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APPLICATION OF SOCIAL NETWORK ANALYSIS FOR COMPARISON AND RANKING OF INTERNET SERVICE PROVIDERS

Tedy Setiadi [a,1,*], Gilang Mukharom [a,2] Beni Suhendra[b,3], Syauqi Bima[c,4]

[a]Department of Informatics, [b]Department of Accountancy
Universitas Ahmad Dahlan,Yogyakarta, Indonesia

[c]Department of Informatics
Telkom University, Bandung,Indonesia

[1]tedy.setiadi@tif.uad.ac.id; [2]gilangmukharom53@gmail.com; [3]beni.winarso@act.uad.ac.id,
[4]syauqibima@act.uad.ac.id

*Corresponding Author

Abstract

In this digital era, the Internet has become a basic necessity in life. This has had a significant impact on the growth of internet service provider (ISP) companies in Indonesia. Comparison and ranking of ISPs is needed to make it easier for users to choose services according to their needs as well as to encourage healthy competition between ISPs in improving their services. The problem is ranking ISPs using conventional methods (surveys) to obtain primary data is expensive and takes a long time. On the other hand, Social Network Analysis (SNA) is a method that has been widely used to understand customer desires by extracting information from social media. This information is in the form of User Generated Content (UGC), namely track records left by customers on social media. This research aims to measure the ISP rankings of Indihome, Biznet and FirstMedia using UGC data. The research method used is to collect consumer tweet data rapidly, carry out preprocessing to eliminate irrelevant data and apply SNA, including network structure analysis in the form of visualization and network property analysis with the Gephi application, as well as network content analysis in the form of sentiment analysis and WordCloud analysis. The number of dominant network properties and sentiment analysis calculates ISP ranking. Apart from that, the results of this SNA are in the form of recommendations for ISPs to improve services to customers.

Keywords: Social Network Analysis, Network Properties, Sentiment Analysis, Internet Service Providers

Abstrak

Di era digital ini, internet menjadi kebutuhan dasar bidang kehidupan. Hal ini berdampak signifikan tumbuhnya perusahaan internet service provider (ISP) di Indonesia. Perbandingan dan pemeringkatan ISP diperlukan untuk memudahkan pengguna dapat memilih layanan sesuai kebutuhan disamping untuk mendorong terjadinya persaingan yang sehat antar ISP dalam meningkatkan layanannya. Permasalahannya, pemeringkatan ISP dengan metode konvensional (survei) untuk mendapatkan data primer membutuhkan biaya mahal dan waktu lama. Disisi lain, Social Network Analysis (SNA) adalah metode yang sudah banyak dimanfaatkan untuk memahami keinginan pelanggan dengan mengekstraksi informasi dari media sosial. Informasi ini berupa User Generated Content (UGC), yaitu rekam jejak yang ditinggalkan pelanggan di media sosial. Tujuan penelitian ini untuk mengukur peringkat ISP Indihome, Biznet dan FirstMedia dengan data UGC. Metode penelitian yang digunakan pengambilan data tweet konsumen dengan rapid manner, melakukan preprosesing untuk menghilangkan data yang tidak relevan, serta menerapkan SNA meliputi analisis struktur jaringan berupa visualisasi dan analisis properti jaringan dengan aplikasi Gephi , serta analisis isi jaringan berupa analisis sentimen dan analisis WordCloud. Peringkat ISP dihitung dengan banyaknya poperti jaringan yang dominan serta analisis sentimennya. Selain itu, hasil SNA ini berupa rekomendasi bagi ISP untuk meningkatkan layanan kepada pelanggan.

Kata kunci: Analisis Jejaring Sosial, Properti jaringan,Analisis Sentimen,Penyedia Layanan Internet

INTRODUCTION

In the current era of information technology, the Internet has become a basic need for society. The Internet is almost inseparable from every aspect of our lives. The success of various sectors, such as education, business and research, now relies heavily on fast and reliable internet connectivity. The increasing need for the Internet has driven the rapid expansion of Internet Service Providers (ISP) (T. G. Soares et al., 2024).

