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Social Network and Sentiment Analysis for Social CRM Optimalization on Indonesian Digital Recruitment Platform

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Abstract

The rapid growth of digital recruitment platforms in Indonesia has generated a large volume of user content on social media, serving as a vital data source for Social Customer Relationship Management (Social CRM) strategies. Consequently, the strategic insights that can be drawn may be limited. This study applied an integrated analytical approach combining Social Network Analysis (SNA) and lexicon-based sentiment analysis to evaluate public interactions regarding Jobstreet, Glints, and Dealls. The research methodology involved collecting data from platform X (previously known as Twitter) during the period of April 1-30, 2025, which was then analyzed using SNA with Gephi to identify influential actors through centrality metrics, alongside sentiment analysis to measure emotional polarity. The main findings revealed that Jobstreet possessed the healthiest conversational ecosystem, characterized by positive and neutral sentiment from its central actors. Glints exhibited sentiment polarization, and Dealls showed reputational vulnerability due to dominant negative sentiment from its influential users. It was concluded that the integration of these two methods provides a robust framework for designing more responsive and data-driven Social CRM strategies.

Keywords: *Social Network Analysis; Sentiment Analysis; Social CRM; Digital Recruitment; Lexicon-Based Features.*

Abstrak

Perkembangan pesat platform rekrutmen digital di Indonesia telah menghasilkan volume besar konten pengguna di media sosial, yang menjadi sumber data vital untuk strategi *Social Customer Relationship Management* (*Social* CRM). Sehingga hal ini dapat menyebabkan insight strategis yang bisa diambil menjadi terbatas. Penelitian ini menerapkan pendekatan analitis terpadu yang menggabungkan *Social Network Analysis* (SNA) dan analisis sentimen berbasis leksikon untuk mengevaluasi interaksi publik mengenai Jobstreet, Glints, dan Dealls. Metodologi penelitian melibatkan pengumpulan data dari platform X (sebelumnya dikenal dengan Twitter) selama periode 1-30 April 2025, yang kemudian dianalisis menggunakan SNA dengan Gephi untuk mengidentifikasi aktor berpengaruh melalui metrik sentralitas, serta analisis sentimen untuk mengukur polaritas emosional. Temuan utama mengungkapkan bahwa Jobstreet memiliki ekosistem percakapan paling sehat, ditandai oleh sentimen positif dan netral dari aktor-aktor sentralnya. Sebaliknya, Glints menunjukkan polarisasi sentimen, dan Dealls menunjukkan kerentanan reputasi karena sentimen negatif yang dominan dari para pengguna berpengaruhnya. Disimpulkan bahwa integrasi kedua metode ini menyediakan kerangka kerja yang kuat untuk merancang strategi *Social* CRM yang lebih responsif dan berbasis data.

Kata Kunci: *Analisis Jaringan Sosial; Sentimen; Social CRM; Rekrutmen digital; Lexicon-Based Features.*

1. Introduction

The rapid evolution of digital infrastructure has fundamentally reshaped various sectors, including professional communication and employment-seeking behaviors. This transformation has amplified the strategic importance of Social Customer Relationship Management (Social CRM), extending conventional CRM principles to manage brand reputation and foster engagement within a globalized digital society [1][2]. The analysis of online interactions, which has advanced to include process-aware prediction models for enterprise social networks [3], has thus become critical for maintaining a competitive advantage and understanding public discourse [4] [5]. In Indonesia, this digital shift is particularly evident in the recruitment sector, where enhanced connectivity has transitioned job searching from conventional methods to dynamic digital platforms.

The significance of this transition is substantial, reflecting broader national labor trends where online platforms have become primary conduits for talent acquisition. Digital recruitment platforms such as Jobstreet, Glints, and Dealls now operate in a highly competitive landscape where user feedback, disseminated through social media, directly impacts brand authority and user trust [3] [6]. However, this abundance of user-generated content (UGC) presents a significant analytical challenge. The unstructured, high-volume, and emotionally charged nature of this data makes it difficult to process using traditional feedback analysis methods, creating a gap between data availability and actionable strategic insights [6].

