Communication Adaptation Under Political Repression of the Muslim Brotherhood

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Introduction

- The Muslim Brotherhood presents an ideal case for examining the evolution of social movements under repression, given its long organizational history, internal complexity, and political prominence (Wickham, 2013; Brown, 2012).
- While prior research has documented internal debates and growing disillusionment through interviews and qualitative analysis, there has been no large-scale, systematic study of how the Brotherhood's rhetoric has shifted in response to internal fragmentation and external pressures (Hamid, 2014; Fahmi, 2019, Al-Anani, 2016; Al-Anani, 2019; Ardovini, 2022; Willi, 2021).
- AI-enhanced feature extraction enables consistent classification of rhetorical features in contexts where manual coding is not feasible and hand-coded measures are insufficient for adequate nuance and complexity.
- This study aims to investigate the means to analyze relationships between political crises and organizational communication adaptation across all dimensions of messaging through a rigorous analytical framework employing descriptive statistics, sentiment evolution, topic shifts, and temporal dynamics.

Methodology

Sample

- Data was collected through web scraping ikhwanweb.com, Ennahdha International Facebook, and ikhwan.site.
- merged data set with 1585 entries after duplicate statements and statements with no body text removed 1445 (Pre-2021 Web 743 posts (51.4%) Post-2021 Site: 293 posts (20.3%) Ennahdha International: 308 posts (21.3%) Post-2021 Web: 101 posts (7.0%))
- Temporal Stratification Data collection stratified across three critical periods: Pre-2013 Coup (2006-2013), Post-2013 Crisis (2013-2021), and Post-Split Fragmentation (2021-2025).

Measures

- Text tokenization, keyword extraction, and sentence features were extracted.
- AI-Enhanced Feature Extraction Natural Language Processing: Employed OpenAI GPT-4 API for content analysis,
- Extracted 6 features including audience targeting, message framing, and political content classification post summary and key event detection.
- Sentiment Analysis Pipeline: AFINN lexicon-based sentiment scoring scores range [-5, +5]
- Topic Modeling with Latent Dirichlet Allocation (LDA) k=7 topics
- Verb tense and event reference extracted using spaCy and regex pipelines