As the number of ISPs increases, it becomes crucial to have a clear comparison and ranking between them. Through comparisons and ratings, it makes it easier for consumers to choose services that suit their needs and preferences. In addition, this also encourages healthy competition among internet service providers to improve the quality of their services and offer more competitive prices. With transparent information, consumers can make smarter decisions, while service providers are encouraged to innovate and continually improve their user experience (Fenton et al., 2023).

Applying social network analysis (SNA) has become an important approach to understanding and analyzing various social phenomena. In this context, social network analysis collects data about interactions between entities in a network, whether individuals, groups, or organizations. Then, it uses statistical and computational techniques to analyze emerging patterns. With social network analysis, we can understand the network structure, identify central actors, detect communities or groups, and analyze how information or influence spreads within the network. This has wide applications in various fields, including market analysis (N. D. Soares et al., 2023), politics (Paulis, 2020), crime (Li et al., 2021), libraries (Setiadi et al., 2023) and company rankings (Jin et al., 2009).

Especially in the comparison and ranking internet service companies, the application of SNA is becoming increasingly relevant and important. Social networks provide a platform for users to share experiences and reviews about various internet services, known as User Generated Content (UGC). UGC provides users with valuable information for comparing internet services, helping them make more informed decisions based on the experiences of other users. For ISPs, UGC provides direct feedback on the quality of their services, allowing them to improve their services and brand reputation in the market. It can also be used as a marketing tool to attract and retain new customers. Thus, UGC becomes an effective instrument in increasing both parties' transparency and quality of internet services (Timoshenko & Hauser, 2019).

The UGC platform popular in SNA is X, previously known as Twitter. With millions of active users globally, X provides a variety of opinions, reviews and user experiences regarding internet services. Data analysis from Twitter can provide valuable insights into user preferences, customer satisfaction, emerging issues, and trends in internet services, helping ISPs to understand market needs better. Through monitoring hashtags, reviews, and discussions, ISPs can track direct feedback from their customers, identify areas for improvement, and respond to issues proactively to improve service quality and overall customer satisfaction (Zhang et al., 2022)

Several studies related to research on the application of SNA for companies (Bratawisnu et al., 2018) applied SNA to determine the top brands of two e-commerce companies, Tokopedia and Bukalapak, by utilizing Twitter data, then Diannzah (Diannzah, 2021) developed the study into three e-commerce companies, namely Tokopedia, Bukalapak and Shopee. Hadiwinata (Hadiwinata et al., 2023) applied SNA to analyze the dissemination of promotional information for electric cars by utilizing YouTube data. The author uses density, diameter, reciprocity, centralization and modularity. The limitation of this research is that it only analyzes one product. Suradihardjo (Suradihardjo et al., 2023) applied SNA to analyze travel agents using Travel Agent object data in Indonesia through Twitter user interactions. As a result, Traveloka was ranked first, Pegipegi was ranked second, and Tiket.com was ranked third. The limitation of this research is that it only analyzes the network structure properties.

SNA research based on network content takes the form of sentiment analysis, some of which was carried out by (Sidauruk & Riza, 2023), analyzing the sentiment of users of the Access KAI application using the k-nearest neighbour method and by (Radiena & Nugroho, 2023) using the k-nearest neighbour method. The data was taken from the Google Play store using web scraping techniques. Jesica et al. (Sibarani et al., 2022) analyzed Amazon product sentiment with the Naive Bayes algorithm. The data used is the Amazon secondary data set on the Kaggle page. Hibatullah(Hibatullah Faisal1, Arafat Febriandirza, 2024) reviewed using the PLN Mobile Application with sentiment analysis using the Support Vector Machine Method. The limitation of this research is that it only analyzes network content.

In this study, we expand the application of SNA for company ranking by integrating network structure analysis with sentiment analysis for ISP ranking by utilizing UGC. The contribution of this research provides an alternative company ranking by utilizing social media and provides recommendations for improvements for ISPs in increasing customer satisfaction.

