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ALGORITHMIC FILTERING OF CLIMATE MISINFORMATION: CULTURAL ORIENTATION AND CONFIRMATION BIAS IN PAKISTAN ONLINE ECOSYSTEM

Tariq Mehmood
Assistant Professor, Department of Mass Communication, BUITEMS Pakistan
tariq.khattak@buitms.edu.pk
Hafiz Muhammad Saad Altaf
Lecturer Iqra University H-9 Campus Islamabad, Department of Media Studies
Saad.altaf@iqraisb.edu.pk
Dr. Majid Ali Shah
Assistant Professor, Iqra University H-9 Campus Islamabad, Department of Media Studies
Majid.ali@iqraisb.edu.pk

ABSTRACT

This study investigates if the algorithmic biases filter online climate misinformation contents in Pakistan in accordance with people cultural orientations making them confirmation bias. While social media is recognized for undemocratic online discussions, concerns arise regarding its potential to disseminate misinformation on climate change. The study is aiming at addressing climate misinformation which are busted as not genuine, how they are algorithmically filtered in online ecosystem where online users in Pakistan are offered with contents amplifying and reinforcing their preexisting beliefs within existing cultural diaspora. The algorithmic filtering theory examines how initially algorithms filter content on digital platforms, based on user preferences, behaviors, and cultural orientations that aligns with users' existing beliefs, potentially reinforcing their confirmation biases. In Pakistan, where religious and cultural beliefs may stimulate climate change perceptions, algorithms may excessively filter content that echoes with their views, thereby spreading misinformation. This study is relying on quantitative content analysis to test the hypothesis if the algorithmically biased climate misinformation tailors content in accordance with individual's interests, preferences and cultural orientation. Having sufficient knowledge of MLA (machine learning algorithm) applied for NLP (natural language processing), the Python software is supervised and trained to identifying and quantifying the prevailing social media misinforming corpora. Results revealed the statistics strongly admitting the hypotheses statements testing if the algorithmically filtered climate misinformation aligns with Pakistan cultural index already provided in Hofstede cultural dimensions' model. Finally, this study provides a valuable insight for future researchers and academics tailoring digital media literacy program, aiming at critically encountering the cultural influence on spreading online misinformation.

Keywords: *Climate, Misinformation, Media Literacy, Cultural Dimensions, Pakistan*

Defining Misinformation

The American Psychological Association (APA), Oxford and Cambridge dictionaries terms misinformation as false wrong inaccurate misleading information the fact that people are misinformed. The European Commission narrates misinformation is shared without harmful intent, but the effects can still be harmful, discovered as "false or inaccurate information regardless of intentional authorship" (Chou et al.,2022). On the other hand, one of the most commonly cited definition of misinformation in early literature occurs when, ''people hold inaccurate beliefs, and do so confidently'' (kuklinski et al.,2000), highlighting how people remain confident over ignorance and lack of knowledge. Other scholarships addressed "inaccurate beliefs," without questioning people confirming existing opinions (Pasek et al.,2015). At the same time, while misinformation often generates misperceptions, two researcher Nyhan and Reifler (2010) distinguished between the misinformation and misperceptions, the information itself and the beliefs that people hold. Other research defined misperceptions occurs when factual matters are not supported by clear evidence and expert opinion.

Pakistan Climate Change Crises

Pakistan has become the epicenter of climate change, ranking among the top 10 countries most vulnerable to natural disasters, including floods. The country is experiencing intense heatwaves, droughts, and catastrophic floods pushing nearly half of population below the poverty line and damaging properties in billions. Pakistan experienced a worse flood in year 2022, causing at least 1,700 deaths, over 12.8 million people affected, 650,000 homes destroyed, 2.2 million acres of crops damaged, 750,000 livestock swept away and damaging a widespread infrastructure, including roads, bridges, and dams. The UN Secretary-General António Guterres described Pakistan climate change as a "monsoon on steroids." The record-breaking rainfall and deadliest floods killed thousands of people and millions severely affected including children rendered homeless in winter nights (Ripple et al,2022; Wyns, A., 2022). Now to mitigate climate disasters, acute media attention is need for climate movements activism (Upadhyaya at al.,2023; Bakaki et al.,2017). Social media online activism plays a significant role in running climate change consequences awareness campaign (Zeng,2022; Basch,2022; Boulianne et al.,2020; Belotti et al.,2022.; Molder et al.,2021; von Zabern and Tulloch,2021). For example, Australian Youth Climate Coalition (AYCC) protested for a sustainable future (Hilder and Collin, 2022). The Swedish youth also digitally blamed the government's inaction (Boulianne et al.,2020), spreading the movement to the UK, Canada, US, and Norway (Martiskainen et al.,2020).