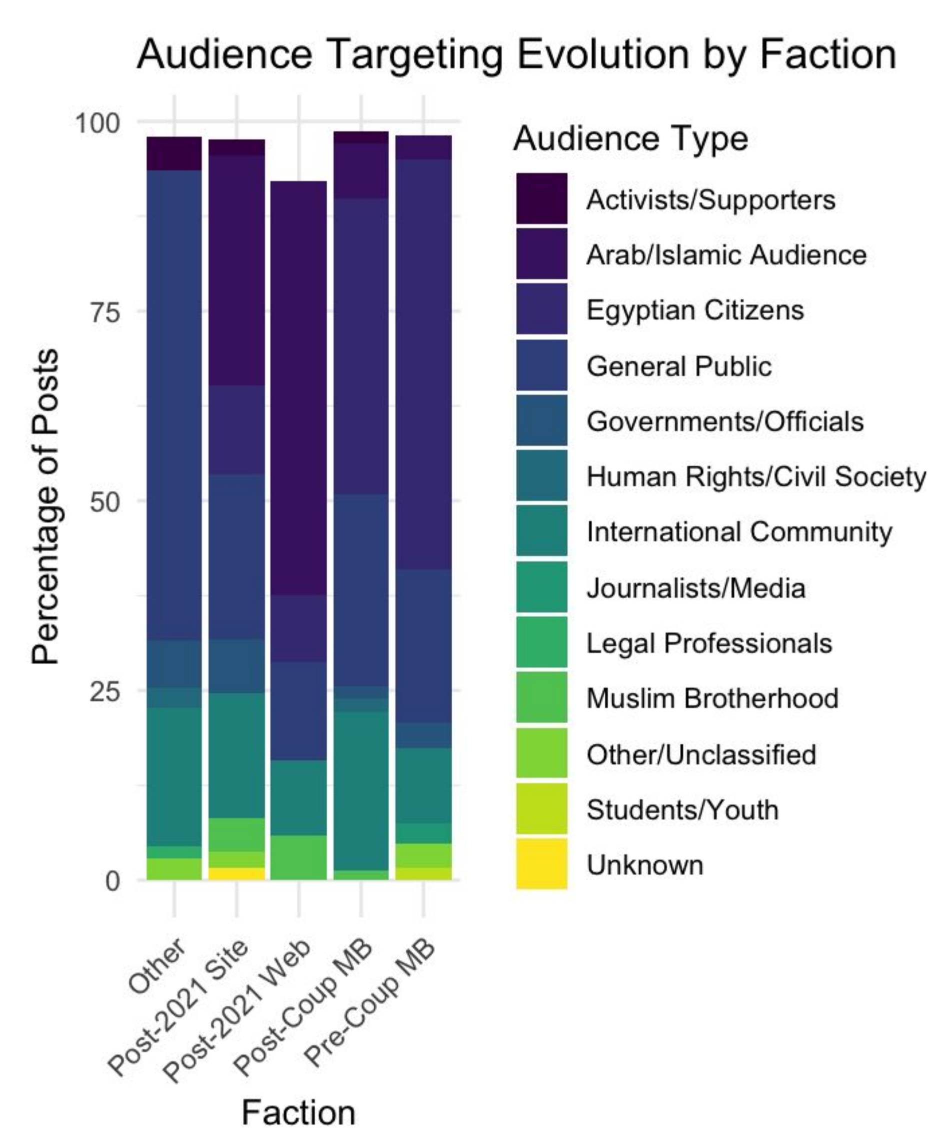
Results

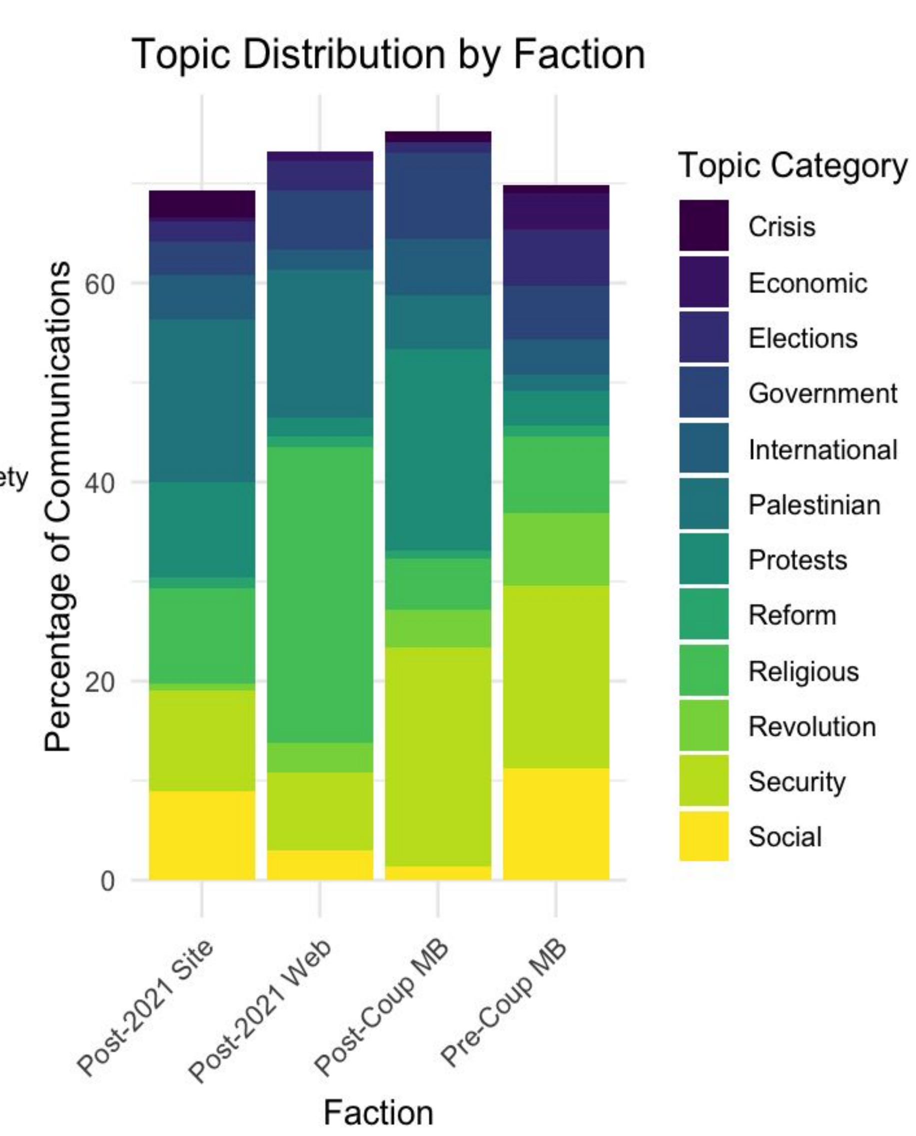
Word Use (per 100 statements)

