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The Relationships between Online Activity and Political Polarization

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Abstract - The new coronavirus control efforts have resulted in a change in the educational environment, with online courses replacing in-person instruction. There has been a shift toward offering courses online in K-12 and higher education. It may be too soon to tell how students and teachers will adjust to online learning as they become aware of its limitations and reorient themselves to meet them, but we have tried to document the viewpoint and preparation of teachers and students as a critical component. The majority of respondents to this study had a positive view of online learning following Hurricane Corona. Since the internet format allowed for more flexibility and convenience, it was deemed successful. Students preferred materials that were well-organized and included filmed movies that were made available on university websites. Students also said that they would recall more material if each course concluded with an exam and a project. However, the majority of students also expressed concern that online classes could be more challenging than face-to-face ones owing to technological constraints, slower feedback, and professors who aren't proficient in effectively using ICTs. In order to create an online course that is effective for its intended audience, it is crucial to consider the aforementioned factors.When the smoke from the COVID-19 epidemic clears, more schools may turn to online learning as a supplementary method of education. As a result, the results of this study will be useful for individuals who are thinking about incorporating online components into more conventional forms of higher education.

Keywords - social media, political loyalty, political engagement, political polarization, Smart partial least square.

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INTRODUCTION

Many indicators suggest that political polarization among Americans has been growing for decades. point out, while only about 5% of Republicans and Democrats in 1960 said they would be "[feel] 'displeased' if their son or daughter married outside their political party, nearly 50% of Republicans and over 30% of Democrats "felt somewhat or very unhappy at the prospect of interparty marriage" in 2010. The percentage of voters who voted for the same party in both the presidential and House elections increased from 71% of reported voters in 1972 to 90% in 2012 and the percentage of party affiliates who had a favorable view of their own party increased by more than 50% between 1980 and 2015. The proliferation of online communities and social media platforms has been blamed by several writers for this shift. that people on the internet may become isolated in "echo chambers" where they only consume information that confirms their own beliefs. Regardless of where people stand on the political spectrum claims that "social media contribute to... greater polarization as the like-minded locate one another and feed one another's biases and frustrations." social media is "one of our major challenges," adding, "I don't see how we can ever trust each other and work together again, so long as we are all immersed in a continual stream of outrageous outrages done by the other side." Former President Barack Obama said of social media's impact on the 2016 election, "the capacity to disseminate misinformation, wild conspiracy theories, to paint the opposition in wildly negative light without any rebuttal—that has accelerated in ways that much more sharply polarize the electorate and make it very difficult to have a common conversation".

These results challenge the idea that the internet and social media are primary causes of growing division. Any such explanation must take into consideration the sharp rise in polarization even among individuals with little internet literacy and social media engagement. However, these kinds of accounts may be made. It's possible that division is exacerbated by social media among young people but is caused by something else among older people. It is possible that polarization among young individuals on social media has a trickle-down effect on the perspectives of older adults, either directly via the election of politicians or through the endogenous positioning of conventional media, or indirectly through other routes. However, the simplest explanations for the rise in polarization being linked to the internet are not supported by our data.

LITERATURE REVIEW

Maria Nordbrandt (2021) Scholars are deeply divided about whether or not social media contributes to societal division. Only a select few, however, have addressed how polarization can influence people's engagement with social media. This research utilizes Dutch panel data to fill this gap by examining whether or not there is any direction to the association between social media usage and emotional polarization. There was no evidence to support the theory that using social media increased emotional polarization. However, the findings are consistent with the theory that the degree of emotional polarization influences later social media usage. Finally, the data show that there is considerable variation between users on both the amount of social media experience they bring to the table and across the various social media sites themselves. Previous research's prevailing notion that social media is a key source of societal division is called into doubt by this study.

Emily Kubina (2021) The fragmentation of the news industry and the proliferation of false information on social media have both been blamed for the increase in political division. The whole spectrum of studies on media and polarization has not been assessed in prior evaluations. The impact of (social) media on political polarization is assessed by a systematic review of 94 papers (121 research). There has been an uptick in quantitative and qualitative studies over the last decade showing that pro-attitude media increases divisiveness. There is a shortage of study looking at how (social) media might reduce polarization, yet there is an abundance of studies analyzing Twitter and American populations. There is also a lack of agreement on how to describe or quantify ideological and emotional polarization. Suggestions for further study are offered.

