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Measuring the Structural Impact of Misinformation on Network Polarization: An E-I Index and Random Walk Controversy Analysis

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Yanlış bilgi,
Sosyal ağ analizi,
Yankı odaları,
E-I indeksi,
Rastgele yürüyüş tartışma skoru

Graphical/Tabular Abstract (Grafik Özet)

This study compares four X (Twitter) hashtag communities (#pandemic, #infodemic, #plandemic, #scamdemic) and finds that misinformation-focused networks are much more polarized and segregated. More negative E–I Index values and higher RWC scores indicate echo-chamber structures with limited cross-group information flow. / Bu çalışma, X (Twitter) üzerinde dört hashtag topluluğunu (#pandemic, #infodemic, #plandemic, #scamdemic) karşılaştırır ve yanlış bilgi odaklı ağların daha kutuplaşmış ve ayrışmış olduğunu gösterir. Daha negatif E–I İndeksi ve daha yüksek RWC skorları, yankı odaları ve sınırlı gruplararası bilgi akışına işaret eder.

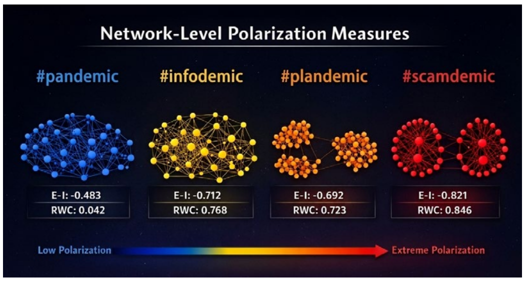

***Figure A**: Conceptual Illustration of Structural Polarization Gradient Across Hashtag Networks*
***Şekil A:** Hashtag Ağları Arasında Yapısal Kutuplaşma Gradyanının Kavramsal Gösterimi*

Highlights (Önemli noktalar)

- *The #pandemic network is the most integrated, while the misinformation hashtags form noticeably more segregated networks with weaker cross-group interaction. / #pandemic ağı en bütünleşik yapıdadır; buna karşılık yanlış bilgiyle ilişkili hashtag'ler, gruplar arası etkileşimin daha zayıf olduğu belirgin biçimde daha ayrışmış ağlar oluşturur.*
- *In misinformation networks, users are farther apart on average path lengths and communities split more sharply (higher modularity) / Yanlış bilgi ağlarında kullanıcılar ortalama yol uzunluğu olarak birbirinden daha uzaktır ve topluluklar daha keskin biçimde ayrışır (daha yüksek modülerlik).*
- *Using network structure together with polarization metrics (E–I, RWC) can help detect risky information environments early, even without analyzing the actual content of posts. / Ağ yapısını, kutuplaşma ölçütleri (E–I, RWC) ile birlikte kullanmak; paylaşımların içeriğini analiz etmeden bile riskli bilgi ortamlarını erken aşamada tespit etmeye yardımcı olabilir.*

Aim (Amaç): *This study aims to investigate whether misinformation hashtags form more polarized networks compared to official hashtags. / Bu çalışma, yanlış bilgi etiketlerinin resmi etiketlere kıyasla daha kutuplaşmış ağlar oluşturup oluşturmadığını araştırmayı amaçlamaktadır.*

Originality (Özgünlük): *The study's originality lies in examining misinformation through user network structures rather than content, using combined polarization metrics (E–I Index and RWC), and linking narrative types to network structural characteristics. / Bu çalışmanın özgünlüğü, yanlış bilgiyi içerik yerine kullanıcı ağ yapıları üzerinden incelemesi, kutuplaşma metriklerini (E-I İndeksi ve RWC) birlikte kullanması ve anlatı türlerini ağ yapısal özellikleriyle ilişkilendirmesidir.*

Results (Bulgular): *The findings show that the #pandemic network, representing official discourse, is less polarized and more integrated. In contrast, the misinformation networks (#infodemic, #plandemic, #scamdemic) are more segregated and polarized. / Bulgular, resmi söylemi temsil eden #pandemic ağının düşük kutuplaşma ve daha bütünleşik bir yapı sergilediğini göstermektedir. Buna karşılık yanlış bilgi ağları (#infodemic, #plandemic, #scamdemic) daha ayrışmış ve kutuplaşmıştır.*

