Journal of Information Technology and Cyber Security 2(1) January 2024: 25-39 EISSN 2987-386X | PISSN 2987-3878
DOI: 10.30996/jitcs.10852

Identifying Dominant Actors of Ferdy Sambo's Case Network on Social Media X/Twitter Using Social Network Analysis for Public Relations Strategy

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Received: 07 May 2024
Revised: 07 July 2024
Accepted: 08 July 2024
Available online: 10 July 2024

To cite this article: Prastiti, N., Satoto, B. D., & Efendi, M. R. (2024). Identifying Dominant Actors of Ferdy Sambo's Case Network on Social Media X/Twitter Using Social Network Analysis for Public Relations Strategy. *Journal of Information Technology and Cyber Security*. 2(1), 25-39. https://doi.org/10.30996/jitcs.10852

Abstract

The Indonesian National Police (Polri) has experienced ups and downs in building a positive image in interacting with the public. This decline in trust is caused by the emergence of various issues that show the low performance of the police. In the Ferdy Sambo case study, the performance and integrity of the police is at stake and the sensitivity of the police to meet public expectations. One solution to im-prove the image is through an effective public relations strategy. However, to develop it, a deep un-derstanding of the characteristics and interaction patterns between social media through social net-work analysis is required. This research aims to identify influential X/Twitter actors in the case study of Inspector General Ferdy Sambo by applying the centrality method in Social Network User Analysis. The results of centrality analysis on the network show a wide variety of centrality levels. The @Zaindamai account dominates with the highest Degree Centrality value of 0.426829, indicating the number of connections in the network. The main role in disseminating information is held by @Zaindamai with the highest Betweenness Centrality value of 0.325748, indicating its role in connect-ing various networks. @Rizkynu46127931 stands out in Closeness Centrality with a high value of 0.497791, signifying quick and efficient access to all parts of the social network. In addition, @Rizkynu46127931 has significant influence in the network based on the highest Eigenvector Cen-trality of 0.245625. This centrality value forms the basis for formulating a more focused public relations strategy, improving the efficiency of communication with stakeholders, and de-signing a more concrete public relations plan.

Keywords: Ferdy Sambo, organization image, public relations strategy, Social Network Analysis, Twitter, X.

1. Introduction

The Indonesian National Police is responsible for maintaining law and order in local communities by protecting the public. However, the police department faces significant challenges in building a positive image within society. Several actions have sparked controversy and criticism from the public (Alfian, 2020).

According to the survey of Litbang Kompas in October 2021, the Indonesian National Police has been attracting increasing negative sentiment, indicating a decline in public trust in the institution (Fig. 1). In October 2021, negative sentiment stood at 18.5%. This number rose to 21.9% in January 2022 and further increased to 24.7% by June 2022. A significant surge occurred between June and October 2022, with negative sentiment skyrocketing to 38.4%. Currently, it stands at 43.1% (Farisa, 2022).

Several notorious incidents in recent months are believed to have triggered negative sentiment towards the Indonesian National Police. One such incident involved the murder case of a police officer, Nofriansyah Yosua Hutabarat, also known as Brigadier J, by his superior, Inspector General Ferdy Sambo, the Head of the Professional and Security Division (Kadiv Propam). Another incident was the use of water cannons to dismiss football supporters during a football match in Kanjuruhan stadium, Malang, East Java, which led to the tragic deaths of 135 people. Additionally, a drug trafficking case involving the former Regional

Chief of Police (Kapolda) of West Sumatera, Inspector General Teddy Minahasa and his subordinates further damaged the police reputation (Farisa, 2022).

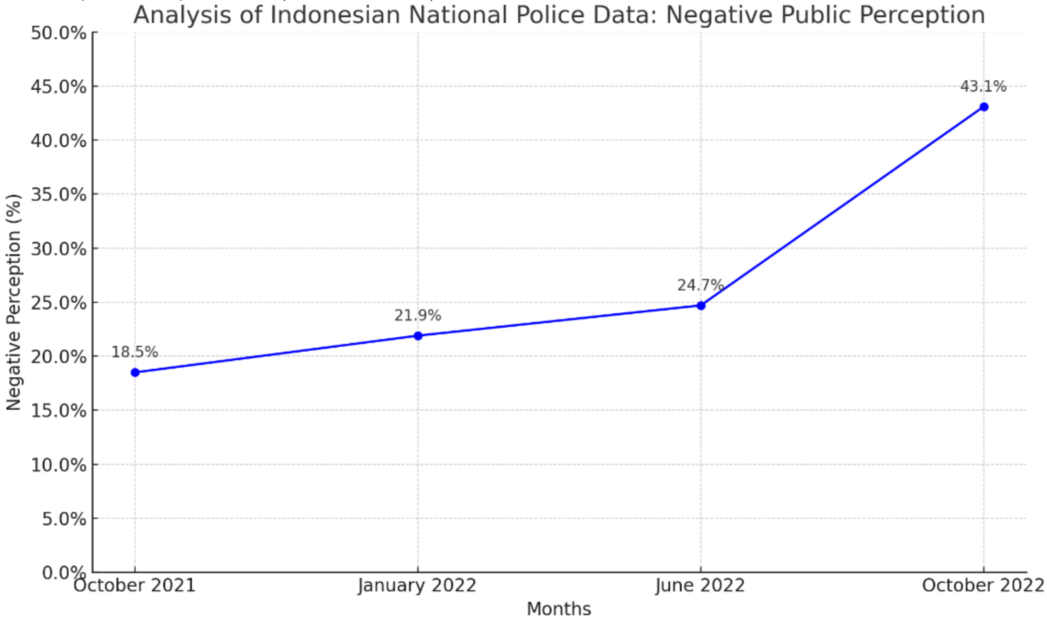

Fig. 1. The increasing of negative sentiment towards the Indonesian National Police (Farisa, 2022).

The decline in public trust in the Indonesian National Police is due to various issues indicating poor police performance in handling cases and misconduct of some police officers tarnishing the reputation of the institution (Syafuddin, 2022). The case of Inspector General Ferdy Sambo has put police performance, integrity, and sensitivity under scrutiny, necessitating efforts to improve institutional sentiment among the public (Indrayani, 2022). To achieve this, a Public Relations (PR) strategy involving social media can be employed to create a positive image for the institution by fostering social bounding virtually (Puspitarini & Nuraeni, 2019; Restanti, 2015). However, to develop an effective PR strategy, a deep understanding of human characteristics and interactions on social media is essential. This can be achieved through Social Network Analysis (SNA), which maps social media structure, and network and interaction patterns among users (Radjah et al., 2023).