RESEARCH METHODS

Our research approach is quantitative, focusing on measuring and analyzing experimental data using numbers (McCusker & Gunaydin, 2015), while the method used is SNA by comparing network properties. Network properties are attributes that can be calculated and analyzed and are used as assessment parameters in research to determine industry rankings (Casas-Roma et al., 2015). This study uses 8 network properties, including:

a. Size

Size indicates the number of nodes and the number of edges present in the network. Semakin besar ukuran jaringan berarti nilanya semakin baik, karena menyatakan banyak user yang aktif berinteraksi.

b. Density

It shows how closely connected the nodes in a network are. The higher the density value, the stronger the relationship between the networks. The density value can be calculated by the equation 2.

$$\Delta = \frac{L}{g(g-1)/2} \quad \text{..........}(2)$$

Δ is the density value, L is the number of edges, and g is the number of nodes.

c. Diameter

The diameter in the network properties is the maximum closest path in a network. Diameter describes the process of disseminating information in a network that is formed. To find the value of the diameter, we can use the calculation of equation 3.

Dmax = (i,j) ....(3)

Based on the equation, it can be interpreted that the diameter is the largest value from the vertices i to j. The smaller diameter of the network indicates a "small world" phenomenon, which means it will be easier for nodes to communicate with each other due to short distances.

d. Modularity

Modularity is often used in community detection and network properties to describe how strong groups are formed on a network (Brandes et al., 2008). The higher the modularity value, the more the network contains groups of groups. To find the value of modularity in the network, we can calculate equation 4.

$$Q=\frac{1}{2m}\sum[A_{ij} - \frac{k_i k_j}{2m}]\delta s\text{i}, sj \text{..........} (4)$$

Q is the modularity value, m is the number of edges, Aij is the actual number of edges between i and j, kikj is the expected number, si, sj is the Kronecker delta δ.

e. Average Degree

The average degree of social network properties is defined as the average number of nodes connected to each node on a network formed. The more links that connect one node to other nodes, the faster and easier the dissemination of information. To find the average degree value, you can calculate the equation 5.

$$P_k = \frac{N_k}{N} \text{..........} (5)$$

Pk is the average degree value, Nk is the number of degrees on node N, and N is the number of nodes on the network.

f. Average Path Length

Average Path Length in social network analysis properties describes the average distance between each node formed on a network. To calculate the value of the average path length in a network, you can use the calculation equation 6.

$$\langle d \rangle=\frac{1}{n(n-1)} \sum_{\text{i,j = 1,n,i≠j}} \text{d}_{i,j} \text{..........} (6)$$

<d> is the average path length value, n is the number of nodes, di,j is the closest distance from node i and node j. The smaller the APL value, the better the information dissemination.

g. Betweenness Centrality

Betweenness Centrality is a reference to measure how often another node passes a node to reach a certain node in a network (Barthélemy, 2004). To calculate the value of betweenness centrality, we can calculate equation 7.

$$C_b(n_i) = \sum_{j=1}^{n}\sum_{k=1}^{j-1}\frac{g_{jk}(ni)}{g_{jk}} \text{..........}(7)$$

Cb(ni) is the betweenness centrality of actor (node) i, g jk(n i) is the geodesic sum of actor j to actor k containing actor i, gjk is the number of geodesic from actor j to actor k, n i is actor (node) i, i≠j, i≠k.

h. Connected Component

is a subgraph where every vertex can be reached from every other vertex by a certain path. The research method we used is shown in Fig. 1.

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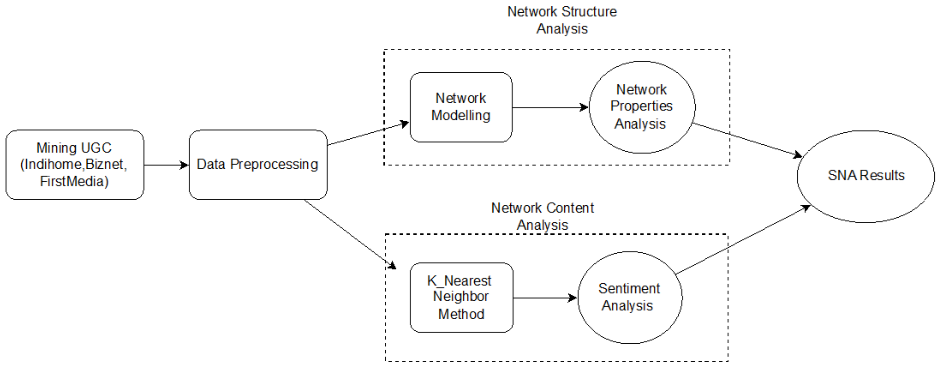