Significance and Objectives

One of the objectives this research is to contributes to more informed climate change communication, climate adaptation awareness, understanding climate science journalism and decision-making at times when social media users face challenges in verifying online information. The study aims at tailoring the digital media literacy curriculum and skills programs to critically encounter the cultural influence on spreading misinformation. One of the significances of this study is introducing a unique understanding how culture influence the acceptance and propagation of misleading climate communication. Also this research provides a nuanced understanding of algorithmic biases how it filters and present online climate misinformation that aligns with online users' cultural phenomena and pre-existing beliefs making them confirmation biases.

Theoretical Framework: Algorithmic Filtering

The term Algorithm is referred to a prominent algebra scholar Al-Khwarizmi making a significant contribution to the numeral system commands or directions planned to execute a particular task or elucidate a problem (Al-Maghribi, 2019; Ausiello at al.,2016). In computer science and mathematics, algorithms process data, perform statistics, and mechanize intellectual tasks, such as artificial intelligence and machine learning (Mühlhoff, 2020). Now, the social media algorithms regulate which information shall appear in online ecosystem that aligns with users' preferences and browsing history (Etta, 2024; Silva et al.,2024.). This concept of algorithmic filtering or algorithmic gatekeeping is mainly derived from the gatekeeping theoretical concept in which information are filtered, how a newspaper editor, referred to as "Mr. Gates," decide which news stories to publish and which to reject (Li,2024; Caswell,2024; Prodnik et al.,2024). Now in the realm of digital era, these are called as algorithmic gates filtering personalized and biased contents based on individual experience and preferences (Shin et al.,2024; Scheffauer et al.,2024; Bhattacharya et al.,2024). This further lead to "filter bubbles,"(Pariser, 2011), where users are mainly exposed to information that aligns with their pre-existing beliefs. Algorithmic filters offer information in online ecosystem that can stimulate user existing opinions. This effect can amplify confirmation bias, supporting users' prevailing opinions while avoiding contradictory perspective (Rodilosso,2024). However, algorithmic filtering theory is often debated in digital media information systems domains, how artificial intelligence machine learning automatically present information in online ecosystem (Bozdag,2013; Calice et al.,2023; Apprich, 2024). This theory is commonly referring to the process in which algorithms pick and order content for online users based on numerous factors (Scheffauer et al.,2024; Springsteen et al.,2024).

Cultural Orientation Impacting Algorithmic Filtering

The factors impacting algorithmic filtering process may include user inclinations, surfing history, demographic and even cultural information (Purificat et al.,2024). Among these factors mainly cultural orientation considerably influences the entire algorithmic filtering process (Shin et al.,2022;). Studies have shown that cultural factors and worldviews primarily dominate shaping people existing perceptions (Cook et al.,2015). Accordingly, recent research claimed in a polarized society cultural values exacerbate misinformation believability (Gupta et al.,2023). For example, in culturally mixed society like Pakistan, where religious and traditional values are deeply rooted (Qadeer, 2006), algorithm is forming political polarization and misinformation (Raza et al.,2024). In these cases, algorithmic filtering may inspire social media content aligned with online users existing opinions within Pakistan culture(Khalil,2024). Additionally, this concept leads to the echo chamber theoretical approach (Bruns, 2017), discovering people confirmation biases on information consumption (Wolfowicz et al,2023; Robson,2023). In Pakistan, a society with robust religious dispositions, online users may refer natural tragedies to divine anger, thereafter distracting people attention from scientific explanations (Khan & Ali, 2022; Chester et al.,2012). This raises serious concern about climate change misinformation prioritizing dramatic discourse over science-based true journalism (Skurka & Cunningham, 2023). These cultural prejudices of religious expositions may confuse people attention from actual scientific results to climate disasters. This proliferate misinformation, particularly on complex issues like climate consequences, where scientific elucidations are concealed by culturally rich narratives. It is crucial to analytically evaluate and highlight these prejudices in such scenario.