The study aims to analyze the social network related to the premediated murder case involving Inspector General Fredy Sambo using SNA approach. The goals are to identify influential social media users in shaping public opinion, determine potential supporters or critics, and analyze interaction patterns among them. The data used in this study consists of tweets from Twitter with the hastag of #ferdysambo. The collected data includes information about user accounts interacting with the topics, as well as their interactions such as tweets, replies, and mentions.

Several studies have demonstrated the effectiveness of SNA in analyzing public trust in police institutions. Handaningtias et al. (2022) used this method to examine social networks with the hastag #percumalaporpolisi to analyze both positive and negative sentiments toward the topic. Similarly, Nugraha et al. (2022) analyzed the structure of social media networks among Twitter users using the hastag #g20indonesia.

Given the situation, we believe that SNA is a suitable approach for examining the structure and interaction patterns within social media networks. This study focuses on the premediated murder case involving Inspector General Fredy Sambo. The data collected will be analyzed using SNA techniques, with a particular emphasis on centrality analysis to identify the most influential users within the network. The analysis will be conducted using Python libraries such as NetworkX will be used. The aim of this study is to provide deeper insights into the key influencers among social media users who shape public opinion and to develop strategies for improving the reputation of the Indonesian National Police through social media.

2. Literature Review

2.1. Public relations strategy

PR plays a crucial function in leadership and management, playing a role in achieving an organization's goals, defining the organization's philosophy, and facilitating changes (Mujianto, 2018). The function of PR includes supporting management activities to achieve organizational goals, creating two-way communication by disseminating information from the company to the public, gathering public opinions, providing services to the public, offering advice to organizational leaders for the public good, and building harmonious relationships between the organizations and both its internal and external publics. Furthermore, PR is responsible for conveying information to the public and making persuasive efforts to influence public attitudes and behaviours or those to support the organization (Supada, 2020).

2.2. Data preparation for social network analysis

Data preprocessing involves a set of procedures to prepare data to meet research needs and be ready for further analysis. In the context of text processing, the focus is on cleaning data from noise, organizing it to be more focused, and ensuring order so that the data can be optimally used (Nurhazizah et al., 2022). Data extracted from social media platforms like Twitter (X) has various types of information, such as numerical data, categorical attributes, and text. To maintain data quality, extraneous elements such as text content, graphical content, graphical identification numbers, and video file IDs are removed, leaving only the node IDs (Das & Sinha, 2017). User interactions are represented using a graph. Each username (@foo) is considered a node, and an edge is added from @foo to @bar every time @foo sends a message or mentions @bar (Ediger et al., 2010). Nodes and edges from data transactions are formatted in adjacency list dan matrix. Data preprocessing process aims to arrange dataset so that it can be run through analysis smoothly and obtain optimal results (Das & Sinha, 2017).

2.3. Social network analysis

Social Network Analysis (SNA) is a study learning human relationships using graph theory (Tsvetovat & Kouznetsov, 2011). SNA is developed from a combination of social theory and the implementation of mathematical methodologies, statistics, and formal computation (Wasserman & Faust, 1994). SNA is a theoretical and methodological approach to learn different social systems. This approach involves data analysis to identify local and global structures and social networks dynamics. This approach aims to reveal human interactions, identify influential actors in a network, and investigate their influence in spreading information or behaviour in the network (Nurhazizah et al., 2022). Relationships in a network are visualized as nodes and edges. From the perspective of social networks, nodes symbolize social actors, such as individuals, communities, companies, or organizations. Meanwhile, edges represent the connections and relationships between different nodes (Zhang & Luo, 2017).

2.4. Centrality metod

Centrality is an important index to indicate which nodes hold critical positions in an entire network. A central position is always associated with outstanding leadership, good popularity, or a very good reputation in a network. When a social actor has higher centrality, it means they are closer to the centre of the network, which implies they may have more power, influence, or benefits from the network. There are four analysis at the actor level: degree centrality, closeness centrality, betweenness centrality and eigenvector centrality (Zhang & Luo, 2017). For better understanding and visualization, Fig. 2 below illustrates an example of an undirect single-line network graph.

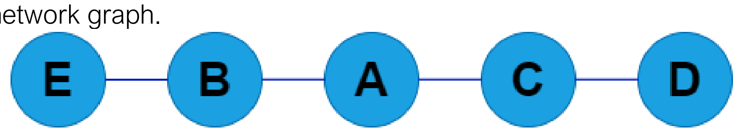

Fig. 2. An example of an undirect single-line network graph.

2.4.1. Degree Centrality

Degree Centrality is a metric used to measure how far a node in a network is connected to other nodes. This metric calculates the number of connections (edges) linked to the node. In other words, Degree Centrality shows an insight on how important or active a node is in interacting with others in the network. The higher the degree of centrality score in a network, the more relationships the actor has and the greater their influence on other actors. Fig. 3 visualizes Degree Centrality, and Degree Centrality can be calculated using equation Eq. (1),

$$C_D(N_i) = \frac{d_{Ni}}{n-1} \tag{1}$$

where $C_D(N_i)$ is Degree Centrality for node N_i, denoted d_{Ni}, is the number of connected relationships within node N_i, and n is the total number of nodes in the network population. Using Eq. (1), the Degree Centrality of Node A is 0.5, $C_D(A) = 0.5$, $C_D(B) = 0.5$, $C_D(C) = 0.5$, $C_D(E) = 0.25$, and $C_D(D) = 0.25$.

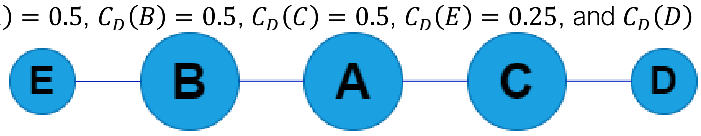

Fig. 3. Degree Centrality visualization.

2.4.2. Betweenness Centrality

Betweenness centrality is used to measure the extent to which a node acts as an “intermediary” in a network. It identifies accounts having the greatest influence in the process of dissemination or as interconnectors in communication and information transfer. If a node is located on the only path that other nodes must traverse within network, such as for communication, connection, or transportation, then this node is considered important and likely has a high betweenness centrality. Eq (2) illustrates the calculation of betweenness centrality,

$$C_B(N_i) = 2\sum_{j<k} \frac{\frac{Gjk\,(N_i)}{Gjk}}{(n-1)\,(n-2)} \tag{2}$$

where $C_B(N_i)$ is Betweennes Centrality for node N_i, $Gjk\ (N_i)$ is a number of the shortest path in a network connecting two nodes j and k, and involding node N_i as an intermediary (geodesics connecting jk passing through N_i), Gjk is a number of the shortest path (geodesics connecting jk), and n is the total number of nodes in the network population. Betweenness Centrality calculation for node A can be performed using Eq. (2), with results as presented in Fig. 4, following these steps:

- First, calculate the total number of the shortest path (geodesics) connecting every pair of nodes within network,
  - Node A is located between 4 pairs of nodes, namely: (E, C), (E, D), (B, C), (B, D),
  - Node B is located between 3 pairs of nodes, namely: (E, A), (E, C), (E, D),
  - Node C is located between 3 pairs of nodes, namely: (D, A), (D, B), (D, E), and
  - Node E and D are located at the edge or end of the network. In other words, they function as the end points of communication path within network.
- The next step is to use Eq. (3), resulting the score of Betweenness Centrality of Node A in the network. It is approximately 0.6667, with $C_B(E) = 0$, $C_B(B) = 0.5$, $C_B(A) = 0.67$, $C_B(C) = 0.5$, and $C_B(D) = 0$.

