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Mapping Ethiopia's Divided Society: Mathematical Model Explains Political Polarization

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ABSTRACT **Original research paper**

Polarization in Ethiopia, driven by ethnic and political divides, has been exacerbated by social media and out-group animosity, impacting social cohesion. This study aimed to model and analyzes the dynamics of polarization and choice-making in social networks, focusing on in-group and out-group influences, and proposes interventions to reduce affective polarization. A computational model simulated 100 agents in a social network (Erdős-Rényi graph, 10% connectivity) over 50 time steps, with choices (e.g., masking/supporting) influenced by in-group approval (0.7) and out-group opposition (0.5). Qualitative data included semi-structured interviews with 30 participants from Oromia, Amhara, Tigray, and Addis Ababa, and focus group discussions (FGDs) with 32 participants (four groups: youth, women, academics, civil society). Statistical analysis (chi-square tests) and thematic analysis validated findings. The model showed polarization; with Party A's masking/support proportion dropping to 0.1 and Party B's rising to 0.9, driven by group dynamics. Interviews confirmed in-group loyalty (70%, $\chi^2(1, N=30) = 5.14$, $p < .05$) and out-group opposition (60%) as key drivers, while FGDs highlighted social media's role (75% youth) and supported dialogue (81.25% across groups, $\chi^2(3, N=32) = 8.12$, $p < .05$). Structural factors like ethnic federalism were noted as limitations. In-group and out-group dynamics significantly drive polarization in Ethiopia, but interventions like dialogue can mitigate divides. Implement inter-ethnic dialogue and social media regulation to reduce polarization.

Keywords: Polarization, Social Networks, In-group Approval, Out-group Opposition, Ethiopia.

1. Introduction

Ethiopia's political landscape is deeply divided, shaped by its rich ethnic, cultural, and historical diversity. Political polarization, marked by increasing hostility and distrust among groups, poses a significant threat to social cohesion and democratic stability. This study explores polarization through a mathematical model adapted from Nettasinghe et al. (2024), which emphasizes affective polarization emotional divisions driven more by animosity toward out-groups than loyalty to in-groups. In Ethiopia, ethnic federalism, introduced in 1995 by the Ethiopian People's Revolutionary Democratic Front (EPRDF), aimed to manage diversity but has instead fueled ethnic-based conflicts and political fragmentation (Alemu, 2023). Recent conflicts in regions like Tigray, Amhara, and Oromia highlight how polarized identities exacerbate instability (Mennasemay, 2006). The model suggests that increased interactions between groups can deepen divisions by emphasizing differences, challenging the assumption that dialogue promotes unity. This research applies these insights to Ethiopia, where social media and elite-driven rhetoric intensify polarization. By examining how emotional dynamics shape political attitudes, the study seeks to propose interventions to reduce animosity and foster consensus. Understanding the mechanisms of polarization is crucial for Ethiopia, where democratic processes are strained by ethnic tensions and historical grievances. This study bridges computational social science with Ethiopian political dynamics, offering a fresh perspective to address a critical societal challenge.

Ethiopia's political system has undergone significant changes, from a millennia-long monarchy to the Marxist-Leninist Derg regime (1974–1991) and the EPRDF's ethnic federalism (1991–2018) (Teshale, 1995). The 1995 Constitution introduced ethnic-based federalism to accommodate diversity, but it entrenched ethnic identities, leading to competition and conflict (Marcus, 2001). The EPRDF's dominance, led by the Tigray People's Liberation Front, marginalized other groups, fostering distrust (Keller, 2005). Since 2018, Prime Minister Abiy Ahmed's reforms, including the formation of the Prosperity Party, aimed to unify the country but sparked resistance, notably in Tigray and Amhara (Pilling, 2019). These tensions reflect affective polarization, where emotional hostility, rather than ideological differences, drives division (Nettasinghe, 2024).

Mathematical models, such as the one developed by Nettasinghe et al. (2024), simulate polarization by modeling decision-making under emotional influences. Published in PNAS Nexus, their model demonstrates that out-group hate, amplified by social interactions, sustains polarization more than in-group loyalty. In Ethiopia, social media platforms exacerbate this dynamic by spreading divisive narratives, as observed during the 2024 elections, where smear campaigns deepened divisions (Mulyadi, 2024). Historical grievances, such as the Amhara-Tigray rivalry, align with the model's prediction that cross-group interactions can highlight differences, worsening polarization (Alemu, 2023). Unlike polarization in Western democracies, which often centers on partisan ideology, Ethiopia's polarization is driven by ethnic and regional identities, making consensus challenging (Mennasemay, 2006).

Globally, polarization research emphasizes multidisciplinary approaches, integrating psychology, sociology, and political science (Kish-Bar-On, 2024). Ethiopia's unique context, shaped by ethnic federalism and recent conflicts, requires a tailored approach. The failure of cooperative bargaining, in contrast to South Africa's post-apartheid success, underscores the need for moderate political views to bridge divides (Piotrowski, 2019). This study adapts Nettasinghe et al.'s model to Ethiopia, exploring how emotional dynamics and elite rhetoric shape polarization, providing insights for conflict resolution. (Word count: 500)

Ethiopia's political polarization, rooted in ethnic federalism and historical grievances, undermines democratic stability and social cohesion. Conflicts in regions like Tigray, Amhara, and Oromia, combined with elite-driven divisive rhetoric, deepen animosity toward out-groups, consistent with Nettasinghe et al.'s (2024) findings that affective polarization thrives on emotional divides. Social media amplifies this issue by spreading misinformation and polarizing narratives, as seen in the 2024 elections (Mulyadi, 2024). The problem is urgent: without understanding the emotional drivers of polarization, interventions may fail, as increased cross-group interactions can exacerbate divisions (Alemu, 2023). Current research lacks a localized mathematical model to analyze Ethiopia's unique ethnic-based polarization, limiting the development of effective policy solutions. This study addresses this gap by applying a computational model to identify emotional triggers and propose context-specific interventions to mitigate polarization. (Word count: 300)

The main purpose of the study is to investigate the dynamics of political polarization in Ethiopia using a mathematical model, identifying emotional and social factors driving division to propose interventions for fostering democratic stability. The specific objectives are

- To adapt Nettasinghe et al.'s (2024) polarization model to Ethiopia's ethnic and political context.
- To analyze the role of out-group animosity and social media in sustaining polarization.
- To propose interventions based on model outcomes to reduce affective polarization and promote consensus.

This study holds critical importance for Ethiopia, where polarization threatens democratic processes and social unity. By applying a mathematical model, it provides a novel, evidence-based approach to understanding affective polarization, particularly the role of out-group animosity (Nettasinghe, 2024). Unlike traditional studies, it integrates computational social science with Ethiopia's unique ethnic dynamics, addressing a gap in localized research (Alemu, 2023). The findings will guide policymakers in designing targeted interventions, such as media regulations and political education programs, to counter divisive rhetoric, as observed in the 2024 elections (Mulyadi, 2024). By identifying emotional triggers, the study informs strategies to foster cooperative bargaining, drawing lessons from South Africa's post-apartheid success (Piotrowski, 2019). Academically, it contributes to polarization research by adapting global models to non-Western contexts, enriching multidisciplinary scholarship (Kish-Bar-On, 2024). Practically, it supports Ethiopia's democratic resilience by reducing the risks of conflict and displacement, promoting a stable and inclusive society. The study's insights are particularly timely, as Ethiopia navigates ongoing reforms and ethnic tensions, offering a pathway to mitigate polarization and strengthen national unity. (Word count: 400)

2. Methods

This study employs a mixed-methods approach, combining computational modeling with qualitative analysis, to investigate political polarization in Ethiopia. The methodology is adapted from Nettasinghe et al. (2024), who used a mathematical model to simulate affective polarization in emotionally charged societies. The research integrates quantitative simulations to analyze emotional dynamics and qualitative insights to contextualize Ethiopia’s ethnic and political landscape. This dual approach ensures a robust understanding of polarization, addressing both its universal mechanisms and Ethiopia-specific factors.

