frames on COVID vaccines serving as a tool to gain political control gained traction beyond self-concealed echo chambers on the right (McNeil-Willson, 2022). A group of researchers analyzing 1,041 within a Turkish online environment demonstrates that conspiratorial thinking ranks as the top reason for vaccine hesitancy in the Turkish society at large (Küçükali, Ataç, Palteki, Tokaç, & Hayran, 2022). This pervasiveness is further confirmed by the content-analysis of 3,915 vaccine-related tweets by Griffith et al. (2021), as about a third of the randomly selected tweets referred to some conspiracy theory on the pandemic being an orchestrated effort by a malign faction. Not only were social media conversations increasingly found to be populated by such content, but anti-vax messages also grossly outperformed pro-content in engagement, as evidenced by Ortiz-Sànchez et al. (2020). These publications solidify the impression that, with the help of social media, fallacious thinking on vaccine safety and efficacy began penetrating the mainstream by early- to mid-2021, coinciding with the authorization of the first COVID vaccines. Nevertheless, researchers find the level to which this mainstreaming occurred varied between countries. Theocharies et al.’s online panel study via Mechanical Turk in 17 European countries confirms Walter and Drochon’s (2020) earlier findings that in terms of COVID conspiracies ‘East European countries [have] the

[1] QAnon is considered an alt-right conspiracy theory that first emerged in 2017 and combines ‘1980s conservative “satanic panic” with centuries-old anti-Semitic tropes of “blood libel”’ (Kuo & Marwick, 2021, p. 3) accusing societal and political elitists, inter alia George Soros, of consuming the blood of infants in their quest for immortality.

highest level of conspiracy beliefs, Nordic countries the lowest, and Mediterranean countries being somewhere in the middle' (2021, p. 12).

QAnon accounts are also considered instrumental for the emergence of a new culprit by June of 2020, joining the colorful potpourri of evildoers next to the likes of the UN, Bill Gates, and George Soros: the World Economic Forum (WEF). In June 2020, the WEF announced its "Great Reset"-program, laying out recovery ambitions for a more resilient global system post-pandemic by redirecting economic policies and activity (WEF, 2021). The program's wording – although benign - instantaneously served as grist to the mill of right-wing conspiracy theorists. QAnon-believers in particular quickly recontextualized this program as an effort of global elites to create a "One World Government" (McNeil-Willson, 2022). As McNeill-Willson's (2022) deep reading of a semi-automatically coded dataset of 2,992 tweets shows, this narrative largely relied on established themes of anti-elitism blended with suspicions toward scientific progress turning the world's citizens into defenseless, impotent appendages of technology. Next to these dominant techno-elitist tropes, the sustainability aspects of the WEF's program also helped to reinvigorate themes that were formerly directed at the United Nations' (UN) "Agenda21"/"Agenda30" being a secret plot to impose a totalitarian/communist/eco-fascist "New World Order" (Beirich & Potok, 2014). By November, also thanks to some popular right-wing commenters, the "Great Reset" conspiracy had generated ten thousands of tweets amongst the alt-right and was eventually accompanied by a call to rebel against this pending doom (O'Connor, 2021). Contrary to anti-vax conspiracy theories, frames of the "Great Reset" remained largely limited to an echo chamber consisting of social media users with hyper-partisan right-wing beliefs though.

This section first defined conspiracy theories more generally before outlining prominent culprits and themes specific to COVID conspiracy theories. Namely, these culprits are George Soros, Bill Gates, Klaus Schwab, the WEF, and the UN who are said to hold sway over the media apparatus to convey their messages. Although varying between culprits, these entities are equally targeted by accusations of secretly plotting the extermination of the masses or controlling the world's population via a bioengineered coronavirus, 5G frequencies, or COVID vaccination programs to achieve the "New World Order", the "Great Reset" or the "Agenda21/Agenda30". It is the usage of these themes through which the multi-tiered content analysis elaborated on in the following section assesses the extent to which EU tweeters supporting Putin's war repurpose conspiratorial COVID motifs.

3 Designing Social Media Research Despite API-challenges: A Multi-tiered Hybrid Methodology

The multi-tiered hybrid methodology employed in this thesis is the product of months of recalibrations and readjustments. *Initially*, this thesis project set out to interrogate the perpetuation of COVID conspiracies on Facebook amongst European users in 2021 by drawing on Meta's "CrowdTangle", a tool that grants researchers access to the Facebook API to – amongst other things - observe and analyze amplification patterns (Bruns et al., 2021; Luna et al., 2022). Just weeks after successfully going through CrowdTangle's application process in mid-2021, Meta began dismantling the CrowdTangle team (Roose, 2021). This dismantling marked the next step toward less data access for critical scholarly interrogation ushered in after the Cambridge Analytica revelations (Bruns, 2019). It comes as no surprise, therefore, that since then publications on the circulation of (COVID-related) mis- and disinformation on Facebook have become fewer than compared to other platforms like Twitter. This is regrettable, as Facebook is being considered more representative of a wider demographic (Auxier & Anderson, 2021; Wojcik & Hughes, 2019), as having a larger user base (Brady et al. 2017), and as being more integral for content-cascades presenting conspiracy-laden views (Theocharis et al., 2021; Yang et al., 2021). Ultimately, access to CrowdTangle was never successfully granted and a dozen follow-up inquiries were left unanswered.

As alluded to above and outlined in the chapter before, Twitter receives extra attention from the academy due to its more laissez-faire API approach (El Bacha & Zin, 2019). Although considered comparatively more open, efforts to obtain access to Twitter's official "academic research" API to browse the entire Twitter archive dating back to March 2006 (Twitter, n.d.-a) were similarly unsuccessful. Nevertheless, "elevated developer", rather than "essential", access to the Platforms API was eventually granted. Concretely, in terms of access levels, this means that tweets of the last 7 days could be extracted, compared to essential access which only allows the scraping of tweets of the last 24 hours, (Twitter, n.d.-b). At this point in February 2022, almost two years after COVID-19 had first emerged, a 7-day limit to historic Twitter data, although better than being restricted to the last 24 hours, held little value for answering how and by whom COVID conspiracies had spread on Twitter during the last two years.

This challenge to data collection coincided with Putin's invasion of Ukraine in late February 2022 and the outsized number of Tweets featuring "#IstandwithPutin". The recent literature on the hashtag's popularity indicates broad support for Putin's action, especially amongst those holding COVID conspiracy beliefs (EDMO, 2022; Jarynowski, 2022). As articulated in the literature review, these publications base their findings either on qualitatively content analysis of tweets or Social Network Analysis (SNA) and, unlike accounts on COVID conspiracies (Bruns et al., 2021), fail to synergize methods. This large volume of pro-Putin online content and met only by a small body of mono-methodological literature either grounded in qualitative or quantitative assessment, opened up a research gap that could be contributed to in a meaningful way with the available elevated developer access.

The multi-methodological approach developed here to compensate for the lack of methodological richness consists of three stages: 1) the process of scraping Tweets featuring pro-Putin hashtags, data cleaning, and locating users to interrogate the size of the pro-Putin conversation in the EU and Member State-specific differences; 2) the conduct of a hybrid-content analysis of the collected tweets by EU users to identify the importance and usage of conspiratorial COVID themes; and finally, 3) algorithmically visualizing accounts retrofitting conspiratorial motifs to assess the level of interconnectedness with the pro-Putin network and their place in the larger Twitter conversation. The following three sub-sections articulate each of these tiers.