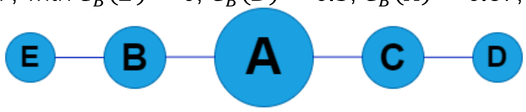

Fig. 4. Betweenness Centrality visualization.

2.4.3. Closeness Centrality

Closeness centrality aims to measure the distance of a particular node to all other nodes within network. If the length of the shortest path from node N to other nodes in a network is relatively short, then node N has a high Closeness centrality score. Closeness centrality can be calculated using Eq. (3),

$$C_C(N_i) = \frac{n-1}{\left[\sum_{j=a}^{n} d(N_i,N_j)\right]}(i \neq j) \tag{3}$$

where $C_C(N_i)$ is the Closeness Centrality of node N_i, $\sum_{j=a}^{n} d(N_i,N_j)$ is the sum of the shortest distances between node N_i and node N_j in the network, and n is the number of nodes in the network population. The calculation of Closeness Centrality for Node A can apply Eq. (3) with results as presented in Fig. 5, with the following steps:

Fig. 5. Closeness Centrality visualization.

- First, calculate the shortest path from node A to all other nodes in a network:
  - Distance from A to B: 1 (because node A is directly connected with node B),
  - Distance from A to C: 1 (because node A is directly connected with node C),
  - Distance from A to D: 2 (via B),
  - Distance from A to E: 2 (via C), and
- The next step is to use Eq. (3), resulting in the Closeness Centrality score of Node A in a network. It is approximately 0.6667, $C_C(E) = 0.4$, $C_C(B) = 0.57$, $C_C(A) = 0.67$, $C_C(C) = 0.57$, and $C_C(D) = 0.4$.

2.4.4. Eigenvector Centrality

Eigenvector centrality, often referred to as eigen centrality, is used to measure the importance of a node in a network. Calculating eigenvector centrality not only considers how many connections the node has, but also the importance of the nodes directly connected to it. This shows that a node with few connections but connected to nodes with important connections can have a higher score of eigenvector centrality. To calculate the eigenvector centrality, the first step is to find the eigenvalue and eigenvector of the adjacency matrix A (a matrix that describes the relationships between nodes in the network). This eigenvalue can be found using Eq. (4),

$$|A - \lambda I| = 0 \quad (4)$$

In this context, A is the adjacency matrix with a size of $N \times N$, where N is the total number of nodes in a network. λ is the eigenvalue (a scalar score) that needs to be found, and I is the identity matrix (a matrix with 1 on the main diagonal element and 0 on the other elements). After finding the eigenvalue, the next step is to find the eigenvector corresponding to the largest eigenvalue. The eigenvector can be calculated using Eq. (5),

$$A\vec{v} = \lambda\vec{v}$$
$$(A - \lambda I)\vec{v} = \begin{bmatrix} 0 \\ \vdots \\ 0 \end{bmatrix} \quad (5)$$

where $\vec{v}$ is an eigenvector with the matrix of $N \times 1$ which can be represented and explained in Eq. (6).

$$\vec{v} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} \quad (6)$$

Eigenvector centrality for node i can be described as a contribution or influence that is given by node i in the vector eigenvector $\vec{v}$, that is calculated using the largest eigenvalue from the adjacency matrix A. To make a more comparable Eigenvector centrality, the vector eigenvector $\vec{v}$ can be normalized by dividing all scores of the vector eigenvector $\vec{v}$ with the highest scores of the vector. As an ilustration, we can use a graph with 3 nodes and 2 sides. The first step is to represent that graph in an adjacency matrix A. Eq. (7) represents an adjacency matrix.

$$A = \begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & 1 \\ 0 & 1 & 0 \end{bmatrix} \quad (7)$$

Next, calculate eigenvalues of the adjacency matrix A using Eq. (4). The results obtain three eigen-values, which are $\lambda_1 = 0$, $\lambda_2 = \sqrt{2}$, and $\lambda_3 = -\sqrt{2}$. It is found that the largest eigenvalue is $\lambda_2 = \sqrt{2}$. The largest eigenvalue has an important role to calculate the eigenvector centrality using Eq. (5). Therefore, the eigenvector centrality for the nodes can be calculated using Eq. (6). The result shows that the eigenvector centrality for the node 1 is 0.7071, for the node 2 is 1, and for the node 3 is 0.7071.

3. Methods

Fig. 6 depicts the structure of research framework that is used to define the procedures of the study. The explanation is as follows:

a. Scraping

The scrapping process is conducted several times in Python using snscrape library. The process uses the keyword of "#ferdysambo. The data collection was started from 18th October 2022 to 27th February 2023. The data scraping resulted in 7,063 tweets. The data has around 8 attributes as presented in Table 1. The obtained data was then exported in .csv format.

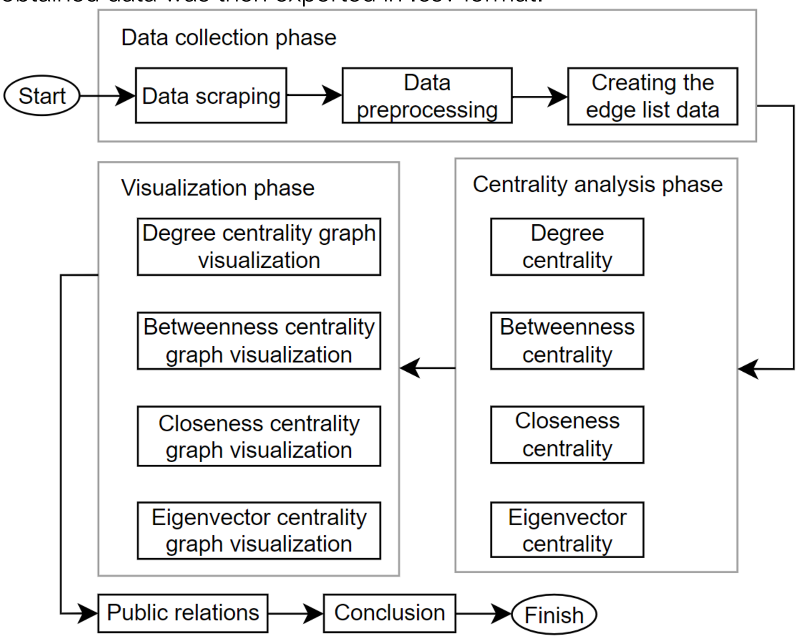

Fig. 6. The diagram block of the Social Network Analysis.

