Argumentation in political Empowerment on Instagram

Aenne Knierim and **Ulrich Heid**
University of Hildesheim
Universitätsplatz 1
31141 Hildesheim
knierim@uni-hildesheim.de
heidul@uni-hildesheim.de

Abstract

This paper adopts a distant reading approach to analyze political empowerment on Instagram. We focus on argument mining and content classification to uncover cooccurences between aspects of political empowerment and argument components. We develop an annotation scheme based on literature in digital political empowerment, classifying content into five primary categories along the aspects of political awareness, personal e-identity and political participation. We implemented the modified toulmin scheme for argument component detection. As an example discourse, we chose the German discourses #WirSindMehr and #NieWiederIstJetzt. The upheaval was targeted against right-wing extremism and antisemitism. Political awareness emerged as the dominant category, highlighting convergent public concern against antisemitism and right-wing extremism. Claims and backings often contain statements about societal change and aim to raise consciousness. Calls for participation in offline events appear mostly in non-argumentative texts.

1 Introduction

Empowerment research has its roots in community psychology. There, it is defined as a "construct that links individual strengths and competencies, natural helping systems, and proactive behaviors to matters of social policy and social change" (Zimmerman and Rappaport, 1988). It is also related to Freire's theory 1970 of conscientization, which describes how critical consciousness is the first step to the ability of transforming one's status in society. Next to social and political understanding, the individual experience of empowerment includes a combination of self-acceptance and the ability to play an assertive role in controlling resources and decisions in one's community, for example through citizen participation (Zimmerman and Rappaport, 1988).

The notion of political empowerment was introduced to overcome the potential lack of citizen participation in democracies (Pirannejad and Janssen, 2019). While there is no set definition of political empowerment, and many theoretical models address empowerment, they all emphasize the need for competence and experience to be enhanced (Amichai-Hamburger et al., 2008). Examples of empowerment outcomes are political participation, influence and perceived control or transfer of power between groups of society, or resource mobilization skills (Leong et al., 2019, 2015; Alexander et al., 2016; Jones, 1978; Pirannejad and Janssen, 2019; Perkins and Zimmerman, 1995).

Researchers have examined political empowerment in the digital setting. Several studies have specifically investigated the role of social networks in promoting political empowerment (Leong et al., 2015, 2019; Waitoa et al., 2015; Hurley, 2021; Halliday and Brown, 2018). Building on this body of work, the present study examines political empowerment in social media. Specifically, we strive to characterize typical characteristics of political empowerment using a birds-eye view.

For this purpose, we perform two classifications. The first classifies political empowerment along the three aspects political awareness, political participation and e-identity, following Amichai-Hamburger et al. (2008) and Pirannejad and Janssen (2019). The goal is to identify how aspects of political empowerment are reflected in the data, as a first step towards a quantitative sketch of the phenomenon. The second classification is an argument mining task. We detect argument components using Habernal & Gurevych's modified Toulmin scheme 2017.

Finally, we want to identify cooccurences of the argument components and aspects of political empowerment. For example, do claims often express group identity towards a political stance?

As an example corpus, we chose the German

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discourses #WirSindMehr ("We are more") and #NieWiederIstJetzt ("Never again is now"). The upheaval was targeted against right-wing voters and took a stance against antisemitism after the attack on Israel on the 7th of October 2023. We investigate Instagram captions because scholars found that captions are where political issues are primarily communicated on the platform (Bast, 2021; Towner and Muñoz, 2018; Liebhart and Bernhardt, 2017; Lalancette and Raynauld, 2019).

2 Related work: digital political empowerment

In this study, we create annotation guidelines that cover all three aspects of political empowerment: e-identity, political participation and political awareness. Importantly, we built on literature that focused on political empowerment via the Internet, rather than political empowerment in an analogous setting. We refer in particular to the studies conducted by Amichai-Hamburger et al. (2008); Pirannejad and Janssen (2019), as these were pivotal for further research.

2.1 E-identity

Scholars argue that blogs and similar venues can serve as "identity workshops", allowing to test social skills (Bruckman, 1992). Besides, the anonymity of communicating online facilitates mastery, increasing self-efficacy. Next to the option of anonymity, the opportunity for editing allows for a (perceivably) highly protected environment. Impression formation also sets differently than in analog settings, as physical cues are often not available (Amichai-Hamburger et al., 2008). Another aspect is the ability for cross-cultural communication and the opportunity of finding similar others. Woo-Young (2005) finds that users can easily express their support or disapproval of opinions expressed online, potentially affecting the formation of public opinion and adding to the formation of group identity.

2.2 Political participation

Digitally enabled interactions between government and citizens can help citizens feel that they may make a significant contribution to politics (Pirannejad and Janssen, 2019; Amichai-Hamburger et al., 2008). The variety of available group decision-making tools eases action taking in the virtual space. Several scholars also found the opportunity for monitoring of government activities empowering (Woo-Young, 2005; Pirannejad and Janssen, 2019). This could include monitoring the allocation of government resources or the legislative activities of politicians (Woo-Young and Won-Tae, 2006). Simpler forms of participation include fundraising or petition signing (Johnson, 2017)

2.3 Political awareness

The Internet can play a critical role at "gathering and distributing a large volume of political information rapidly and at low cost"(Pirannejad and Janssen, 2019). Next to this, the availability of digital resources informs people about parties' efforts. Social communication enabled through social network sites also increases access to political information. Amichai-Hamburger et al. (2008) find that citizens can quickly find, for example, comparative stances taken by elected or potential representatives. Freire (1970) introduced the concept of conscientization, illustrating how empowerment can occur through critical consciousness of one's situation.