Fig 1. Research Methods

The process of retrieving UGC data or UGC mining is carried out on the X. Mining UGC social media by utilizing the Rapid Miner application to crawl tweets containing the keywords "Indihome", "Biznet", and "FirstMedia. The data set obtained is saved in CSV format for use at the preprocessing stage.

In the preprocessing stage, irrelevant data such as punctuation, numbers and emojis are cleaned. The actors (nodes) interacting with each tweet are determined for network structure analysis. In contrast, for network content analysis, case folding is carried out (converting all letters to lowercase), tokenizing (breaking the text into tokens), normalization (changing the data in a certain range), removing stop words (words that are not important), and stemming (removing affixes to get basic words) and carrying out transformation using the tf-idf method to determine the weight of words in the document.

The network structure analysis stages are carried out by modeling and visualizing the network with the Gephi application. Nodes represent actors, and edges represent interactions between actors in a social network. Network properties for comparing social networks between businesses can be seen from the social networks that have been modelled. In the social network properties analyzed in this research are the 8 properties mentioned previously. The results of the comparison of network properties can be used as an alternative for analyzing top ISP brands, which symbolize the level of actor awareness regarding the company.

Meanwhile, the network content analysis stage uses the K-Nearest Neighbor method to classify positive, neutral and negative sentiment. Wordcloud analysis is carried out to strengthen words often related to product sentiment. The network structure and sentiment analysis results will be combined into an integrated SNA.

RESULTS AND DISCUSSION

Mining UGC

The initial step is Mining the UGC of three popular ISPs in Indonesia, namely Indihome, Biznet and FirstMedia, which was carried out on social media Twitter (X) for one week from 10 July 2023 to 17 July 2023 using the Rapid Miner application. The crawled tweet data contains the date, tweet username, and reply username, which shows interactions between users on social media X regarding the ISP company. The results of crawling Indihome amounted to 3572 tweets, BiznetHome amounted to 2804 tweets, and FirstMedia amounted to 2014 tweets during the data collection.

Network Modelling

For network modeling, we use Gephi software, the results of which are shown in Figure 2, which is a visualization of the Indihome network, Figure 3 is a visualization of the Biznet network, and Figure 4 is a visualization of the First Media network.

Fig. 2 Network Visualization (a) Indihome (b)Biznet (c) FirstMedia

Network Structure Analysis

After modeling the social network, an analysis of the network properties was carried out to determine the value of the social network and its ranking, and the results are shown in Table 1.

The first network property is size. A good and active network has a large size. The results of crawling data for a week show that the Indihome social network is the largest with the most actors and relationships, followed by Biznet and FirstMedia.

The second property is diameter. The smaller the diameter, the easier it will be for nodes to communicate with each other because the distance is short. FirstMedia's social network has the smallest diameter, followed by Biznet and Indihome.

Table 1. Calculation and Comparison of Network Properties

Network Properties	Indihome	Biznet	First Media	Rank
Size	Nodes: 320 Edges: 253	Nodes: 272 Edges: 181	Nodes: 240 Edges: 139	1. Indihome 2. Biznet 3. First Media
Diameter	9	5	2	1. First Media 2. Biznet 3. Indihome
Density	0.00495	0.00491	000671	1. Indihome 2. First Media 3. Biznet
Modularity	0.81	0.87	0.76	1. Biznet 2. Indihome 3. First Media
Average Degree	1.58	1.33	1.36	1. Indihome 2. First Media 3. Biznet
Average Path Length	3.03	2.07	1.93	1. First Media 2. Biznet 3. Indihome
Connected Component	70	92	65	1. Biznet 2. Indihome 3. First Media
Betweenness Centrality	0.35	0.06	0.30	1. Indihome 2. First Media 3. Biznet

The third property is density. The greater the density value obtained, the denser the internet provider's network. The ISP ranking based on density is Indihome, followed by FirstMedia and Biznet.

