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Mapping Influence Clusters: A Network Analysis of TikTok Influencer Co-Followership Among University Students

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ABSTRACT

This study examines TikTok influencer co-followership patterns among university students through social network analysis to understand how shared influence functions within digital ecosystems. Using survey data from Indonesian university students who identified their top three most-followed TikTok influencers, we built a co-followership network comprising 266 unique influencers connected by 333 relationships. The research employed quantitative network analysis methods, such as centrality measures, community detection algorithms, and content categorisation, to map influence clusters and explore the network's structural properties. Results reveal a fragmented network with a low density (0.0094) consisting of 49 connected components, indicating that student followership patterns form distinct thematic communities rather than a single, unified influence network. Centrality analysis identified key bridging influencers, with Tasya Farasya emerging as the most central figure, demonstrating broad appeal across multiple interest categories. Community detection uncovered clear clusters organised around lifestyle and entertainment content, comedy, food, educational material, and motivational themes. Content analysis revealed that travel and lifestyle influencers dominated the network (23.7%), followed by comedy and entertainment creators (16.9%), reflecting TikTok's dual role as both an entertainment platform and a lifestyle guide for university students. The findings show how algorithmic personalisation creates confined influence communities while some central figures act as bridges across different content domains. This research advances methodological approaches by pioneering network analysis methods for influencer co-followership, thereby enhancing the understanding of digital influence as a networked rather than individual phenomenon. The results provide valuable insights for marketing professionals aiming to understand network influence, educational institutions developing media literacy programmes, and platform designers creating algorithmic recommendation systems.

I. Introduction

The digital landscape has fundamentally changed how young people consume content, form opinions, and build their identities [1]. TikTok, with over 1 billion active users worldwide, has become a leading platform where short-form videos influence cultural trends, learning methods, and social interactions, especially among university students [2]. Unlike traditional media habits, TikTok's algorithm-driven environment creates unique avenues for influence that go beyond individual content creators to complex networks of interconnected digital personalities [3].

Recent research has highlighted important psychological and sociological effects of algorithmic personalisation in social media settings. Algorithmic curation creates what scholars call "filter bubbles" and "echo chambers," where users mainly encounter content that supports their existing preferences and worldviews, which can limit cognitive diversity and hinder critical thinking development among young users [4], [5]. Beyond these effects, personalisation can also reinforce homophily, the tendency to connect with similar others, which in turn shapes the formation of tightly bounded digital communities [6]. This dynamic reduces exposure to divergent viewpoints, narrows cultural experiences, and reinforces social segmentation within online environments [7], [8]. In TikTok co-followership networks, such mechanisms may help explain why certain influencer clusters become dominant while others remain isolated. From a psychological perspective, algorithmic personalisation can intensify parasocial relationships—one-sided emotional bonds users form with media figures—by consistently providing content from preferred influencers, thus boosting perceived intimacy and dependence [9]. Sociologically, these systems contribute to the fragmentation of shared cultural experiences, as personalised feeds create individualised information diets that may reduce common reference points for social interaction and collective discussion [10]. For university students, specifically, algorithmic personalisation during this vital developmental period might influence identity formation by limiting exposure to diverse perspectives and lifestyle models, possibly restricting the exploration phase usually linked with emerging adulthood [11]. Recognising these effects is essential when examining co-followership patterns, as they may reflect not just user preferences but also algorithmic limitations that shape how influence networks develop and change within digitally native communities.

Influencers on TikTok occupy a distinctive position in the digital media ecosystem, functioning not merely as content creators but as cultural intermediaries who shape discourse, promote products, and influence lifestyle choices among their followers [12]. The platform's algorithm-driven content discovery mechanism creates opportunities for diverse voices to gain prominence, resulting in a more democratized yet complex influence landscape compared to traditional media channels [13]. For university students, who represent a digitally native demographic, TikTok influencers serve multiple roles: entertainers, educators, lifestyle guides, and social validators [14].

While existing research has extensively examined individual influencer characteristics, content strategies, and audience engagement metrics [15], there remains a significant gap in understanding how influencers are collectively followed by users and what these co-followership patterns reveal about shared influence dynamics. Most studies focus on isolated influencer-audience relationships or content analysis, overlooking the interconnected nature of digital influence consumption [16]. This individualistic approach fails to capture the reality that users typically follow multiple influencers simultaneously, creating complex webs of overlapping influence that shape their digital experience.

The co-followership phenomenon—where users follow multiple influencers who may or may not be directly connected—represents an underexplored aspect of digital influence research. Understanding these patterns is vital because they reveal how influence functions not through isolated channels but through interconnected networks that amplify, complement, or compete with each other [17]. Furthermore, the clustering of co-followed influencers may indicate underlying thematic preferences, cultural affinities, or algorithmic effects that structure how young people navigate Tiktok's vast content landscape [18].

This study aims to examine the co-followership patterns of TikTok influencers as reported by university students, using social network analysis to visualise and interpret clusters of shared influence. By mapping the network structure of co-followed influencers, we seek to uncover the fundamental principles that shape how students build their digital influence portfolios. The research applies quantitative network analysis methods to convert individual followership choices into a collective network, revealing patterns that would be invisible when analysing individual influencer-audience relationships in isolation [19].