2.4 Empowerment in social media

An aspect of political empowerment unique to social media is the overlap between personal and public space, which encourages the preservation of the underlying network (Leong et al., 2019). In addition, social networks generate options for people to participate based on their interests, capabilities and capacities (Leong et al., 2019) – although this might also be true for ICTs in general. Another opportunity social media offer is the management of resources, and quick information coordination (Leong et al., 2019, 2015). Waitoa et al. (2015) also highlight that "the promise that social networks hold for diasporic populations is the ability to connect with their language and culture remotely".

2.5 Studying Instagram captions

Instagram's multimodal environment offers great potential for political communication (Bast, 2021). With 41% of the population in Germany using the platform (statista.com, accessed 01/2025), it is no surprise that Instagram reflects political moments of citizen engagement or plays a role in agenda-setting (Towner and Muñoz, 2018; Barbala, 2024). Following Bast (2021), Instagram is a popular tool for promoting a political image. In her review of the platform, Bast (2021) found that most studies focus on the self-representation of political actors on Instagram, particularly examining whether they use the platform to discuss political issues, share campaign information and mobilize voters.

Visual Instagram contents like images and videos have been studied to uncover macro-visual patterns of colors, photo-filters used and selfie-styles (Manovich, 2017), in attempt to study its visual culture (Caliandro and Graham, 2020; Gibbs et al., 2015). But Instagram is not limited to visual content, as it offers users the possibility of adding long captions to their posts which is where political issues are primarily communicated (Bast, 2021; Towner and Muñoz, 2018; Liebhart and Bernhardt, 2017; Lalancette and Raynauld, 2019). Therefore, in this study, we investigate political empowerment in Instagram captions. We use #NieWiederIstJetzt and #WirSindMehr as an example discourse.

2.6 Argument Mining

Argument Mining is an area of natural language processing defined by a variety of tasks, aiming to extract and structure arguments from unstructured text (Galassi et al., 2023). Most commonly, argument mining is defined as a classification task for detecting argumentative units such as premises or claims. It can also be defined as a relation extraction task, aiming to identify support or attack relations between argumentative units. Others have investigated argument facet similarity (Swanson et al., 2015), argument mining and fact checking (Dusmanu et al., 2017), usefulness of arguments (Passon et al., 2018), argument similarity (Boltuzic and Snajder, 2015) and even argument clustering (Reimers et al., 2019). Falk and Lapesa (2022) investigated reports of personal experiences in argumentation.

Common approaches to argument mining include traditional supervised machine learning approaches such as Support Vector Machines (Palau and Moens, 2011) or Logistic Regression (Goudas et al., 2014). Since the introduction of BERT (Devlin et al., 2019), many researchers made use of deep learning models for argument mining tasks, for example Bhatti et al. (2021) and Schaefer and Stede (2022). Both approaches rely on manually annotated datasets (Habernal and Gurevych, 2015). Due to the recent advent of large language models (LLMs), researchers have tested the performances of fewshot and zeroshot settings, finding that LLMs significantly outperformed the best performing RoBERTa-based baseline on a relation-based argument mining task (Gorur et al., 2025). This is very promising, as only few publicly available datasets exist for German, and annotations are costly. Other research tests the applicability of LLMs for argumentation corpora. For example, Mirzakhmedova et al. (2024) investigated their application for the annotation of argument quality. Ni et al. (2024) tested LLMs for a argumentative unit detection task.

Argument mining tasks can be performed on the micro-level (monological), macro-level (dialogical), or rhetoric models. Micro-level models “pinpoint an individual argument’s components and internal organization”, while “the macro-level model focuses on the relations between arguments and their external structure” (Patel, 2024). Next to the simple claim-premise scheme, two standard micro-level models are Walton’s scheme and Toulmin’s model, which Habernal and Gurevych updated for user-generated web discourse (modified Toulmin model) 2017; 2008; 2003. Argument mining on user-generated web content is typically performed on the micro-level, as user posts are typically short. As Schaefer and Stede (2022) stated, the language specific to social media proposes challenges for arguments, due too its linguistic characteristics such as spelling and grammar, hashtags, emoticons, and abbreviations. Boltuzic and Snajder (2015) point out that “unlike in debates or other more formal argumentation sources, the arguments provided by users, if any, are less formal, ambiguous, vague, implicit, or simply poorly worded”.