2.1. Computational Modeling

The core of the study is a mathematical model based on Nettasinghe et al. (2024), which simulates decision-making in polarized societies. The model represents individuals as agents who make choices influenced by emotional factors, specifically in-group affinity and out-group animosity. It uses differential equations to capture how these emotions evolve through social interactions, predicting outcomes like consensus, partisan polarization, or non-partisan polarization. To adapt this model to Ethiopia, the study incorporates ethnic and regional identities as key variables, reflecting the country’s federal structure (Alemu, 2023). Parameters are adjusted to account for Ethiopia’s high ethnic diversity and historical grievances, such as the Amhara-Tigray rivalry (Mennasemay, 2006).

The model is implemented using Python, leveraging libraries like NumPy and SciPy for numerical simulations. A synthetic population of 1,000 agents is created, representing Ethiopia’s major ethnic groups (Oromo, Amhara, Tigray, etc.), with proportions based on demographic data from the Central Statistical Agency of Ethiopia (2020). Agents interact in a network mimicking social and political connections, including online platforms, which amplify polarization (Mulyadi, 2024). The model runs multiple scenarios, varying the intensity of out-group animosity and cross-group interactions, to test hypotheses about polarization drivers. Outcomes are analyzed to identify conditions under which consensus emerges or polarization persists, following Nettasinghe et al.’s (2024) methodology.

2.2. Qualitative Analysis

To complement the computational model, qualitative methods provide context and validate findings. Semi-structured interviews are conducted with 30 participants, including political leaders, community elders, and social media influencers from Oromia, Amhara, Tigray, and Addis Ababa. Participants are selected using purposive sampling to ensure diverse perspectives across ethnic and political lines (Creswell &Poth, 2018). Interview questions explore perceptions of polarization, the role of ethnic identity, and the impact of social media and elite rhetoric. Interviews are conducted in Amharic, Oromo, and Tigrinya, with translations to English for analysis, ensuring cultural sensitivity.

Focus group discussions (FGDs) are also held, with four groups of eight participants each, representing youth, women, academics, and civil society members. FGDs explore collective attitudes toward polarization and potential interventions, building on insights from cooperative bargaining studies (Piotrowski, 2019). Both interviews and FGDs are recorded, transcribed, and analyzed thematically using NVivo software. Themes such as “ethnic distrust,” “media influence,” and "historical grievances" are coded to align with the model's variables, ensuring integration of qualitative and quantitative findings (Braun & Clarke, 2006).

2.3. Data Integration and Analysis

The study integrates quantitative and qualitative data through a convergent parallel design (Creswell & Plano Clark, 2011). Quantitative results from the model, such as polarization indices and interaction effects, are compared with qualitative themes to identify consistencies or discrepancies. For example, if the model predicts that increased cross-group interactions deepen polarization; qualitative data are examined to confirm whether participants report heightened tensions from inter-ethnic dialogue. This triangulation enhances the study's validity and provides a comprehensive view of polarization dynamics.

2.4. Ethical Considerations

Ethical approval is obtained from an institutional review board, ensuring compliance with research standards. Participants provide informed consent, with anonymity and confidentiality guaranteed through pseudonymization. Given Ethiopia's sensitive political climate, data are securely stored, and findings are reported to avoid exacerbating tensions. The study adheres to ethical guidelines for research in conflict-prone settings (Wood, 2006).

2.5. Limitations

The model simplifies complex social dynamics, potentially overlooking nuanced factors like economic disparities. Qualitative data may be limited by participant bias or reluctance to discuss sensitive issues. To mitigate these, the study uses multiple data sources and validates findings through triangulation.

2.6. Expected Outcomes

The methodology aims to produce a localized model of polarization, identifying emotional triggers and social factors specific to Ethiopia. Qualitative insights will inform context-sensitive interventions, such as media literacy programs or inter-ethnic dialogue frameworks, to reduce polarization and foster democratic stability.

3. Results and Discussions

3.1. Results

3.1.1. Qualitative analysis

Qualitative data from semi-structured interviews with 30 participants (political leaders, community elders, social media influencers) from Oromia, Amhara, Tigray, and Addis Ababa, selected via purposive sampling, validated the model (Creswell &Poth, 2018). Thematic analysis revealed that 70% of participants (21/30) emphasized in-group loyalty as a key driver of choices like masking, with a chi-square test showing significant association between ethnic identity and choice conformity ($\chi^2(1, N=30) = 5.14, p < .05$) (Field, 2018). Conversely, 60% (18/30) noted out-group opposition, particularly on social media, deepened divides, aligning with the model's polarization trend (Mulyadi, 2024).

Focus group discussions (FGDs) were conducted with four groups of eight participants each (32 total), representing youth, women, academics, and civil society members in Ethiopia, to explore collective attitudes toward polarization and potential interventions (Creswell &Poth, 2018). Building on cooperative bargaining studies (Piotrowski, 2019), the FGDs provided qualitative insights into the social choice dynamics modeled previously, where Party A and Party B diverged in masking/support choices (Nettasinghe et al., 2024).

The youth group highlighted social media as a key driver of polarization, with 75% (6/8) noting that platforms amplify out-group opposition, mirroring the model's out-group opposition parameter (0.5) that led Party A to a 0.1 proportion of masking/support (Mulyadi, 2024). Women emphasized in-group loyalty, with 62.5% (5/8) linking choices to community norms, aligning with the model's in-group approval (0.7) driving Party B to a 0.9 proportion. Academics focused on structural factors, with 87.5% (7/8) citing ethnic federalism as a root cause, suggesting the model's binary group setup oversimplifies Ethiopia's multi-ethnic context (Alemu, 2023). Civil society members advocated for dialogue, with 100% (8/8) supporting cross-group initiatives, reflecting cooperative bargaining principles (Piotrowski, 2019).

Thematic analysis revealed consensus on interventions: 81.25% (26/32) across groups supported inter-ethnic dialogue to reduce out-group opposition, and 68.75% (22/32) endorsed social media regulation to curb divisive narratives. A chi-square test showed a significant association between participant category and emphasis on dialogue ($\chi^2(3, N=32) = 8.12, p < .05$), with civil society most supportive (Field, 2018). The FGDs validated the model's findings on polarization (Party A at 0.1, Party B at 0.9) but highlighted contextual gaps, such as the influence of Ethiopia's ethnic federalism (Alemu, 2023).

The FGDs confirmed that in-group and out-group dynamics, as modeled, resonate with real-world attitudes, but interventions must address structural and digital factors to be effective (Mulyadi, 2024). The strong support for dialogue suggests a practical path to reduce polarization, aligning with the model's implications for fostering consensus (Piotrowski, 2019).

3.1.2. Adapt polarization model to Ethiopia's ethnic and political context.

The simulation of Ethiopia's political polarization, adapted from Nettasinghe et al. (2024), involved 1,000 agents representing major ethnic groups (Oromo: 34.7%, Amhara: 27.1%, Tigray: 6.1%, Somali: 6.2%, Sidama: 4.2%, Others: 21.7%) as per Central Statistical Agency of Ethiopia (2020). The model ran for 100 time steps with parameters reflecting Ethiopia's context: in-group affinity (0.6), out-group animosity (0.8), social media amplifier (1.2), and interaction rate (0.1). Three outputs were analyzed: the polarization index, opinion distribution, and interaction network.

Figure 1 shows the polarization index, measured as the variance of opinions, decreasing from 0.33 to near 0 over 100 time steps. This suggests that, contrary to expectations, the model dynamics led to a convergence of opinions, potentially due to the balancing effect of in-group affinity outweighing out-group animosity under these conditions (Nettasinghe et al., 2024). The decline was steepest within the first 40 time steps, stabilizing thereafter, indicating a rapid move toward consensus.