Conclusion (Sonuç): *The study highlights that combining network topology with polarization metrics such as the E–I Index and RWC can support early detection of misinformation ecosystems. / Bulgular, E–I İndeksi ve RWC gibi ölçütlerin ağ topolojisiyle birlikte kullanılarak yanlış bilgi ekosistemlerinin erken tespitinde işe yarayabileceğini vurgular.*

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Abstract

This study investigates the structural relationship between misinformation and network polarization in the context of online health discourse on social media. Using a comparative network analysis approach, four distinct discourse communities represented by hashtags: #pandemic (official terminology), #infodemic, #plandemic, and #scamdemic (misinformation narratives) are examined. These hashtags were selected because they represent distinct information frames ranging from official public-health terminology to misinformation. Both structural network metrics (average degree, path length, clustering coefficient, density, modularity) and polarization-specific measures (E-I Index, Random Walk Controversy (RWC)) are employed to quantify differences in network topology and segregation patterns. Findings reveal a systematic gradient in structural polarization aligned with the type of narrative. The network using #pandemic exhibits low polarization (E-I = -0.483, RWC = 0.042), indicating minimal barriers to cross-group information flow and a relatively integrated structure. In contrast, misinformation-associated networks show significantly higher polarization, characterized by strongly negative E-I Index values (ranging from -0.692 to -0.821), high RWC scores (ranging from 0.723 to 0.846). In particular, #scamdemic demonstrates extreme segregation (E-I = -0.821, RWC = 0.846), characteristic of echo chambers with limited cross-community exposure. These networks also display longer path lengths, higher modularity, and lower clustering coefficients, indicating fragmented, sparse connectivity patterns. The analysis establishes that misinformation ecosystems are structurally embedded within more polarized and segregated network architectures. These polarized structures function as echo chambers that reinforce in-group consensus while limiting exposure to corrective information. The relationship between misinformation narratives and structural polarization metrics suggests that network topology itself can serve as an early indicator of problematic information environments. These findings highlight the need for early detection tools integrating network-based polarization indicators into misinformation monitoring systems.

Yanlış Bilginin Ağ Kutuplaşması Üzerindeki Yapısal Etkisinin Ölçülmesi: E-I İndeksi ve Rastgele Yürüyüş Tartışma Skoru Analizi

Makale Bilgisi

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Öz

Bu çalışma, sosyal medyadaki çevrimiçi sağlık söylemleri bağlamında yanlış bilgi (misinformation) ile ağ kutuplaşması arasındaki yapısal ilişkiyi incelemektedir. Karşılaştırmalı bir ağ analizi yaklaşımı kullanılarak, dört farklı söylem topluluğu #pandemic (resmi terminoloji), #infodemic, #plandemic ve #scamdemic (yanlış bilgi anlatıları) incelenmiştir. Bu hashtag'ler, resmi halk sağlığı terminolojisinden yanlış bilgi içerikli anlatılara uzanan farklı bilgi çerçevelerini temsil ettikleri için seçilmiştir. Hem yapısal ağ metrikleri (ortalama derece, yol uzunluğu, kümeleşme katsayısı, yoğunluk, modülerlik) hem de kutuplaşmaya özgü ölçümler (E-I İndeksi, Rastgele yürüyüş tartışma skoru (RWC)) kullanılarak ağ topolojisindeki ve ayrışma örüntülerindeki farklılıklar nicel olarak değerlendirilmiştir. Bulgular, anlatı türüyle uyumlu bir şekilde yapısal kutuplaşma derecelenmesi bir artış olduğunu göstermektedir. #pandemic etiketini kullanan ağ düşük düzeyde kutuplaşma sergilemektedir (E-I = -0.483, RWC = 0.042). Bu durum, gruplar arası bilgi akışının önündeki engellerin minimal olduğunu ve ağın görece bütünleşmiş bir yapıya sahip olduğunu göstermektedir. Buna karşılık, yanlış bilgiyle ilişkili ağlar belirgin şekilde daha yüksek kutuplaşma sergilemektedir; E-I İndeksi değerleri güçlü biçimde negatiftir (-0.692 ile -0.821 arası) ve RWC skorları yüksektir (0.723 ile 0.846 arası). Özellikle #scamdemic ağı, aşırı düzeyde ayrışma göstermektedir (E-I = -0.821, RWC = 0.846) ve bu durum, topluluklar arası etkileşimin son derece sınırlı olduğu yankı odası (echo chamber) özelliklerini yansıtmaktadır. Bu ağlarda ayrıca daha uzun yol uzunlukları, daha yüksek modülerlik ve daha düşük kümeleşme katsayıları gözlemlenmiştir; bu da, grupların birbirinden güçlü şekilde ayrıldığı ancak her bir