In modern digital communication era, where the rise of misinformation shape social media users' narratives (Mwangi, 2023). Though available scholarships climax how misinformation spread and build public perceptions (Jahng et al., 2023; Vasist et al., 2023). But a rare literature is available investigating how cultural positioning guide the process of algorithmic filtering climate misinformation in Pakistan online echo system.

Meanwhile to comprehend cultural orientations of Pakistan, a German scientist Hofstede offers following six dimensions' indices broadly evaluating their impact on misinformation occurrence, treatment, and confirmation biases (Hofstede, 2011; Arrese, 2022).

- Power Distance Index (PDI): This dimension measures the degree to which society accepts hierarchical power structures (Zhou et al., 2024). For example, in Pakistan high PDI index (55) means the anti-state climate adaptation misinformation may relatively spread fast.

- Individualism (IDV) vs. Collectivism: This dimension examines whether people prefer individual or group issues (Gupta et al., 2023). For example, with the lowest IDV index (05) of Pakistan being a collectivists culture, the misinformation targeting groups institutions not an individual responsibility of climate mitigating may spread fast.
- Masculinity (MAS): This dimension measures the influence of gender role in societies (Silva et al., 2023). For example, in Pakistan with a well-adjusted MAS index (50), the misinformation may correspondingly equally spread against male and female responsibility of climate adaptation.
- Uncertainty Avoidance (UAI): This aspect discovers people ignoring hesitation and apprehension (Xu et al.,2023). For example, with the high UAI index (70), online users would probably not spread misinformation claiming climate insecurity.
- Long-Term Orientation (LTO) vs. Short-Term Orientation: This phenomenon distinguishes if people prioritize long term or the short term planning (Kapoor et al., 2023). For example, with low LTO index (19), people would relatively less reactive to long term alarms anticipated in climate misinformation.
- Indulgence vs. Restraint (IVR): This aspect determine how people are responsive to emotionally stirring online contents (Hatamleh et al.,2023). For example, with IVR index (00), people would not respond to emotionally charged climate misinformation.

Hypotheses

The research aims at testing following six hypotheses exploring the occurrence and impact of cultural positioning in the process of algorithmic filtering disseminating online climate misinformation in Pakistan. For example,

H1: Power Distance Index (high PDI) comparatively favours algorithm spreading misinformation arguing government not public responsibility of climate mitigation

H2: Individualism (low IDV) favors algorithm diffusing misinformation levelling institutions not individual responsibility of climate mitigation.

H3: Masculinity (balanced MAS) equally favors algorithm spreading misinformation against male and female role of climate mitigation.

H4: Uncertainty Avoidance Index (high UAI) absolutely favors algorithm spreading misinformation ignoring climate uncertainty.

H5: Long-Term Orientation (low LTO) favors algorithm spreading misinformation regarding short term climate concerns.

H6: Indulgence vs. Restraint (low IVR) favors algorithm spreading climate misinformation with no emotions.

Method:

This study employ quantitative content analysis of social media climate misinformation, employing Machine Learning Algorithms (MLAs) for Natural Language Processing (NLP) (Arowolo et al., 2023; Govers et al., 2023). Having sufficient knowledge of this versatile programming language with libraries and tools suitable for social media data mining, the Python software systematically help web scraping, data collection, processing, and analysis (Mayopu et al., 2023; Patel et al., 2023; Amin et al., 2023). It identifies prevailing large scale online misinformation contents clusters, quantifying trends and patterns of users' responses across cultural diaspora. Grounding on theoretical framework, this study investigates the prevalence and influence of cultural orientation in the process of algorithmic filtering spreading online climate misinformation in Pakistan. The study considers year 2022 till 2024 social media APl libraries from the Facebook, Instagram, and Twitter as the most widely online tools for dissemination and interactive debates on climate change. The following data is retrieved and analyzed after employing API libraries into the Python programming tool.