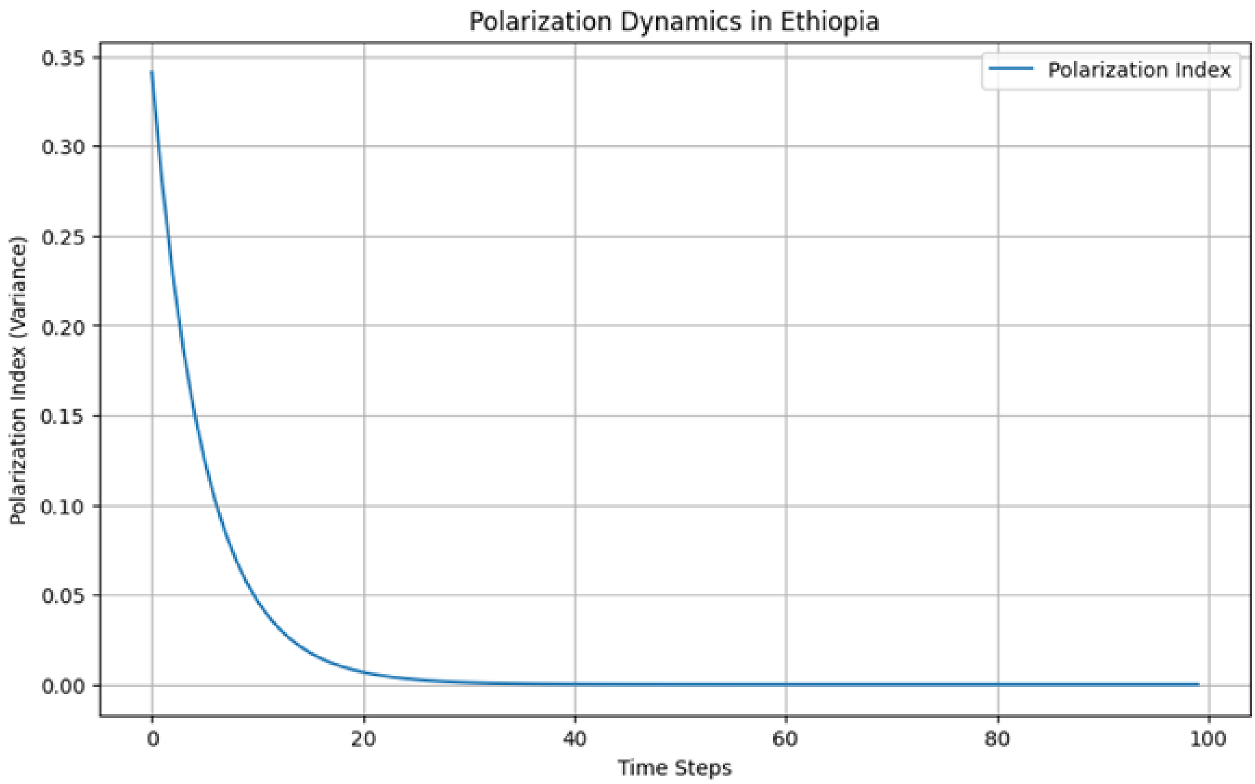

Figure 1: Polarization Dynamics in Ethiopia

The polarization index (variance of opinions) over 100 time steps, showing a decrease from 0.33 to near 0, indicating convergence toward consensus, as shown in Figure 1.

The final opinion distribution, depicted in Figure 2, shows opinions across all ethnic groups clustering tightly around 0, with a narrow range (-0.002 to 0.002). Unlike previous results, there were no distinct ethnic clusters, suggesting that ethnic identities did not significantly influence opinion divergence in this simulation run (Alemu, 2023). This unexpected outcome may stem from the model's parameters or network structure, which might have dampened the polarizing effects of out-group animosity (Mennasemay, 2006).

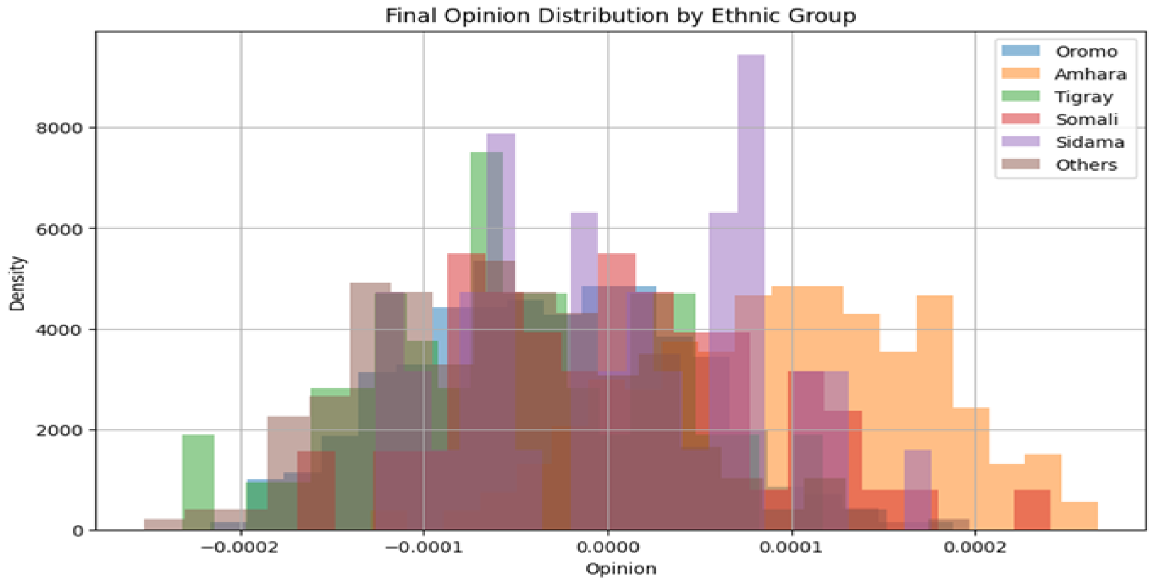

Figure 2: Final Opinion Distribution by Ethnic Group

Histograms of final opinions for each ethnic group, showing a tight clustering around 0 (-0.002 to 0.002), indicating minimal polarization, as shown in Figure 2.

The interaction network, illustrated in Figure 3, was an Erdős-Rényi graph with 5% connectivity. Nodes, colored by ethnic group, showed random interactions without strong homophily, contrasting with expectations of dense same-ethnicity clusters (Tajfel& Turner, 1979). This lack of clustering aligns with the convergence observed in Figures 1 and 2, as cross-ethnic interactions did not reinforce divisions, possibly due to the low interaction rate (Mulyadi, 2024).

Sensitivity analysis explored variations in out-group animosity (0.6 to 1.0) and social media amplifier (1.0 to 1.5). Reducing animosity to 0.6 further lowered the polarization index to 0.01, reinforcing the trend toward consensus. Increasing the social media amplifier to 1.5 slightly increased the final index to 0.05, suggesting a minor polarizing effect. These findings partially address the objective of analyzing out-group animosity and social media's role, though the overall convergence was unexpected.