To address this challenge, this study proposes an integrated analytical approach combining two computational methods. First, Social Network Analysis (SNA) is employed to map the structure of user interactions and identify influential actors, or opinion leaders, who drive conversations [7]. The influence of these nodes is quantified through various centrality metrics, a concept whose robustness is well-established in comprehensive surveys on network resilience [8] and influential node detection [9], as well as in predictive modeling studies [10]. Second, lexicon-based sentiment analysis is employed to systematically quantify the emotional polarity of user-generated content (UGC). This approach has demonstrated its efficacy for analyzing Indonesian-language text using established sentiment dictionaries such as SentiWords, a method validated by numerous systematic reviews [11] and application-based studies [12], standing alongside machine learning approaches that utilize tools like SentiStrength and Naïve Bayes classifiers [13]. The core of the proposed methodology lies in integrating these two analyses, where centrality scores from SNA are correlated with aggregated sentiment scores. This fusion enables a nuanced understanding not only of *who* is driving the conversation but also of the *emotional context* they are conveying.

Previous studies have applied SNA and sentiment analysis independently. Navisha et al. [4] employed Twitter-based network modeling to investigate customer engagement on e-commerce health platforms. Setatama et al. [7] demonstrated the role of central users in propagating Indonesia's country branding. On the sentiment side, Nooryuda et al. [12] and Fauziah et al. [11] showcased the reliability of lexicon-based methods for classifying emotional nuance in public discourse. However, this combines these two dimensions in a unified model for Social CRM optimization, especially in the Indonesian digital recruitment context. This study addresses that gap by systematically integrating SNA centrality metrics with sentiment scores to map not only structural influence but also emotional dispositions among users.

This study aims to address this gap by conducting an integrated analysis of UGC about Jobstreet, Glints, and Dealls. The data collected from the platform X between April 1st and April 30th, 2025—a period selected for its strategic significance, often characterized by increased hiring activities following a new fiscal quarter. By merging SNA with lexicon-based sentiment analysis, the objective is to identify key opinion leaders and quantify the sentiment they generate, thereby providing a data-driven foundation for strategic recommendations.

Ultimately, this study is expected to contribute actionable, data-driven recommendations to help digital recruitment platforms enhance their Social CRM strategies. By identifying and understanding influential user segments and their perceptions, these platforms can develop more adaptive and responsive engagement tactics. On a broader scale, the findings aim to support the qualitative improvement of Indonesia's digital job-seeking ecosystem.

2. Research Method

This research employs a qualitative approach, combined with computational techniques, to analyze user-generated content on social media. The goal is to identify influential users and sentiment dynamics related to digital recruitment platforms in Indonesia. The research process was designed as a multi-stage pipeline that includes data collection, preprocessing, social network analysis, lexicon-based sentiment analysis, integration of findings, insight interpretation, and recommendation formulation. Each stage was executed using Python in Google Colab and supported by Gephi for network modeling. The complete methodology is illustrated in Figure 1.

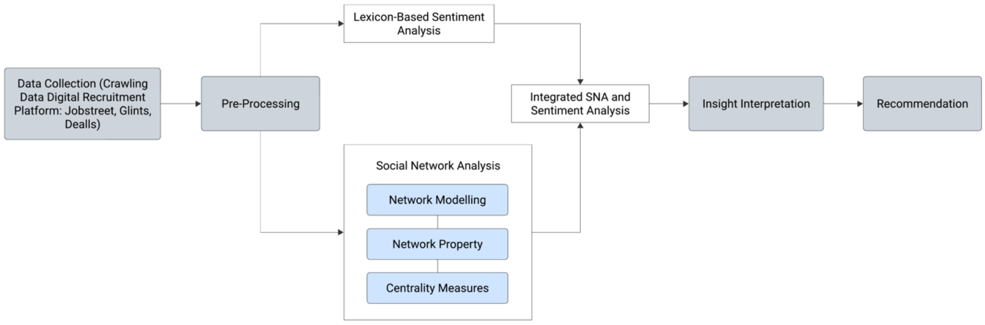

Figure 1. Research Process

2.1 Data Collecting

The data in this study was gathered from platform X through a targeted data crawling process based on specific keywords. This activity was carried out during a designated observation period, from April 1 to April 30, 2025, which was strategically chosen due to its alignment with the typical company budget cycle when hiring activities generally increase. The data collection targeted public tweets written in Bahasa Indonesia that mentioned the selected digital recruitment platforms' keywords—Jobstreet, Dealls, and Glints.