3.1 Scraping Hashtag Data and Data Cleaning

The recalibrated research project clearly made #IstandwithPutin the starting point of the data collection, as accounts coming out in support of Ukraine's invasion began flocking to the hashtag in early March of 2022 (CASM, 2022; Le Roux, 2022). The approach to data collection employed here takes inspiration from academic publications on Twitter research (Albrecht et al., 2021; Mayr & Weller, 2016), online "how-to"-guides (Pratama, 2020; Strick, 2020), and expert training by the Atlantic Council's DFRLab[2]. This triangulation resulted in a Python[3]-script that made use of the "elevated" access to Twitter's API in order to scrape Twitter data on the specified hashtag(s) from 20 March to 4 April 2022, the day of the Bucha revelations. The Python code (Appendix 1) was refined through a series of "trial-and-error"-iterations and scraped a variety of data points (Table 1). In the first run, this code was exclusively executed with #IstandwithPutin as a search input.

[2] The DFRLab is an initiative hosted by the renowned think-tank "Atlantic Council" that specializes in researching online disinformation (Lapowsky, 2019).

[3] Python is a programming language commonly used in data science and praised for very its near-humanlike syntax which renders this coding language more accessible than others. Hence, its widespread use in the digital humanities.

Data point	Explanation
Username	Retrieves the @ of the Tweeter handle which tweeted using a specific hashtag
Description	information on an extracted user's self-description
Tweet Text	the Tweet in which the specified hashtag is used
Created at	date and time the Tweet was published
Location	Self-declared location of the user
Following	Number of accounts this user follows
Followers	Number of accounts that follower this user
Total tweets	Number of all Tweets this account has published
Retweet count	Number of times a Tweet featuring a specified hashtag has been retweeted
Hashtags	All hashtags used in a specified tweet

Table 1: Data Points for Twitter Scraping via API

Inspired by DeVerna et al.'s (2021) snowball sampling technique, popular hashtags used in connection with #IstandwithPutin were identified and informed additional data extractions with adjusted Python scripts during the same period to generate a broader corpus of tweets in support of Putin's invasion and thus capture the pro-Putin conversations more comprehensively. Tweets for the following three hashtags were scraped: #NaziUkraine, #AbolishNATO, and #IstandwithRussia. Exploratory trials that included non-English hashtags, for example, in French (#proPoutine, #proRussie, #NazieUkraine), German (#fürPutin, #fürRussland, #NATOTerroristen), or Spanish (#EstoyconPutin, #EstoyconRusia, #NaziUcrania) to retrieve a data collection more representative of a wider EU-population by means of language was nugatory. This is because some of these non-English hashtags had not been used at all, while the few mentions that some of these hashtags did experience were either from years before the invasion or used to criticize Putin's actions instead. The lack of usage of non-English hashtags can be attributed to the fact that while a tweet may be written in another (EU-) language, tweeters still use English hashtags to further boost the popularity of an existing hashtag on a specific issue (Jurgens et al., 2014). Therefore, rather than including non-English hashtags introducing unnecessary noise, scraping remained restricted to pro-Putin hashtags in English only.

This repeated scraping generated a meta-dataset of 33,918 tweets by 12,848 users that featured one or multiple of the identified hashtags. Further adjustments were necessary to arrive at a dataset that provides the foundation to generate meaningful insights on the extent to which EU tweeters supporting Putin's war in Ukraine repurpose conspiratorial COVID motifs. These adjustments concerned 1) the deletion of duplicates, and 2) the identification of Tweets by (non-)EU-based Twitter accounts. The first step was necessary as the repeated scraping of Tweets that featured either of these hashtags led to duplicate entries of Tweets that contained more than one of these hashtags simultaneously. After the successful removal of duplicates via basic Excel-functionalities, and in line with the research question, accounts were screened for their location so that only those accounts situated in the EU were subject to further analysis. Amongst these non-duplicate tweets coming from 12,848 tweeters, a majority of 6,904 users (53,7 %) identified their location. This level of disclosure is rather high, as most research indicates that only about 1 to 3% of Twitter users normally disclose their location (Schlosser et al., 2021; Sloan, 2018). Yet, the validity of this data should be taken with a pinch of salt, as users are frequently found to provide false information to deceit their audience (Sloan, 2018) or because '34% of users [do] not provide real location information, frequently incorporating fake locations or sarcastic comments' (Hecht et al., 2011, p. 238). Indeed, regarding the latter, much of the location data in the dataset was found to be outright bogus (e.g., "#plagueisland?", "your brain", "Absurdistan").

Hence, to clean the dataset of non-EU users, *all* 12,848 user locations needed to be verified or approximated based on profile information. Rather than retreating to using other computational quantitative methods like geoparsing, a labor-intensive qualitative hand-coding was conducted. This is because computational approaches for locating users are still in their nascency and while some authors claim a steep increase in the accuracy of their models in the last years (Karimzadeh et al., 2019; Middleton et al., 2018), others cast more doubt on their validity, arguing that these models, for the most part, generate an 'erroneous and unrepresentative classification of toponyms' (Gritta et al., 2020, p. 684). Given the lack of reliability of such models, the coding of the country of origin was based on manually consulting Twitter profiles. This hand-coding was done based on contextual factors machine-learning approaches would also try to fetch: 1) profile information besides location, 2) tweet language, and 3) topics discussed. For example, accounts whose bio mentioned "proud Virginian", tweeted in (US) English, and exclusively or mainly mentioned US politics were labeled as "US". In cases where an account's language was neither German, English, French, or Dutch, translation was necessary to determine the discussed topics accurately. This translation was executed with the free-of-charge machine translator "Deepl" which is widely deemed the most accurate automated translator available (Volkart et al., 2018).

The remaining tweets by EU users delivered the foundation for the hybrid content analysis but also gave a first indication of the usage levels of these four hashtags in the EU and whether these hashtags maintained their popularity after networks of accounts displaying inauthentic coordinated behavior had been removed in early March (Collins & Korecki, 2022). Further, the data set also already generates an understanding from which Member States users actively featuring such hashtags are coming from.

3.2 Hybrid Content Analysis

The remaining tweets of EU users were then subject to a hybrid-content analysis that combines the quantitative method topic modelling and qualitative content analysis to interrogate the role of conspiratorial COVID tropes in pro-Putin tweets. Topic modelling is a text-mining technique to identify latent topic patterns in given *texts* through statistical models, and is increasingly popularized in the digital humanities due to its capacity to analyze large corpora of text, ranging from uncovering patterns within poetry, speeches, or other forms of *written word* (Drucker, 2021). The statistical model opted for here is Latent Dirichlet Allocation (LDA) (Blei, Ng, & Jordan, 2003), as it is the most heavily used model for identifying co-occurring word clusters (Jacobs & Tschötschel, 2019). Accordingly, the LDA-based topic modelling found wide application amongst social scientists to research online conversations on the COVID pandemic. For example, Kurten and Beullens (2021) uncover the motifs used by Belgian Twitter users when talking about COVID, by Xue et al. (2020) combine LDA and sentiment analysis to uncover the emotional responses of English-speaking Twitter users to the pandemic. All of these publications, however, only rely on what Drucker calls a “distant reading” (2021, p. 110), achieved by computational means only. This distant reading, although insightful in its own right, falls short of contextualizing the generated insights in a way that a close reading would (Grimmer & Stewart, 2013).