3 Data compilation and description

In the German political conversations of #WirSindMehr and #NieWiederIstJetzt, a group of civilians reacted to the political shift to the right in the country, taking a stance against racism and antisemitism. Formerly called “silent majority” by German newspapers (Stuttgarter Zeitung, accessed 01/2025), the upheaval was targeted against right-wing voters and politicians of the AfD party. The upheaval was a reaction to the Düsseldorfer Forum, a right-wing meet-up that was planning the “remigration” of Germans with migration background and refugees; and antisemitic incidences in Germany after the terrorist attack of the Hamas on Israel (Bensmann, Marcus et al., 2024). Over a period of three months, a total of two million people protested across Germany (Sauerbrey, 2024). We collected the data with Crowdtangle in the period between 10/07/2023 and 03/31/2024[1]. The

[1] crowdtangle.com

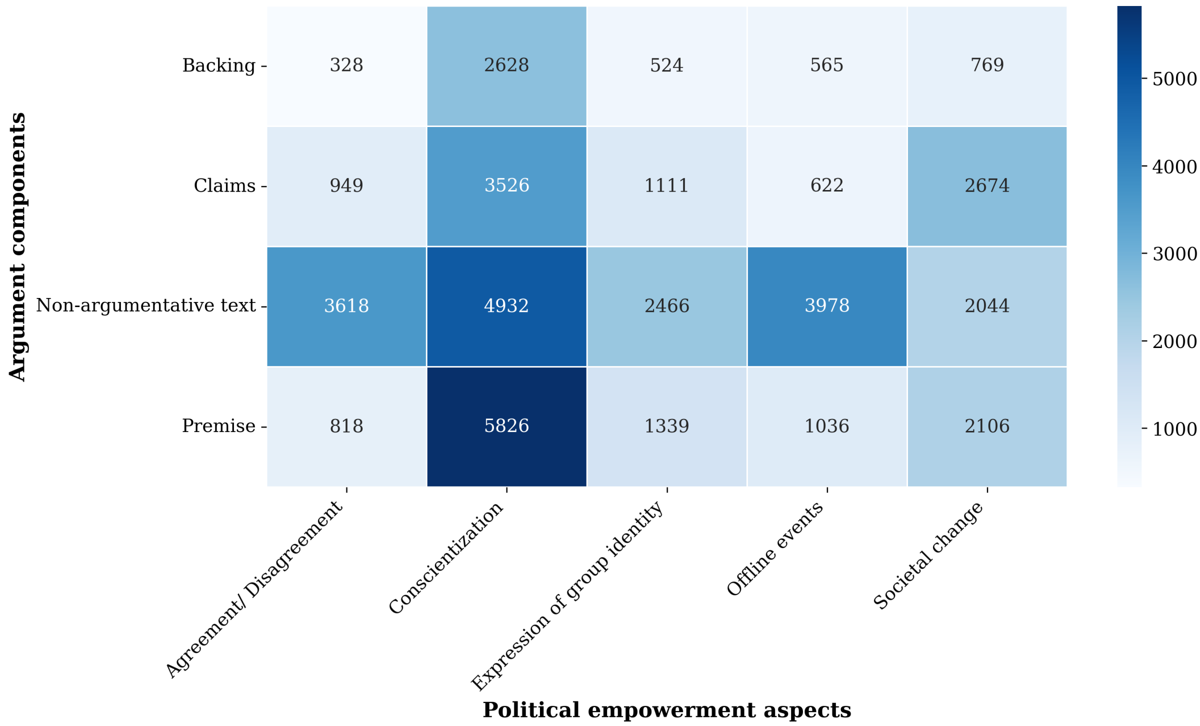

Figure 1: Cooccurences between argument components and political empowerment aspects.

search terms used were the hashtags #wirsindmehr or #niewiederistjetzt and spelling variants. The tool automatically searches for the words even without hashtags. We collected data from Instagram. The dataset comprises 13469 posts with the post length being 91 words on average. The total token count is 1279585. Two samples of around 1200 posts each were annotated for content and argument components. The annotation process is described in the sections 4 and 5.

4 Annotation process

4.1 Annotating for political empowerment

Based on the literature review presented in chapter 3, we initially extracted eleven possible labels (see apx. tab. 1). Two trained annotators labeled 1200 posts, a random sample from our corpus.

We iteratively worked with our annotators, which resulted in one additional category not present in the literature. We found that, next to calls for participation in offline events, users often report from offline events in their posts. We could not classify using all twelve categories, because not all classes sufficiently present in our dataset (see apx. tab. 1). Although six classes were annotated between 104 and 732 times, the other six were annotated between two and eight times. We also merged the classes "call for participation" and "report from political events" to handle class imbalances. The five resulting classes used to train our classifier are displayed in Table 3. A complete overview of our annotation scheme is visualized in Table 1 in the apx.

Interestingly, five of the six classes that have been annotated less than ten times cover aspects of political participation. They describe interactive tasks such as petition signing, fundraising, or inquiries to politicians. They might be more common on internet sites, as for example on funding and petition websites such as gofundme.com or change.org as well as other formats native to the internet like e-mail.

4.2 Annotating for argument mining

We define argument mining as a component classification task. A micro-level model is required, since Instagram captions typically consist of only 91 words. We use the modified Toulmin model introduced by Habernal and Gurevych (2017), since it was specifically adapted to user-generated web content. The modified Toulmin model comprises the argument components claim, premise, backing, rebuttal, and refutation (Habernal and Gurevych, 2017). We added non-argumentative text as a component. We adopted all other guidelines of the modified Toulmin model. The annotation was con-

Table 1: Count of annotated labels. Labels are performed by two annotators. Labels beneath the line are excluded from classification due to a low count.