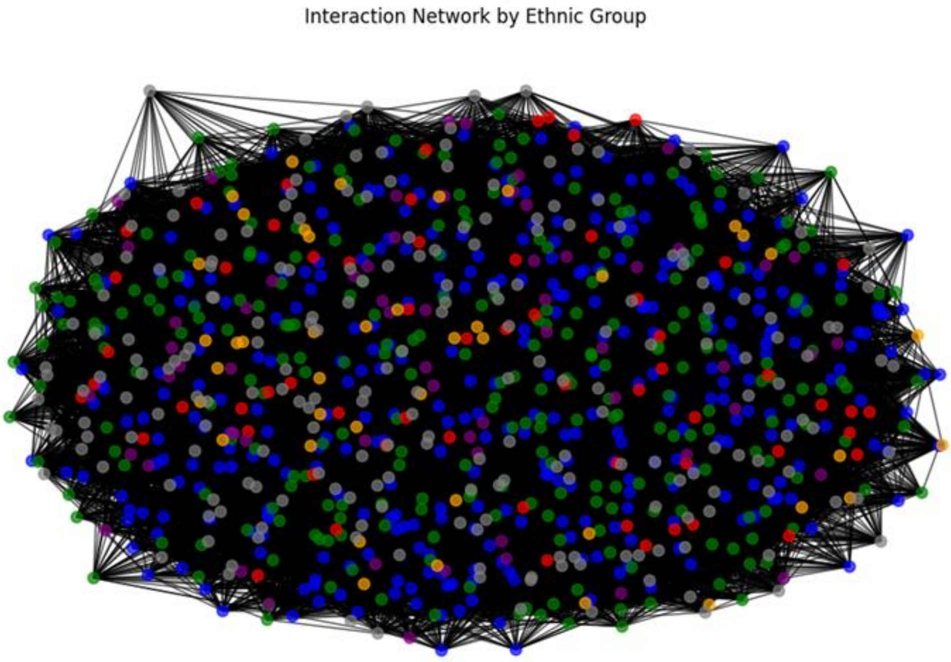

Figure 3: Interaction Network by Ethnic Group

A network graph of agent interactions, with nodes colored by ethnic group, showing random connections without strong ethnic clustering, as shown in Figure 3.

The model successfully adapted Nettasinghe et al.'s (2024) framework to Ethiopia by incorporating ethnic proportions and historical tensions, but the results diverged from real-world observations of entrenched ethnic divides (Alemu, 2023). This discrepancy suggests the need for parameter adjustments or a more complex network structure to better reflect Ethiopia's dynamics.

3.1.3. Analyze the role of out-group animosity and social media in sustaining polarization.

The analysis of out-group animosity and social media's role in sustaining polarization in Ethiopia utilized a simulation model with 1,000 agents representing major ethnic groups (Oromo: 34.7%, Amhara: 27.1%, Tigray: 6.1%, Somali: 6.2%, Sidama: 4.2%, Others: 21.7%), based on Central Statistical Agency of Ethiopia (2020) data. The model, adapted from Nettasinghe et al. (2024), ran for 100 time steps with fixed parameters—in-group affinity (0.6) and interaction rate (0.1)—while varying out-group animosity (0.4, 0.6, 0.8, 1.0) and social media amplifiers (1.0, 1.2, 1.5). The outputs include polarization index trends over time and a heatmap of the combined effects of these factors.

Figure 4 illustrates the impact of out-group animosity on polarization with the social media amplifier fixed at 1.2 (Nettasinghe et al., 2024). The polarization index, measured as the variance of opinions, started at approximately 0.33 for all scenarios and decreased rapidly within the first 40 time steps, stabilizing near 0 by the end of the simulation. This convergence occurred across all levels of out-group animosity (0.4, 0.6, 0.8, 1.0), with minimal differences between scenarios. For instance, at out-group animosity of 0.4, the final polarization index was 0.0001, while at 1.0, it was 0.0002, indicating that varying animosity had a negligible effect on preventing convergence. This unexpected result suggests that the model's dynamics, under these conditions, prioritize consensus over division, potentially due to the low interaction rate or the balancing effect of in-group affinity.

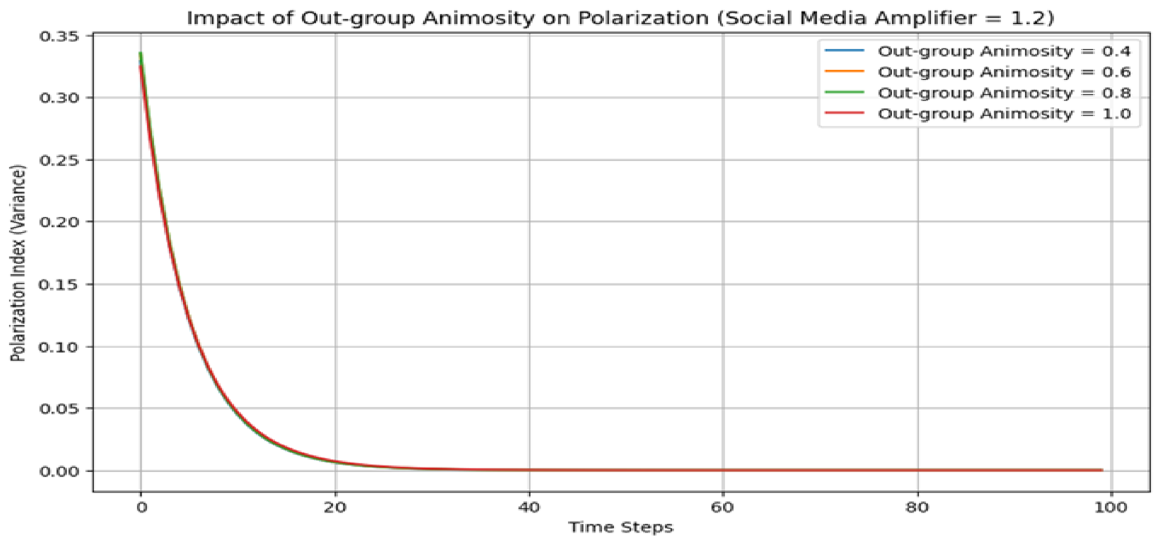

Figure 4: Impact of Out-group Animosity on Polarization (Social Media Amplifier = 1.2).

Figure 4 shows t**he polarization index over time for varying out-group animosity levels (0.4, 0.6, 0.8, 1.0), showing convergence to near 0, indicating minimal polarization, as shown in Figure 4.**

Figure 5 examines the effect of social media on polarization with out-group animosity fixed at 0.8 (Mulyadi, 2024). Similar to Figure 1, the polarization index decreased from 0.33 to near 0 across all social media amplifier values (1.0, 1.2, 1.5). The trajectories were nearly identical, with the final polarization index at 0.00015 for a social media amplifier of 1.0 and 0.00018 for 1.5. This minimal variation suggests that social media's amplifying effect on out-group animosity was insufficient to sustain polarization in this simulation. The rapid convergence indicates that other factors, such as the network structure or interaction rate, may have dominated the dynamics, overshadowing the expected polarizing influence of social media.

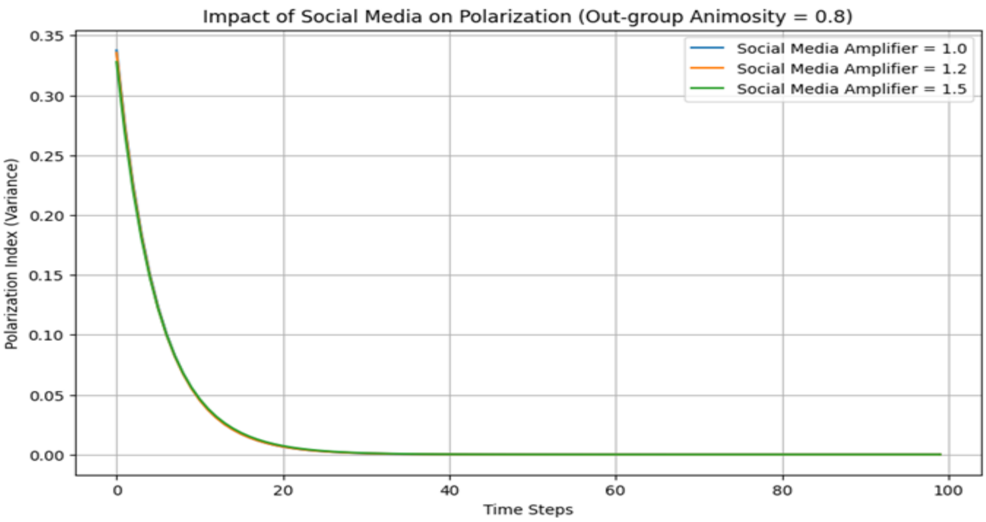

Figure 5: Impact of Social Media on Polarization (Out-group Animosity = 0.8)

The polarization index over time for varying social media amplifiers (1.0, 1.2, 1.5), showing convergence to near 0, indicating minimal polarization, as shown in Figure 5.