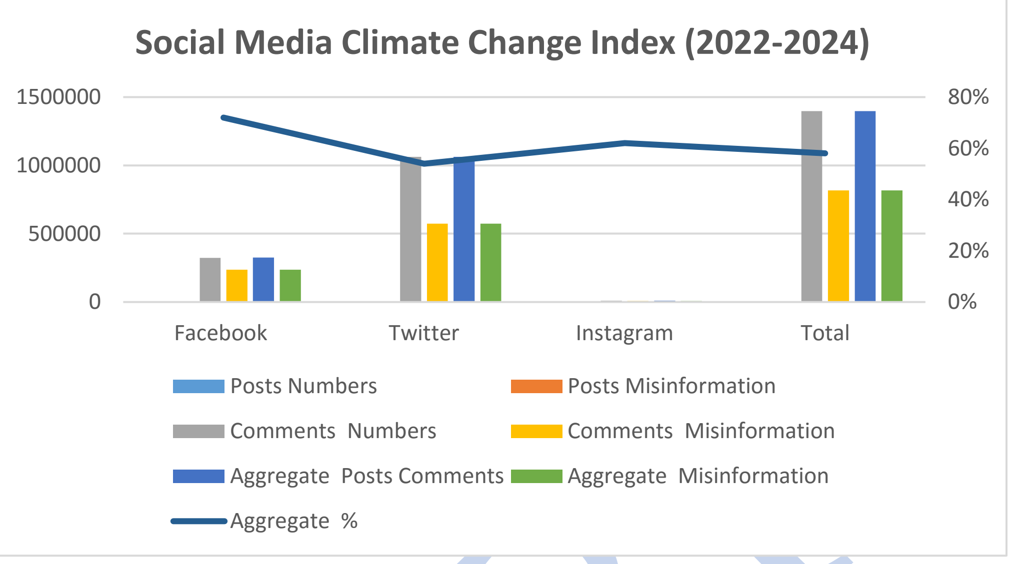
Findings:

The data mentioned in Table 1 and presented in Figure 1, indicate social media activities related to climate change in Pakistan. The total number of posts are 474, with Facebook leading at 273, followed by Twitter with 146 and Instagram with 55. However, comments are significantly higher, totaling 1,397,808, with Twitter contributing the most. Misinformation rates are 72% on Facebook, 54% on Twitter, and 62% on Instagram. The aggregate data showed a high prevalence of misinformation, highlighting the critical need for accurate information dissemination on social media platforms.

Table 1: Social Media Climate Change Index (2022-2024)

Social Media	**Online Posts**		**Online Comments**		**Aggregate**		
Activities	Posts	Misinformation	Comments	Misinformation	Posts Comments	Misinformation	%
Facebook	273	117	324,206	236,670	324479	236,787	72%
Twitter	146	32	1,063,585	574,336	1063,731	574,368	54%
Instagram	55	18	10,017	6,211	10,072	6,229	62%
Total	474	167	1397,808	817,217	1,398,282	817,384	58%