Aspect	Label	Explanation	Count	Literature
Political Awareness	Conscientization	Raising consciousness about political circumstances	732	Freire 1970, Woo-Young & Won-Tae 2006
	Societal change	Post talks about a change in societal stance	169	Pirannejad & Jannsen 2019
	Participation in offline events	Call to participate in political events non-digitally	109	Pirannejad & Jannsen 2019
	Report from offline events	Posts reports from protests or other political action	104	
E-Identity	Group identity	Expresses a feeling of group identity in the context of political stance	373	Amichai-Hamburger et al. 2008, Yuce et al. 2014
	Agreement or disagreement	Expression of agreement or disagreement with a point of view	445	Yuce et al. 2014, Woo-Young 2005
	Networking	Networking with other groups with a similar stance	8	Tye et al. 2018, Jackson et al. 2020, Leong et al. 2019
Political Participation	Monitoring	Monitoring of government	6	Woo-Young & Won-Tae 2006
	Request	Request to parties or politicians	3	Amichai-Hamburger et al. 2008, Pirannejad & Jannsen 2019
	Fundraising	Fundraising for activist purposes	2	Johnson 2017, Amichai-Hamburger et al. 2008, Pirannejad & Jannsen 2019
	Interactive decision-making	Group decision-making facilitated by the platform	2	Leong et al. 2015; 2019, Amichai-Hamburger et al. 2008

Label	Count
Non-argumentative text	658
Claim	282
Premise	193
Backing	121

Table 2: Count of annotated component labels for argument mining. Labels performed by one annotator.

ducted by only one trained, paid annotator. Similar to the annotation of political empowerment, there was a class imbalance, making it impossible to detect all components automatically. As a result, we defined four classes: claims, premises, backing, and non-argumentative text.

5 Classifying political empowerment

5.1 Component detection

We use our annotated dataset of 1200 posts to train and compare the performance of three deep learning models. Two of the models are German language models, gbert-base (Chan et al., 2020) and GottBERT_base_last (Scheible et al., 2024). We used one multilingual model, xlm-roberta-base (Conneau et al., 2019). We chose sentence as unit of analysis, instead of a post-based analysis, as one sentence often presented one argument component. We also performed hyper-parameter finetuning with the goal to minimize the loss function. For gbert-base, 14 epochs, a batch_size of 16, learning rate =5e-5 yielded the best results. The results were cross-validated as averages from ten runs.

The multi-label classification model demonstrates strong overall performance, achieving a macro-average F1-score of 0.90, with balanced precision (0.90) and recall (0.89) across all categories. The "non-argumentative" category exhibits near-perfect classification (F1 = 0.98), indicating the model's high confidence in distinguishing non-argumentative text from argumentative components. Among the argument components, Premise (F1 = 0.88) and Claim (F1 = 0.86) are well-identified, though the slightly lower recall for Claim (0.85) suggests room for improvement in capturing all relevant instances. Similarly, Backing (F1 = 0.86) performs reliably, though differentiation between Premise and Backing could be further refined. These results indicate that the model is highly effective in identifying argument structures, with minor areas for enhancement in recall for specific argumentative components.

Additionally, we tested one large language model in a zeroshot setting, Em_german_7b_v01, a Llama2-based model (Touvron et al., 2023). As annotated data for argument mining are scarce and expensive, zero-shot learning and few-shot learning are promising tools for the task. Gorur et al. (2025) and Ni et al. (2024) also demonstrate the potential of zeroshot and fewshot settings for argument mining. In our setting, all finetuned deep learning models significantly outperformed the zeroshot model. All results of the comparison are visible in Table 4. As gbert-base outperformed the other models with a macro f1-score of 0.90, we used gbert-base to perform the classification on our entire dataset (13469 posts with ca. 40000 sentences).

5.2 Classifying empowerment aspects

For the classification of empowerment aspects, we also used gbert-base, since it performed well on our corpus in the previous classification. Table 3 shows which classes we used, while Table 1 in the appendix shows which classes could not be used due to class imbalances. We also used sentences as unit of analysis. For the hyperparameter finetuning, 8 epochs, a batch_size of 5, learning rate =5e-5 yielded the best results. We had an f1-score of 0.81, suggesting balanced performance across all categories. Conscientization has the highest performance, which is consistent with the fact that it had most examples in the training data. Participation in offline events and expression of agreement/disagreement perfom consistently well across precision, recall and f1-score. Societal change shows weaker recall, suggesting more training data would be needed. In Table 5, the performance of gbert-base for each class is visualized.

6 Cooccurences

Finally, we want to identify cooccurences between argument components and aspects of political empowerment. For example, are premises typically used in a way that spreads consciousness? Is the expression of group identity used to support one's claims? We visualize the cooccurences in a heatmap (see Figure 1.). The heatmap shows the relations between the argument components, premise, backing, claim, and non-argumentative text; and aspects of political empowerment. This section shows results in the cooccurences.

Label	Explanation
Conscientization	Raising consciousness about political circumstances
Participation in offline events	Call to participate in pol. events; or report from participation
Group identity	Expresses a feeling of group identity in the context of political stance
Societal change	Post talks about a change in societal stance
Agreement or disagreement	Expression of agreement or disagreement with a point of view

Table 3: Labels for the annotation of political empowerment aspects.

	GBERT	GottBERT	RoBERTa	Em_german_7b_v01
Precision	0.86	0.85	0.89	0.39
Recall	0.89	0.84	0.89	0.50
Macro F1-Score	**0.90**	0.84	0.89	0.43

Table 4: Comparison of the different models for the argument mining task.