Data extraction was performed using a Python-based tool named *Tweet-Harvest*, which ran on the Google Colab platform. Using academic research access, the tool authenticated itself with a bearer token to retrieve data from Twitter API V2, enabling automated retrieval of tweets that matched the predefined criteria: keyword, language, and date range. The output from each query was exported in .csv format, serving as raw input for subsequent data cleaning and analysis procedures in the research workflow.

2.2 Pre-Processing

The preprocessing stage was executed in Python within the Google Colab environment and covered both textual and network data. For sentiment analysis, each tweet was cleaned by removing non-alphanumeric characters, mentions, hashtags, links, emojis, and numbers; followed by case folding, tokenization using the whitespace splitting, stopword removal using the Sastrawi list, and stemming to reduce words to their base forms. Simultaneously, reply-based interactions were extracted to form directed edges between users. Duplicate replies and self-loops were removed to ensure network integrity. The final edge lists were exported as .csv files.

2.3 Social Network Analysis

Network data processing for this study was executed using Gephi version 0.10.1. The software facilitated the entire analytical workflow, which included importing the constructed network module, applying visualization and spatialization algorithms, filtering relevant nodes, manipulating the network structure, and exporting the final results.

1) Network Modelling

Each dataset (Jobstreet, Glints, Dealls) was modeled into its graph. The structure was loaded using Gephi's edge list import. Visualization was performed using the ForceAtlas2 layout for organic and distance-sensitive node clustering.

2) Network Property

A network property analysis was then performed to understand key structural metrics, namely the shape, density, and clustering behavior of each conversation network. The following properties were computed:

a. Nodes and Edges

Nodes represent unique users involved in replies, while edges represent directed interactions between them. These values were automatically counted in Gephi during graph import.

b. Average Degree

To assess how actively users interacted with others on average, the average degree was calculated. This metric gives insight into how densely connected the users are in each network.

c. Density

Density describes how closely connected the network is. A higher value implies tighter interaction between users.

d. Average Path Length

This metric shows the typical number of steps needed to reach from one user to another across the network. It was generated automatically in Gephi's network statistics.

e. Network Diameter

Diameter refers to the length of the longest shortest path between any two users. It reflects how far apart users can be in the worst-case scenario.

f. Modularity

Modularity identifies tightly clustered communities within the graph. It was computed using the Louvain method provided in Gephi. A higher modularity score implies stronger community separation.

2.4 Centrality Measures

In addition to examining the structural characteristics of each network, this study further evaluated the roles and positions of individual users through a set of centrality measurements. These metrics were essential in identifying which users were most influential, not only based on how active they were, but also on how strategically positioned they were in facilitating the flow of information within the network. The analysis focused on four key centrality types—degree, betweenness, closeness, and eigenvector centrality—which together provided a multi-dimensional understanding of user prominence and relational power in the digital conversation space of each recruitment platform.

a. Degree Centrality

Degree centrality measures the total number of direct connections a user has within the network. In this study, a user with a high degree centrality is considered to be highly visible or active in the recruitment discourse, either by replying to others or receiving replies.

b. Betweeness Centrality

Betweenness centrality identifies users who frequently lie on the shortest paths between other users. These users act as bridges that connect different parts of the network and have a strong potential to influence how information is transmitted.

c. Closeness Centrality

Closeness centrality assesses how quickly a user can reach all other users in the network. A high closeness score indicates a user's efficiency in accessing or disseminating information. In the context of CRM, such users are ideal for amplifying strategic messages.

d. Eigenvector Centrality

Eigenvector centrality also considers the quality of those connections by assigning higher influence to users connected to other high-influence users. This recursive measure highlights users who are not just active, but also structurally important. The eigenvector scores were computed using Gephi's standard eigenvector algorithm.