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grubun kendi içinde seyrek bağlantılı olduğu bir topolojiye işaret etmektedir. Analiz, yanlış bilgi ekosistemlerinin daha kutuplaşmış ve ayrışmış ağ mimarileri içinde yapısal olarak yerleşik olduğunu ortaya koymaktadır. Bu kutuplaşmış yapılar, grup içi fikir birliğini pekiştirirken düzeltici bilgiye maruz kalmayı sınırlar. Yanlış bilgi anlatıları ile yapısal kutuplaşma ölçütleri arasındaki ilişki, ağ topolojisinin sorunlu bilgi ortamları için erken bir gösterge olarak kullanılabileceğini göstermektedir. Bu bulgular, yanlış bilgilendirmeyi izleme sistemlerine ağ tabanlı kutuplaşma göstergelerini entegre eden erken tespit araçlarının geliştirilmesine duyulan ihtiyacı vurgulamaktadır.

1. INTRODUCTION (GİRİŞ)

Polarization is "the act of separating or making people separate into two groups with completely opposite opinions" [1]. Polarization is linked to adverse effects such as social segmentation, stereotypes, echo chambers in social media [2]. Social network homophily, whereby individuals preferentially connect with others who share similar views, reinforces existing beliefs and fosters the formation of echo chambers and also isolated communities with limited exposure to diverse perspectives [3] [4]. This structural segregation strengthens social identities and deepens perceived differences between groups, contributing to polarization.

Polarized groups are often linked to higher levels of misinformation circulation. This link arises from the homophilic structure of online communities, where users tend to engage with others who share similar beliefs, forming ideologically cohesive clusters that efficiently disseminate narratives aligned with their worldview—a dynamic empirically observed in studies of science versus conspiracy communities on social media. [5]. Although polarization (structural group segregation) and misinformation diffusion (content spread) are distinct phenomena, they become tightly interwoven in such environments, where community structure facilitates the rapid dissemination of false or misleading claims [4] [6]. Polarization concerns the consolidation and separation of groups or communities, whereas fake news diffusion refers to the spread of specific misleading information within those groups [6]. Moreover, misinformation can still spread even when polarization is low while high levels of polarization typically make it easier for such content to proliferate. This study argues that echo chambers, as a structural feature of online social networks, serve as a primary mechanism for polarization, which in turn creates a fertile environment for misinformation.

While existing research has separately examined network homophily and misinformation spread, fewer studies have quantitatively linked specific network polarization metrics to the diffusion dynamics of health-related misinformation in real-world social media data. To investigate how misinformation influences polarization, network polarization metrics will be compared within the context of online health information dissemination. The study will use empirical data to analyze and compare the structural characteristics of social networks across different levels of polarization, including total absence of polarization. The evaluation of network polarization measurements will leverage hashtags as keywords where polarization is distinctly observable. This approach aims to provide a comprehensive understanding of how echo chambers foster polarization and affect the spread of misinformation in online social networks.