6.1 Claims

Claims in Instagram captions most commonly express aspects of political awareness building. The most common is conscientization, defined after Freire (1970) as political consciousness building. For example, one user claimed, referring to the Düsseldorfer Forum: "Such secret meetings remind us of Germany's darkest days." Claims which express that society changes are second most common and appear in 2674 sentences. An example claim is: "The majority of people do not want a society in which people are pitted against each other". This exemplifies how people use Instagram to build and share critical consciousness. Additionally, in more than 25% of claims, group idenitity is expressed.

6.2 Backing

Supporting components most often contain conscientizatizing statemens. Despite, conscientization occurs more often in claims than in supporting components (3526 vs 2628 times). Many backings draw parallels between the deportations imagined at the Düsseldorfer Forum and the deportations resulting in the Shoa. One user posted in a conscientizing backing: "#weremember between 1933 and 1945, the Nazi regime cost millions and millions of people their lives." Just as in claims, the second most frequent category is societal change. Reports from participation in offline events, and calls to participate in such, occur just as often as group identity is expressed. The expression of agreement or disagreement appears seldomly in backings.

6.3 Premises

Premises occur most in the data, even before the class "non-argumentative text". Premises mainly express conscientizing statements (5826), a simple example is: "A democracy needs democrats". 2000 premises comment on changes in society. This shows that in claims, backings, and premises, conscientization and societal change appear most frequently in the discourse around #WirSindMehr and #NieWiederIstJetzt. This makes political awareness the most prominent aspect of political empowerment in our dataset.

6.4 Non-argumentative text

Non-argumentative texts are the second biggest component after the premise class. Unlike in other argument components, aspects of political empowerment occur in a more balanced fashion. Although "conscientization" is still the most frequent class, "participation in offline events" is expressed nearly 4000 times within this class. This means non-argumentative sentences often call for political participation; or share a report from political events. Examples are simple reports: "Today we were 2,000 in Sigmaringen and 2,500 in Balingen" and calls to participate – "Come in large numbers! #theaterkiel #democracy #tolerance #solidarity #niewiederistjetzt". Calls also included memorial marches and commemorative events; like: "You are cordially invited to the commemorative event in St. Paul's Church on Sunday, 28". Agreement and disagreement are also frequently expressed in non-argumentative text, often in the form of several hashtags.

Argumentative texts primarily contain aspects of political awareness, which shows that users want to convince their network of the urgency of taking a political stance. Non-argumentative posts reflect political awareness aspects and e-identity as-

Component	Precision	Recall	F1-score
Non-argumentative text	0.98	0.98	0.98
Claim	0.87	0.85	0.86
Premise	0.87	0.89	0.88
Backing	0.86	0.86	0.86
Macro Average	0.90	0.89	0.90

Table 5: Performance of GBERT on the argument component classification.

Component	Precision	Recall	F1-score
Conscientization	0.86	0.81	0.84
Participation in offline events	0.82	0.82	0.82
Group identity	0.78	0.83	0.80
Societal change	0.80	0.71	0.75
Agreement/ Disagreement	0.81	0.83	0.82
Accuracy		0.81	
Macro Average	0.81	0.80	0.81

Table 6: Performance of GBERT on multilabel classification for political empowerment.

pects. Opinion-forming processes and community building with others are evident. Different communication goals may be evident in the different text types: Non-argumentative texts more frequently express feelings of group identity and more often contain reports of political events or calls to attend them.

7 Discussion

In this paper, we take a distant reading perspective on the discourse around the hashtags #WirSindMehr and #NieWiederIstJetzt. We made use of argument component detection and performed a content classification to identify cooccurences between argument components and aspects of political empowerment.

For this purpose, we designed an annotation scheme based on the literature around digital political empowerment. The content classification was performed with only five classes instead of ten. This has two reasons: Firstly, the aspects of personal e-identity and political awareness building stood out more prominently. This most definitely is a result of investigating Instagram captions, as platform functionalities such as surveys or requests to parties typically appear in other platform affordances such as Instagram stories or private chats, and not in captions. For example, an aspect introduced by Woo-Young and Won-Tae (2006) is interactive decision-making, which could happen in the "survey" button in stories. Stories also contain a button for fundraising, but link to a new website.

The second reason were class imbalances: It was not the case that aspects of political empowerment did not appear in the captions at all, but they appeared less than 10 times in the training data, unlike other classes which appeared between 104 and 732 times. This made it impossible to train our classifier for all classes. The decision to reduce classes to yield a clear classification result was thus a pragmatic but necessary one.

For the annotation of argument components, we made use of the modified toulmin scheme (Habernal and Gurevych, 2017). Since we had big class imbalances again, we performed a multilabel classification with four classes: claim, backing, premise and non-argumentative text. To maintain class balance, we used a random sample of 300 posts from all data labeled as "non-argumentative text" (see tab.2 for count of annotated component labels).