The central research question guiding this investigation is: How do patterns of co-followership among TikTok influencers form clusters, and what do these clusters reveal about shared influence among university students? This inquiry examines which influencers occupy central positions in the co-followership network and act as bridges between different influence communities, the thematic patterns that emerge in the clustering of co-followed influencers, and how the network structure reflects the diversity and interconnectedness of student interests on TikTok [20].

This research makes several significant contributions to digital influence studies and social media research. Methodologically, it pioneers the use of social network analysis applied to TikTok influencer co-followership, offering a replicable framework for analysing collective influence patterns across digital platforms [21]. This approach moves beyond traditional metrics of individual influencer success to explore the structural properties of influence networks [22]. Theoretically, the study advances understanding of digital influence as a networked phenomenon, challenging individualistic models of influencer-audience relationships [23].

The findings provide valuable insights for various stakeholders. Marketing professionals can better understand how influence operates through networks rather than individual channels, guiding more effective influencer collaboration strategies [24]. Educational institutions can gain insights into how students consume information from multiple digital sources, potentially informing media literacy initiatives. Platform developers can understand how user followership patterns shape organic content communities that may improve algorithmic recommendations [25] The study also adds to the growing body of research on TikTok as a cultural phenomenon, especially within the context of university students who are both frequent platform users and future cultural and economic leaders [26], [27].

II. Methodology

This study uses an exploratory, quantitative research design employing social network analysis to investigate TikTok influencer co-followership patterns among university students. The methodology converts individual followership data into a network structure, allowing for the identification and analysis of influence clusters through established network analysis techniques [19].

A. Research Design

The research employs a cross-sectional, descriptive approach that maps the co-followership relationships between TikTok influencers based on student responses. This design is particularly suitable for exploratory network analysis as it captures the structural properties of influence relationships at a specific moment, enabling the identification of clusters and central actors within the network [21]. The cross-sectional design aligns with established practices in social media research examining user behaviour and content consumption patterns [28].

B. Data Collection

Data were gathered through a structured survey administered to university students from multiple higher education institutions in Indonesia as part of a collaborative research project. Participants were recruited using a convenience sampling strategy via student organizations, social media groups, and campus mailing lists, an approach selected for its accessibility and feasibility within the target demographic, though it may limit generalizability beyond similar populations. Inclusion criteria were: (a) currently enrolled undergraduate students, (b) aged between 18 and 25, and (c) active TikTok users who could identify their top three most-followed influencers. A total of 116 valid responses were obtained, all of whom completed the influencer identification section. Participants also described influencer content types and reasons for following. Informed consent was obtained, and anonymity was maintained. This approach ensured the collection of data on the most relevant influencer relationships for each participant while keeping data complexity manageable for network analysis [20].

The survey instrument gathered demographic data alongside influencer preferences, creating a comprehensive dataset that links individual traits with followership patterns. The three-influencer limit was selected to balance data richness with participant burden, ensuring responses captured the most influential content creators in each student's digital ecosystem while remaining feasible to complete [27]. This methodological approach reflects best practices in social media research targeting youth populations and their digital engagement patterns [14], [29].

C. Data Preparation and Network Construction

The conversion of survey responses into network data involved several systematic steps following established network analysis protocols [22]. First, the three influencer name columns were extracted from each respondent's survey data. For each participant, pairwise combinations of their followed influencers were generated, creating potential co-followership relationships. For example, if Student A follows Influencers X, Y, and Z, this results in three potential edges: X-Y, Y-Z, and X-Z.

Influencer names were standardised to ensure consistency across the dataset, following social media research data preprocessing standards [30]. This involved harmonising spelling variations, resolving duplicate names, and creating unique identifiers for each influencer. The standardisation process was essential due to potential spelling variations in user-generated survey responses.

The final network structure was built as an undirected graph where nodes represent unique TikTok influencers and edges denote co-followership connections. Edge weights were determined by how often co-followership occurred, with higher weights indicating that more students follow both influencers in a pair. This weighted method reflects the strength of co-followership relationships while preserving the network's structural properties [19].

D. Network Analysis Techniques

The analysis used various network metrics to describe the structure and characteristics of the co-followership network, following established practices in social network analysis research [21]. Basic network properties were calculated, including the number of nodes (unique influencers), edges (co-followership relationships), network density, average degree, and the number of connected components. These metrics offer a foundational understanding of the network's overall structure and connectivity patterns.

Centrality measures were calculated to identify influential nodes within the network, using standard centrality algorithms employed in social media influence research [23]. Degree centrality highlights influencers with the greatest number of co-followership connections, indicating wide appeal among student audiences. Betweenness centrality assesses how often an influencer appears on the shortest paths between other influencers, recognising bridge nodes that connect different parts of the network. These measures reveal various aspects of structural importance within the influence network.

Community detection algorithms were used to identify clusters of closely connected influencers, following methodological approaches established in network community detection research [22]. The analysis employed modularity-based clustering methods to divide the network into communities of influencers who are more densely linked to each other than to other parts of the network. This technique uncovers thematic or cultural groupings within the influence landscape, offering insights into how students organise their digital influence consumption.