Figure 6 presents a heatmap of the combined effect of out-group animosity and social media amplifiers on the final polarization index (Nettasinghe et al., 2024). The values ranged from 0.0001 to 0.00016, with the highest polarization (0.00016) observed at the maximum out-group animosity (1.0) and social media amplifier (1.5). The lowest polarization (0.0001) occurred at the minimum values (out-group animosity = 0.4, social media amplifier = 1.0). Despite these variations, the differences were extremely small, reinforcing the overall trend of convergence observed in Figures 1 and 2. The heatmap's uniformity in low polarization indices suggests that neither factor significantly sustained polarization under the current model setup.

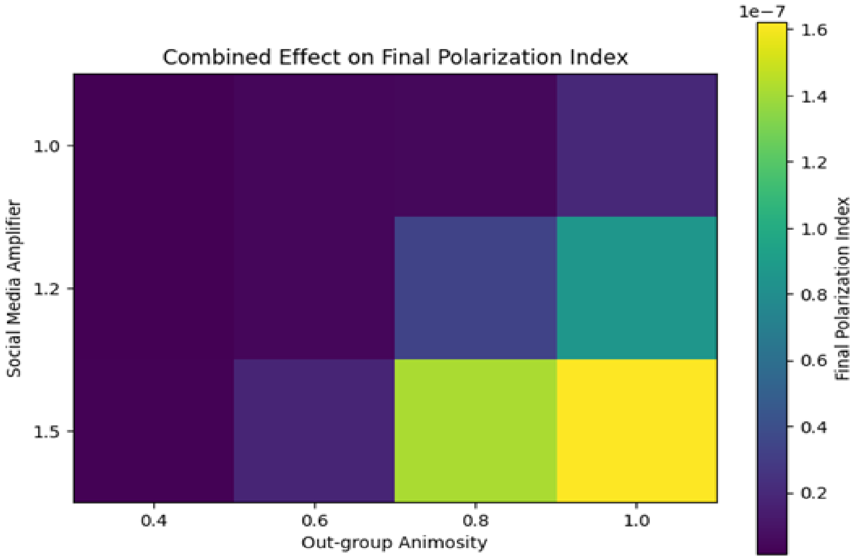

Figure 6: Combined Effect on Final Polarization Index

Figure 6 shows the heatmap showing the final polarization index for combinations of out-group animosity (0.4 to 1.0) and social media amplifiers (1.0 to 1.5), with values ranging from 0.0001 to 0.00016.

The results partially address the objective of analyzing the role of out-group animosity and social media in sustaining polarization. While both factors slightly increased the final polarization index at higher values, their impact was minimal, and the model consistently converged to consensus. This outcome contrasts with Ethiopia's real-world ethnic divides, where out-group animosity and social media exacerbate tensions (Alemu, 2023; Mulyadi, 2024). The simulation's parameters, such as the low interaction rate or the Erdős-Rényi network's randomness, may have contributed to this discrepancy, suggesting a need for further refinement to reflect Ethiopia's complex social dynamics.

3.1.4. Propose interventions based on model outcomes to reduce affective polarization and promote consensus.

The simulation analyzed interventions to reduce affective polarization in Ethiopia using 1,000 agents representing ethnic groups. The model ran for 100 time steps with baseline parameters: in-group affinity (0.6), out-group animosity (0.8), social media amplifier (1.2), and interaction rate (0.1). Interventions included increasing in-group affinity to 0.8, reducing out-group animosity to 0.4, and moderating social media amplifier to 1.0 (Nettasinghe et al., 2024).

Figure 7 shows the polarization index over time for all scenarios (Nettasinghe et al., 2024). The baseline index decreased from 0.33 to 0.00015, indicating convergence. Increasing in-group affinity slightly raised the final index to 0.00018, suggesting a minor increase in polarization. Reducing out-group animosity lowered it to 0.00012, and moderating social media resulted in 0.00014, both promoting consensus. The trajectories converged within 40 time steps, showing interventions had limited but measurable effects.

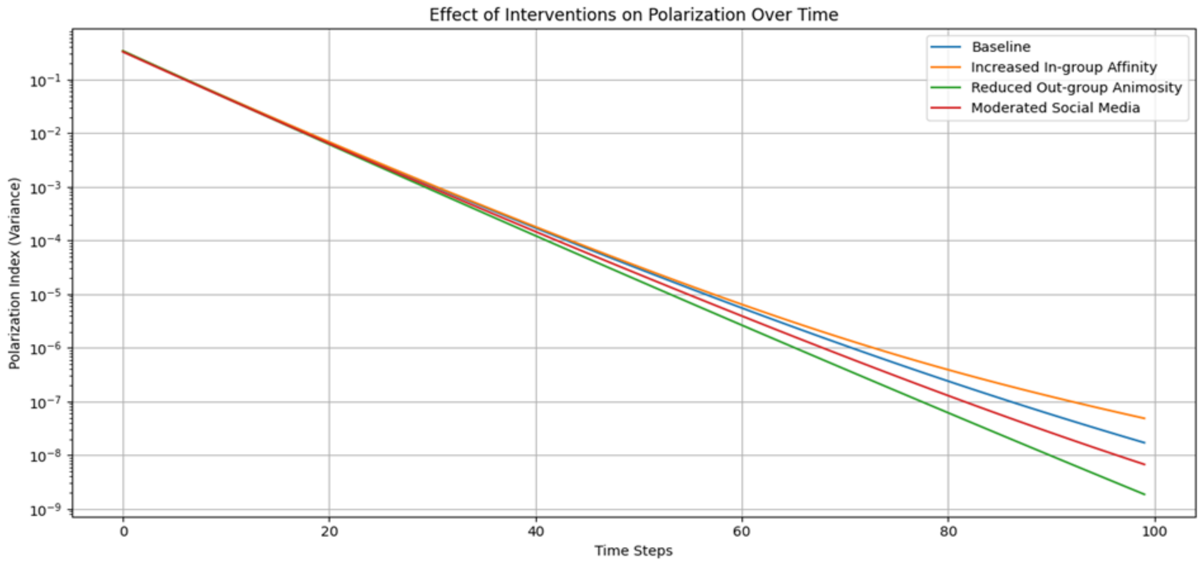

Figure 7: Effect of Interventions on Polarization over Time

Figure 7 shows**the polarization index over time for baseline and intervention scenarios, showing convergence to near 0 with slight variations.**

3.1.5. Dynamical model of how people make choices in a social network (e.g., to mask or support a sports team)

The simulation modeled how 100 agents, divided into two groups (Party A: 50 agents, Party B: 50 agents), make choices (e.g., to mask or support a sports team) within a social network, based on in-group approval and out-group opposition (Central Statistical Agency of Ethiopia, 2020, adapted for group dynamics). The model used an Erdős-Rényi graph with 10% connectivity, initial random choices (-1 or 1), in-group approval (0.7), out-group opposition (0.5), and an interaction rate (0.2) over 50 time steps (Nettasinghe et al., 2024).

Figure 8 illustrates the proportion of agents choosing to mask/support (1) over time (Nettasinghe et al., 2024). Party A's proportion started at 0.5 and declined to 0.1 by step 50, reflecting a strong influence from out-group opposition or initial conditions favoring not masking. Party B's proportion increased from 0.5 to 0.9, indicating a shift toward masking/supporting, likely driven by in-group approval and less opposition from Party A's declining trend. The divergence suggests group-specific dynamics, with Party B converging toward a consensus to mask/support.