Figure 1



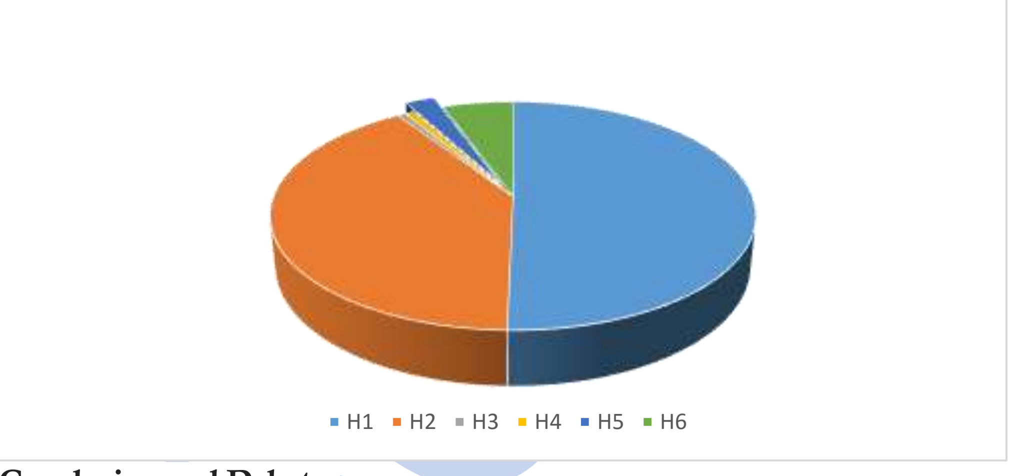
Hypotheses and Corresponding Results

The study analyzed Facebook, Twitter, and Instagram total 817,384 climate misinformation activities including posts and comments to test six hypotheses, categorized by Hofstede's cultural dimensions. The data described in ***Table 2*** and presented in ***Figure 2*** indicates hypotheses and their corresponding data includes H1(power distance-411,418), H2 (collectvism-30,385), H3 (gender role-5,076), H4 (avoiding unctainity-6,229), H5 (short term-19,118), and H6 (ignoring emotions -45,158). The expected frequency for each hypothesis, assuming equal distribution, is total 136,230.67 misinformation. The results outline significant deviations from the expected values, with chi-square contributions of 582,434.51 for H1, 284,025.84 for H2, 124,553.77 for H3, 122,582.98 for H4, 106,845.05 for H5, and 66,602.47 for H6. The p-values for all above six hypotheses are effectively 0.0, indicating strong statistical significance (p-value < 0.05) admitting the hypotheses statements. These findings highlight the prevalence of climate change misinformation across different cultural dimensions, with particularly high misinformation to PDI-power distance, IDV-collectivism and low misinformation rates related to Masculinity (MAS), Uncertainty Avoidance Index (UAI), Long-Term Orientation (LTO) and Indulgence vs. Restraint (IVR). The results underscore the critical need for targeted strategies to combat misinformation within specific cultural contexts.

Table:2

Table 2:	Hypotheses Index	Percentage (%)	Expected Frequency	Chi-Square Contribution (χ^2)	Statistical Significance (p-value)
H1	411,418	50%	136,230.67	582,434.51	<0.000001
H2	330,385	40%	136,230.67	284,025.84	<0.000001
H3	5,076	01%	136,230.67	124,553.77	<0.000001
H4	6,229	01%	136,230.67	122,582.98	<0.000001
H5	19,118	02%	136,230.67	106,845.05	<0.000001
H6	45,158	06%	136,230.67	66,602.47	<0.000001

Figure 2: Climate Misinformation Hypotheses Index



Conclusion and Debates

The study reveals that Pakistan's cultural dynamics significantly influence the susceptibility of its population to confirmation biases in the context of online misinformation, particularly regarding climate change. With a high Power Distance Index (PDI), results indicate anti-state feelings in Pakistan influence its citizens to believing misinformation blaming government for inadequate climate mitigation efforts. Similarly, as a collectivist society considered as a low Individualism Index (IDV), the study reveals online users are persuaded to admit misinformation targeting groups and institutional responsibilities, not individual actions for climate adaptation. These cultural locations apparently effect algorithmic filtering processes to spreading misinformation on state institutions, not personal accountability. Moreover, Pakistan with a stable Masculinity (MAS) index, results suggests that both genders are equally vulnerable to climate misinformation, regardless of gender roles. However, with low Long-Term Orientation (LTO) index, findings show online users are interested in climate short-term consequences, making population more vulnerable to misinformation regarding immediate climate impacts. Unexpectedly, although Pakistan is culturally passionate and emotional county, but Hofstede categorized its people with low Uncertainty Avoidance (UAI) and low Indulgence vs. Restraint (IVR) indices. However, the study finds online users are not easily influenced by emotionally stimulating climate misinformation. Possibly because recent historical events, including horrifying attacks and natural calamities, have desensitized online users to emotionally sentimental content. Despite deep-seated religious and political sentiments county, fervently inspiring climate misinformation fails to grab online populace. Moreover, the study accentuates the need for fostering critical digital literacy that aligns with Pakistan's unique cultural dispositions. By doing so, it aims to equip online users with essential tools to distinguish and encounter misleading climate online discourse efficiently. The anticipated for digital media literacy skill set curriculum is not merely a reaction to misinformation but a hands-on measure to nurture informed climate activism deeply rooted in cultural awareness and resilience.

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