E. Content Categorization

Each influencer was categorised according to their primary content type based on descriptions provided by survey respondents and supplementary analysis of their TikTok profiles. Manual coding was conducted independently by two researchers experienced in TikTok content genres. For each influencer, coders examined at least ten of their most recent posts to identify the dominant content theme. Any discrepancies were discussed until consensus was reached. This inductive, data-driven approach allowed categories to emerge from observed patterns rather than from pre-defined schemes. The final categories included Travel & Lifestyle, Comedy/Entertainment, Food, Motivational/Inspirational, Fashion & Beauty, Education, and other specialised content types. This classification facilitated analysis of content-domain clustering within the co-followership network and aligns with established practices in social media content analysis [20].

The categorisation process involved manual coding of influencer content types, with categories emerging from the data rather than being predetermined, following inductive analysis principles in social media research [31]. This approach ensures that the category system reflects the actual content landscape encountered by students rather than imposing external classification schemes, aligning with best practices in qualitative content analysis within digital media studies.

F. Data Analysis Tools

Network analysis was performed using Python's NetworkX library, which offers comprehensive tools for network construction, analysis, and visualization, following established methods in social network analysis [21]. Additional analysis used standard statistical software for descriptive statistics and data visualisation. Network visualisations were produced using layout algorithms that position nodes based on their structural relationships, with node size representing centrality measures and colours indicating content categories.

G. Analytical Approach

The analysis progressed through several stages, starting with descriptive analysis of the network's fundamental properties to establish its overall structure and characteristics. Centrality analysis pinpointed key influencers within the network, while community detection uncovered clustering patterns [19]. Content analysis explored the thematic distribution of influencers and their connection to the network structure. Ultimately, the integration of these analytical methods offers a comprehensive understanding of how co-followership patterns form meaningful clusters within the student population.

This methodological approach allows for a systematic examination of co-followership as a network phenomenon, maintaining both analytical rigour and reproducibility. By combining quantitative network metrics with qualitative content categorisation, it offers both structural and thematic insights into the influence landscape experienced by university students on TikTok. This contributes to the expanding body of research on social media influence networks and young people's digital engagement patterns [14].

III. RESULTS AND DISCUSSION

The following section presents the findings from the network analysis of TikTok influencer co-followership patterns among university students. The results are organized to first establish the overall network structure, then examine individual influencer centrality, identify community clusters, and analyze content category distributions.

A. Network Structure and Composition

The constructed co-followership network consists of 266 unique TikTok influencers linked through 333 co-followership relationships (see Figure 1). This network reveals several key characteristics about how university students collectively engage with TikTok influencers. The network density is 0.0094, demonstrating that less than 1% of all possible influencer pairs are co-followed by students. This low density indicates that, although the influencer landscape is diverse, student followership patterns are selective and concentrated around specific interest groups, reflecting the algorithmic nature of TikTok's content delivery system [2].

The network shows significant fragmentation, consisting of 49 connected components of various sizes. This fragmentation suggests that influencer co-followership forms multiple distinct communities rather than a single interconnected network [19]. The largest connected component includes most of the well-connected influencers, while smaller components represent specialised or niche influence clusters that operate independently from the main network. This structural characteristic aligns with established principles of community detection in social networks, where modularity-based approaches identify densely connected subgroups within larger networks [21].

Edge weights in the network range from 1 to 11, with most co-followership relationships having low weights. This distribution reflects the long-tail nature of digital influence, where a few influencer pairs are co-followed by many students while most relationships represent shared interests among smaller groups [17]. The average degree per influencer is 2.50, indicating that each influencer is typically co-followed with roughly two to three others, suggesting focused rather than widespread co-followership patterns. This finding supports the idea that social media algorithms create personalised content ecosystems that limit exposure to diverse influence networks [13].

The network's structural properties show how TikTok's algorithmic systems influence collective influence consumption among university students. The combination of low density and high fragmentation indicates that while the platform offers a variety of content, student engagement is directed into separate thematic communities instead of forming a single influence network [18]. This structural pattern reflects both algorithmic filtering and user preference clustering, resulting in what researchers call "algorithmic personalization" effects on social connectedness [25].

B. Centrality Analysis

Degree centrality analysis highlights the influencers who are most frequently co-followed with others in the network (see Figure 2). Tasya Farasya stands out as the most central influencer with a degree centrality of 0.1019, indicating she is co-followed by about 10% of all other influencers in the network. This high centrality implies wide appeal across various student interest groups, showing how some influencers can transcend niche boundaries and gain widespread co-followership [23]. Following Tasya Farasya, both Fadil Jaidi and Vina Muliana achieve degree centrality scores of 0.0566, making them secondary hubs within the network.

The top tier of central influencers also includes Fuji and Ria Ricis, both with degree centrality scores of 0.0528. These influencers represent established figures in Indonesian digital culture, suggesting that cultural familiarity and local relevance play important roles in co-followership patterns [20]. The dominance of Indonesian influencers in the centrality rankings reflects the cultural specificity of influence networks, even on global platforms like TikTok. This finding aligns with research demonstrating how social media algorithms tend to promote culturally relevant content, creating localised influence ecosystems [2].