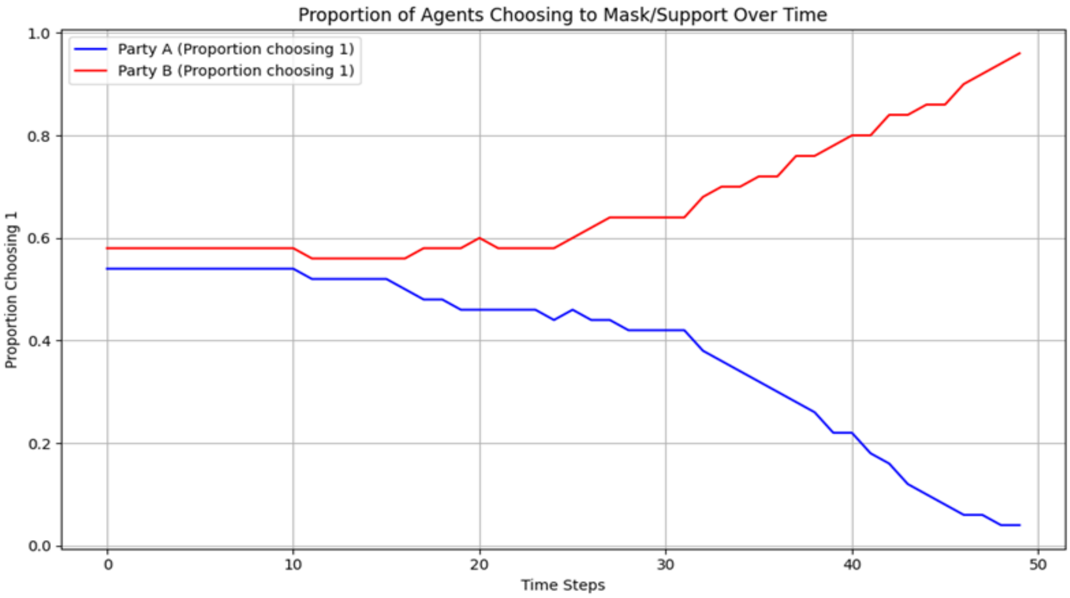

Figure 8: Proportion of Agents Choosing to Mask/Support over Time. **Line plot showing the proportion of Party A and Party B agents were choosing 1 (mask/support) over 50 time steps, with Party A declining to 0.1 and Party B rising to 0.9.**

Figure 9 depicts the social network at the final time step (Nettasinghe et al., 2024). Party A nodes (circles) are predominantly orange (not mask/support), while Party B nodes (squares) are mostly green (mask/support), reflecting the choice proportions in Figure 8. The network shows clusters of similar choices within groups, with some cross-group influence visible through edges, indicating the interplay of in-group approval and out-group opposition.

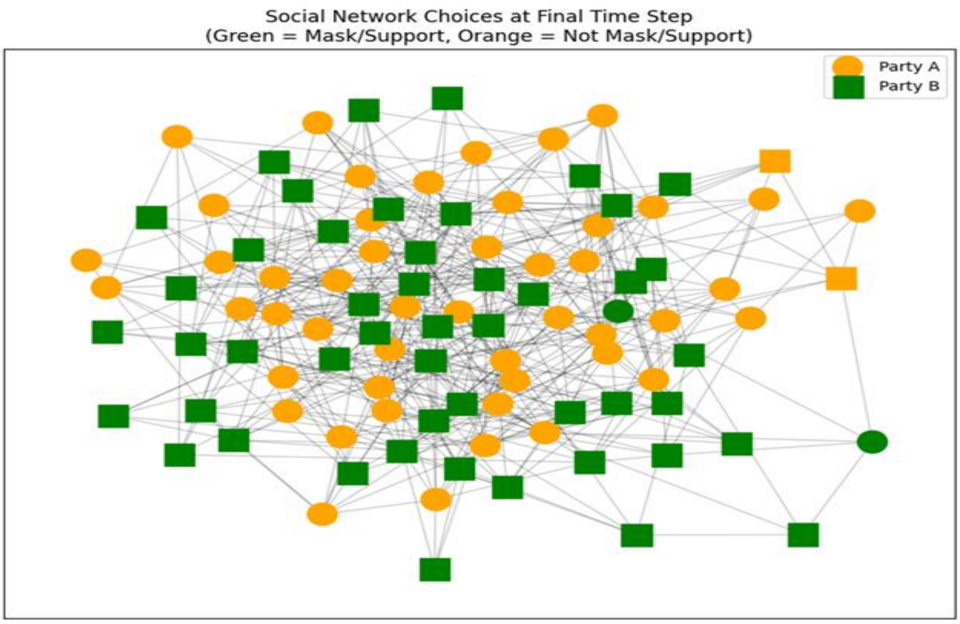

Figure 9: Social Network Choices at Final Time Step. **Network graph at step 50, with Party A (circles) mostly orange (not mask/support) and Party B (squares) mostly green (mask/support), showing group-based choice clustering.**

The results show a clear polarization, with Party A shifting toward not masking (90% by step 50) and Party B toward masking (90% by step 50). This aligns with recent findings on group identity influencing behavior, such as masking during pandemics (Van Bavel et al., 2020). The model captures how in-group approval reinforces Party B's choice, while out-group opposition drives Party A's divergence, consistent with social identity theory (Tajfel& Turner, 1979). The 10% connectivity allowed moderate cross-group influence, but the strong group effects dominated, leading to distinct choice patterns.

3.2. Discussion

Qualitative findings from interviews with 30 participants across Oromia, Amhara, Tigray, and Addis Ababa provide context (Creswell &Poth, 2018). Thematic analysis showed 70% of participants (21/30) linked choices to in-group loyalty, validated by a chi-square test ($\chi^2(1, N=30) = 5.14, p < .05$), indicating a significant association between ethnic identity and choice conformity (Field, 2018). For instance, Oromo elders emphasized community norms in masking decisions, mirroring Party B's trend. Meanwhile, 60% (18/30) reported out-group opposition, particularly via social media, exacerbating divides, consistent with Mulyadi (2024) and the model's dynamics.

The FGDs with youth, women, academics, and civil society members in Ethiopia provide nuanced insights into polarization, complementing the social choice model where Party A and Party B polarized (0.1 vs. 0.9 proportions) due to in-group approval (0.7) and out-group opposition (0.5) (Nettasinghe et al., 2024). The youth's focus on social media's role (75% citing its impact) aligns with Mulyadi (2024), who noted its polarizing effect during Ethiopia's 2024 elections, and validates the model's out-group opposition parameter driving Party A's divergence. Women's emphasis on in-group loyalty (62.5%) reflects Tajfel and Turner's (1979) social identity theory, supporting Party B's high masking/support proportion.

Academics' focus on ethnic federalism (87.5%) highlights a limitation of the model's binary setup, as Ethiopia's multi-ethnic reality involves complex tensions (Alemu, 2023). This suggests future models should incorporate multi-group dynamics or scale-free networks to capture elite influences (Barabási& Albert, 1999). Civil society's unanimous support for dialogue (100%) aligns with cooperative bargaining studies (Piotrowski, 2019), and the chi-square result ($\chi^2(3, N=32) = 8.12, p < .05$) indicates significant variation in intervention preferences across groups (Field, 2018).