Thus, topic modelling alone might present information on which topics the tweet collection consists of, is dominated by, and the words co-occurring within each topic, however, for interrogating the extent to which accounts using pro-Putin hashtags rely on COVID conspiracies, additional analysis is required. This is the rationale for complimenting topic modelling with content analysis, as the ‘combination of computational processing power with human intelligence ensures high levels of reliability and validity for the analysis of latent content, particularly in an environment where character restrictions can heighten the importance of context when analyzing content’ (Su et al., 2017, p. 422). Content analysis allows for exactly the kind of context-rich close reading that topic modelling falls short of. Further, a close reading of tweets also allows for interrogating an element of tweets that is neglected by the topic modelling’s focus on *text* but can convey much meaning: embedded media (Goodman & Light, 2016). In the case of Twitter and conversations on Putin’s war therein, embedded media concern, for example, pictures, like memes or caricatures in relation to the invasion, videos displaying war footage, witness reports or political speeches, and hyperlinks to external resources like (Russian) news outlets. Publications on content analysis of Twitter data on COVID-19 conspiracies by Küçükali et al. (2022) and Griffith et al. (2021) served as the methodological basis of how this content analysis was conducted.

This hybrid content analysis first executed the topic modeling, which required some data cleaning. In order to render tweets interpretable for a machine learning algorithm, the dataset is rid of all punctuation and hashtags. In the next step, all non-English tweets are translated by using Deepl again. Although multi-lingual datasets can theoretically be processed using topic modelling, this linguistic diversity is hardly useful for the sake of researching the pro-Putin conversation in the EU as, in its standard configuration, LDA might wrongfully identify different topics based on foreign words conveying the same meaning. It might be insightful to look at differences in specific language communities, identifying Member State-specific differences may however also be achieved through the hand-coded labeling of locations elaborated on in section 3.1. The now uniformly English content is normalized through import in an open-source Python-tool. Normalization, in this case through "stemming", refers to the algorithmically driven process of reducing words to their word stems, so that patterns can be detected more accurately (Grimmer & Stewart, 2013). This marked the end of the preparatory steps and then allowed for the application of the LDA to deduce topics. The most dominant topics throughout the tweet corpus are then visualized via word clouds and then followed by the content analysis. Given the research question, this qualitative analysis pays special attention to COVID-conspiracy tropes of mass extermination or population control and alleged schemers (New World Order, Qanan, the Great Reset, Bill Gates, George Soros, WEF) identified in the literature review. Once users applying such themes are identified, their country of origin is analyzed to (dis)confirm that COVID conspiracy theories are indeed most widespread in Eastern European countries (Theocharis et al., 2021; Walter & Drochon, 2020).

3.3 Social Network Analysis - Algorithmic Visualization

At this point, the employed method generated insights into the kinds of motifs and themes that Twitter accounts posting content in favor of Putin's invasion feature, the extent to which these are laden with COVID conspiracies, and from which Member States users employing such motifs are coming from. Yet, no conclusions on whether accounts tweeting such tropes serve as amplifiers of content or functioning as hubs for content-cascaded in vast echo chambers can be made. So even if the prior hybrid content analysis demonstrates that only a small number of accounts retrofit such themes to the Ukrainian context, they might still be highly influential on Twitter as their content reaches a broad audience or because it promulgates intensely amongst like-minded others. To assess how and if the analyzed accounts, specifically those perpetuating COVID conspiracies, are connected amongst one another, with other handles using pro-Putin hashtags, and the wider Twitter population, a social network analysis (SNA) is thus conducted.

SNA is theoretically grounded in graph theory and was introduced to the social sciences in 1967 by Stanley Milgram (Milgram, 1967; Watts, 2014). Since then, SNA has seen wide application across disciplines (Newman, 2011), but has received special attention for explaining the dynamics behind content-cascades and information diffusion on social media, for example, in publications dedicated to investigating inauthentic behavior or foreign interference (Starbird, 2017, 2018). In interrogating the online conversations on the COVID-19 pandemic, SNA has been found to be particularly insightful (Eskandari et al., 2022; Yum, 2020). Hence, SNA is deemed best-fit to make a valuable contribution in answering how pro-Putin users tweeting COVID conspiracies are connected with others in the dataset that do not and if they play an important role in this particular conversation. In this part of the analysis, and to be consistent with graph theory lingo, users will be referred to as “nodes” and user connections, based on online interactions as “edges”.

To conduct this SNA, Gephi, an ‘open-source network exploration and manipulation software’ (Bastian et al. 2009, p. 361) was chosen. This is because the program features a variety of spatialization layout algorithms that enable the algorithmic visualization of a network and retrieve information on a node’s centrality. All EU-users priorly identified are imported into Gephi via a CSV file. Their retweet behavior is then monitored and recorded through the built-in “Twitter Streaming Importer” over a 7-day-period. I focus on retweets, rather than other key metrics such as liking, following, or commenting, as retweets are considered the golden standard to identify network dynamics. This is because users, by ‘broadcasting messages .... become part of a broader conversation’ (Boyd, Golder, & Lotan, 2010, p. 10). It is this broader debate of pro-Putin accounts that is important for elucidating the importance that tweeters applying COVID conspiracy theories have in the larger network of these accounts participating. To give visual meaning to this randomized network of nodes, the Force Atlas 2 spatialization algorithm is used, as this spatialization algorithm is based on repulsion by degree, meaning sets of nodes closely connected gravitate toward another visually and thereby demarcate sub-communities (Jacomy et al., 2014). Additionally, and to give more visual cues to the graph, nodes are scaled according to their degree centrality (the number of edges that they are connected with). Bigger nodes, therefore, show comparatively highly connected nodes central to the network in connecting different clusters or because they function as the source of much-retweeted content. Also, nodes featured in the original dataset are colored as either “wider network” (dark blue), “pro-Putin” (neon green), or “COVID conspiracist” (bright yellow) to emphasize the sub-classes of nodes in the network (Theocharis et al., 2021).

The mixed-method approach outlined in this chapter introduces a mode of multi-tiered hybrid analysis to the current discussion on the role of COVID conspiratorial motifs in tweets supporting the invasion of Ukraine, combining qualitative and quantitative methods throughout every step. From 20 March 2022 up to and including 4 April 2022, the day the world learned of the Bucha massacre, 33,918 tweets featuring pro-Putin hashtags were collected through two scraping iterations. These tweets were then filtered, categorized, and analyzed through a series of qualitative and quantitative methods, namely topic modelling content analysis and SNA.

4 Tales of Western Imperialism and Ukrainian Nazism

In this empirical chapter, the developed multi-tiered hybrid methodology is applied in a stringent manner, resulting in three sections that correspond with the outlined steps in chapter three. Namely, 1) the data collection, data cleaning, and hand-coding to identify the volume of tweets featuring pro-Putin hashtags in the EU and differences amongst Member States; 2) the hybrid content analysis of pro-Putin tweets by EU-users to elucidate the extent to which these tweets repurpose COVID conspiracies; and finally 3) the SNA for answering the sub-question on how users that apply COVID-related conspiracies to the Ukrainian context are connected to other tweeters in the extracted dataset as well as the wider Twitter population. This chapter closes with an interim conclusion that summarizes the findings.

4.1 The Pro-Putin Conversation in the EU: Declining and Concentrated in the West & South

The first round of the Python-based scraping of #IstandwithPutin from 20 March 2022 to 4 April 2022 extracted 7,101 Tweets. The additional scraping iterations with the three hashtags identified as commonly used in pro-Putin conversations via snowball sampling (#NaziUkraine, #AbolsihNato, #IstandwithRussia) retrieved another 26,818. In total, these repeated iterations resulted in a dataset consisting of 33,918 entries, with #NaziUkraine being the most used hashtag with 11,880 mentions, closely followed by #IstandwithRussia, used 10,547 times. #Abolishnato was featured 4,391 times and, hence, is the least shared hashtag in comparison. The removal of duplicates generated by the repeated scraping left 31,475 unique tweets that served as the basis of the manual coding of user locations and comparisons of hashtag use in the EU once users were located.