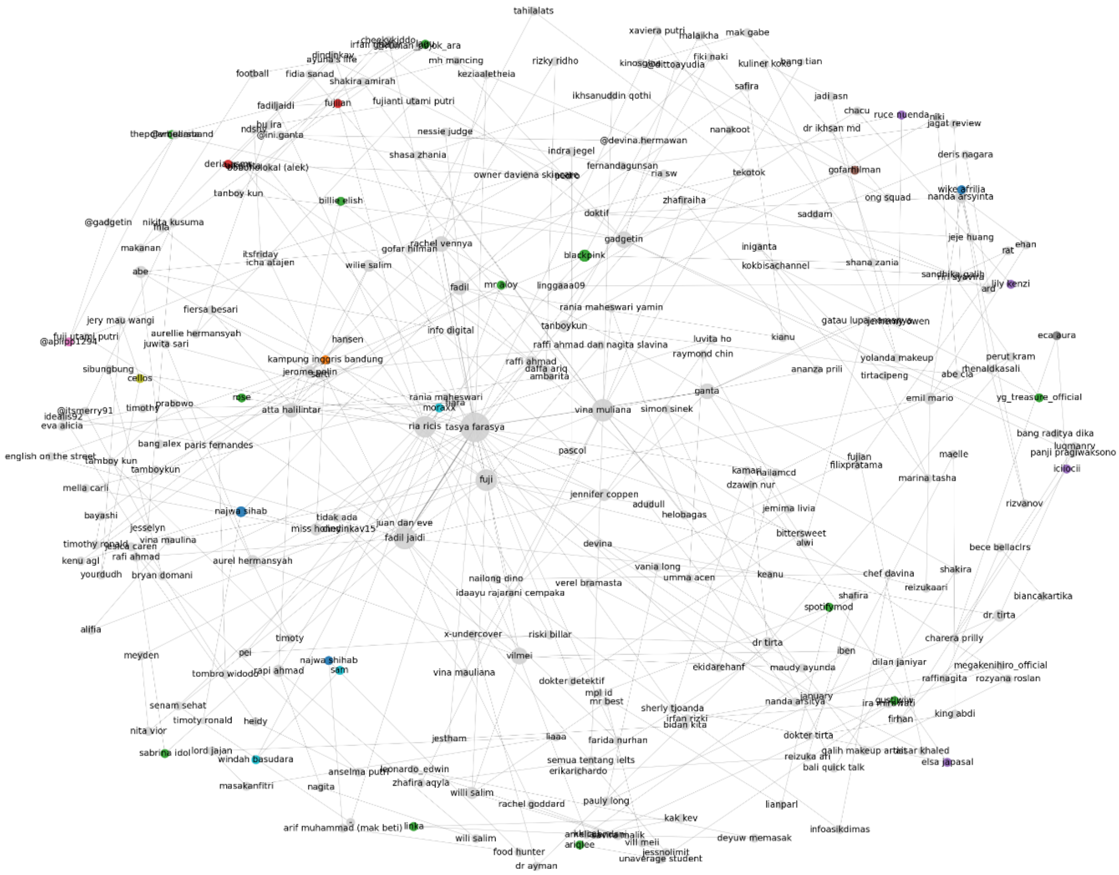

Figure 1. Representation of the network structure

Betweenness centrality analysis identifies influencers who act as bridges within different parts of the network, revealing their role as connectors in the influence ecosystem [22]. Tasya Farasya again ranks highest with a betweenness centrality of 0.0581, indicating she not only has many co-followership connections but also functions as a pathway between otherwise disconnected influencer communities. This dual role as both a hub and bridge suggests her content appeals across multiple interest areas, positioning her as a vital node in the network's structural integrity [19].

Ria Ricis and Fuji demonstrate high betweenness centrality scores of 0.0417 and 0.0393 respectively, positioning them as key connectors within the network. Their bridging roles suggest these influencers attract followers from diverse interest categories, potentially serving as entry points between different content domains [21]. The presence of these bridge influencers indicates that the network, while fragmented, contains important connecting nodes that facilitate cross-pollination between different influence communities.

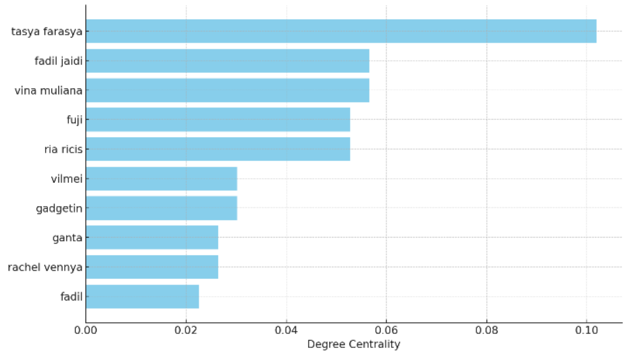

Figure 2. Top 10 influencers by degree centrality

The centrality findings (Figure 3) show how certain influencers occupy strategically important roles within the co-followership network, acting both as popular content creators and as structural connectors between communities. This pattern indicates that influence on TikTok functions through a hierarchical system where a few central figures enable broader network connectivity, reflecting established principles of social network analysis in digital media contexts [17]. The high centrality among Indonesian influencers further demonstrates how cultural proximity and algorithmic personalisation combine to produce localised influence hierarchies within global social media platforms [13].