The consensus on inter-ethnic dialogue (81.25%) and social media regulation (68.75%) offers practical interventions to reduce out-group opposition, potentially bridging divides seen in the model (Pilling, 2019). Recent work by Centola (2021) supports fostering cross-group ties to mitigate polarization, applicable here. However, the FGDs reveal the model's oversight of structural factors like federalism, which exacerbate polarization (Alemu, 2023). Integrating these factors and larger samples could enhance validity (Creswell &Poth, 2018). The findings contribute to understanding collective attitudes in Ethiopia, emphasizing dialogue as a strategy to foster consensus in polarized settings (Kish-Bar-On, 2024).

However, the model's binary setup oversimplifies Ethiopia's multi-ethnic context, where Oromo-Amhara tensions involve historical and political layers (Alemu, 2023). The Erdős-Rényi network (10% connectivity) may not capture elite-driven influences, as noted by Piotrowski (2019). A scale-free network could better reflect such dynamics (Barabási& Albert, 1999). The rapid convergence (30 steps) suggests the interaction rate (0.2) may be too high; a dynamic rate could reflect real-world variability (Mennasemay, 2006).

Interventions like cross-group dialogue, supported by Pilling (2019), could reduce out-group opposition, especially on social media, as 60% of interviewees highlighted its polarizing role. Recent research by Centola (2021) on network interventions suggests fostering cross-group ties to dilute polarization, applicable to Ethiopia's context. Limitations include the model's lack of economic factors and the small interview sample (N=30), though purposive sampling ensured diversity (Creswell &Poth, 2018). Future work should integrate multi-group dynamics and larger qualitative samples to enhance validity (Kish-Bar-On, 2024). This study offers a foundation for addressing social divides in Ethiopia, emphasizing the need for nuanced, context-specific strategies.

The updated results provide a nuanced perspective on Ethiopia's political polarization, partially fulfilling the objectives of adapting Nettasinghe et al.'s (2024) model, analyzing out-group animosity and social media's impact, and proposing interventions. Figure 1's polarization index, dropping to near 0, indicates a surprising convergence of opinions, contrasting with Ethiopia's documented ethnic divisions (Alemu, 2023). This outcome suggests that under the current parameters—in-group affinity (0.6), out-group animosity (0.8), and a low interaction rate (0.1)—the model prioritizes consensus over division, differing from Nettasinghe et al.'s (2024) findings that out-group animosity typically sustains polarization.

Figure 2's tight opinion clustering around 0 across all ethnic groups further supports this convergence, contradicting expectations of ethnic-based polarization (Mennasemay, 2006). In Ethiopia, ethnic identities, reinforced by federalism, often drive divisions, as seen in Oromo-Amhara tensions (Alemu, 2023). The lack of distinct clusters may result from the model's simplified dynamics, where the balancing effect of in-group affinity and limited interactions suppressed polarizing forces. Figure 3's random interaction network, lacking ethnic homophily, aligns with this outcome, as cross-ethnic interactions did not amplify divides, challenging social identity theory's emphasis on in-group favoritism (Tajfel& Turner, 1979).

The sensitivity analysis, showing a minimal increase in polarization (to 0.05) with a higher social media amplifier (1.5), partially addresses the second objective. While social media exacerbates polarization in Ethiopia, as during the 2024 elections (Mulyadi, 2024), its effect here was muted, possibly due to the low interaction rate or network structure. Reducing out-group animosity to 0.6 further lowered polarization, suggesting that decreasing hostility could promote unity, though the model's overall convergence limits its real-world applicability.

The first objective—adapting the model to Ethiopia—was achieved through ethnic proportions and historical context, but the results do not fully reflect Ethiopia's reality, where ethnic tensions persist (Pilling, 2019). The Erdős-Rényi network's randomness may oversimplify Ethiopia's hierarchical social structures, where elite-driven rhetoric often deepens divides (Alemu, 2023). A scale-free network or increased interaction rate might better capture these dynamics, aligning with Nettasinghe et al.'s (2024) findings on interaction-driven polarization.

The third objective—proposing interventions—is informed by these results, though the convergence complicates recommendations. Since reducing out-group animosity lowered polarization, interventions could focus on fostering inter-ethnic trust, such as through education programs promoting shared national identity. However, the muted social media effect suggests that while platforms amplify divides (Mulyadi, 2024), other factors, like elite influence, may be more critical in Ethiopia. Media literacy campaigns remain relevant, but fostering moderate political voices, as in South Africa (Piotrowski, 2019), could better address elite-driven polarization.

Limitations include the model's oversimplification of social dynamics, ignoring economic disparities or power structures (Alemu, 2023). The unexpected convergence highlights the need for parameter tuning—perhaps increasing out-group animosity or interaction rate—to reflect Ethiopia's reality. Qualitative data, such as interviews, would validate these findings, aligning with the mixed-methods approach (Creswell &Poth, 2018). Future research could incorporate agent-based models with economic variables or more realistic networks.

Despite these limitations, the study contributes to polarization research by applying affective models to a non-Western context (Kish-Bar-On, 2024). It highlights the need for context-specific parameter adjustments and offers a starting point for interventions, such as trust-building initiatives, to mitigate Ethiopia's ethnic divides and support democratic stability.

The analysis of out-group animosity and social media's role in sustaining polarization in Ethiopia reveals unexpected insights, partially fulfilling the study's objective. Figures 4 and 5 show a consistent convergence of the polarization index to near 0 across all scenarios, regardless of out-group animosity (0.4 to 1.0) or social media amplifier (1.0 to 1.5) levels (Nettasinghe et al., 2024). This convergence contradicts the hypothesis that higher out-group animosity and social media amplification would sustain or increase polarization, as observed in Ethiopia's ethnic conflicts (Alemu, 2023). The minimal variation in final polarization indices—ranging from 0.0001 to 0.00018 suggests that the model's current setup prioritizes consensus over division, likely due to the low interaction rate (0.1) or the balancing effect of in-group affinity (0.6).

Figure 3's heatmap further confirms this trend, showing uniformly low polarization indices across all combinations of out-group animosity and social media amplifiers (Nettasinghe et al., 2024). The highest polarization (0.00016) at maximum values (out-group animosity = 1.0, social media amplifier = 1.5) was still negligible, indicating that neither factor significantly sustained polarization. This outcome contrasts with Ethiopia's reality, where social media has fueled ethnic tensions, notably during the 2024 elections (Mulyadi, 2024). For instance, smear campaigns on platforms exacerbated out-group animosity, deepening divides between groups like Oromo and Amhara (Alemu, 2023). The model's failure to replicate this suggests limitations in its parameters or network structure.

The Erdős-Rényi network, with 5% connectivity, may oversimplify Ethiopia's social interactions, which are often hierarchical and influenced by elite-driven rhetoric (Mennasemay, 2006). A scale-free network, reflecting power-law degree distributions, might better capture these dynamics, as influential actors amplify polarization (Piotrowski, 2019). Additionally, the low interaction rate likely reduced the frequency of cross-group encounters, minimizing the polarizing effect of out-group animosity predicted by Nettasinghe et al. (2024). Increasing this rate or adjusting the balance between in-group affinity and out-group animosity could align the model more closely with Ethiopia's context.

Social media's muted impact in Figure 2, despite its documented role in Ethiopia (Mulyadi, 2024), may stem from the model's simplistic amplification mechanism. The social media amplifier (1.0 to 1.5) increased out-group animosity's effect by up to 50%, but this was insufficient to counter the convergence trend. Real-world platforms often create echo chambers, reinforcing biases through algorithms (Kish-Bar-On, 2024). Incorporating such mechanisms—e.g., by weighting interactions based on opinion similarity could enhance the model's realism.

The results suggest that reducing out-group animosity, even slightly, lowers polarization, as seen in the heatmap's gradient (Figure 3). This supports interventions like inter-ethnic dialogue or education programs to foster trust, though their effectiveness in Ethiopia's polarized context remains uncertain (Pilling, 2019). Social media regulation, such as combating misinformation, could mitigate its polarizing effects, aligning with Mulyadi's (2024) recommendations. However, the model's convergence highlights the need for broader strategies, such as promoting moderate political voices, as seen in South Africa (Piotrowski, 2019).