To locate tweeters geographically, the 31,475 unique tweets from 12,848 users were subject to the qualitative hand-coding outlined earlier. The location of about half of these accounts, comprising about a third of the total tweet volume, could not be approximated, as profile consultation did not deliver a conclusive assessment or because these accounts had been removed since. These accounts were, therefore, classified as “untraceable” (Figure 1). The majority of tweets (51%) and 49% of account locations could be identified, however. Amongst those, 14,420 tweets from 4,567 users, representing 46% of all extracted tweets and about a third of inspected users, were found to be non-EU. “Untraceable” accounts and accounts found to be situated outside of the EU were subsequently cleaned from the dataset. Afterward, 4,599 tweets (15%) from 1,793 EU users (14%) of the original dataset remained.

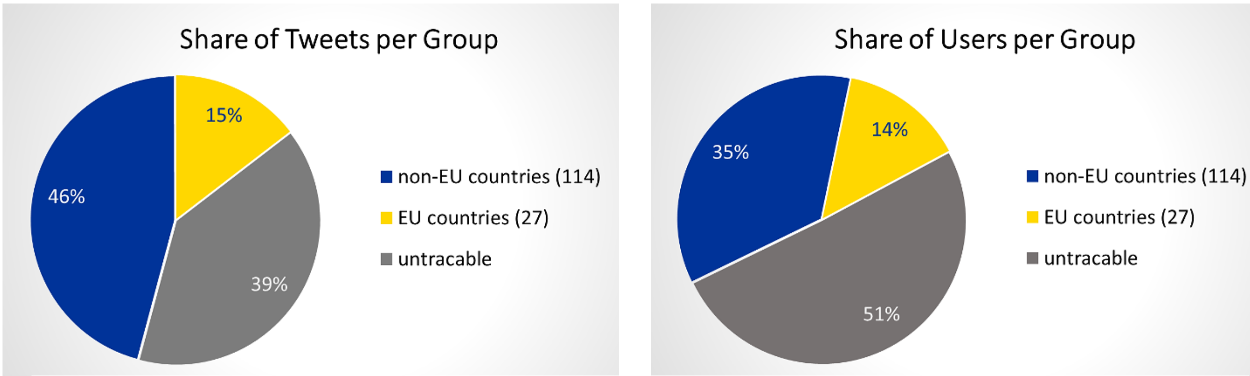

Figure 1: Share of Tweets vs Users Grouped into EU, Non-EU, and Untraceable

In terms of country representation, besides Malta, all other 26 of the EU-27 are represented in the dataset, evidencing that the identified hashtags enjoyed application across the EU. However, the number of users coming out in support of Putin's actions varied considerably between Member States (Figure 2). Amongst the countries with the most users are Italy (446 users), France (371), the Netherlands (187) and at the lower end, Slovakia (3), Latvia (3) and Bulgaria (2). Generally speaking, we see the largest share of the user base coming from Western Europe and the Mediterranean, except Portugal (only 28 users) and Malta, which had no users in the dataset to begin with. Eastern European and Northern European show low numbers throughout.

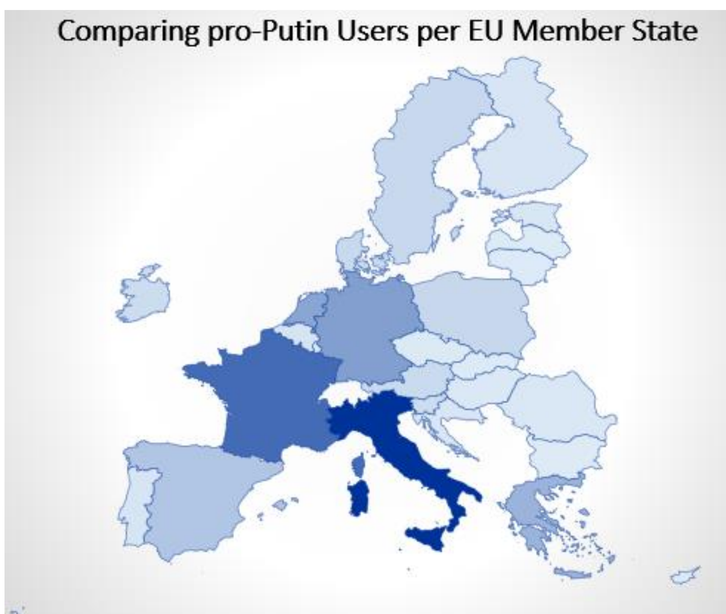

Figure 2: Comparing the Number of Pro-Putin Users per EU Member State

After having identified the geographic composition of the corpus and having cleaned the dataset accordingly, the daily share of tweets featuring hashtags in support of Putin in the EU could be inspected (Figure 3). During the observed period, the daily use of #IstandwithPutin in the EU was in decline but generally meager with 86 mentions on 20 March 2022 and mentioned just 37 times on 4 April 2022. This usage-level is nowhere near the popularity that propelled the hashtag to become one of Twitter's international top trends on 28 February 2022 (citations). Although widely popular in the original dataset with 4,392 tweets featuring the hashtag, #AbolishNato received very little attention by EU-user during this 16-day long period, even plunging down to a single mention on 31 March 2022. #IstandwithRussia initially also experienced a negative trend, but consistently gained popularity from 31 March onward, with a notable increase of mentions on the day of the Bucha revelations to 125 features. #NaziUkraine with 3,024 total mentions was the most used hashtag in the EU and outperformed #IStandwithRussia almost fourfold. Features of the hashtag spiked on 22 March 2022 with 310 mentions. This outlier can be linked to a gaining of traction of visual content on Ukrainian citizens being punished for marauding and subsequently taped to lampposts.

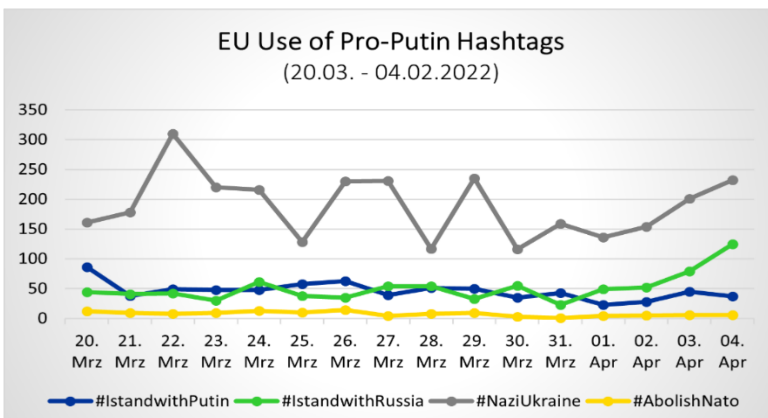

Figure 3: Use of Pro-Putin Hashtags in the EU

Taken together, the illustrated uptake-levels demonstrate that #IstandwithPutin did not maintain its level of popularity from back in late February (Le Roux, 2022) and although #NaziUkraine is the most widely used hashtag in pro-Putin conversations in EU Member States, the combined tweet volume demonstrates that the conversation as such has considerably lost momentum compared to the hundred thousands of features #IstandwithPutin enjoyed on a single day back in February (CASM, 2022; EDMO, 2022). This waning resonance might be attributed to the effectiveness of Twitter's actions to remove accounts exhibiting inauthentic coordinated behavior in early March (Collins & Korecki, 2022) but might also be indicative of an organic decline in Putin-support on Twitter during the specified time as a result of large numbers of accounts coming out to counter such narratives (Chen & Ferrara, 2022). Importantly, the diminishing volume of tweets backing the Kremlin's action does demonstrate that positive sentiments toward the invasion are held by a relatively small number of EU users only, which is consistent with earlier findings (CASM, 2022). This, by default, already limits the widespreadness of COVID conspiracies to the Ukrainian context in the first place, as research indicates that it is mostly within pro-Putin conversation that these motifs are applied in (EDMO, 2022). Amongst the declining number, as the country-based comparison shows, EU users supporting the invasion are predominantly situated in Western and Southern Europe. At this point of the analysis, this geographically specific resonance cannot be attributed to conspiratorial thinking being more present amongst these constituencies, for that, the hybrid content analysis delivers answers. Further, the popularity of #NaziUkraine within this conversation already hints at disinformation on Nazism in Ukraine, rather than conspiratorial motifs, playing a more fundamental role in justifying the Kremlin's actions, (Hanley et al., 2022).