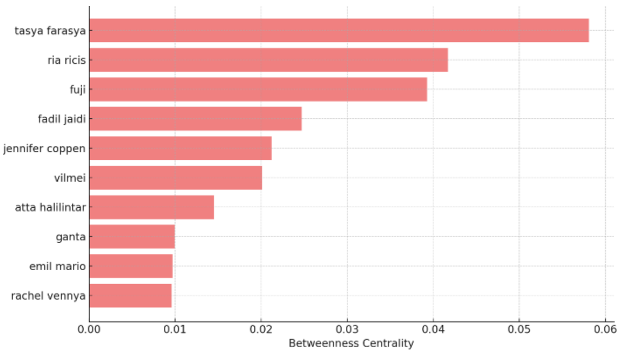

Figure 3. Top 10 influencers by betweenness centrality

C. Community Detection and Clustering

Network clustering analysis uncovers distinct communities of co-followed influencers that reflect thematic and cultural groupings within the student population (see Figure 4). The largest identified cluster revolves around lifestyle and entertainment content, with influencers like Tasya Farasya, Ria Ricis, and other prominent Indonesian content creators forming a cohesive community. This cluster represents mainstream Indonesian digital culture, integrating elements of lifestyle documentation, entertainment, and cultural commentaries [20]. The emergence of this dominant cluster shows how algorithmic content delivery systems generate concentrated influence networks around culturally relevant personalities [2].

A secondary cluster forms around comedy and entertainment content, featuring influencers who specialise in humorous videos, sketches, and comedic commentary. This cluster exhibits strong internal connections, indicating that students who follow one comedy influencer are likely to follow others within the same genre [12]. The clustering pattern suggests that humour preferences tend to be consistent within individual students' followerships, reflecting the influence of parasocial relationships in shaping content consumption patterns on social media platforms [32]. This finding aligns with research showing how algorithmic recommendation systems reinforce existing preferences, creating echo chambers within specific content categories [25].

Educational content creators form a smaller but distinct group, characterised by influencers who produce factual content, tutorials, and informational videos. This group has less connection to entertainment-focused communities, indicating that students seeking educational content on TikTok tend to follow different patterns from those mainly interested in entertainment. The separation of educational influencers within the network reflects the platform's main role as an entertainment medium, where educational content occupies a specialised niche [14].

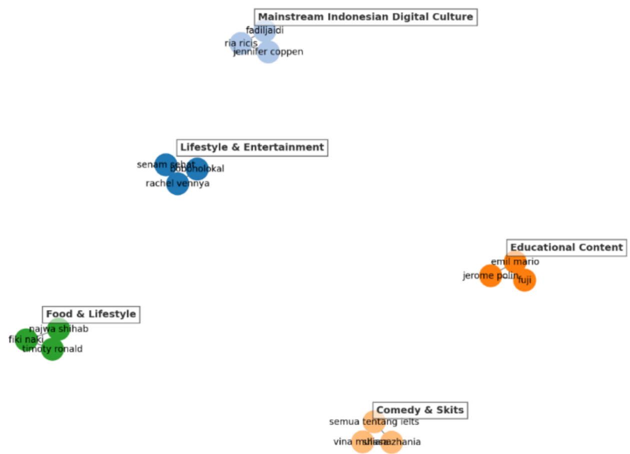

Figure 4. Community clusters of influencers

Food and lifestyle influencers form another identifiable group, comprising cooking content creators, restaurant reviewers, and food enthusiasts who are interconnected. This group highlights the specialised nature of food content consumption, where interest in one type of food content often leads to exploring related topics. creators within the same domain [17]. The close clustering around food content indicates that culinary interests are a distinct category of influence consumption among university students, possibly reflecting lifestyle aspirations and practical needs.

The community detection analysis used modularity-based clustering algorithms to identify these distinct groups, following established methods in network analysis research [19] The identified clusters show how TikTok's algorithmic systems form thematic communities of influence, where users encounter similar content creators within their areas of interest [22]. This clustering pattern demonstrates the platform's ability to segment audiences into separate interest-based communities, creating what researchers call "algorithmic personalisation" effects that restrict cross-category exposure [18].

The organisational structure of these clusters shows how social media algorithms influence collective influence consumption by forming bounded communities of related content creators. The relative separation between different thematic clusters indicates that although students may follow several influencers, their choices are limited by algorithmic recommendations that strengthen existing preferences rather than encouraging diverse influence exposure [13]. This finding has significant implications for understanding how digital platforms shape information consumption patterns among young users, especially in educational and cultural settings.

D. Content Category Distribution

Analysis of influencer content categories reveals the thematic preferences reflected in the co-followership network (Table 1). Travel and lifestyle influencers constitute the largest category with 63 influencers (23.7% of the network), emphasising the importance of lifestyle content in student TikTok consumption. This category includes daily routine documentation, travel vlogs, and general life advice content that resonates with university student experiences [14]. The dominance of lifestyle content reflects TikTok's role in identity development among young users, where influencers serve as lifestyle guides and social validators in the digital environment [2].

Comedy and entertainment influencers make up the second-largest group with 45 influencers (16.9% of the network). This significant presence highlights TikTok's main role as an entertainment platform where humorous content primarily attracts student audiences [12]. The comedy category includes sketch creators, comedic commentators, and influencers who blend humour into other types of content, showing the platform's ability to foster parasocial relationships through entertainment-focused interactions [32].

Food influencers comprise 33 creators (12.4% of the network), highlighting the important role of food content in student TikTok engagement. This category includes recipe sharing, restaurant reviews, cooking tutorials, and food culture commentary, reflecting both practical and cultural interests in food-related content [17]. The prominence of food content indicates that TikTok functions not only as entertainment but also as a source of practical lifestyle information for university students managing independent living.