Variable	Pre-Coup	Post-Coup	Post-Split Web	Post-spltSite
Opposition Verb Count	47.6	50.9	34.7	60.8
Support Verb Count	39.0	69.2	175.0	126.0
Mobilization Verb Count	119.0	129.0	200.0	130.0
Expression Verb Count	71.8	109.0	160.0	69.3
Past Terms Count	10.2	24.7	67.3	24.6
Present Terms Count	67.5	112.0	140.0	62.1
Future Terms Count	183.0	200.0	469.0	132.0
Governance Terms Count	119.0	221.0	163.0	96.9
Opposition Terms Count	132.0	138.0	177.0	82.3

Content Proportions

Variable	Pre-Coup	Post-Coup	Post-Split Web	Post-Split Site
Political Content	58.4%	71.8%	78.3%	73.1%
Religious Content	63.2%	48.1%	34.7%	41.2%
Both Pol. & Rel.	21.6%	19.9%	13.0%	14.3%
Statement	69.3%	76.4%	81.2%	78.9%
Call to Action	27.4%	33.2%	38.6%	35.1%
Cross-Ideological	22.1%	31.4%	41.3%	35.7%
International Focus	29.6%	36.1%	44.8%	38.2%
Domestic Egyptian	70.4%	63.9%	55.2%	61.8%





Analysis

Longitudinal model

- Fixed-effects panel regression modeling log-posts:
- ln(Postsit)=αi+β1Coup2013t+β2Split2021t+β3Controlsit where i indexes factions (n=4), t monthly periods (2006–2025).
- Strong positive effects of 2013 coup (β=3.229, p<0.001, large effect) and 2021 split (β=1.847, p=0.002, medium effect) on communication volume. Political event index positively associated with smaller effect (β=0.156, p=0.048).

AFINN Sentiment scoring

- **AFINN lexicon** assigns predefined scores to individual words ranging from –5 (strongly negative) to +5 (strongly positive)
- **Total sentiment score** is calculated as the sum of its scored words then normalized
- **Average sentiment per period**:

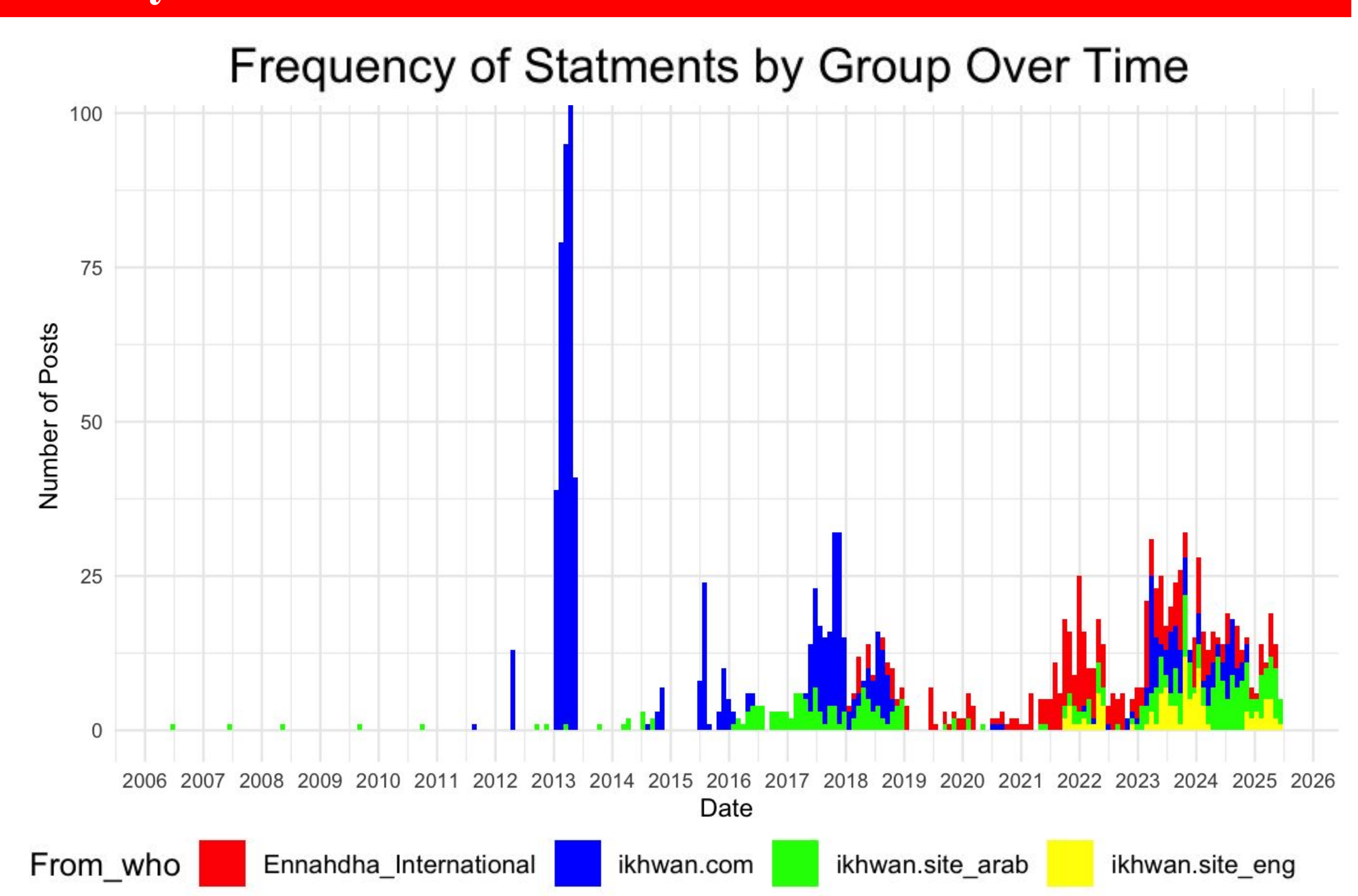
Pre-2013: +**0.121** Post-2013: **–0.614** Post-Split Web: **+0.648** Post-Split Site: -0.0296