2.5 Lexicon-Based Sentiment Analysis

To identify the emotional tone of user-generated content, this study implemented a lexicon-based sentiment analysis approach. This method involves assigning polarity scores to individual words based on a precompiled lexicon, which was then used to classify the overall sentiment of tweets as positive, negative, or neutral. The lexicon employed was sentiwords_id.txt, a manually curated sentiment dictionary in Bahasa Indonesia, containing words labeled with associated scores: +1 for positive, −1 for negative, and 0 for neutral or unmatched entries.

The sentiment classification pipeline was implemented in Python using Google Colab. Each tweet, having undergone text preprocessing, was tokenized into individual words. For every word w_i in a tweet, the algorithm searched for its presence in the lexicon and retrieved its sentiment value $s(w_i)$. The sentiment score of a tweet was then calculated as the sum of scores of all matched words, defined by the formula:

$$S = \sum_{i=1}^{n} s(w_i) \quad (1)$$

where S is the aggregate sentiment score of the tweet, n is the number of matched words, and $s(w_i)$ is the sentiment score of token w_i.
Based on the final score S, tweets were categorized into sentiment classes using threshold boundaries. If $S > 0.1$, the tweet was labeled as positive; if $S < -0.1$, it was labeled as negative; and if $-0.1 \leq S \leq 0.1$, it was considered neutral. These thresholds were chosen based on previous research on lexicon-based sentiment classification in Indonesian-language tweets, and validated through manual inspection of sample outputs.

2.6 Integrated SNA result with Sentiment Analysis

To generate a comprehensive understanding of influential actors and their emotional tones, this study integrated the outcomes of Social Network Analysis (SNA) and sentiment classification. This integration was performed by merging the centrality score outputs (specifically degree, betweenness, closeness, and eigenvector centrality) with the sentiment-labeled tweets for each user. The merge was based on matching unique platform X usernames between the SNA node list and the sentiment dataset.

The goal of this integration was to map the sentiment distribution of the most influential actors—those with the highest centrality scores. By aligning user influence with sentiment polarity, the research sought to identify not only *who* drives conversations within the recruitment discourse but also how their emotional stance contributes to the public perception of each platform. This insight is particularly valuable for platform owners aiming to design responsive and data-driven Social CRM strategies.

For visualization, sentiment proportions (positive, negative, and neutral) were aggregated for each central actor and displayed using stacked bar charts. These visualizations reveal the dominant emotional tone of each influential user, helping to distinguish between high-centrality actors with predominantly positive sentiment and those potentially critical or dissatisfied. This synthesis of structural and emotional dimensions offers a nuanced basis for CRM decision-making and targeted user engagement.

3. Result and Discussion

3.1 Data Collecting

The data crawling process, conducted from April 1 to April 30, 2025, successfully gathered a total of 2,297 Indonesian-language tweets relevant to three digital recruitment platforms: Jobstreet, Glints, and Dealls. Of this total, the data distribution per platform revealed that Jobstreet had the highest conversation volume with 985 tweets, followed by Glints with 730 tweets, and Dealls with 582 tweets. This dataset comprises original tweets and replies containing the keywords “Jobstreet”, “Glints”, and “Dealls”. Table 1 presents several representative samples of the collected tweets.