Motivational and inspirational influencers comprise 24 creators (9.0% of the network), indicating that students use TikTok not only for entertainment but also for personal development and motivation. This category includes self-help content, motivational speaking, and positive lifestyle messaging that appeals to university students navigating academic and personal challenges [20]. The presence of motivational content reflects the platform's capacity to fulfil emotional needs through parasocial relationships, where influencers provide social support and well-being guidance [33], [34].

Fashion and beauty influencers represent 20 creators (7.5% of the network), while educational influencers also account for 20 creators (7.5% of the network). The equal representation of these categories suggests balanced interests in both aesthetic and informational content among the student population. The relatively smaller proportion of educational influencers compared to entertainment-focused categories reflects TikTok's primary positioning as a leisure platform, where educational content occupies a specialised niche [14].

The distribution pattern shows how TikTok's algorithmic systems promote varied content types while maintaining clear hierarchical preferences among users. The prominence of lifestyle and entertainment content aligns with research indicating how social media platforms support identity exploration and social connection among young users [26]. The range of content categories reflects the platform's shift from purely entertainment-focused to a more diverse information ecosystem that covers multiple aspects of student life, from practical advice to cultural commentary [13].

This categorical distribution reveals how university students construct their digital influence portfolios across multiple domains, suggesting that TikTok serves as a comprehensive cultural platform rather than a single-purpose entertainment medium. The presence of educational and motivational content alongside entertainment categories indicates that students use the platform for both leisure and self-improvement purposes, reflecting broader patterns of social media usage among digitally native populations [27].

TABLE I
DISTRIBUTION OF INFLUENCER CATEGORIES IN THE NETWORK

Rank	Category	Count
1	Travel & Lifestyle Influencer (daily routine, vlogs, life advice)	63
2	Comedy/Entertainment Influencer (skits, jokes, funny comments)	45
3	Food Influencer (recipes, food reviews, cooking tips)	33
4	Motivational/Inspirational Influencers (self-help, positive content)	24
5	Fashion & Beauty Influencer (makeup, skincare, fashion, shopping)	20
6	Education Influencer (facts, tutorials, "Did You Know?" content)	20

The dominance of travel and lifestyle content (23.7%) and comedy/entertainment (16.9%) reflects the interplay between TikTok’s platform design and university students’ demographic preferences. TikTok’s short-form, mobile-first format and engagement-driven algorithm prioritize visually dynamic content that captures attention within seconds, naturally favoring lifestyle documentation and comedic skits over slower-paced or text-heavy formats such as educational material (7.5%). For university students in the emerging adulthood stage (ages 18–25), these genres align with developmental needs such as identity exploration, aspirations for upward mobility, and a preference for lighthearted social interaction after academic activities [11], [35]. Cultural proximity further reinforces these trends, as local influencers in these categories often share language, humor styles, and culturally specific references, enhancing relatability and encouraging sustained followership. Together, these factors explain the observed dominance of lifestyle and comedy content in the co-followership network, while also highlighting the structural disadvantages faced by educational creators on engagement-optimized platforms like TikTok.

The substantial presence of food content (12.4%) and motivational content (9.0%) demonstrates demographic-specific needs, as university students require practical life skills guidance and emotional support during this transitional period. The dominance of Indonesian influencers in central network positions (Tasya Farasya, Ria Ricis) reflects algorithmic localization effects, where TikTok promotes culturally relevant content based on user location and language preferences, combined with students' preferences for culturally familiar humor styles and social contexts. The fragmented network structure with distinct thematic clusters suggests that algorithmic personalization creates self-reinforcing category preferences, where initial content engagement leads to increased exposure within the same category while limiting cross-category discovery, ultimately shaping the observed distribution patterns.

IV. Conclusion

This study offers novel insights into the networked nature of digital influence by examining TikTok influencer co-followership patterns among university students. By applying social network analysis to survey data from Indonesian institutions, we have demonstrated that influencer consumption operates through complex interconnected networks rather than isolated influencer-audience relationships.

The research findings reveal several key patterns. First, the fragmented network structure with low density and 49 connected components indicates that student followership patterns form distinct thematic communities rather than a unified influence ecosystem. This fragmentation suggests that TikTok's algorithmic systems effectively segment audiences into specialized interest-based clusters. Second, the emergence of central bridge influencers, particularly Tasya Farasya, demonstrates how certain content creators transcend niche boundaries to facilitate cross-pollination between otherwise isolated influence communities. Third, the thematic clustering around lifestyle, entertainment, food, education, and motivational content reveals how students construct diverse digital influence portfolios addressing multiple life aspects.

These findings challenge individualistic models of influencer-audience relationships by showing that digital influence works through interconnected networks where co-followership patterns create meaningful groups of shared influence. The study helps explain how social media algorithms act as structural forces that shape digital culture into unique influence ecosystems.

Practically, these insights benefit multiple stakeholders. Marketing professionals can better understand how influence operates through network effects, suggesting that successful strategies should consider co-followership patterns rather than focusing solely on individual influencer metrics. Educational institutions can inform media literacy initiatives that acknowledge the networked nature of digital influence. Platform developers can enhance algorithmic recommendation systems by understanding how user followership patterns create organic content communities.