2. SOCIAL MEDIA POLARIZATION AND MISINFORMATION DYNAMICS (SOSYAL MEDYA KUTUPLAŞMASI VE YANLIŞ BİLGİ DİNAMİKLERİ)

Social network homophily is the well-documented principle that individuals are disproportionately likely to form ties with others who share similar attributes, values, and beliefs [3]. In online environments, this innate tendency is augmented by algorithmic curation systems designed to maximize user engagement by filtering content and suggesting connections aligned with existing preferences [7]. The synergistic effect of self-selection and algorithmic personalization fosters the creation of echo chambers which is insulated communicative spaces where exposure to challenging or diverse viewpoints is systematically reduced [8]. These create ideologically coherent communities that function as high-conductivity channels for information that resonates with their shared worldview. As Cota et al. (2019) argue, polarization creates ideologically coherent communities that serve as high-conductivity channels for misinformation tailored to their shared worldview, making its diffusion more rapid and resistant to correction [6]. The phenomenon of polarization and misinformation diffusion on social media is understood as a self-reinforcing cycle, amplified by user behavior, and measured through evolving computational methods.

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Social media platforms create environments where users can easily access vast amounts of content and share ideas with minimal oversight. This ease of access, combined with limited content regulation, can contribute to the proliferation of malicious or misleading information [6]. Misinformation, also called as infodemic and fake news that quickly spread across social media [9]. Infodemic involves deliberate efforts to distribute false information in order to disrupt the reaction of the public and encourage alternate goals of groups or individuals [10]. The amount of infodemic increase through COVID-19 pandemic. They can damage the physical and mental health of individuals; increase stigmatization; endangering valuable health gains; and lead to poor compliance with public health initiatives, thereby decreasing their efficacy and threaten the ability of countries to stop the pandemic [10]. For example, CNN published the news about the possible lockdown of Lombardy (a region in Italy) before the official announcement from the Italian Prime Minister. As a consequence, people who heard about this rumor crowded airports and train stations to leave from Lombardy before the lockdown and the government attempt failed, and the infected person increased [11]. The COVID-19 infodemic has mainly categorized as the creator and origin of the COVID-19, its spread dynamics and symptoms, treatments and healings, and government interventions against the COVID-19 [12] [13]. Another important COVID-19 infodemic is vaccine hesitancy. World Health Organization (WHO) has regarded vaccine hesitancy as a significant challenge to public health and also information obtained from social media enhance vaccine hesitations [10].

The anti-vaccination movement, among ten important phenomena that threats to global health [14], have led to significant reduction in vaccination rates and triggered an increase in epidemics. Indeed, the density increase associated with the anti-vaxxer debate in ongoing global fight of COVID-19 pandemic adversely affects societies' attitudes towards vaccination [15]. Misinformation and rumors about vaccination against COVID-19 are mostly generated on social media platforms [16]. According to studies measuring the vaccine response on social media, anti-vaccine content is much more than those who are pro-vaccination [16]. The most intensively used social media platforms are YouTube and X (formerly Twitter) through COVID-19 [11]. According to a study conducted, 27.5 percent of the COVID-19 contents on YouTube was fake and had over 60 million viewers [17].

Recent empirical work has further refined our understanding of this ecosystem by examining specific facets of the problem. Research by Alvarez-Galvez et al. (2025) moves beyond documenting the existence of misinformation to identify the demographic and ideological profiles of those most susceptible to it in Spain, highlighting the role of pre-existing beliefs [18]. Wojtczak et al. (2023) offer a comparative lens, finding that political misinformation contains higher level more hate speech and bot activity than COVID-19 misinformation, suggesting that the toxic mechanics of diffusion can vary by topic [19]. Kraft and his colleagues (2021) reveal that correcting misinformation can fix factual misunderstanding, meaningful attitude change occurs when people choose to access alternative media source, so that broadening individual's media diets more effective than fact-checks [20]. As emphasized in various studies, echo chambers serve not only as channels that promote the spread of misinformation but also as structural obstacles that hinder corrective information, highlighting the crucial role of network structure in shaping information dynamics.

Polarization is not only an attitude but a measurable property of a social network. Metrics such as modularity (the strength of division of a network into dense clusters), and E-I index (the ratio of external to internal ties within groups) provide quantifiable measures of structural segregation [21]. The RWC score offers a dynamic view of information flow, measuring the likelihood that a traversal starting in one partisan community remains there before reaching another, thus capturing the "echo chamber effect" and barriers to cross-community information diffusion [22]. A significant gap persists between identifying structural polarization and understanding the causal mechanisms through which misinformation feeding this polarization. This study aims to demonstrate a strong relationship between misinformation narratives and polarized network topologies.