Anindita Borah (2022) The influence of social media on the flow of information between political groups is substantial. The effect of politicians' social media use and interactions on political polarization has been the subject of much study. For politically divided countries like India, where cooperation between parties is crucial for gaining parliamentary support, the study of political polarization takes on added significance. The degree of polarization between political groups may increase or decrease depending on the nature of the conversation at hand. The purpose of this research is to analyze the level of polarization among Indian politicians discussing various political issues on the social media site Twitter. The analysis is predicated on two competing hypotheses on the role of social media in stoking political divisions. The first view sees social media as a platform where people of different ideologies may communicate with one another. However, the second view emphasizes the role that selective exposure plays in social media platforms in fostering division. The research will look at how Twitter is being used to build relationships inside and between political parties, as well as how much disagreement there is within political commentators. The inquiry analyzes the tweets of Indian politicians during key events in India from 2019 to 2021 by doing social network analysis and content analysis. Some significant themes linked to Indian government policies, national security, and natural catastrophe occurrences have been explored for an objective topic-specific examination of polarization. According to the study's results, political Twitter users in India are more likely to engage in heated online debates than those who don't use the platform. The degree of polarization also varies according on the subject matter of political debates. More so than with less contentious matters, polarization occurs in discussions about contentious and contentious issues.

Petter Törnberg (2022) Intense division in politics has emerged in the last several decades. Despite mounting empirical evidence to the contrary, the so-called "echo chamber" idea continues to dominate explanations that include digital media. This study argues that this growing body of data not only disproves the echo chamber theory but also establishes the groundwork for a different mechanism of causality. This study proposes such a mechanism by reviewing existing research on emotional polarization, new media, and the dynamics of public opinion. The research on emotional polarization shows that there has been a shift away from seeing polarization as a result of opposing views on issues and toward viewing it as the result of sorting, or the alignment of differences that is essentially splitting the electorate in two more similar megaparties. The paper uses research on opinion dynamics and digital media to present a model that inverts the echo chamber to explain the rise in sorting, arguing that it is interaction with people who hold different opinions, rather than the isolation of people who hold the same ones, that drives polarization. When people engage with one another on a small scale, they create a stable plural patchwork of overlapping conflicts. Digital media promotes nonlocal engagement, which in turn drives disputes to align along party lines and makes local variability less noticeable. Even if there is convergence as a consequence of individual contact, the overall effect is polarization. According to the concept, therefore, digital media polarize via partisan sorting, resulting in a whirlwind in which an increasing number of people's identities, values, and cultural preferences are swept up in an increasingly stark social divide.

METHODS

Data

The COVID-19 Twitter data collection utilized in this study was compiled by Chen et al. [19] and includes

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tweets sent between January 21, 2020, and July 31, 2020 (v2.7). The gathered tweets all use COVID-19-related hashtags. The tweets may be either new ones or retweets, quoted ones, or responses to others. In addition to the user's location, their profile description, and the number of people that follow them are all included in every tweet. Verified users have had their identities confirmed by Twitter, lessening the likelihood that their accounts are automated software [20]. Personal identifiers (such as "Dog-lover"), professional ones (such as "Senator"), and political and activist affiliations (such as "Republican" or "#BLM") are all welcome in the optional profile description field that all users may fill out.

Interaction Networks

GR=(V,E) is a directed, weighted graph representation of the retweet network. A retweet from user u to user v is represented as an edge (u,v) in the graph, and the weight of that edge, w(u,v), is equal to the number of times u has retweeted v's tweets. Edges of the retweet network and retweet interactions were used interchangeably. We have built a network called GM, where mentions are used as edges instead of retweets. A user may be cited in any tweet in a number of ways, including retweets, quoted tweets, replies, and direct mentions.