The fourth network property is modularity, which measures the strength of groups in the network. Each group formed can be assumed to be a different community. As the number of communities in the network increases, we can expect more personalized community topics or more specific product features in each community. Thus, higher modularity can form higher communities. The ISP network with the best modularity value is Biznet, followed by Indihome and FirstMedia.

The fifth property is the average degree of links connecting a node to other nodes. The higher the average degree value, the greater the links connecting the nodes and the faster the information dissemination. ISP network ranking is based on average level; first is Indihome, followed by FirstMedia, and finally Biznet. The sixth property is average path length, which shows the average distance between a node and another node. The smaller the average path length value, the better because the faster the information spreads. The ISP network ranking based on average path length is FirstMedia, followed by Biznet and Indihome.

The seventh property is the Connected Component, a mutually exclusive subgraph. The smaller the connected component value in the network, the better the network because the network is more integrated. The first ranking based on connected components is Biznet, followed by Indihome and finally FirstMedia. Meanwhile, the eighth property is betweenness centrality. This high average betweenness centrality indicates that the network has many nodes that function as bridges or links between different network parts. This could indicate the network has good and efficient connections between its nodes. Indihome ranks best in this property, followed by FirstMedia and Biznet.

In summary of the network properties above, Indihome has a lead of 4, and Biszent and Firstmedia have 2 properties each. This means that Indihome is slightly superior to Biznet and First Media, while Biznet and FirstMedia have relatively the same ranking.

Indihome has the highest network properties in terms of size, density, average degree, and betweenness centrality, and it shows that their network has wide coverage, strong relationships between nodes, a high level of connectedness, and a significant role in connecting parts. Important in networking. The large size indicates the total amount. The interpretation is that Indihome is a large, dense, well-connected network that is central in facilitating communication and information flow throughout its network.

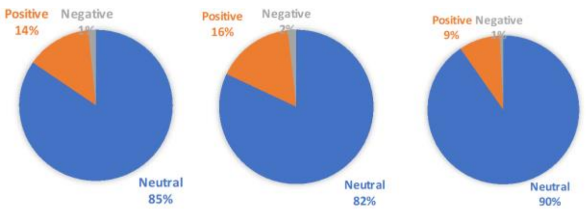
Biznet has network properties with connected components and high modularity, which indicates that the network is divided into separate groups but remains connected efficiently throughout the network. A highly connected component indicates that many connection paths are available, allowing for a smooth exchange of information between network nodes. High modularity indicates the existence of a well-functioning cluster or community, where nodes within the cluster have closer relationships with each other than with nodes outside the cluster. These two traits combined indicate that Biznet has a robust and well-organized network structure, facilitating efficient communication and effective management within its network.

FirstMedia is considered superior in diameter and average path length, indicating that its network has desirable properties in terms of efficiency and connectivity. A lower diameter indicates the shortest distance between the two furthest nodes in the network. In contrast, a shorter average path length indicates that data can move faster and more efficiently between nodes in the network. This represents a robust and well-organized infrastructure that enables fast and effective exchange of information across the

FirstMedia network. Thus, these results demonstrate FirstMedia's superiority in providing reliable and efficient services to their customers. To date, Indihome has the largest number and network in Indonesia.

Network Content Analysis

Network content analysis includes positive, neutral, and negative sentiment analysis, as well as analyzing positive and negative word clouds on each ISP network.



(a) (b) (c)

Fig. 3. Sentiment Analysis (a) Indihome (b) Biznet (c) FirstMedia

The results of sentiment analysis for each ISP can be seen in Fig. 3(a),(b),(c). It can be seen that the sentiment analysis of Indihome, Biznet and FirstMedia users has the same classification, namely dominated by (above 80%) neutral sentiment, a small portion (less than 20%) negative sentiment, and very few users (less than 2%) positive sentiment. Bisnet and Indihome have the same positive sentiment (2%), and First Media is slightly below (1%). Meanwhile, the one that received the most negative sentiment was Biznet (16%), followed by Indihome (14%) and finally FirstMedia (9%).