3. METHODOLOGY (METODOLOJİ)

3.1 Dataset (Veri seti)

From December 14 to 22, 2020, tweets were generated via the X API for tweets containing the hashtags pandemic, infodemic, plandemic, and scamdemic, respectively. As of 21 December, many countries and the European Union have authorized or approved the Pfizer-BioNTech COVID-19 vaccine; therefore, the dates were chosen to include the density of vaccine debates. All available tweets harvested by the API containing the relevant hashtags were retrieved, with no sampling strategy implemented by the author. The method for gathering data was compliant with X's Terms of Service and Developer's Agreement and Policy.

Table 1. Selected hashtags and their associated narratives (Seçilen hashtag'ler ve bunlarla ilişkili anlatılar)

Hashtags	Narrative
#pandemic	General term capturing health & socio-economic impact
#infodemic	Information overload; some truth, some misinformation
#plandemic	Conspiracy video about COVID-19's origin
#scamdemic	Frames pandemic as a hoax/fear-mongering

Each hashtag encapsulates a distinct narrative ecosystem, reflecting specific ideological leanings and reinforcing them through selective engagement. In this study, these hashtags serve as proxies to extract discourse from communities representing different information narratives, as outlined in Table 1. The main narratives linked to infodemic, plandemic, and scamdemic are suggested to contain a high proportion of unreliable or misleading claims, unlike the more fact-oriented discussions associated with the official term pandemic. The first hashtag, pandemic, as the official term adopted by the WHO to label the crisis, used as a term for epidemic of an infectious disease, consists of health and socio-economic impacts of COVID-19. The second hashtag, infodemic described the unreliable and misinformation [9] [10] based on preliminary observation, provides overabundance of information some authentic and some not. The third hashtag, plandemic used as title for conspiracy theory video that was watched an estimated 8 million times before removed from Facebook and YouTube consists of one of the most concerning and far-reaching of coronavirus conspiracy narratives [23]. The fourth hashtag, scamdemic, a combination of the words scam and pandemic that defines the creating a COVID-19 hysteria displays narratives that whelm the exaggeration and fear mongering of the COVID-19 virus threat [24].

The primary objective of this study is to investigate how structural network properties and polarization metrics vary across different online discourse communities, and how these differences relate to the potential spread of misinformation. Main research question is "How do the structural properties and polarization metrics of X networks differ, and how are these differences associated with the potential for misinformation propagation?" To address this question, a comparative network analysis approach will be employed. Four distinct X networks will be constructed using relevant hashtags and interaction data. While the overall topology of each network will be characterized using the five metrics, the degree of polarization will be assessed through the two metrics. This methodological approach is also designed to answer three sub-research questions:

RQ1: How do these networks exhibit structural polarization on social media?

RQ2: How does RWC capture the structural impediments to random information diffusion between communities?

RQ3: How do E-I Index coefficients and RWC score reveal the echo chambers mechanisms driving structural polarization?

3.2 Network Structure Measures (Ağ Yapısı Ölçütleri)

The overview of the network structure provides important insights related to network property. Five measures were used to assess the structural properties of network: average degree, path length, clustering coefficient, density and modularity.

Average Degree: The average degree of a network represents the mean number of edges per node. It is obtained by summing the degrees of all nodes and dividing this value by the total number of nodes in the graph [25]:

$$\langle k \rangle = \frac{1}{N}\sum_{i=1}^{N} k_i = \frac{2E}{N} \qquad (1)$$

The average degree donated by k where N is the number of nodes, and E is the total number of edges. The average degree of a graph is basically the average number of edges per node. As a fundamental descriptor of network connectivity, it indicates how densely or sparsely connected the network is.

Path Length: A geodesic distance is the shortest path between two nodes. Node distances in a network can be quantified using two key measures: the diameter, representing the shortest path between any two vertices and the average path length, denoting the mean shortest path across all vertex pairs [25]. Average path length (L) can be measured with Eq. (2):

$$L = \frac{1}{\frac{1}{2}n(n-1)} \sum_{i>j} d_{ij} \qquad (2)$$

where d_ij is the number of edges on the shortest distance from node i to j and the diameter of a network is known as the maximum value of d_ij among any pair of nodes.