Finally, we identified cooccurences of argument components and the content aspects of digital political empowerment (tab. 3). In general, "premises" and "non-argumentative text" are the most frequent argument components. Claims were most frequently concerned with conscientization and societal change. According to our analysis, a typical backing contained conscientizing statements. All other aspects only appeared less than 1000 times. This might indicate that a claim about societal change might frequently be backed by a conscientizing statement. This hypothesis needs to be tested in future work on relation-based argument mining. A typical example could be:

- **Claim:** "Right-wing extremism and antisemitism is on the rise."

- **Backing:** "Jews have been assaulted on German streets, their homes marked with Stars of David and synagogues pelted with Molotov cocktails."

Looking at the bigger picture, we can see that political awareness is the most frequent category in the corpus: Conscientizing statements and statements about societal change appear most often. This is plausible, because #NieWiederIstJetzt is a statement against antisemitism and refers to the Shoa, expressing: The shoa shoud never happen again. It is thus no surprise that users want to raise awareness for antisemitic hate and the rise of right-wing extremism in Germany and Europe. These concerns are frequently stated in all three components; premises, claims, and backings. One aspect of political awareness is commented on less frequently – reports from participation in offline events and calls to participate. Within argument components, it is most frequently found in the class "non-argumentative text" which comprises non-argumentative texts, rebuttals, refutations.

Aspects of e-identity appear second most in our data. The expression of agreement or disagreement with a point of view was most often found in class "Non-argumentative text" (3618 times), and appeared around 1000 times in each of the other classes. Likely, users stated their approval with the stance in the hashtags #WirSindMehr or #NieWiederIstJetzt, but made no substantial argument. It is also probable that disapproval was expressed, as counter discourse is commonly tagged with the same hashtags.

The expression of group identity appeared between 500 and 1500 times per component type, which is less than expected. One might think that the hashtag #WirSindMehr already expresses a feeling of identity; as participants are opponents of right-wing voters and belong to the former "silent majority" as expressed by the Stuttgarter Zeitung. Potentially, this result is due to the preprocessing, as the hashtags #WirSindMehr and #NieWiederIstJetzt were removed from the training data due to their frequent occourence.

In this paper, political empowerment language is characterized by its aspects political awareness, political participation and e-identity. Importantly, we only look at one aspect of Instagram's archictecture, the caption. Although the caption is where political messages are primarily communicated (Bast, 2021; Towner and Muñoz, 2018; Liebhart and Bernhardt, 2017; Lalancette and Raynauld, 2019), we acknowledge that political empowerment should be studied in ephemeral content such as Instagram stories (Bainotti et al., 2021) which offer different functionalities. For a holistic approach to the analysis of empowerment in social media, a close reading approach should complement this work.

Political awareness has shown to be the most frequent category of political empowerment in this corpus. We believe that this could be corpus-specific, because the hashtags' topics were meant to build consciousness of antidemocratic forces in Germany and Europe. Therefore, future work should test if this distribution also shows in other corpora of political empowerment.

This work also illustrates the difficult bridge between humanities theories and applicability in machine-learning, as we had to follow a more coarse-grained approach due to practicalities of machine learning. Nevertheless, we recommend the iterative process of starting with fine-grained approaches informed by extensive humanities theory.

8 Future work

In future work, we will investigate relations between argument components. Like this, we want to extract typical argument relations which would be particularly interesting for content analysis of #NieWiederIstJetzt and #WirSindMehr. Future research could also include fact-checking of common claims, as well as experiment with argument similarity. Additionally, a comparison with image texts on Instagram would be fruitful. This would add insights about the use of different modalities of the platform. It could be interesting to explore whether the participatory aspect of political empowerment is conveyed through image captions. Future work could expand this research to other platforms.

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References

Amy C Alexander, Catherine Bolzendahl, and Farida Jalalzai. 2016. Defining women's global political empowerment: Theories and evidence. *Sociology Compass*, 10(6):432–441.

Yair Amichai-Hamburger, Katelyn YA McKenna, and Samuel-Azran Tal. 2008. E-empowerment: Empowerment by the internet. *Computers in Human Behavior*, 24(5):1776–1789.

Lucia Bainotti, Alessandro Caliandro, and Alessandro Gandini. 2021. From archive cultures to ephemeral content, and back: Studying instagram stories with digital methods. *New Media & Society*, 23(12):3656–3676.

Astri Moksnes Barbala. 2024. Reassembling# metoo: Tracing the techno-affective agency of the feminist instagram influencer. *Convergence*, 30(3):992–1007.

Jennifer Bast Jennifer Bast. 2021. Politicians, parties, and government representatives on instagram: A review of research approaches, usage patterns, and effects. *Review of Communication Research*, 9.

Bensmann, Marcus, von Daniels, Justus, Dowideit, Annette, Peters, Jean, and Keller, Gabriela. 2024. Neue Rechte – Geheimplan gegen Deutschland. *CORRECTIV Recherchen für die Gesellschaft*.

Muhammad Mahad Afzal Bhatti, Ahsan Suheer Ahmad, and Joonsuk Park. 2021. Argument mining on twitter: A case study on the planned parenthood debate. In *Proceedings of the 8th Workshop on Argument Mining, ArgMining@EMNLP 2021, Punta Cana, Dominican Republic, November 10-11, 2021*, pages 1–11. Association for Computational Linguistics.

Filip Boltuzic and Jan Snajder. 2015. Identifying prominent arguments in online debates using semantic textual similarity. In *Proceedings of the 2nd Workshop on Argumentation Mining, ArgMining@HLT-NAACL 2015, June 4, 2015, Denver, Colorado, USA*, pages 110–115. The Association for Computational Linguistics.