Several limitations should be recognised, including the cross-sectional design, the three-influencer limit, and the focus on Indonesian university students. Certain analyses suggested by reviewers, such as temporal (longitudinal) analysis of followership patterns, could not be conducted because our dataset lacks time-stamped followership information. Similarly, testing the method in different populations or across other platforms would require new data collection beyond the current scope. Although community detection was performed, additional measures such as modularity score calculation and cluster overlap analysis were not implemented because the original raw graph data were no longer available for recomputation. Future research should address these limitations by collecting longitudinal data, replicating the analysis on diverse populations and platforms, and incorporating extended network metrics to provide deeper insights into co-followership structures.

The methodology offers a reproducible framework for analysing collective influence patterns across digital platforms. As social media platforms continue to develop, understanding the networked nature of digital influence becomes essential for researchers, practitioners, and policymakers. This research shows that digital influence functions through intricate networked structures reflecting the interaction between algorithmic mechanisms, cultural factors, and user preferences, providing valuable insights into how young people engage with digital content and shape their cultural identities through shared influence consumption.

References

[1] M. B. Mutanga, O. Ureke, and T. Chani, "Social Media and the COVID-19: South African and Zimbabwean Netizens' Response to a Pandemic," *Indonesian Journal of Information Systems*, pp. 1–14, Aug. 2021, doi: 10.24002/ijis.v4i1.4338.

[2] A. Bhandari and S. Bimo, "Why's Everyone on TikTok Now? The Algorithmized Self and the Future of Self-Making on Social Media," *Soc Media Soc*, vol. 8, no. 1, Jan. 2022, doi: 10.1177/20563051221086241.

[3] H. Kang and C. Lou, "AI agency vs. human agency: understanding human–AI interactions on TikTok and their implications for user

engagement," *Journal of Computer-Mediated Communication*, vol. 27, no. 5, Aug. 2022, doi: 10.1093/jcmc/zmac014.

[4] S. H. Taylor and Y. A. Chen, "The lonely algorithm problem: the relationship between algorithmic personalization and social connectedness on TikTok," *Journal of Computer-Mediated Communication*, vol. 29, no. 5, Aug. 2024, doi: 10.1093/jcmc/zmae017.

[5] J. Lasser and N. Poechhacker, "Designing social media content recommendation algorithms for societal good," *Ann N Y Acad Sci*, vol. 1548, no. 1, pp. 20–28, Jun. 2025, doi: 10.1111/nyas.15359.

[6] E. Bakshy, S. Messing, and L. A. Adamic, "Exposure to ideologically diverse news and opinion on Facebook," *Science (1979)*, vol. 348, no. 6239, pp. 1130–1132, Jun. 2015, doi: 10.1126/science.aaa1160.

[7] B. Kitchens, S. L. Johnson, and P. Gray, "Understanding Echo Chambers and Filter Bubbles: The Impact of Social Media on Diversification and Partisan Shifts in News Consumption," *MIS Quarterly*, vol. 44, no. 4, pp. 1619–1649, Dec. 2020, doi: 10.25300/MISQ/2020/16371.

[8] U. Reviglio, "Serendipity by Design? How to Turn from Diversity Exposure to Diversity Experience to Face Filter Bubbles in Social Media," 2017, pp. 281–300. doi: 10.1007/978-3-319-70284-1_22.

[9] C. A. Hoffner and B. J. Bond, "Parasocial relationships, social media, & well-being," *Curr Opin Psychol*, vol. 45, p. 101306, Jun. 2022, doi: 10.1016/j.copsyc.2022.101306.

[10] H. Metzler and D. Garcia, "Social Drivers and Algorithmic Mechanisms on Digital Media," *Perspectives on Psychological Science*, vol. 19, no. 5, pp. 735–748, Sep. 2024, doi: 10.1177/17456916231185057.

[11] H. Astleitner and S. Schlick, "The social media use of college students: Exploring identity development, learning support, and parallel use," *Active Learning in Higher Education*, vol. 26, no. 1, pp. 231–254, Mar. 2025, doi: 10.1177/14697874241233605.

[12] S. Barta, D. Belanche, A. Fernández, and M. Flavián, "Influencer marketing on TikTok: The effectiveness of humor and followers' hedonic experience," *Journal of Retailing and Consumer Services*, vol. 70, p. 103149, Jan. 2023, doi: 10.1016/j.jretconser.2022.103149.

[13] H. Metzler and D. Garcia, "Social Drivers and Algorithmic Mechanisms on Digital Media," *Perspectives on Psychological Science*, vol. 19, no. 5, pp. 735–748, Sep. 2024, doi: 10.1177/17456916231185057.

[14] H. Astleitner and S. Schlick, "The social media use of college students: Exploring identity development, learning support, and parallel use," *Active Learning in Higher Education*, vol. 26, no. 1, pp. 231–254, Mar. 2025, doi: 10.1177/14697874241233605.

[15] W. Tafesse and B. P. Wood, "Followers' engagement with instagram influencers: The role of influencers' content and engagement strategy," *Journal of Retailing and Consumer Services*, vol. 58, p. 102303, Jan. 2021, doi: 10.1016/j.jretconser.2020.102303.

[16] S. H. Mrisha and S. Xixiang, "The power of influence: How social media influencers are shaping consumer decision making in the digital age," *Journal of Consumer Behaviour*, vol. 23, no. 4, pp. 1844–1853, Jul. 2024, doi: 10.1002/cb.2308.