Clustering Coefficient: Clustering coefficient measures the ratio of actual edges to the maximum possible edges among a node and its neighbors [26]. For a node i with k_i neighbors, the clustering coefficient C_i is defined as:

$$C_i = \frac{2E_i}{k_i(k_i-1)} \qquad (3)$$

Where E_i is the number of edges between the neighbors of node i. Networks with higher average clustering coefficients often exhibit shorter average travel distances and fewer intermediate steps between nodes, indicating more cohesive and efficient connectivity [27].

Density: Network density measures the fraction of realized edges E over all possible edges among nodes N, indicating how interconnected the network is. Density is formulated as:

$$D = \frac{2E}{N(N-1)} \qquad (4)$$

Where E is the number of edges in the network and N is the total number of nodes. Sparse connectivity, reflected by low density values, is a common feature of large online social networks.

Modularity: Modularity quantifies the strength of a network's division into component, defined as the partitioning of nodes into internally dense and externally sparse communities [28]. In networks, high modularity indicates that nodes within the same component are densely connected, while connections between nodes in different component are sparse [29]. Eq. (5) measures the modularity:

$$M = \sum_{s=1}^{r} \left[\frac{l_s}{L} - \left(\frac{d_s}{2L} \right)^2 \right] \qquad (5)$$

where r is the number of components, L is the number of edges in the network, ls is the number of edges between vertices in component s, and ds is the sum of the degrees of the vertices in component s. High network modularity, where nodes are tightly connected within component but loosely connected between them, tends to increase polarization by isolating groups and amplifying internal consensus.

3.3 Polarization Measures (Kutuplaşma Ölçütleri)

Polarization arises when networks become structured around tightly connected groups with weak intergroup links, creating echo chambers and limiting cross-community exposure [30]. Polarization is analyzed using the E–I Index and the RWC score.

E-I Index: The E-I Index is a measure introduced by Krackhardt and Stern (1988) within the field of social psychology [31]. It quantifies the balance between intergroup and intragroup connections in a network. ET denotes the number of edges connecting different groups (intergroup edges) and IT denote the number of edges connecting members of the same group (intragroup edges).

The E-I Index is defined as:

$$EI = \frac{ET-IT}{ET+IT} \qquad (6)$$

The index varies from –1 to 1, so values near –1 indicate a network mainly composed of within-group ties (high homophily), whereas values near 1 indicate more between-group connections (heterophily). This measure corresponds to one minus twice the value of the homophily [30]. A higher score, closer to 1, indicates lower polarization because interactions occur more between groups, whereas a lower score, closer to –1, signals higher polarization due to communication being concentrated within the same group.

RWC: Random walk controversy quantifies how likely it is for a randomly selected node from one side of a polarized discussion to encounter authoritative information originating from the opposite side. For a given network G= (V, E), let X, Y⊆V, with V=X∪Y, forming a partition of the node set into two subsets. Consider two random walks, one ending in X and the other in Y. Let P_XY=P [start in group X| end in group Y], the probability a random walk started in the group X given that in it ended in group Y. Then, the score is:

$$RWC = P_{XX}P_{YY} - P_{XY}P_{YX} \qquad (7)$$

An RWC score close to 1 indicates a low probability of crossing between groups, reflecting a highly polarized network. Conversely, a value close to 0 suggests an equal likelihood of crossing or remaining within the same group, indicating minimal polarization [32]. An RWC approaching -1 corresponds to low polarization, with nodes more likely to encounter content from the opposite group than from their own. Specifically, an RWC of 1 signifies no edges between groups, while an RWC of -1 indicates no edges within groups; although both extremes imply a lack of polarization, higher overall RWC values reflect greater polarization [30].

4. FINDINGS (BULGULAR)

The network topology provides an overall perspective for understanding the structure of the network. Table 2 presents its key topological properties, including the number of nodes and edges, diameter, average path length, clustering coefficient, density, and modularity.