4.2 Covid Conspiracy Theories: A Rare Occurrence in the Pro-Putin Conversation

The topic modelling via the Python-based open-source application identified four latent topic patterns in the corpus of 4,599 tweets. In terms of dominance, pattern 1 (1,434 tweets) and pattern 3 (1,419) compromise almost an equal share of the source collection, with 31,1% and 30,9% respectively. The remaining tweets are largely dominated by topic 4 (1,049), equaling 22,8% of the corpus, while 697 tweets, or 15,6%, were labeled as belonging to topic 2. The computational illustration of the most dominant words within each topic via word clouds shows considerable overlap in key terms (Figure 4). For example, "Ukraine" or "Ukrainian" are found in each of these patterns, while "NaziUkraine" is depicted as a key phrase in both, topic 1 and topic 3. The distant reading achieved via topic modelling would thus suggest that tweets – especially in pattern 1 and 3 - cover similar topics. Nevertheless, the word clouds also feature unique words, such as "roma", "nato", "lie", or "Bucha". Interestingly though, and besides mentions of "lie" and "media" in topic 2, there is little indication of general conspiratorial rhetoric in the tweet collection. In terms of conspiratorial COVID motifs, the topic patterns are devoid of any mention of "the Great Reset", "biolabs", "the WEF", "Klaus Schwab", "Soros", or "New World Order" (Bruns et al., 2021; Imhoff & Lamberty, 2020; SOMA, 2020). At this point of the analysis, this lack of conspiratorial key terms suggests that such established themes are of minor importance for pro-Putin Twitter content by EU users and that narratives on Nazism are of greater significance, which solidifies the impression the analysis of hashtag use has hinted at previously.

Figure 4: Four Dominant Topic Patterns within Tweets by EU-users (Generated via Topic Modelling)

A close reading of tweets and embedded media demonstrates that regardless of terminological similarity between different topics ("Ukraine", "Naziukraine"), reasons for condoning Putin's actions are distinctly different per pattern. As such, topic 1, the most dominant topic, largely contains tweets that articulate how the encroaching Western imperialism, specifically through the continuous 'eastward expansion of NATO' that followed the collapse of the Soviet Union, has provoked Russia for the longest time and, ultimately, left Putin 'no other option' than to go on the offense (Figure 5). EU-based tweeters using this line of argument also urge Western leaders to refrain from supporting Ukraine financially and militarily to avoid being dragged into a war fueled by US President Biden to advance a fascist American geopolitical agenda, hence the keywords "fascism", "presid", and "nato". Despite speaking of such an agenda and the need for a multipolar world order, this dominant narrative does not incorporate established tropes on the Agenda21/Agenda30 or a New World Order (Beirich & Potok, 2014; O'Connor, 2021). Further, tweets in this topic do not explicitly take reference to a supposed Nazi-problem, regardless of naziukraine" being a key term in pattern 1 and many of these tweets contain #NaziUkraine. Therefore, the usage of the hashtag can be understood as an attempt to expose these tweets to a larger audience, rather than picking up Nazi disinformation.

Figure 5: Example of Tweet in Topic 1 (User Anonymized)

On the other hand, for content in topic 3, the second largest topic, the usage of #NaziUkraine is explicitly connected to accusations of rampant Nazism within the Ukrainian forces and used to legitimize Putin's actions. The emphasis of narratives on widespread Nazism in Ukraine detected here is again consistent with Hanley et al.'s (2022) analysis, but no conclusions on whether or not these are part of a Kremlin-sponsored campaign can be drawn. To back these Nazi allegations, a variety of visual content is utilized (Figure 6). For example, a collage of female civilians/soldiers said to belong to the Azov battalion and posing with various Nazi symbols, is frequently used. Content featuring this particular collage or similar depictions is often complemented by statements on the 'special military operation' being necessary to protect historic Russians in the Donbass region who are said to have suffered at Zelensky's hands for the past eight years. Further and connected to the key terms "tied" and "roma" of this pattern, priorly mentioned pictures of marauders tied or glued to lampposts are widely circulated. Rather than directed at marauders and understood as acts of vigilantism, these pictures are reinterpreted as emblematic of Ukraine's Nazi problem, as these victims are said to belong to the Roma community. Such stories on racial discrimination, as these tweeters argue, are deliberately not reported on by Western media. This lack of reporting, however, is not found to be associated with a secretive plan by a sinister elite, unlike earlier framings (Kharazian & Knight, 2020), but more so linked to a supposed Russophobic bias by journalists.

Figure 6: Example of Tweets in Topic 3 (Users and Persons Anonymized out of Ethical Considerations)

The 1,049 tweets in Topic 4, with #IstandwithPutin being the most important key term, are a miscellany of pledges of allegiance to Putin. Many of these tweets link to speeches of the Russian president, commending him for his 'outstanding statesmanship' and praising him as an 'inspirational and charismatic' leader, traits that his Western pendants are argued to lack. Others share videos of a pro-Russia auto convoy in Berlin from the 9th of April and interpret this protest as a sign that many EU citizens are empathetic of Putin's actions. The key term "Bucha" already alluded to the Bucha massacre playing a prominent role in this pattern. As these gruesome revelations are inconsistent with claims of Putin as an honorable leader, the massacre is outright denied or reinterpreted as a false flag operation staged by alternating (foreign) secret services, including the MI6 and the CIA (Figure 7). These tweets are the first so far that speak to a conspiratorial mindset, as they conjure up imagery of malign and secretive machinations (Douglas et al., 2019; Sunstein & Vermeule, 2009), yet are devoid of specific mentions of COVID-related motifs. Rather than popular scapegoats like Bill Gates or George Soros (Ball & Maxmen, 2020; Bruns et al., 2021), top politicians in the West are accused of conspiring to bring about the downfall of the Russian state, demonstrating COVID themes are also largely absent in this dominant narrative.

Figure 7: Examples of Tweets in Topic 4 (User and Persons Anonymized out of Ethical Considerations)

Topic 2, the topic with the smallest number of tweets, with “media” and “lies” as key terms was the only word cluster in which the distant reading hinted at conspiratorial thinking (Kharazian & Knight, 2020; Marwick & Lewis, 2017). Largely, however, tweets on a lying media apparatus argue in the same vein as was the case in topic 3, namely that Western media intentionally turn a blind eye to wrongdoings by the Ukrainian side due to their supposed anti-Russian stance. These accusations are repeatedly accompanied by extreme footage of war crimes allegedly committed by the Ukrainian forces. The most widely shared piece of such content is a violent video depicting presumably Ukrainian soldiers kneecapping Russian prisoners of war, followed by another video showing a soldier – allegedly Ukrainian – stabbing out the eyes of another man in uniform[4]. These videos are consistently accompanied by calls to end support for Ukraine in face of such “barbarity”, declarations of unwavering support to Russia in face of such atrocities, and further complaints on anti-Russian Western media intentionally turning a blind eye to such instances.