Table 1
Data tweet attributes.

No.	Attribute
1	id
2	conversation_id
3	created_at
4	user_id
5	username
6	mentions
7	reply_to
8	tweets

Table 2
Node and edge attributes.

No.	Attribute
1	username
2	mentions
3	reply_to

b. Data Preprocessing

Data scrapping process results in an unstructured format. Therefore, the information contained in the data cannot be directly extracted in the format required by the SNA method. The data must be preprocessed to remove duplication, ensuring the authenticity of the data. In the context of SNA, each Twitter user is represented as a “node”, while the relationships or activities such as mentions and replies are represented by “edge” or lines connecting those nodes. After the data is cleaned, the next step is to proceed data into the suitable format. This data has attributes such as "mention" dan "reply_to," indicating two types of edges, namely "Mention" dan "Reply."

The hypothesis of this study is that each tweet can have one or more edges, but it can also have no edges at all. Therefore, in this algorithm, the data will be separated based on username as a node or source, and mention or reply_to as edge or target, as presented in Table 2. This hypotesis indicates variations in Twitter user engagement in retweeting or replying to other tweets. Fig. 7 shows preprocessing resulted in 926 data, because one username or source has several targets in different types of edges, namely mention and reply.

	username	target	type
0	Zaindamai	Bambang48835243	mentions
1	kp3_i	Zaindamai	mentions
2	Bambang48835243	Whisnu606	mentions
3	KompastvJatim	SAFANews3	mentions
4	busjro	magalitorre02	mentions
...	...	...	...
921	jakadoding	indopos_id	mentions
922	magalitorre02	sibakso77	mentions
923	TheUncleDee	medcom_id	mentions
924	TheUncleDee	Hiexma_UFA	mentions
925	dedysubhan_s	rudymulyadi	mentions

926 rows × 3 columns

Fig. 7. Data Preprocessing results.

c. Centrality

To obtain the scores of Degree Centrality, Betweenness Centrality, Closeness Centrality, and Eigenvector Centrality, the next step is calculating the results of preprocessing data using Networkx library.

- Degree Centrality

  In order to obtain the score of Degree Centrality, the steps are as follows:
  1) Calculate centrality in the graph using NetworkX library.
  2) Create a graph from the DataFrame using function `from_pandas_edgelist`, where the column of the 'username' and 'target' act as source and target for each side of the graph.

3) Save the graph into CSV file using function `write_edgelist.
4) Calculate degree centrality for each node in the graph using function degree centrality from the NetworkX library. Save the results in a DataFrame column using Pandas as 'Username' and 'Result'.
5) Show the first ten nodes with the highest score of Degree Centrality using function ‘nlargest’.

- Betweenness Centrality
  In order to obtain the score of Betweenness Centrality, the steps are as follows:
  1) Calculate betweenness centrality using function ‘betweenness_centrality’ from the library of NetworkX.
  2) Get the normalization score using parameter ‘normalized=True’ and ‘endpoints=False’ to ignore the end node.
  3) Save the results in a DataFrame as 'Username' dan 'Result'.
  4) Show the first ten nodes with the highest score of betweenness centrality using function `nlargest`.
- Closeness Centrality
  In order to obtain the score of Closeness Centrality, the steps are as follows:
  1) Calculate closeness centrality using function nx.closeness_centrality from the library of NetworkX.
  2) Save the results in a DataFrame as 'Username' dan 'Result'.
  3) Show the first ten nodes with the highest score of closeness centrality using function `nlargest`.
- Eigenvector Centrality
  In order to obtain the score of Eigenvector Centrality, a function of nx.eigenvector centrality was used. This function gets a parameter of ‘max_iter=200’ to determine the number of maximum iterations in the power iteration method.

d. Visualization step is conducted using Python for each Centrality to provide conclusions based on the scores of Centrality.
   - Degree Centrality: Resulted in graphical visualization of the Degree Centrality. The Degree Centrality of each node is visualized through the node, the color, and the size of nodes. This visualization is important to understand network structure and identify the most influential nodes in the context of analysis that is being conducted.
   - Betweenness Centrality: Visualize Betweenness Centrality using scatter plot in a graph. The Betweenness Centrality is represented by the color and the size of the nodes.
   - Closeness Centrality: Visualize Closeness Centrality using matplotlib. The Closeness Centrality is represented by the color and the size of the nodes.
   - Eigenvector Centrality: Visualize Eigenvector Centrality using function nx.eigenvector centrality for each node in the G graph.

e. Evaluate the analysis results to determine PR strategy. This can be done by evaluating the SNA results and considering appropriate strategies to improve the image of the Indonesian National Police, particularly related to the premediated murder case involving police officer Inspector General Ferdy Sambo.

4. Results and Discussion

4.1. Results and discussion

This study focused on the social networking analysis to obtain the most influential community in the network of "#ferdysambo". It is found that there are interactions connecting nodes or entities, where the interactions are classified into two main types: "mention" and "reply". Therefore, the nodes used in this study is username, while the target or edge is reply.

Fig. 8 shows the percentage of interaction types in the network related to the case of Inspector General Ferdy Sambo, where the majority of interactions are in the form of “mentions” at 92.22%, while “replies” account for only 7.78%.

According to the percentage of the edge types that are used to obtain the score of:

1) Degree Centrality
   The preprocessing data obtains ten nodes with the highest scores of Degree Centrality in a network, presented in Table 3. Those nodes are considered to have a high level of connectivity with other network members, and therefore, they can be regarded as key or important actors in the network. Visually, nodes with higher degree centrality have larger sizes and more prominent color, while nodes with lower degree centrality have smaller sizes and darker colors (Fig. 9).

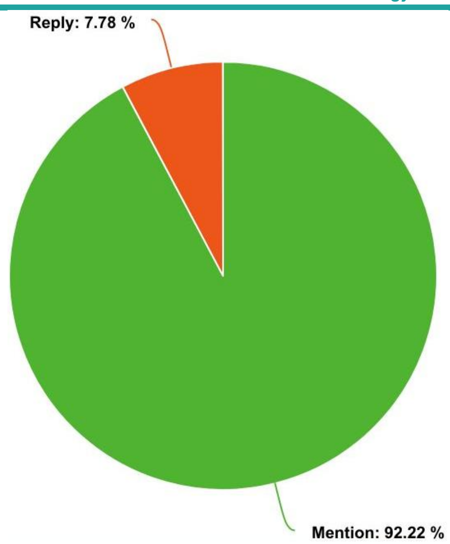

Fig. 8. Persentage of edge types.