Amy Bruckman. 1992. Identity workshop: Emergent social and psychological phenomena in text-based virtual reality.

Alessandro Caliandro and James Graham. 2020. Studying instagram beyond selfies. *Social media+ society*, 6(2):2056305120924779.

Branden Chan, Stefan Schweter, and Timo Möller. 2020. German's next language model. In *Proceedings of the 28th International Conference on Computational Linguistics, COLING 2020, Barcelona, Spain (Online), December 8-13, 2020*, pages 6788–6796. International Committee on Computational Linguistics.

Alexis Conneau, Kartikay Khandelwal, Naman Goyal, Vishrav Chaudhary, Guillaume Wenzek, Francisco Guzmán, Edouard Grave, Myle Ott, Luke Zettlemoyer, and Veselin Stoyanov. 2019. Unsupervised cross-lingual representation learning at scale. *CoRR*, abs/1911.02116.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of deep bidirectional transformers for language understanding. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 4171–4186, Minneapolis, Minnesota. Association for Computational Linguistics.

Mihai Dusmanu, Elena Cabrio, and Serena Villata. 2017. Argument mining on twitter: Arguments, facts and sources. In *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing, EMNLP 2017, Copenhagen, Denmark, September 9-11, 2017*, pages 2317–2322. Association for Computational Linguistics.

Neele Falk and Gabriella Lapesa. 2022. Reports of personal experiences and stories in argumentation: datasets and analysis. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), ACL 2022, Dublin, Ireland, May 22-27, 2022*, pages 5530–5553. Association for Computational Linguistics.

Paulo Freire. 1970. Cultural action and conscientization. *Harvard educational review*, 40(3):452–477.

Andrea Galassi, Marco Lippi, and Paolo Torroni. 2023. Multi-task attentive residual networks for argument mining. *IEEE ACM Trans. Audio Speech Lang. Process.*, 31:1877–1892.

Martin Gibbs, James Meese, Michael Arnold, Bjorn Nansen, and Marcus Carter. 2015. # funeral and instagram: Death, social media, and platform vernacular. *Information, communication & society*, 18(3):255–268.

Deniz Gorur, Antonio Rago, and Francesca Toni. 2025. Can large language models perform relation-based argument mining? In *Proceedings of the 31st International Conference on Computational Linguistics, COLING 2025, Abu Dhabi, UAE, January 19-24, 2025*, pages 8518–8534. Association for Computational Linguistics.

Theodosios Goudas, Christos Louizos, Georgios Petasis, and Vangelis Karkaletsis. 2014. Argument extraction from news, blogs, and social media. In *Artificial Intelligence: Methods and Applications - 8th Hellenic Conference on AI, SETN 2014, Ioannina, Greece, May 15-17, 2014. Proceedings*, volume 8445 of *Lecture Notes in Computer Science*, pages 287–299. Springer.

Ivan Habernal and Iryna Gurevych. 2015. Exploiting debate portals for semi-supervised argumentation mining in user-generated web discourse. In *Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing, EMNLP 2015, Lisbon, Portugal, September 17-21, 2015*, pages 2127–2137. The Association for Computational Linguistics.

Ivan Habernal and Iryna Gurevych. 2017. Argumentation mining in user-generated web discourse. *Computational linguistics*, 43(1):125–179.

Aria S Halliday and Nadia E Brown. 2018. The power of black girl magic anthems: Nicki minaj, beyoncé, and "feeling myself" as political empowerment. *Souls*, 20(2):222–238.

Zoe Hurley. 2021. # reimagining arab women's social media empowerment and the postdigital condition. *Social Media+ Society*, 7(2):20563051211010169.

Sarah J Jackson, Moya Bailey, and Brooke Foucault Welles. 2020. *# HashtagActivism: Networks of race and gender justice*. Mit Press.

Hayley Johnson. 2017. # nodapl: Social media, empowerment, and civic participation at standing rock. *Library Trends*, 66(2):155–175.

Mack H Jones. 1978. Black political empowerment in atlanta: Myth and reality. *The ANNALS of the American Academy of Political and Social Science*, 439(1):90–117.

Mireille Lalancette and Vincent Raynauld. 2019. The power of political image: Justin trudeau, instagram, and celebrity politics. *American behavioral scientist*, 63(7):888–924.

Carmen Leong, Shan L Pan, Shamshul Bahri, and Ali Fauzi. 2019. Social media empowerment in social movements: power activation and power accrual in digital activism. *European Journal of Information Systems*, 28(2):173–204.

Carmen Mei Ling Leong, Shan L Pan, Peter Ractham, and Laddawan Kaewkitipong. 2015. Ict-enabled community empowerment in crisis response: Social media in thailand flooding 2011. *Journal of the Association for Information Systems*, 16(3):1.

Karin Liebhart and Petra Bernhardt. 2017. Political storytelling on instagram: Key aspects of alexander van der bellen's successful 2016 presidential election campaign. *Media and Communication*, 5(4):15–25.

Lev Manovich. 2017. Instagram and contemporary image.