Wordcloud is used to provide a visual representation of the most dominant keywords in user conversations or reviews. The positive and negative word clouds for each ISP can be seen in Fig. 4. (a)-(e).

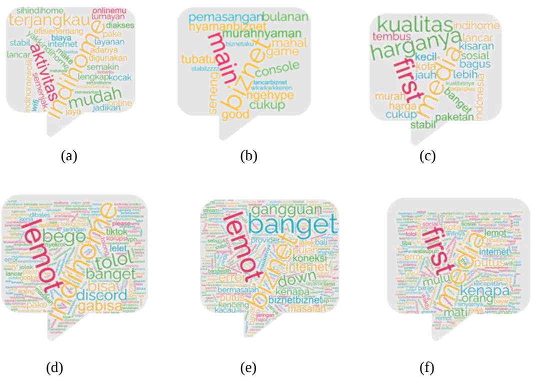


Fig. 4. Positive WordCloud: (a) Indihome (b) Biznet (c) FirstMedia, Negative WordCloud: (d) Indihome (e) Biznet (f) FirstMedia

The words that often appear are related to aspects of connection speed, connection stability, service variety and price.

Positive sentiments in the form of words of appreciation that are often expressed by ISP users for Indihome are "affordable", "easy", "stable", and "complete" on Biznet. They are "cheap", "monthly installation", "enough", and "game", while in FirstMedia, it is "price-quality", "stable", "package", and "smooth". From positive workload, almost the same words appear on all three ISPs. There are different words on Biznet, namely "monthly installation is possible", and on FisrtMedia, "the package is stable".

Meanwhile, negative sentiments are expressed in the form of words of complaint or criticism, which ISP users often express. Negative words for Indihome are "slow", "can there be a discount", stupid". At the same time, those aimed at Biznet are "slow", "disorder", and "down", and for FirstMedia, it is "the internet is dead", "slow" "error". From the negative workload, the complaints that appear on the three ISPs are almost the same, except that there is an additional word on Indihome, namely the word "price discount" which shows that Indihome's prices are considered expensive by its users.

CONCLUSIONS AND SUGGESTIONS

Conclusion

It can be concluded that through SNA of ISP social networks on social media, it can be used as an alternative for ranking ISP brands by looking at social networks on media X . Based on the results of the network structure analysis, it is found that each ISP has relatively balanced strengths and weaknesses. Indohome is slightly superior to Biznet and Firstmedia in terms of the number of customers and a wider network. Meanwhile, from the analysis of user sentiment of the three ISPs, the pattern is almost the same, namely dominated by neutral sentiment, and negative sentiment is much greater than positive sentiment. The issue of network stability appears on all ISPs, both with positive sentiment and negative sentiment. However, the number of negative sentiments is much greater than the positive sentiments, meaning more people are questioning this. Regarding subscription prices, all ISPs are still affordable, but especially for Indihome, there is a sentiment of wanting a price discount. Some recommendations for ISPs: (i) regarding slow networks and unstable connections, ISPs need to improve network infrastructure to increase connection speed and reliability, as well as reduce

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instability in services (ii) for high price complaints, ISPs need to evaluate their pricing policies and provide more affordable package options or discounts for loyal customers (iii) regarding complaints of poor service, ISP must be proactive and focus more on improving customer service by providing responsive, clear and friendly support. With this comprehensive approach, ISPs can improve the quality of their services, improve competitive pricing, and improve their brand image in the market.

Suggestion

The SNA results in the form of a comparison and ranking of the ISP above provide a more holistic insight into the ISP user experience. However, the SNA method has limitations in that it tends to be more subjective depending on the data used and the parameters applied. SNA results are influenced by factors such as how open customers are in sharing information or how often they interact on the analyzed platform. Another approach in the form of using ISP industry standards that focus on technical performance such as download speed, upload speed, and network reliability can be added so that the results complement each other in providing a comprehensive picture of ISP reputation, service quality, and customer preferences..

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