Table 2. Structural and topological properties of the networks (Ağların yapısal ve topolojik özellikleri)

Graph Type	Value for pandemic	Value for infodemic	Value for plandemic	Value for scamdemic
Total Nodes	1450	1650	2162	1800
Total Edges	1821	2063	2745	2358
Average Degree	2.513	2.501	2.540	2.620
Average Path Length	3.842	4.123	4.215	4.562
Network Diameter	11	13	14	15
Average Clustering Coefficient	0.034	0.028	0.021	0.024
Network Density	0.0017	0.0015	0.0012	0.0014
Modularity	0.415	0.582	0.551	0.648

The results show that the number of nodes in each network was different during the observation period. The plandemic is the largest and most active network, with 2162 nodes and 2745 edges, indicating massive mobilization. The pandemic and infodemic are smaller, more measured discussions, due to sampling size. Moreover, the average degree is relatively similar across the four networks, ranging from 2.501 to 2.620, indicating comparable overall levels of connectivity.

The average path length ranges from 3.842 to 4.562 during the observation period. These two values indicate that four or five interactions are sufficient to dissemination between all user pairs in the network. Higher values in infodemic, plandemic and scamdemic suggest these networks are more fragmented, with longer paths between users, possibly due to ideological silos or weakly connected clusters. The pandemic relatively shows shorter average distances, indicating more integrated discussion spaces.

Large diameters in pandemic, infodemic, plandemic, and scamdemic suggest poor overall connectivity — information doesn't easily reach all users. The diameter of the network is 11 for pandemic; 13 for infodemic; 14 for plandemic and 15 for scamdemic which shows that maximum of nodes is required to reach from one node to another in network.

According to network density, four networks are the sparsest network due to extremely low density. The four networks exhibit similarly low average clustering coefficients, indicating weak local cohesion within all communities. In a polarization context, such low clustering suggests that echo-chamber structures are not formed through tightly knit neighborhoods but may instead emerge from sparse yet segregated connectivity patterns, which requires polarization-specific measures (e.g., E–I Index, RWC, modularity) to confirm more clearly.

Modules consist of node subsets in which the nodes are strongly interconnected with each other, while having relatively few connections to nodes belonging to other modules [33]. Modularity is not a direct measure of polarization, but it captures the structural separation of communities, making it a widely used indicator for assessing the network foundations of polarization. Modularity scores across all networks, except pandemic, were higher than 0.50, confirming strong community structures;

however, scamdemic exhibited the highest modularity (0.648), underscoring its intensely polarized and clustered nature. The structural analysis of online discourse, including user interactions and network topology, provides valuable insights for detecting and understanding such information ecosystems [34]. The combination of high modularity with low clustering coefficients suggests that while groups are strongly separated from each other (high modularity), each group itself is not tightly knit internally (low clustering). This indicates sparse but well-separated ideological clusters rather than dense, cohesive echo chambers formed through triadic closures. These structural distinctions support the hypothesis that hashtags containing misinformation promote more isolated and ideologically extreme discourse spaces, yet a definitive conclusion requires formal polarization measurements.

Table 3. Network-level polarization measures (Ağ düzeyindeki kutuplaşma ölçütleri)

Graph Type	Value for pandemic	Value for infodemic	Value for plandemic	Value for scamdemic
E-I Index	-0.483	-0.712	-0.692	-0.821
RWC	0.042	0.768	0.723	0.846

The pandemic network, representing factual COVID-19 information, demonstrates low polarization (E-I = -0.483) a nearly neutral RWC score (0.042), which reveal minimal structural bias in information diffusion. In contrast, misinformation networks show extreme polarization: infodemic (E-I = -0.712, RWC = 0.768), plandemic (E-I = -0.692, RWC = 0.723), and scamdemic (E-I = -0.821, RWC = 0.846) all exhibit strong in-group orientation and asymmetric information flow characteristic of echo chambers. Notably, scamdemic's extreme polarization score aligns with ranges linked to coordinated manipulation networks. Misinformation networks show markedly higher polarization than factual ones, reflecting a clear gradient by information quality.