The hybrid content analysis evidences that besides tweets in topic 4 appealing to conspiratorial imaginary more generally, COVID conspiracy theories play no prominent role in either of the four topics. Deeper engagement with the tweet corpus identifies only a very limited subset of 60 users who explicitly reference such motifs in 111 tweets. Interestingly, this subset of users is localized in only ten Western and Southern European countries from the 26 Member States identified in the collection earlier (Table 2). The Netherlands with 24, Italy with 13, and France with 7 such accounts, rank amongst the top three, comprising almost three-quarters of this limited subset. Contrary to what the literature says on conspiracy

[4] I deliberately choose to not include screenshots of tweets displaying such explicit violence in this thesis, hence the lack of visual evidence here.

theories and COVID tropes specifically resonating most successfully in Eastern European countries (Theocharis et al., 2021; Walter & Drochon, 2020), the composition of the dataset here points to the opposite, with no user from Eastern Europe retrofitting COVID conspiratorial themes in pro-Putin conversations.

Country	Accounts Using COVID Tropes
Netherlands	24
Italy	13
France	8
Germany	6
Spain	3
Austria	2
Belgium	1
Greece	1
Sweden	1
Ireland	1

Table 2: Number of Accounts from 10 Member States Using COVID Tropes

Content-wise, such tweets are scattered across patterns and combine each topic's dominant strand with established COVID themes, besides 5G hoaxes, who are the only conspiratorial motifs such tweets are devoid of (Figure 10). In topic 1, NATO joins the ranks of sinister organizations and is framed as the new culprit behind establishing the "New World Order", instrumentalizing Zelensky, who is regarded as a puppet leader, to achieve this end and as financing biolabs in Ukraine to engineer the next wave of coronaviruses ("plandemics"). In the second most dominant pattern (topic 3), tweets heavily reference George Soros, Bill Gates, and Klaus Schwab as being part of a WEF operation to render #NaziUkraine an international superpower and ultimately actualize the "Great Reset" to subjugate the world. The pledges of allegiance to Putin in topic 4 are also picked up on in tweets repurposing COVID themes, overtly praising Putin as being the only one that may bring a halt to the "Great Reset" or the UN's "Agenda30" and allowing the world to finally throw off the heavy yoke of Western oppression. Under topic 2, although the least dominant topic, a distinct narrative speaking of a perceived subservience by vaccinated citizens emerges amongst Dutch accounts only, who – as shown priorly - make up the biggest share of users retrofitting COVID motifs.

Figure 8: Examples of Tweets Featuring COVID Conspiracy Theories (Users Anonymized)

This hybrid content analysis demonstrates that COVID-related conspiratorial themes are hardly applied by EU tweeters supporting Putin's war with only 111 of the 4,599 tweets in the scraped dataset from 20 March 2022 to 4 April 2022 conjuring up such imagery. Rather, dominant narratives in pro-Putin conversation center around Anti-NATO talk, disinformation on Ukraine having a Nazi-problem, Putin praises, or war crime footage to illustrate the brutality of Ukrainian forces and the lack of reporting by Western media on such instances. The 60 accounts retrofitting COVID tropes are concentrated in a small number of EU countries, namely, the Netherlands, Italy, and France, evidencing that the occurrence of such online behavior is further restricted to some Member States in the west and south of the EU only.

Given this lack of uptake in the specified period, there is little indication of COVID conspiracy theories having regained the pervasiveness they enjoyed priorly (Griffith et al., 2021), disconfirming other findings on these themes being widely adopted in conversations supporting Putin's war (EDMO, 2022). However, although COVID themes are rarely repurposed in these conversations and only present in a few EU Member States, users employing such themes might still be endorsed by a larger network or influential in a vast echo chamber and, hence, are potentially taking on an important role for fermenting such views (Benkler, Faris, & Roberts, 2018; McNeil-Willson, 2022; Sunstein, 2001). The following SNA generates insights into the importance of these accounts to the wider network and hence answers the sub-research question.

4.3 Covid Conspiracists: A Small and Secluded but Cross-European Echo Chamber in the Wider Pro-Putin Network

The import of the 1,793 EU handles from the dataset of tweets featuring pro-invasion hashtags into Gephi and the subsequent tracking of retweet behavior via the "Twitter Streaming Importer" over a 7-day period generates a wider network compromising 7,703 nodes connected through 18,945 edges (Figure 9). Algorithmic visualization of the network via the Force Atlas 2 layout depicts this graph to be split across four sub-communities that are bridged by one central account: Elon Musk[5]. The color-coding and the scaling of nodes according to their degree centrality (the sum of times they retweet or are retweeted) shows that pro-Putin accounts play an outsized role in the network. While only representing about 9% of all nodes, users identified to be in favor of the invasion earlier but not adopting COVID conspiratorial motifs, make up almost 60% of all interactions in the graph, hence, showing a high level of activity and interconnectedness with the wider Twitter population.

The 60 users identified to repurpose COVID tropes, on the other hand, are only responsible for 2.7% of total interactions. Their network activity was in fact so meager that the color coding and the scaling of nodes based on degree centrality did not allow for visual identification of COVID conspiracists in the network. Given this lack of importance for the wider network, these accounts are found to be neither instrumental for content-cascades by being retweeted nor important as amplifiers by retweeting others' content. Only after adding labels to the most central tweeters amongst the 60 accounts could their place in the network be ascertained. With the exception of "artimesia_black" (Italy), "_babacar" (France), and

[5] Why Elon Musk is found at the center of this network cannot be determined via SNA and also does not contribute to answering the research question. However, further research into this matter is encouraged.

"xabasso" (France), all other 56 accounts coming from 10 EU Member States who were identified as applying COVID motifs in pro-Putin tweets are nestled around the Dutch user "slechtvolk" in the upper left sub-community. Hence, "Slechtvolk", the account with the highest degree centrality making up almost a fifth of the combined edges amongst this user set, serves as a hub for this small sub-community of COVID conspiracists coming from the ten Western and Southern European Member States outlined above. The secluded nature of this sub-community with most of the interactions being directed to only a few other COVID conspiracists nearby indicates the existence of a small echo chamber amongst such users.