Data Preprocessing

We focused only on individuals whose self-reported location indicated they were in the United States . we kept only retweet network edges with weights greater than 2. Since retweets are typically seen as a kind of endorsement, the findings would be more trustworthy if a user retweeted the same person several times. Users who did not provide usable profiles were excluded from our analysis. Since inactive Twitter users tend to have less than 10 degrees (in or out) in the retweet network, we also deleted them. We estimated a score from 0 (presumably human) to 1 (likely bots) using the approach proposed and then excluded the top 10% of users based on bot scores, as recommended.

We were able to compile a dataset containing 232,000 users and 1.4 million retweet exchanges. On average, a tweet's retweet network had 6.15 degrees of separation. There were 10,000,000 mention interactions amongst the same group of individuals, with an average degree of 46.19 in the mention network. About 18,000 users, or about 8% of the total, have been confirmed.

Estimating User Polarity

Our suggested approach to estimating the polarity of users over a spectrum is outlined in this section. We started by doing a literature review and using weak-supervision to identify two distinct user populations who we then employed as seeds. Then, we looked at several models to determine consumers' political preferences. Finally, using 5-fold cross-validation, the best model was selected and applied to the remaining users to get polarity ratings.

RESULTS

The mediating role of political engagement and political loyalty between social media use and political polarization was estimated using a structural equation model (SEM) with Partial least squares (PLS), specifically Smart PLS v. 3.2.7. PLS's many benefits, including its ability to estimate complicated models like parallel mediating effects and its relaxed statistical assumptions, make it the ideal choice for our investigation. To measure the reliability of the structural model's path coefficient estimates, a t-statistic and standard error based on a 5000-sample bootstrap were calculated. Measurement Model (External) Evaluation. The reliability, convergent validity, and discriminant validity of the measuring instruments were determined using confirmatory factor analysis (CFA). Table 1 demonstrates that all alpha coefficients, CR estimations, and AVE values above the minimum acceptable values of 0.7, 0.7, and 0.50, respectively. Examining the factor loadings of scale items on their respective constructs allowed us to evaluate convergent validity. Each item's loading was more than 0.7, the cutoff value established. The percentages of explained variation for each category were as follows: usage of social media 55%, political involvement 53%, polarization based on leadership 52%, polarization based on party 52%, and polarization based on issues 52%. While Cronbach's alpha and composite dependability were both in the high-to-moderate 80s.

Table 1: Psychometric Properties of Social Media Use, Political Engagement, Leadership Based Polarization, Party Based Polarization, and Issue Based Polarization.

Variables	K	λ Range	α	CR	AVE
Social Media Use	5	0.70-0.80	0.79	0.86	0.55
Political Engagement	7	0.56-0.82	0.85	0.89	0.53
Political Loyalty	8	0.67-0.78	0.87	0.90	0.53
Leadership Based Polarization	7	0.58-0.79	0.84	0.88	0.52
Party Based Polarization	7	0.61-0.78	0.83	0.88	0.50
Issue Based Polarization	6	0.56-0.82	0.81	0.87	0.52

Note. k = number of items, CR = composite reliability, AVE = Average variance extracted, λ (lambda) = standardized factor loading α = Cronbach's alpha

The ability to discriminate between groups was evaluated in two methods. To begin, the maximum shared variance (MSV) between a construct and all other components was lower than the square root of the average variance (AVE) retrieved from each scale (Table 2). Finally, we calculated the correlation ratio between heterotraits and monetarist. For comparison, the more cautious cut-off value (Table 3). Convergent and discriminant validity were supported by the aforementioned findings.

Table 2: Mean, Standard Deviation and Correlation among Factors

Variables	M	SD	1	2	3	4	5	6
1. Social Media Use	13.92	4.67	0.74	0.47	0.25	0.01	0.16	0.08
2. Political Engagement	21.06	6.00		0.73	0.48	0.28	0.57	0.35
3. Political Loyalty	24.40	7.19			0.73	0.35	0.50	0.34
4. Leadership Based Polarization	20.25	5.61				0.72	0.57	0.66
5. Party Based Polarization	20.95	5.44					0.71	0.48
6. Issue Based Polarization	16.11	3.73						0.72

Note. M = mean, SD = standard deviation

Table 3: Heterotrait-Monotrait Ratio HTMT Matrix

Variables	1	2	3	4	5	6
1. Social Media Use		0.55	0.29	0.12	0.2	0.17
2. Political Engagement			0.55	0.32	0.67	0.41
3. Political Loyalty				0.4	0.58	0.4
4. Leadership Based Polarization					0.69	0.78
5. Party Based Polarization						0.57
6. Issue Based Polarization						

Examining the Internal Structural Model. See Tables 4 and 5 for the assessment of the structural model's direct influence and indirect effect (mediation).