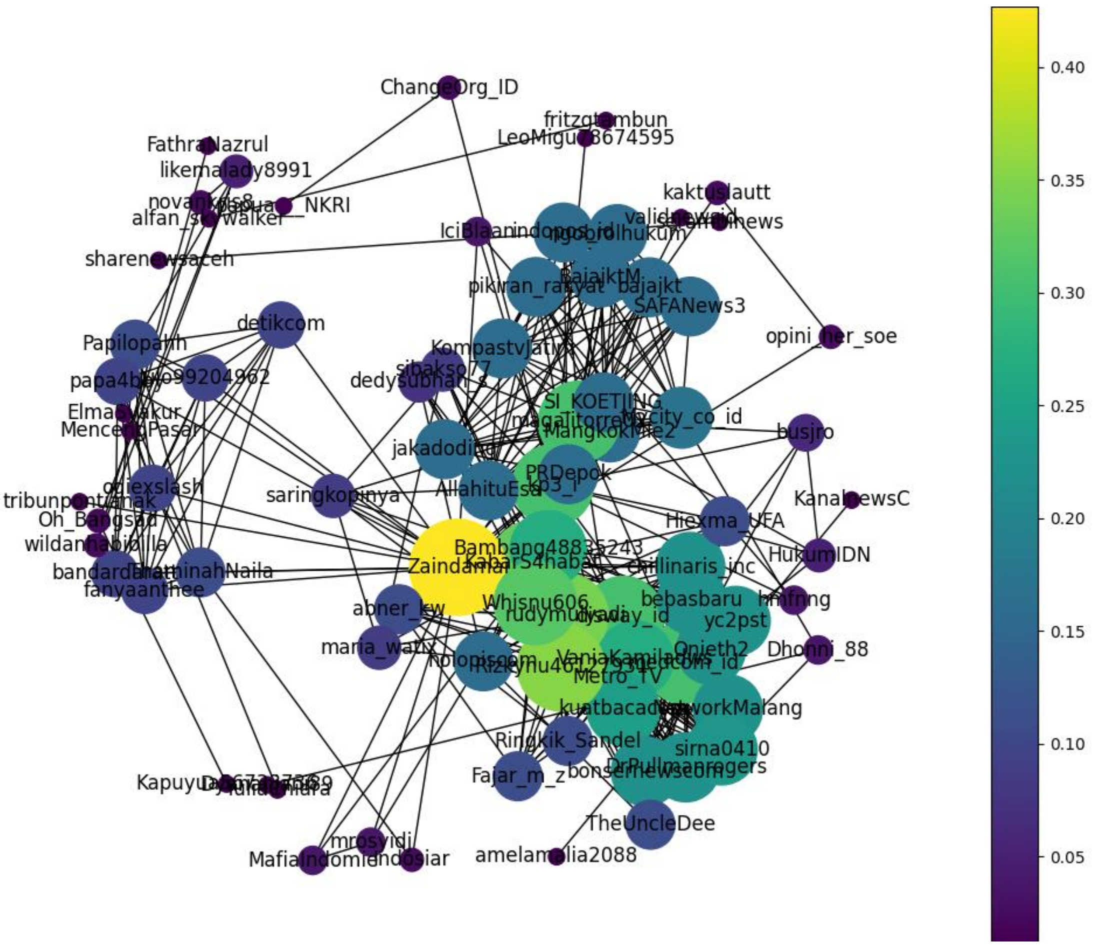

Fig. 9. Visualization of Degree Centrality in the case study of Inspector General Ferdy Sambo.

2) Betweenness Centrality

Table 4 presents the top ten nodes with the highest betweenness centrality. Many of those nodes do not significantly differ compared to the results of the top 10 nodes in the Degree Centrality. For example, the account named @Zaindamai still maintained the top position in the Betweenness Centrality. This result indicates that @Zaindamai plays a key role in disseminating information within the network in the case study of the Inspector General of Ferdy Sambo. Fig. 10 shows nodes with the higher scores of Betweenness Centrality have bigger sizes and more prominent color. This visualization helps in identifying nodes that play important roles in connecting differen parts in a network.

Table 3
Degree centrality score.

X/Twitter Account	Score
@Zaindamai	0.426829
@Rizkynu46127931	0.353659
@rudymulyadi	0.341463
@KabarS4habat	0.329268
@Metro_TV	0.329268
@Whisnu606	0.317073
@magalitorre02	0.304878
@kp3_i	0.304878
@disway_id	0.304878
@medcom_id	0.304878

Table 4
Betweenness Centrality score.

X/Twitter Account	Score
@Zaindamai	0.325748
@magalitorre02	0.241384
@kp3_i	0.125750
@Papilopahh	0.100873
@likemalady8991	0.083107
@Rizkynu46127931	0.053502
@rudymulyadi	0.053360
@KabarS4habat	0.049468
@Metro_TV	0.047821
@medcom_id	0.046659

3) Closeness Centrality

Closeness Centrality aims to determine the popularity of actors in a social network based on their relationships. This score is important because it reflects the extent to which an actor in a social network is closely connected to other actors which can illustrate their role and influence in the network.

Table 5 depicts the highest scores of the Closeness Centrality in the case study, where the account named @Rizkynu46127931 ranks first. The result indicates that the account has efficient access to all the information within the network. It is followed by @rudymulyadi and @Metro_TV, who rank second and third, subsequently. These three accounts have quick and efficient access to information related to the case study.

Table 5
Closeness Centrality score.

X/Twitter Account	Score
@Rizkynu46127931	0.497791
@rudymulyadi	0.493902
@Metro_TV	0.490074
@KabarS4habat	0.490074
@Zaindamai	0.486304
@medcom_id	0.482592
@kp3_i	0.478936
@Whisnu606	0.439024
@disway_id	0.435997
@VaniaKamiladws	0.427159

Fig. 11 is a visualization of the Closeness centrality, where the higher score indicates the larger size of the node. To provide good contrast, the color follows viridis color map. This visualization can provide a visual understanding of how close each node is to other nodes in the network. It is useful for identifying key nodes that can play important roles in dissemining information or maintaining connectivity within the network.

4) Eigenvector Centrality

Eigenvector Centrality is useful to evaluate actor popularity in a social network based on their relationships with other actors. Eigenvector Centraliy is important because it can reflect a stronger level of those actors within the network.