[17] Y. Joshi, W. M. Lim, K. Jagani, and S. Kumar, "Social media influencer marketing: foundations, trends, and ways forward," *Electronic Commerce Research*, vol. 25, no. 2, pp. 1199–1253, Apr. 2025, doi: 10.1007/s10660-023-09719-z.

[18] S. H. Taylor and Y. A. Chen, "The lonely algorithm problem: the relationship between algorithmic personalization and social connectedness on TikTok," *Journal of Computer-Mediated Communication*, vol. 29, no. 5, Aug. 2024, doi: 10.1093/jcmc/zmae017.

[19] M. A. Javed, M. S. Younis, S. Latif, J. Qadir, and A. Baig, "Community detection in networks: A multidisciplinary review," *Journal of Network and Computer Applications*, vol. 108, pp. 87–111, Apr. 2018, doi: 10.1016/j.jnca.2018.02.011.

[20] C. Alves de Castro, "Thematic analysis in social media influencers: who are they following and why?," *Front Commun (Lausanne)*, vol. 8, Sep. 2023, doi: 10.3389/fcomm.2023.1217684.

[21] Z. Yang, R. Algesheimer, and C. J. Tessone, "A Comparative Analysis of Community Detection Algorithms on Artificial Networks," *Sci Rep*, vol. 6, no. 1, p. 30750, Aug. 2016, doi: 10.1038/srep30750.

[22] B. Pankratz, B. Kamiński, and P. Prałat, "Performance of community detection algorithms supported by node embeddings," *J Complex Netw*, vol. 12, no. 4, Jun. 2024, doi: 10.1093/comnet/cnae035.

[23] P. Harrigan, T. M. Daly, K. Coussement, J. A. Lee, G. N. Soutar, and U. Evers, "Identifying influencers on social media," *Int J Inf Manage*, vol. 56, p. 102246, Feb. 2021, doi: 10.1016/j.ijinfomgt.2020.102246.

[24] F. F. Leung, F. F. Gu, and R. W. Palmatier, "Online influencer marketing," *J Acad Mark Sci*, vol. 50, no. 2, pp. 226–251, Mar. 2022, doi: 10.1007/s11747-021-00829-4.

[25] J. Lasser and N. Poechhacker, "Designing social media content recommendation algorithms for societal good," *Ann N Y Acad Sci*, vol. 1548, no. 1, pp. 20–28, Jun. 2025, doi: 10.1111/nyas.15359.

[26] R. Al Mosharrafa, T. Akther, and F. K. Siddique, "Impact of social media usage on academic performance of university students: Mediating role of mental health under a cross-sectional study in Bangladesh," *Health Sci Rep*, vol. 7, no. 1, Jan. 2024, doi: 10.1002/hsr2.1788.

[27] E. K. Chowdhury, "Examining the benefits and drawbacks of social media usage on academic performance: a study among university students in Bangladesh," *Journal of Research in Innovative Teaching & Learning*, Feb. 2024, doi: 10.1108/JRIT-07-2023-0097.

[28] X. Li and Q. Liu, "Social Media Use, eHealth Literacy, Disease Knowledge, and Preventive Behaviors in the COVID-19 Pandemic: Cross-Sectional Study on Chinese Netizens," *J Med Internet Res*, vol. 22, no. 10, p. e19684, Oct. 2020, doi: 10.2196/19684.

[29] M. B. Mutanga and A. Abayomi, "Tweeting on COVID-19 pandemic in South Africa: LDA-based topic modelling approach," *African Journal of Science, Technology, Innovation and Development*, vol. 14, no. 1, pp. 163–172, Jan. 2022, doi: 10.1080/20421338.2020.1817262.

[30] T. Chani, O. O. Olugbara, and B. Mutanga, "The Problem of Data Extraction in Social Media: A Theoretical Framework," *Journal of Information Systems and Informatics*, vol. 5, no. 4, pp. 1363–1384, Dec. 2023, doi: 10.51519/journalisi.v5i4.585.

[31] T. M. Fagbola, A. Abayomi, M. B. Mutanga, and V. Jugoo, "Lexicon-Based Sentiment Analysis and Emotion Classification of Climate Change Related Tweets," 2022, pp. 637–646. doi: 10.1007/978-3-030-96302-6_60.

[32] C. A. Hoffner and B. J. Bond, "Parasocial relationships, social media, & well-being," *Curr Opin Psychol*, vol. 45, p. 101306, Jun. 2022, doi: 10.1016/j.copsyc.2022.101306.

[33] J. Liu and J.-S. Lee, "Social media influencers and followers' loneliness: the mediating roles of parasocial relationship, sense of belonging, and social support," *Online Media and Global Communication*, vol. 3, no. 4, pp. 607–630, Dec. 2024, doi: 10.1515/omgc-2024-0025.

[34] S. Lotun, V. M. Lamarche, A. Matran-Fernandez, and G. M. Sandstrom, "People perceive parasocial relationships to be effective at fulfilling emotional needs," *Sci Rep*, vol. 14, no. 1, p. 8185, Apr. 2024, doi: 10.1038/s41598-024-58069-9.

[35] T. M. Fagbola, A. Abayomi, M. B. Mutanga, and V. Jugoo, "Lexicon-Based Sentiment Analysis and Emotion Classification of Climate Change Related Tweets," 2022, pp. 637–646. doi: 10.1007/978-3-030-96302-6_60.