Table 4: Direct Effects of Social Media Use, Political Engagement, Political Loyalty and Political Polarization

Direct effects	Coeff.	Standard Deviation	T-Statistics	P-Values
Social Media Use → Political Engagement	0.47	0.05	10.49	0.000
Social Media Use → Political Loyalty	0.25	0.05	4.64	0.000
Social Media Use → Issue Based Polarization	-0.12	0.06	2.02	0.044
Social Media Use →Leadership based Polarization	-0.17	0.06	2.78	0.006
Social Media Use → Party Based Polarization	-0.15	0.06	2.49	0.013
Political Engagement → Issue Based Polarization	0.22	0.06	3.84	0.000
Political Engagement →Leadership based Polarization	0.29	0.06	5.02	0.000
Political Engagement → Party Based Polarization	0.30	0.06	5.06	0.000
Political Loyalty→Issue Based Polarization	0.30	0.06	4.85	0.000
Political Loyalty→ Leadership based Polarization	0.21	0.06	3.33	0.001
Political Loyalty→ Party Based Polarization	0.50	0.06	8.48	0.000

Note. Coeff. = standardized regression coefficient

Direct impact analyses revealed that social media use was a very significant, positively correlated predictor of both political participation and partisanship. However, it was shown to be a strong inverse predictor of all three types of political division (over issues, over leadership, and over parties). Nonetheless, both active participation in politics and party allegiance were shown to be strong predictors of partisanship along all three dimensions of the political spectrum. So, we may accept H1, H2, and H3.

Table 5: Indirect Effects of Political Engagement and Loyalty between Social Media Use and Political Polarization

Mediators	Issue Based Polarization		Leadership based Polarization		Party Based Polarization	
	Coeff.	SE	Coeff.	SE	Coeff.	SE
Political Engagement	0.14***	0.03	0.10***	0.03	0.23***	0.03
Political Loyalty	0.05**	0.02	0.07***	0.02	0.07***	0.02

Note. Coeff. = standardized regression coefficient

We observed that political participation and loyalty significantly mediated the relationship between social media usage and all three types of political polarization (issue, leadership, and party). This means that both H4 and H5 are true.

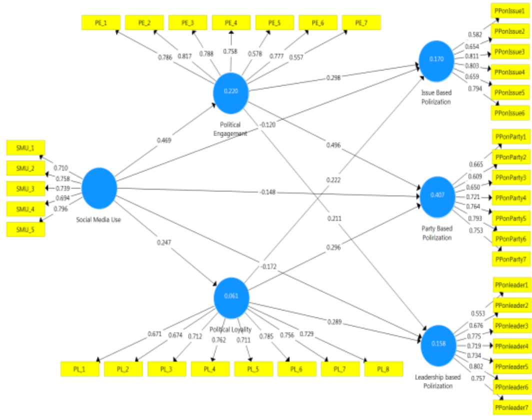

Figure 1: Structural Model

CONCLUSION

The impact of the media on an individual's political beliefs and actions is a hotly discussed issue in the academic community today. For a long time now, academics have been attempting to figure out what changed to alter people's political conduct. There has been a change in the researcher's attention from the traditional internet to social media platforms. A growing body of academic literature blames young people's growing political division on their selective exposure to conflicting political messaging on social media. However, there is a dearth of studies that detail the impact of various mediating factors (such as political participation and party allegiance) on polarization in politics. Therefore, we surveyed undergrads and grads at a variety of Lahore institutions in order to experimentally explore the link between social media usage and political polarization. We investigated whether or whether social media usage increases political polarization, both immediately and over time.

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