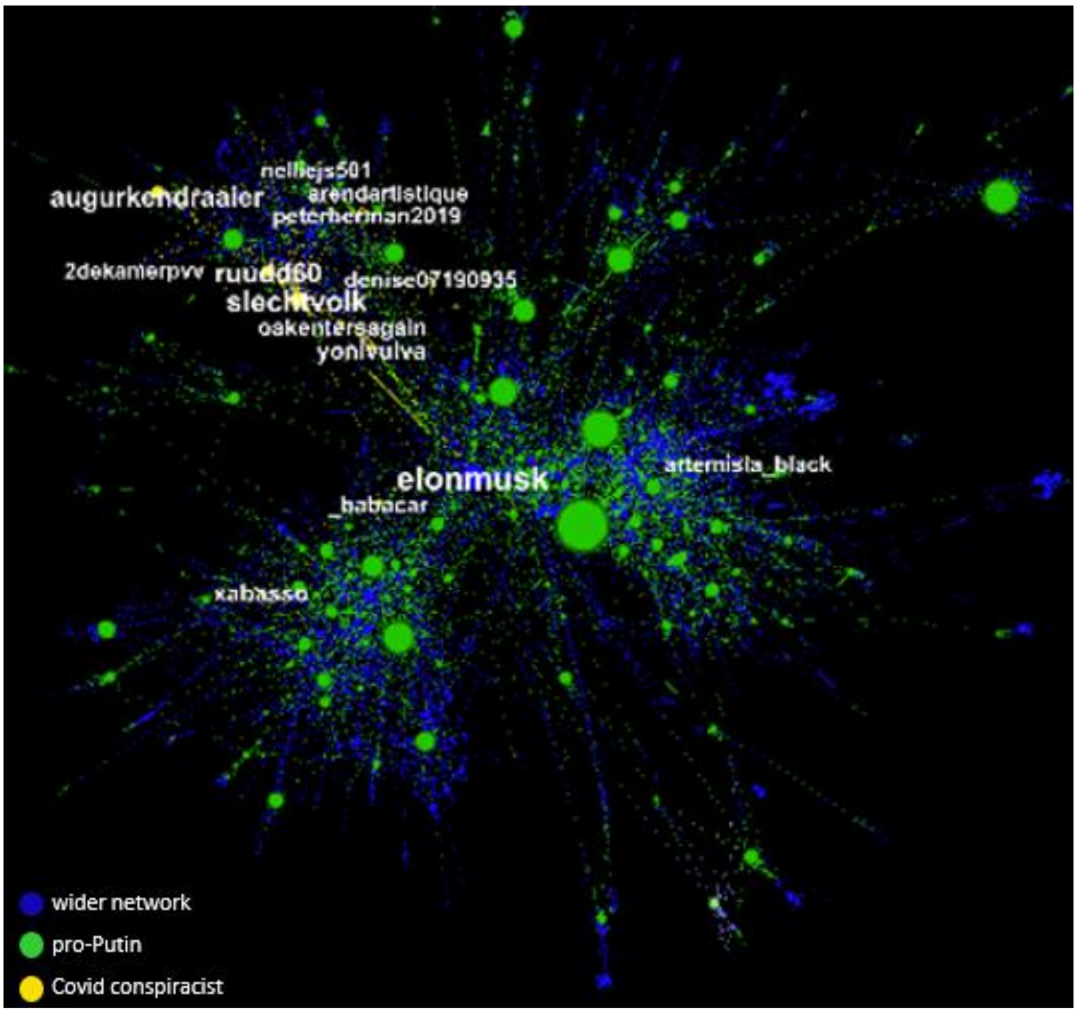

Figure 9: Social Network Analysis Based on Retweets

The SNA demonstrates that users employing such themes are found to be situated in a small and secluded but cross-European echo chamber in a wider pro-Putin Twitter network. These findings complement the earlier hybrid content analysis, evidencing that COVID conspiratorial themes do not only play a minor role in online conversations supporting the Kremlin's actions content-wise but that uptake of such tweets/importance of such tweeters is also not reminiscent of the viral network dynamics observed during the pandemic, with conspiracy theories first promulgating in echo chambers before penetrating the mainstream (McNeil-Willson, 2022; Ortiz-Sánchez et al., 2020). Instead, the SNA further evidences the popularity of the four dominant narratives identified earlier via analysis of the topic patterns, as accounts feeding into this narrative are highly connected to and influential for the wider Twitter network.

4.4 Interim Conclusion

This multi-tiered hybrid methodology applied in this chapter began by making use of the elevated access to Twitter's API, scraping tweets featuring #IstandwithPutin via a Python-script from 20 March 2022 to 4 April 2022. To get a more exhaustive impression of the pro-Putin conversation in the EU, this scraping was then repeated for #NaziUkraine, #AbolishNato, and #IstandwithRussia, hashtags which had been identified to be commonly used in connection with #IstandwithPutin. The 33,918 tweets collected that way were then rid of duplicates and non-EU users by a qualitative hand-coding based on consultation of 12,848 user profiles. This data cleaning left 4,599 tweets from 1,793 users in the remaining data set of now only EU users active in supporting the invasion of Ukraine, representing 15% of tweets and 14% of users from the entire corpus. In terms of user origin, besides Malta, tweeters taking part in this conversation were found to be spread throughout all Member States but concentrated in the West and South of the EU. Analysis of hashtag use demonstrated that #NaziUkraine is the most successful hashtag in the EU but that the total volume of tweets coming out in support of the Kremlin has nevertheless decreased compared to February 2022. Whether this decline in resonance is attributable to the removal of accounts exhibiting inauthentic behavior, or rather the result of an organic decline in people backing Putin's actions could not be determined. However, as prior findings suggest that COVID motifs saw application especially amongst users in support of the war (EDMO, 2022), this decreased popularity already limited how widely these tropes were repurposed.

The processing of these 4,599 tweets through an open-source topic modelling application then detected four latent topic patterns. The qualitative content analysis that followed identified four dominant narratives corresponding to these patterns, that being Anti-NATO sentiments in Topic 1, the most dominant topic, Nazi disinformation targeting Ukraine in Topic 3, pledges of allegiance to Putin in Topic 4, and war footage used to articulate an anti-Russian bias in reporting by Western journalists in Topic 2, the least dominant pattern in the corpus of EU users. COVID tropes are found to be rarely applied, featured only in 111 tweets by 60 users. In these tweets, the identified dominant narratives per pattern were merged with established COVID themes, like the "New World Order", the "Great Reset", the "Agenda30", or biolabs and culprits, such as George Soros, the WEF or Bill Gates, but also introduced a new perpetrator: NATO. Interestingly, users employing such themes predominantly come from the Netherlands (23 users), Italy (13), and France (8), contradicting earlier studies that evidenced such thinking being more present in Eastern European countries (Theocharis et al., 2021; Walter & Drochon, 2020).

An SNA was then conducted to analyze the 1,793 EU users' retweet behavior in order to determine the composition of the wider network and the role that the 60 accounts retrofitting such themes play within the broader conversation on the invasion of Ukraine. The visualized graph via Force Atlas 2 based on recorded data during a 7-day period illustrates that these 60 accounts, coming from ten different Member States, are largely centered around the Dutch user "Slechtvolk" but lack connectivity to the wider network, especially compared to other pro-Putin accounts who were responsible for 60% of retweets in the graph. Since almost all accounts repurposing COVID motifs are concentrated in this sub-community with few or no linkages to other nodes outside this sub-community, this user network is understood as a small and isolated echo chamber that has little impact on the adoption of such themes for the larger network. This runs counter to what the literature says on how the infodemic further compounded the popularization of conspiratorial (COVID) content with echo chambers spanning across large sets of users (Leitner et al., 2021; McNeil-Willson, 2022). Overall, the developed multi-tiered hybrid method applied in this thesis demonstrates that EU tweeters supporting Putin's war in Ukraine repurpose conspiratorial COVID motifs to a *very* limited extent and that tweeters sharing such content are hardly connected to the wider Twitter network. Therefore, this thesis does not share assessments on such theories having regained momentum since the outbreak of the war and or sizeable echo chambers of COVID conspiracists have started to share this content to a wider network (EDMO, 2022; Jarynowski, 2022; Kayali & Scott, 2022).