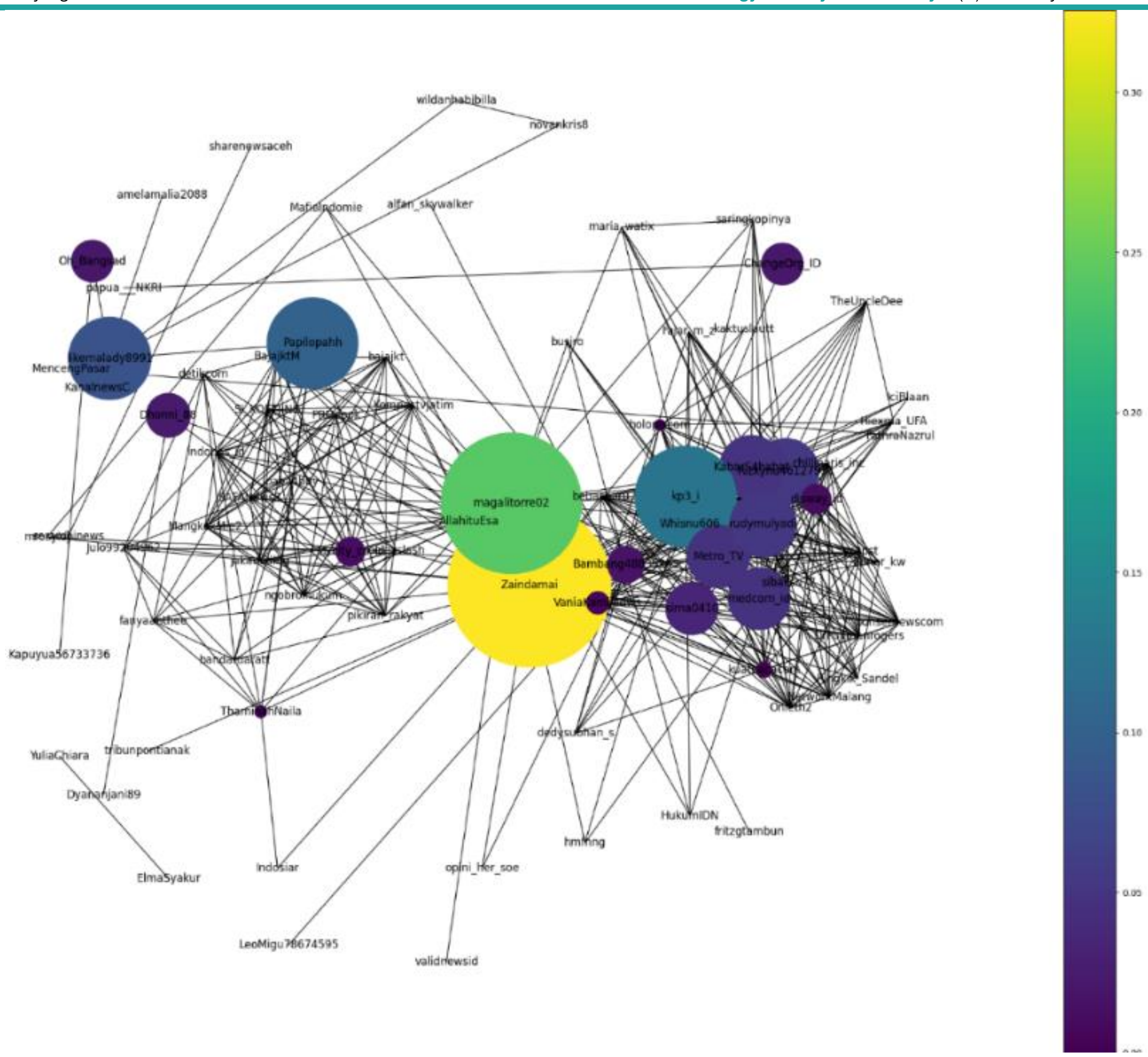

Fig. 10. Visualization of the Betweenness Centrality in the case study of Inspector General Ferdy Sambo.

Table 6
Eigenvector Centrality score.

X/Twitter Account	Score
@Rizkynu46127931	0.245625
@rudymulyadi	0.239911
@Metro_TV	0.239526
@Whisnu606	0.236566
@KabarS4habat	0.235841
@disway_id	0.233482
@medcom_id	0.227905
@Zaindamai	0.218863
@VaniaKamiladws	0.218600
@Bambang48835243	0.209649

Fig. 11 is a visualization of the Closeness centrality, where the higher score indicates the larger size of the node. To provide good contrast, the color follows viridis color map. This visualization can provide a visual understanding of how close each node is to other nodes in the network. It is useful for identifying key nodes that can play important roles in dissemining information or maintaining connectivity within the network.

5) Eigenvector Centrality

Eigenvector Centrality is useful to evaluate actor popularity in a social network based on their relationships with other actors. Eigenvector Centraliy is important because it can reflect a stronger level of those actors within the network.