Nailia Mirzakhmedova, Marcel Gohsen, Chia-Hao Chang, and Benno Stein. 2024. Are large language models reliable argument quality annotators? In *Robust Argumentation Machines - First International Conference, RATIO 2024, Bielefeld, Germany, June 5-7, 2024, Proceedings*, volume 14638 of *Lecture Notes in Computer Science*, pages 129–146. Springer.

Jingwei Ni, Minjing Shi, Dominik Stammbach, Mrinmaya Sachan, Elliott Ash, and Markus Leippold. 2024. Afacta: Assisting the annotation of factual claim detection with reliable LLM annotators. In *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), ACL 2024, Bangkok, Thailand, August 11-16, 2024*, pages 1890–1912. Association for Computational Linguistics.

Raquel Mochales Palau and Marie-Francine Moens. 2011. Argumentation mining. *Artif. Intell. Law*, 19(1):1–22.

Marco Passon, Marco Lippi, Giuseppe Serra, and Carlo Tasso. 2018. Predicting the usefulness of amazon reviews using off-the-shelf argumentation mining. In *Proceedings of the 5th Workshop on Argument Mining, ArgMining@EMNLP 2018, Brussels, Belgium, November 1, 2018*, pages 35–39. Association for Computational Linguistics.

Tavisha Patel. 2024. Machine learning and applications in argumentation mining. *International Journal of High School Research*, 6(1).

Douglas D Perkins and Marc A Zimmerman. 1995. Empowerment theory, research, and application. *American journal of community psychology*, 23:569–579.

Ali Pirannejad and Marijn Janssen. 2019. Internet and political empowerment: Towards a taxonomy for online political empowerment. *Information Development*, 35(1):80–95.

Nils Reimers, Benjamin Schiller, Tilman Beck, Johannes Daxenberger, Christian Stab, and Iryna Gurevych. 2019. Classification and clustering of arguments with contextualized word embeddings. In *Proceedings of the 57th Conference of the Association for Computational Linguistics, ACL 2019, Florence, Italy, July 28- August 2, 2019, Volume 1: Long Papers*, pages 567–578. Association for Computational Linguistics.

Anna Sauerbrey. 2024. Opinion | Germany Has Finally Woken Up — nytimes.com. https://www.nytimes.com/2024/01/31/opinion/germany-protests-far-right.html. [Accessed 04-09-2024].

Robin Schaefer and Manfred Stede. 2022. Gercct: An annotated corpus for mining arguments in german tweets on climate change. In *Proceedings of the Thirteenth Language Resources and Evaluation Conference, LREC 2022, Marseille, France, 20-25 June 2022*, pages 6121–6130. European Language Resources Association.

Raphael Scheible, Johann Frei, Fabian Thomczyk, Henry He, Patric Tippmann, Jochen Knaus, Victor Jaravine, Frank Kramer, and Martin Boeker. 2024. Gottbert: a pure german language model. In *Proceedings of the 2024 Conference on Empirical Methods in Natural Language Processing, EMNLP 2024, Miami, FL, USA, November 12-16, 2024*, pages 21237–21250. Association for Computational Linguistics.

Reid Swanson, Brian Ecker, and Marilyn A. Walker. 2015. Argument mining: Extracting arguments from online dialogue. In *Proceedings of the SIGDIAL 2015 Conference, The 16th Annual Meeting of the Special Interest Group on Discourse and Dialogue, 2-4 September 2015, Prague, Czech Republic*, pages 217–226. The Association for Computer Linguistics.

Stephen E Toulmin. 2003. *The uses of argument*. Cambridge university press.

Hugo Touvron, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, Nikolay Bashlykov, Soumya Batra, Prajjwal Bhargava, Shruti Bhosale, et al. 2023. Llama 2: Open foundation and fine-tuned chat models. *arXiv preprint arXiv:2307.09288*.

Terri L Towner and Caroline Lego Muñoz. 2018. Picture perfect? the role of instagram in issue agenda setting during the 2016 presidential primary campaign. *Social science computer review*, 36(4):484–499.

Michelle Tye, Carmen Leong, Felix Tan, Barney Tan, and Ying Hooi Khoo. 2018. Social media for empowerment in social movements: the case of malaysia's grassroots activism. *Communications of the Association for Information Systems*, 42(1):15.

Joanne Waitoa, Regina Scheyvens, and Te Rina Warren. 2015. E-whanaungatanga: The role of social media in māori political empowerment. *AlterNative: An International Journal of Indigenous Peoples*, 11(1):45–58.

DN Walton. 2008. *Argumentation schemes*. Cambridge University Press.

Chang Woo-Young. 2005. Online civic participation, and political empowerment: Online media and public opinion formation in korea. *Media, Culture & Society*, 27(6):925–935.

Chang Woo-Young and Lee Won-Tae. 2006. Cyberactivism and political empowerment in civil society: A comparative analysis of korean cases: A comparative analysis of korean cases. *Korea Journal*, 46(4):136–167.

Serpil T Yuce, Nitin Agarwal, Rolf T Wigand, Merlyna Lim, and Rebecca S Robinson. 2014. Bridging women rights networks: Analyzing interconnected online collective actions. *Journal of Global Information Management (JGIM)*, 22(4):1–20.

Marc A Zimmerman and Julian Rappaport. 1988. Citizen participation, perceived control, and psychological empowerment. *American Journal of community psychology*, 16(5):725–750.