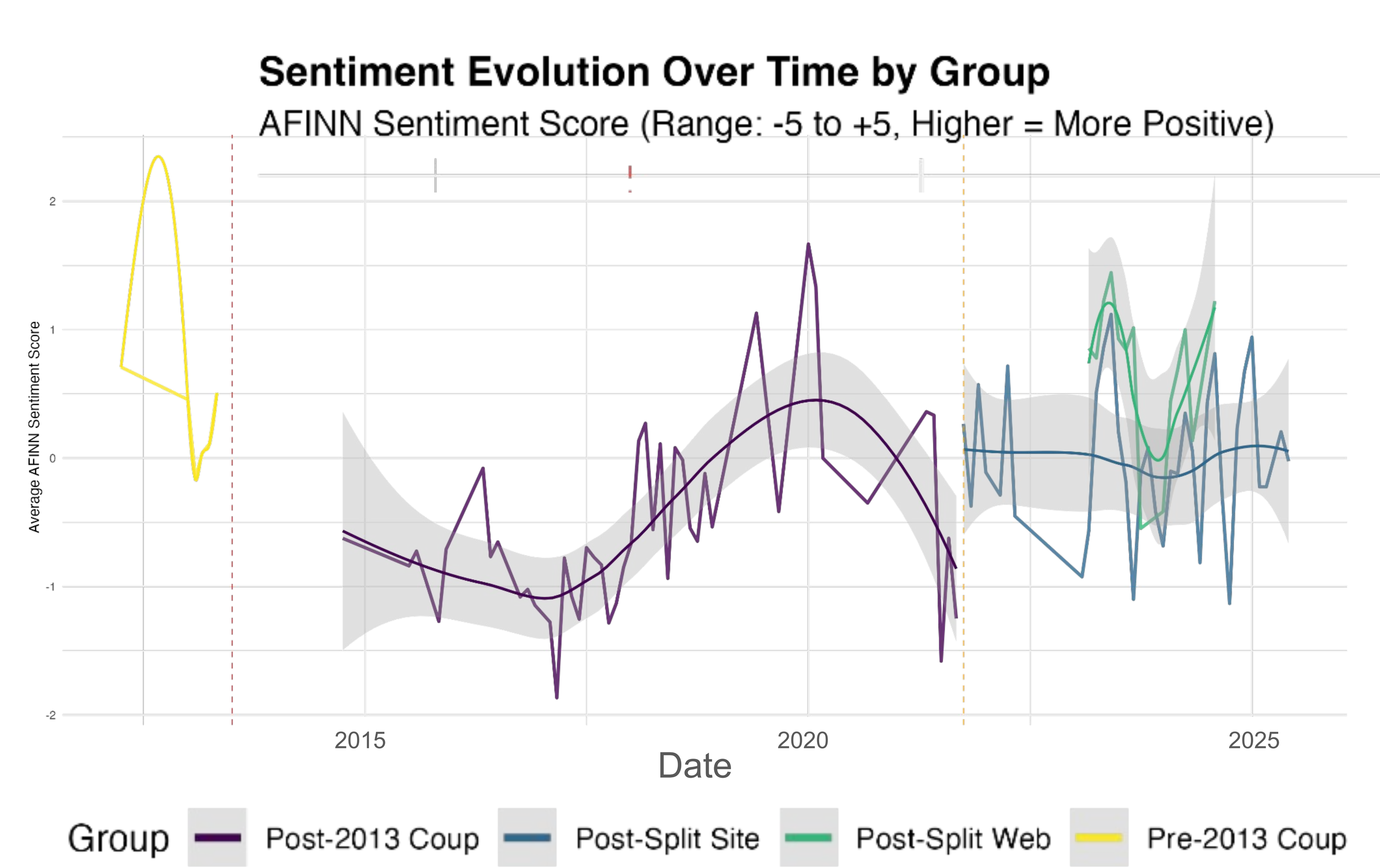
LDA Topic Modeling (k = 7)

- Latent Dirichlet Allocation (LDA) is an unsupervised machine learning method that assigns each document a distribution over a fixed number of topics, each defined by a set of frequently co-occurring words.
- Created topics for individual groups and time periods and for all statements to compare topic similarity and proportion over time
- Post-split: more focused topic profiles (↓Shannon entropy, ↑ exclusivity)
- Chi² tests confirm **significant topic shifts (p < 0.001)** across periods

Retrieval-augmented generation (RAG)

- Created RAG, witch combines a neural language model with a retrieval system, enabling the model to pull relevant documents from a dataset and generate context-aware outputs based on retrieved content.
- Created Streamlit app for online access
- Hand coded in depth statement retrieval strategies using semantic similarity, keyword matching, temporal prioritization, entity discovery, thematic inference





Discussion

Next Steps

- Develop more complex time-series models (e.g., structural break analysis, VAR) to better capture the temporal effects of political events on communication volume and topic shifts.
- Incorporate external media and state response data.
- Conduct comparative analysis with Ennahdha movement (1991–2011) to to compare adaptation patterns across Islamist movements in exile.
- Link communication patterns to movement outcomes (e.g., protest participation, fundraising, international engagement) to assess the strategic effectiveness of different messaging styles.

Limitations

- Only using Publicly available statements without all non-english statements able to be incorporated
- Hand coded content proportions rely in manual key word identification
- Does not use comparative analysis with other movements
- Some data incomplete with 3.2% variable entries missing in original data
- Sentiment scoring limited by translation loss and lexicon generality
- Imperfect AI validation relying on manual comparison of features extracted from 20 statement subset

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Thank you to Professor Maryam Gooyabadi and Professor Emy Matesan for their invaluable guidance and support that made this project possible.