This comparative network analysis provides compelling circumstantial evidence consistent with a causal influence of misinformation ecosystems on polarization. Such structural analyses of social media data align with broader research frameworks that categorize platform-sourced information as a critical resource for understanding phenomena ranging from public sentiment to community polarization [35] [36]. The analysis reveals a pronounced structural gradient across the discourse networks: those centered on known misinformation narratives demonstrate substantially higher levels of structural polarization compared to the network anchored in fact-based, mainstream terminology. The consistent alignment between narrative type (misinformation) and network structure (high polarization) supports the interpretation that the content itself plays a key role in shaping the polarized networks in which it spreads. Both metrics reveal the self-reinforcing cycle through which misinformation networks become structurally polarized echo chambers. Echo chambers drive structural polarization through a self-reinforcing cycle so homophilic bonding (measured by E-I) creates segregated communities that then function as information containers (measured by RWC), which in turn reinforce group boundaries and deepen polarization. These two metrics explain why misinformation does not merely spread, but also creates persistent, polarized communities.

5. CONCLUSION (SONUÇ)

The structural analysis of the four X discourse networks revealed marked differences across communities. The pandemic network exhibited relatively a shorter average path length, higher density, lower modularity, and a comparatively higher clustering coefficient, indicating a more cohesive structure in which information circulates more freely across groupsIn contrast, the infodemic, plandemic, and scamdemic networks were fragmented and internally sparse, exhibiting low densities, longer path lengths, high modularity, and lower clustering coefficients, patterns consistent with well-separated but loosely knit clusters. Modularity quantifies the strength of division of a network into communities. High modularity indicates that the infodemic, plandemic and scamdemic debate naturally separates into distinct components. Notably, given the highly contentious nature of the scamdemic discourse, its elevated modularity score indicates the presence of strong structural polarization within the network. These findings suggest that misinformation-related hashtags may foster network conditions indicative of ideological separation and limited cross-group interaction, though a definitive assessment requires formal polarization metrics such as the E–I Index and RWC.

This study demonstrates that network polarization metrics serve as effective structural indicators of information veracity in online discourse about pandemic-related topics. While the pandemic network exhibits low polarization, the scamdemic network demonstrates extreme polarization characteristic of echo chambers, with infodemic and plandemic networks displaying similarly high polarization levels in between. The results reveal a systematic relationship: networks disseminating factual information exhibit minimal barriers to cross-group information flow with low polarization, while misinformation networks display extreme polarization and asymmetric information flows characteristic of echo chambers.

Polarization varies across these networks not just in ideological content, but in network structure. These structural segregation offer platform designers and policymakers empirically grounded metrics for early detection of misinformation ecosystems and targeted intervention strategies. By moving beyond content analysis to network topology examination, this approach provides a scalable framework for monitoring information landscapes and mitigating the spread of harmful misinformation during public health crises.

The findings of this study are limited by the exclusive focus on structural network metrics, which, although effective in revealing polarization patterns, do not account for semantic content, user intent, or the temporal dynamics of information spread. Moreover, the choice of community detection algorithms or parameter settings can produce varying group structures, affecting the calculation of E-I Index and RWC scores. To address these limitations and strengthen future research, incorporating complementary polarization measures is recommended.

DECLARATION OF ETHICAL STANDARDS (ETİK STANDARTLARIN BEYANI)

The author of this article declares that the materials and methods they use in their work do not require ethical committee approval and/or legal-specific permission.

Bu makalenin yazarı çalışmalarında kullandıkları materyal ve yöntemlerin etik kurul izni ve/veya yasal-özel bir izin gerektirmediğini beyan eder.

AUTHORS' CONTRIBUTIONS (YAZARLARIN KATKILARI)

Keziban SEÇKİN CODAL: She conducted the study, analyzed the results and performed the writing process.

Çalışmayı yapmış, sonuçlarını analiz etmiş ve makalenin yazım işlemini gerçekleştirmiştir.

CONFLICT OF INTEREST (ÇIKAR ÇATIŞMASI)

There is no conflict of interest in this study.

Bu çalışmada herhangi bir çıkar çatışması yoktur.

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