5 Conclusion

This thesis set out to interrogate the extent to which EU tweeters supporting Putin's war in Ukraine repurpose conspiratorial COVID motifs and, given the importance of echo chambers in festering conspiratorial thinking and their role in exposing such themes to a wider audience, how tweeters applying such motifs are connected to other (pro-Putin) users on Twitter. Through the first step of the multi-tiered hybrid analysis, 33,918 tweets of pro-Putin conversations were collected based on scraping of the hashtags #IstandwithPutin, #NaziUkraine, #AbolishNato, and #IstandwithRussia from 20 March 2022 to 4 April 2022 globally. Data cleaning and locating users left 4,599 tweets coming from 1,793 EU users in the remaining corpus and located across 26 of the EU-27, with most of them situated in Western and Southern Member States. Analysis of hashtag use shows that #NaziUkraine outperformed other hashtags, but that pro-Putin content has overall declined on Twitter compared to late February. The hybrid content analysis highlights that rather than COVID tropes, other dominant narratives emerged in conversation backing the Kremlin's maneuvers. Specifically, anti-NATO sentiments, an uptake of disinformation on Ukrainian Nazism, frames of Putin as an excellent leader, and alleged Russophobia amongst Western journalists. Only in about 111 pro-Kremlin tweets (2.4% of the entire corpus) were COVID conspiratorial themes found to take explicit reference to, for example, the WEF, the pseudo-documentary "plandemic", the UN, George Soros, or biolabs. These tweets were authored by only 60 accounts (3.3% of the recorded users) and highly concentrated in ten Member States to the west and south of the EU, disconfirming findings on COVID conspiracy theories being especially successful in the Eastern Member States. In the last step of this method, the SNA evidenced that the small number of tweeters applying these motifs are isolated from the wider retweet-network in the pro-Putin conversation, neither responsible for the successful amplification of content or largely ignoring and ignored by accounts outside of their sub-community, forming a secluded echo chamber with users from the ten identified EU countries. To conclude, conspiratorial motifs have been found to be repurposed to a very limited extent only and the small number of tweeters applying such themes are isolated in the wider pro-Putin conversation.

Naturally, this thesis comes with some limitations. Firstly, basing the data collection on #IstandwithPutin and three other associated hashtags might have failed to capture other pertinent hashtags under which pro-Putin content and COVID conspiracy theories have started to flourish since the onset of the war. Secondly, as outlined in chapter three, other social networks – specifically Facebook – have a larger user base and are considered more representative of a wider population than Twitter and, hence, the detected behavior here might not be consistent with analysis based on data from other social network platforms.

Thirdly, by focusing only on the 16-day period between 20 March 2022 to 4 April 2022, longer-term developments in the resonance of COIVD motifs across the EU could not be recognized, hence, solely providing a snapshot of the network behavior during this specific period. However, especially the latter two limitations were the result of API restrictions problematized earlier, with Facebook stopping to onboard academics to their CrowdTangle program and Twitter denying me “academic” access to their Twitter archive dating back to March 2006, rather than linked to faulty research design. As such, this thesis joins in the choir of scholars calling for greater access to social media data to generate more holistic findings and encourages research to elaborate on platform-specific differences in the future.

Despite these constraints, through the multi-tiered hybrid method developed here, this thesis contributes to answering the academy’s call for exploring methodological synergies between different disciplines in the study of social media’s effect on society. As stressed in the literature review, publications on social media’s role in and for the war in Ukraine, especially when it comes to the application of COVID conspiracies therewithin, have largely not incorporated such rich methods yet. Based on my findings, claims of COVID motifs being extensively repurposed in this context and the pivotal role of echo chambers that emerged during the infodemic in amplifying such content could not be sustained. Hence, the weakening of this strand of the ongoing debate reinforces accounts that point more toward social media benefiting the collective countering of propagandistic attempts by malign forces. Perhaps, this momentary departure from negative conceptions may translate into a lasting reconsideration of the dooms-bringer framings awarded to social media since 2016, reinvigorating the moderate appraisals from 2011 that brought forth nuanced analysis. Of course, only once the war has come to an end, such conclusions can be more firmly drawn based on retrospective analysis.

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Appendix:

Appendix 1: Python-script for data collection

```
# import modules
import pandas as pd
import tweepy

# function to display data of each tweet
def printtweetdata(n, ith_tweet):
        print()
        print(f"Tweet {n}:")
        print(f"Username:{ith_tweet[0]}")
        print(f"Description:{ith_tweet[1]}")
        print(f"Tweet Text:{ith_tweet[2]}")
        print(f"Created at:{ith_tweet[3]}")
        print(f"Location:{ith_tweet[4]}")
        print(f"Following Count:{ith_tweet[5]}")
        print(f"Follower Count:{ith_tweet[6]}")
        print(f"Total Tweets:{ith_tweet[7]}")
        print(f"Retweet Count:{ith_tweet[8]}")
        print(f"Hashtags Used:{ith_tweet[9]}")

# function to perform data extraction
def scrape(words, date_since, numtweet):

        # Creating DataFrame using pandas
        db = pd.DataFrame(columns=['username',
                                   'description',
                                   'Tweet Text',
                                   'Created at',
                                   'location',
                                   'following',
                                   'followers',
                                   'totaltweets',
                                   'retweetcount',
                                   'hashtags'])

        # We are using .Cursor() to search through twitter
        tweets = tweepy.Cursor(api.search_tweets, words, since_id = date_since,
        until = date_until,
         tweet_mode='extended').items(numtweet)
```

```
      # .Cursor() returns an iterable object. This object can be altered
        list_tweets = [tweet for tweet in tweets]

        # Counter to maintain Tweet Count
        i = 1
        for tweet in list_tweets:
                username = tweet.user.screen_name
                description = tweet.user.description
                location = tweet.user.location
                createdat = tweet.created_at
                following = tweet.user.friends_count
                followers = tweet.user.followers_count
                totaltweets = tweet.user.statuses_count
                retweetcount = tweet.retweet_count
                hashtags = tweet.entities['hashtags']

                try:
                        text = tweet.retweeted_status.full_text
                except AttributeError:
                        text = tweet.full_text
                hashtext = list()
                for j in range(0, len(hashtags)):
                        hashtext.append(hashtags[j]['text'])

                # Here I am appending all the
                # extracted information in the DataFrame
                ith_tweet = [username, description, text, createdat,
                             location, following,
                             followers, totaltweets,
                             retweetcount, hashtext]
                db.loc[len(db)] = ith_tweet
                printtweetdata(i, ith_tweet)
                i = i+1

        #saves database as a CSV file.
        db.to_csv('C:/Users/Kevin_/Documents/CodeTrial.csv')

if __name__ == '__main__':
```

```
# These are the credentials I obtained with the developer access
# Because of privacy concerns and legal reasons, these are left blank
consumer_key = "XXX"
consumer_secret = "XXX"
access_key = "XXX"
access_secret = "XXX"

auth = tweepy.OAuthHandler(consumer_key, consumer_secret)
auth.set_access_token(access_key, access_secret)
api = tweepy.API(auth, wait_on_rate_limit=True)

# Entering Hashtag and initial date
words = "IstandwithPutin"
date_since = input()
date_until = input()

# number of tweets to extract in one run
numtweet = 5000
scrape(words, date_since, numtweet)
```

Verklaring van originaliteit / Declaration of originality

By submitting this test, I certify that:

- ✓ this work has been drafted by me without any assistance from others (not applicable to group work);
- ✓ I have not discussed, shared, or copied assessment work from/with other students;
- ✓ I have not used sources that are not explicitly allowed by the course instructors and I have clearly referenced all sources (either from a printed source, internet or any other source) used in the work in accordance with the course requirements and the indications of the course instructors;
- ✓ this work has not been previously used for other courses in the program, unless explicitly allowed by the instructors.

I understand that any false claim in respect of this work will result in disciplinary action in accordance with university regulations and the program regulations, and that any false claim will be reported to the Board of Examiners. Disciplinary measures can result in exclusion from the course and/or the program, and in a permanent endorsement on my diploma.

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