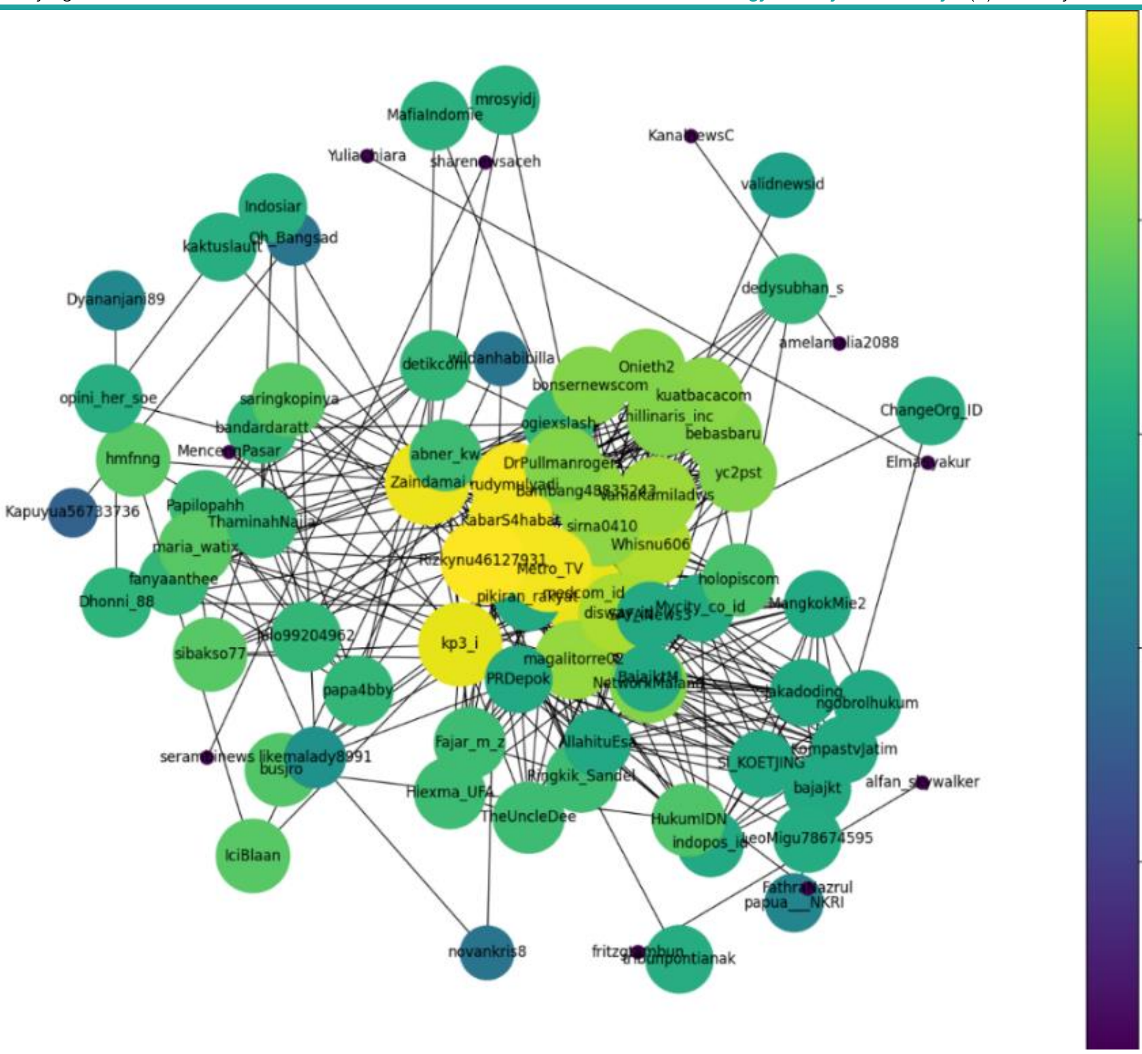

Fig. 11. Visualization of Closeness Centrality in the case study of Inspector General Ferdy Sambo.

Table 6 shows the top ten nodes with the highest score of the Eigenvector Centrality. It is important to note that eigenvector centrality calculates how important or influential a node in a network. According to Table 6, it is depicted that an account namely @Rizkynu46127931 ranks first in Eigenvector Centrality. The result indicates that the account has efficient access to the enrire information network. The second rank was obtained by @rudymulyadi, which also has significant access within the network. Meanwhile, the third rank was the account of @Metro_TV, a leading media information in Indonesia. Those three accounts have capability to quickly and effieicntly access information related to the case study of Inspector General Ferdy Sambo.

Fig. 12 visualizes the score of Eigenvector Centrality of each node using size and color of node. A node with a higher Eigenvector Centrality has more prominent color and bigger size. This visualization helps to identify influential roles and the involvement of these accounts in the network.

4.2. Recommendation of the public relations strategy

The recommendation of the PR strategy is determined by analyzing the PR strategy based on the SNA results. The results identified roles and influences of different actors in social networks related to the case study of Inspector General Fredy Sambo. The information can be used to recommend effective and relevant PR strategies based on the centralities results previously revealed in this study. Each type of centrality, such as Degree Centrality, Betweenness Centrality, Closeness Centrality, and Eigenvector Centrality, can provide insights related to the role and impact of individuals within the social network. To provide a more detailed understanding, several tables with the centrality results are presented.

Table 7 shows the Degree Centrality scores for several relevant Twitter accounts within the social network of the Inspector General Fredy Sambo case study. Degree Centrality measures the extent to which an account has connections or interactions with other accounts in the network. Accounts with high Degree Centrality scores can be considered as having many connections within the network.