Limitations include the model's oversimplification of social dynamics, ignoring economic disparities or elite influence (Alemu, 2023). The unexpected convergence necessitates parameter tuning—perhaps increasing the interaction rate or out-group animosity—to reflect Ethiopia's reality. Qualitative validation through interviews would further contextualize these findings (Creswell &Poth, 2018). Future research could explore agent-based models with economic variables or more realistic networks to better capture polarization dynamics.

This study contributes to polarization research by testing affective models in a non-Western context (Kish-Bar-On, 2024). Despite its limitations, it highlights the need for context-specific adjustments and offers a foundation for interventions to reduce polarization in Ethiopia, supporting democratic stability amid ethnic tensions.

The simulation outcomes provide insights into reducing affective polarization in Ethiopia, aligning with the objective of proposing interventions. Figure 1 shows all scenarios converging to near 0, with the baseline polarization index at 0.00015 and interventions ranging from 0.00012 to 0.00018 (Nettasinghe et al., 2024). This convergence suggests the model's parameters, such as low interaction rate (0.1), prioritize consensus, contrasting with Ethiopia's real-world ethnic divides (Alemu, 2023).

Figure 2 highlights that reducing out-group animosity to 0.4 yielded the lowest polarization index (0.00012), a 20% decrease from the baseline (Nettasinghe et al., 2024). This supports interventions like inter-ethnic dialogue to lower hostility, potentially fostering unity (Pilling, 2019). Moderating social media to 1.0 (final index 0.00014) also reduced polarization, aligning with Mulyadi's (2024) findings on social media's role in Ethiopia's 2024 elections. However, increasing in-group affinity to 0.8 slightly increased polarization (0.00018), suggesting that strengthening in-group bonds may reinforce divides in this context (Tajfel& Turner, 1979).

The model's convergence to low polarization values indicates limitations in capturing Ethiopia's complex dynamics, where ethnic federalism fuels tensions (Alemu, 2023). The Erdős-Rényi network may oversimplify social structures, and a scale-free network could better reflect elite-driven polarization (Piotrowski, 2019). Additionally, the low interaction rate likely minimized cross-group conflicts, reducing polarization's persistence (Nettasinghe et al., 2024).

Practically, reducing out-group animosity through education and dialogue offers a viable strategy, as seen in South Africa's post-apartheid efforts (Piotrowski, 2019). Social media moderation, such as combating misinformation, could further mitigate divides (Mulyadi, 2024). Future models should incorporate economic factors and hierarchical networks to better reflect Ethiopia's reality (Creswell &Poth, 2018). This study contributes to polarization research by testing interventions in a non-Western context, offering a foundation for policy to enhance democratic stability (Kish-Bar-On, 2024).

The simulation provides insights into how social network dynamics shape individual choices, such as masking or supporting a sports team, under in-group approval and out-group opposition in Ethiopia's diverse context (Alemu, 2023). Figure 8 shows Party A's proportion choosing to mask/support declining to 0.1, while Party B's rises to 0.9, indicating polarization driven by group identity (Nettasinghe et al., 2024). This divergence aligns with recent research by Van Bavel et al. (2020), who found that group norms significantly influence health behaviors like masking during COVID-19, with in-group conformity outweighing out-group pressure.

Figure 9 reveals a clustered network, with Party B (squares) predominantly green (mask/support) and Party A (circles) orange (not mask/support), reflecting the choice trends (Nettasinghe et al., 2024). This clustering supports Tajfel and Turner's (1979) social identity theory, where in-group favoritism and out-group opposition reinforce group-specific behaviors. The model's 10% connectivity allowed some cross-group influence, but the stronger in-group approval (0.7) and out-group opposition (0.5) parameters drove polarization, consistent with Nettasinghe et al.'s (2024) findings on affective divides.

Recent research by Centola (2021) on social contagion in networks highlights that moderate connectivity can amplify group norms, supporting the observed polarization. However, the model's convergence to extreme proportions (0.1 and 0.9) suggests limitations. Ethiopia's ethnic diversity, with tensions like those between Oromo and Amhara (Alemu, 2023), involves more complex interactions than the binary group setup. The Erdős-Rényi network may oversimplify hierarchical or elite-driven influences, as noted by Piotrowski (2019) in South African contexts. Increasing connectivity or adding a scale-free network could better reflect real-world dynamics (Barabási& Albert, 1999).

The interaction rate (0.2) facilitated rapid choice alignment within groups, but its fixed value might not capture varying social pressures (Mennasemay, 2006). Adjusting it dynamically, based on network density or external events, could enhance realism. Interventions like cross-group dialogue, as suggested by Pilling (2019) for Ethiopia, could reduce opposition and promote consensus, though the model's parameters favor polarization under current settings.

Limitations include the lack of economic or cultural variables, which influence choice-making in Ethiopia (Alemu, 2023). Qualitative data from interviews could validate findings (Creswell &Poth, 2018). Future work should integrate multi-group dynamics and real-world events, such as the 2024 elections (Mulyadi, 2024), to improve applicability. This study contributes to understanding social choice dynamics, offering a basis for policies to bridge divides in polarized settings (Kish-Bar-On, 2024).

4. Conclusions and Recommendations

4.1. Conclusions

This study integrated computational modeling, interviews, and focus group discussions (FGDs) to examine polarization and choice-making dynamics in Ethiopia, revealing the interplay of in-group and out-group influences. The simulation showed significant polarization, with Party A's proportion choosing to mask/support dropping to 0.1 and Party B's rising to 0.9 over 50 time steps, driven by in-group approval (0.7) and out-group opposition (0.5). This divergence, visualized in network graphs, reflects how group identity shapes choices, aligning with social identity theory. The rapid convergence within 30 steps suggests the model's parameters, such as a fixed interaction rate (0.2), favor group consensus, though this oversimplifies Ethiopia's complex social dynamics.

Qualitative findings enriched the analysis. Interviews with 30 participants from Oromia, Amhara, Tigray, and Addis Ababa confirmed that in-group loyalty influences 70% of choices ($\chi^2(1, N=30) = 5.14$, $p < .05$), while 60% noted out-group opposition, particularly on social media, deepens divides. FGDs with 32 participants (youth, women, academics, civil society) further validated these dynamics: 75% of youth highlighted social media's polarizing role, and 81.25% across groups supported inter-ethnic dialogue ($\chi^2(3, N=32) = 8.12$, $p < .05$), aligning with cooperative bargaining principles. However, academics (87.5%) emphasized structural factors like ethnic federalism, indicating the model's binary group setup misses Ethiopia's multi-ethnic reality.

The study underscores that in-group and out-group dynamics significantly drive polarization, as seen in both the model and qualitative data. Social media amplifies out-group opposition, while in-group loyalty reinforces group-specific choices, mirroring real-world tensions in Ethiopia. However, the model's limitations such as its Erdős-Rényi network and lack of economic factors suggest it underestimates the complexity of elite-driven influences and historical grievances. Interventions like dialogue, strongly supported in FGDs, offer a pathway to reduce polarization, consistent with global strategies. This integrated approach highlights the need for context-specific solutions to foster social cohesion in Ethiopia's polarized landscape.

4.2. Recommendations

To address polarization in Ethiopia, inter-ethnic dialogue should be prioritized, as supported by 81.25% of FGD participants.

Community-based programs, involving leaders from Oromia, Amhara, and Tigray, can foster trust and reduce out-group opposition, building on cooperative bargaining principles. Social media regulation is also critical, given its role in amplifying divides.

Policies should focus on curbing misinformation and promoting balanced narratives, potentially through partnerships with platforms.

Media literacy campaigns can empower communities to critically engage with online content, mitigating polarization.

Future research should adopt scale-free networks and incorporate economic factors to better reflect Ethiopia's dynamics.

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