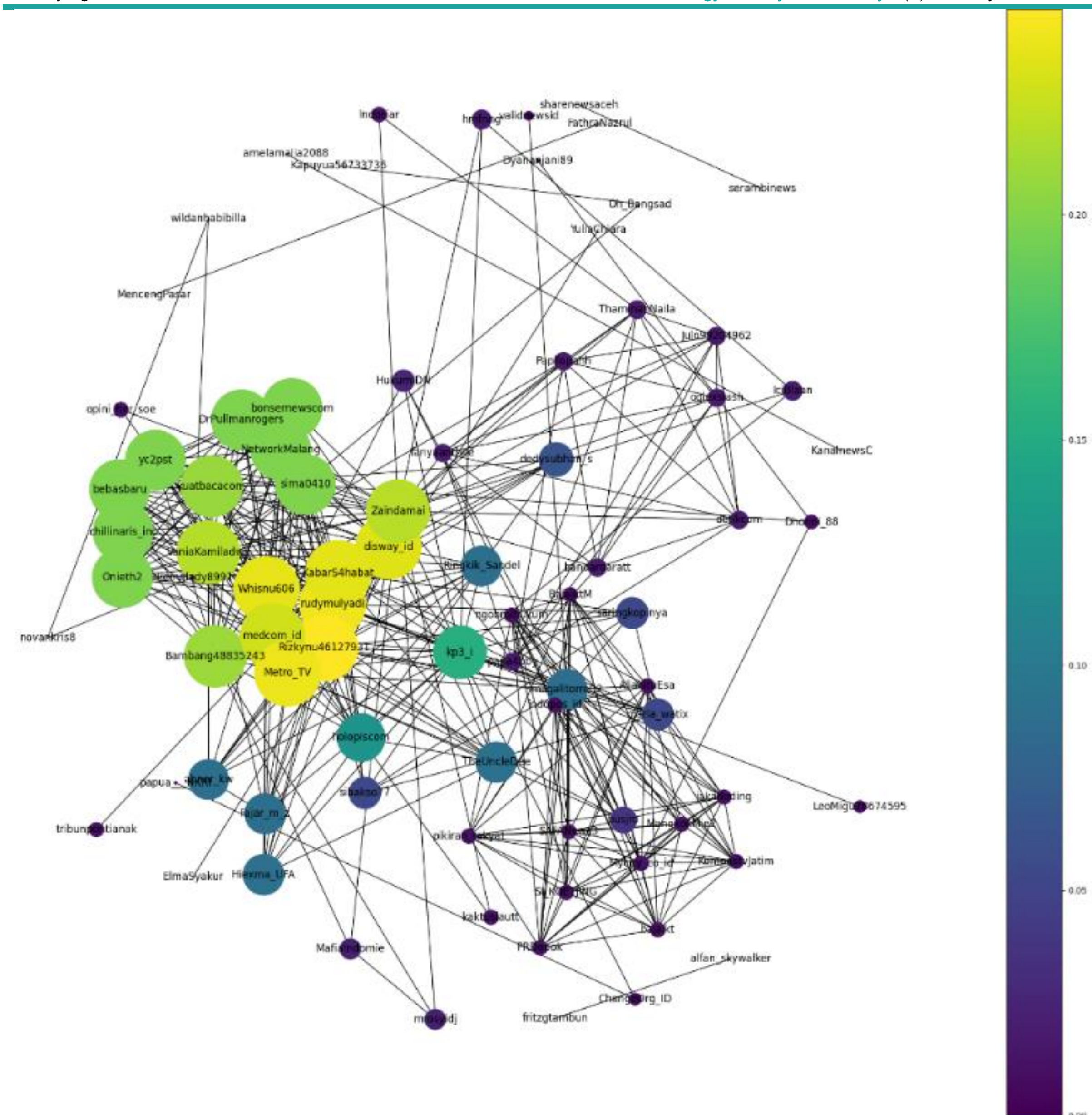

Fig. 12. Visualization of Eigenvector Centrality in the case study of Inspector General Ferdy Sambo.

Table 7
The top five scores of the Degree Centrality.

X/Twitter Account	Score
@Zaindamai	0.426829
@Rizkynu46127931	0.353659
@rudymulyadi	0.341463
@KabarS4habat	0.329268
@Metro_TV	0.329268

Table 8
The top five scores of the Betweenness Centrality.

X/Twitter Account	Score
@Zaindamai	0.325748
@magalitorre02	0.241384
@kp3_i	0.125750
@Papilopahh	0.100873
@likemalady8991	0.083107

The Indonesian National Police can contact accounts with the highest Degree Centrality scores, such as “@Zaindamai”, “@Rizkynu46127931”, “@rudymulyadi”, and “@KabarS4habat” to involve them in educational campaigns or positive police activities. Proactively engaging with these accounts can enhance the positive image of the police institution on social media. Furthermore, collaborating with the account “@Metro_TV” as a media partner can provide positive coverage related to the police achievements and contributions in maintaining public security. These would not only improve the police image in a public but also provide deep insights into the stragegic roles of police institutions in ensuring public safety and order.

Table 8 shows Betweenness Centrality scores for several twitter accounts. Betweenness Centrality measures how far an account can function as intermediary to spread information within a network. Accounts with the highest Betweenness Centrality can be considered as accounts having important roles in connecting different parts of the network.

The Indonesian National Police can establish relationships with the top five accounts having the highest Betweenness Centrality, such as "@Zaindamai", "@magalitorre02", "@kp3_i", "@Papilopahh", and "@likemalady8991". Proactively interacting with these accounts can help the police institutions disseminate positive information, respond to critical issues, and develop a stronger presence on social media platforms. The use of accounts with high score of Betweenness Centrality can significantly contribute to spreading information and developing positive relationships between the police and the public.

Table 9
The top five scores of the Closeness Centrality.

X/Twitter Account	Score
@Rizkynu46127931	0.497791
@rudymulyadi	0.493902
@Metro_TV	0.490074
@KabarS4habat	0.490074
@Zaindamai	0.486304

Table 10
The top five scores of the Eigenvector Centrality.

X/Twitter Account	Score
@Rizkynu46127931	0.245625
@rudymulyadi	0.239911
@Metro_TV	0.239526
@Whisnu606	0.236566
@KabarS4habat	0.235841

Table 9 shows the scores of Closeness Centralities for certain twitter accounts. Closeness Centralities measure how quickly and efficiently an account can access all parts of the social network. Accounts with high Closeness Centralities can be considered as having the ability to reach information quickly.

The Indonesian National Police can strengthen its engagement with accounts having the highest Closeness Centrality, such as "@Rizkynu46127931", "@rudymulyadi", "@Metro_TV", "@KabarS4habat", and "@Zaindamai". By focusing on more intensive interactions with these accounts, the police institution can enhance their accessibility and ensure quick responses to information or issues emerging in social media environment. This will not only strengthen connectivity with users, but also to create a closer relationship and more responsive with the entire community.

Table 10 shows the Eigenvector Centrality from several Twitter accounts. Eigenvector Centrality measure account influence in a network by considering the influence of other accounts that are connected to. Accounts with higher score of Eigenvector Centrality can be considered as having significant influence within the social network.

The Indonesian National Police can leverage connections with accounts that have the highest Eigenvector Centrality, such as "@Rizkynu46127931", "@rudymulyadi", "@Metro_TV", "@Whisnu606", and "@KabarS4habat". By collaborating and engaging these accounts in activities or campaigns, the police institution can expand their reach and influence in the social media community. Utilizing accounts with high Eigenvector Centrality can help the police institution to reach larger audience and enhance their positive impacts in digital environment effectively.

According to the recommendations, the Indonesian National Police can optimize their PR stratefy to fix their image effectively. These tables can be used as baseline to formulate more focused PR strategy, including more efficient communication with stakeholders, utilizing more appropriate platforms, and developing more concrete action plans. These efforts will support goal achievement in the context of case study of the Inspector General Fredy Sambo more effectively through PR strategy.

5. Conclusions

According to the PR strategy analysis using SNA, several conclusions can be drawn: 1) The identification of roles and influences of Twitter accounts using SNA was successfully conducted by employing different Twitter accounts in the social network related to the case study of Inspector General Ferdy Sambo; 2) Centrality analysis, including Degree Centrality, Betweenness Centrality, Closeness Centrality, and Eigenvector Centrality, revealed different level of centrality within the network.

The account @Zaindamai has the highest Degree Centrality with a score of 0.426829, indicates the number of connections in the network. Additionally, @Zaindamai acts as a key intermediary in disseminating information with the highest score of Betweenness Centrality of 0.325748. The account @Rizkynu46127931 has a high score of Closeness Centrality with the score of 0.497791, indicating quick access and efficient to the entire parts within the social network. Furthermore, the account @Rizkynu46127931 has significant influence within the social networks according to the Eigenvector Centrality with the score of 0.245625.

Those centralities provide strong foundation to formulate more focused PR strategies to support efficient communication with stakeholders and design more concrete action plan. This analysis contributes to provide valuable insights for improving the image of the Indonesian National Police through more targeted and effective PR.

6. CRediT Authorship Contribution Statement

Novi Prastiti: Conceptualization, Data curation, Formal Analysis, Funding acquisition, Investigation, and Methodology. Budi Dwi Satoto: Project administration and Writing – original draft. Moch. Rizal Efendi: Resources, Software, Visualization, and Writing – review & editing.

7. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

8. Data Availability

The dataset used in this study was obtained through scraping from Twitter.

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