Table 1. Sample of Crawled Tweets

Username	Tweet
darjofess	sdf! Udah kurang lebih sebulan saya pake glints saya merasa di glints kok cepet bgt ya proses nya bisa langsung chat HRD nya alhamdulillah kerjaan fulltime pertama saya dari glints dan saya dipaksa merantau ke Jakarta wkwkwkw. yang punya pengalaman serupa cerita dong...
9reenvelvet	@leonayza Linkedin ku kosongan asal taut ke google. Alasannya kaya lebih takut privasi terlalu gampang ke akses aja sih hehe emg sengaja gamau banyak jejak. Btw sejauh ini nyangkutnya justru di info lowongan di jobstreet web resmi

Username	Tweet
goonerals	sm akun ig official gtt Udh gk pernah pake dealls gk pernah dapat balasan. Mending kalibrr

3.2 Pre-processing

After completing the data collection, to show how the raw tweet data was processed before analysis, a representative tweet sample was selected and run through the pre-processing pipeline described in the methodology section. Tables 2 display the outputs of text cleaning and case folding that removes unnecessary characters such as punctuation, symbols, and emojis. All text is also converted to lowercase to maintain consistency.

Table 2. Result of Text Cleaning & Case Folding Stage

Before Cleansing & Case Folding	After Cleansing & Case Folding
Udh gk pernah pake dealls gk pernah dapat balasan. Mending kalibrr	udh gk pernah pake dealls gk pernah dapat balasan mending kalibrr

The next step is tokenization. This process involves splitting the cleaned sentence into individual words or tokens, allowing each term to be analyzed separately in later stages. Table 3 displays the output sample of the process.

Table 3. Result of Tokenization Stage

Before Tokenizing	After Tokenizing
udh gk pernah pake dealls gk pernah dapat balasan mending kalibrr	['udh', 'gk', 'pernah', 'pake', 'dealls', 'gk', 'pernah', 'dapat', 'balasan', 'mending', 'kalibrr']

After tokenization, the next stage is stopword removal, which eliminates common words that do not contribute significant meaning to the analysis. Table 4 presents the output after stopword removal is applied.

Table 4. Result of Stopword Removal Stage

Before Stopword Removal	After Stopword Removal
['udh', 'gk', 'pernah', 'pake', 'dealls', 'gk', 'pernah', 'dapat', 'balasan', 'mending', 'kalibrr']	['udh', 'gk', 'pernah', 'pake', 'dealls', 'gk', 'pernah', 'balasan', 'mending', 'kalibrr']

Stemming is then performed to reduce each word to its root form. This helps to standardize variations and enhance data consistency. Table 5 shows the result after the stemming process.

Table 5. Result of Stemming Stage

Before Stemming	After Stemming
['udh', 'gk', 'pernah', 'pake', 'dealls', 'gk', 'pernah', 'balasan', 'mending', 'kalibrr']	['udh', 'gk', 'pernah', 'pake', 'dealls', 'gk', 'pernah', 'balas', 'mending', 'kalibrr']

This final step summarizes all stages of the pre-processing pipeline. Table 6 displays the cleaned, tokenized, filtered, and stemmed text, which is now ready for further analysis.

Table 6. Pre-processing Final Result

Before	After
Udh gk pernah pake dealls gk pernah dapat balasan. Mending kalibrr	udh gk pernah pake dealls gk pernah balas mending kalibrr

3.3 Network Modelling

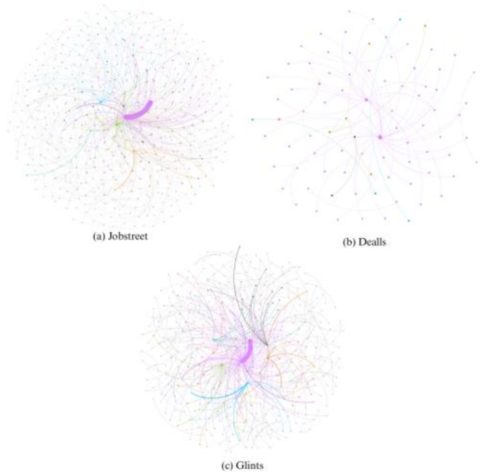

Figure 2. Social Network Visualization of (a) Jobstreet, (b) Dealls, (c) Glints

Figure 2 displays the interaction networks on Jobstreet, Dealls, and Glints, modeled using Gephi and visualized through the ForceAtlas2 layout. Each node corresponds to a unique user, while each directed edge represents a reply interaction. The resulting graph layout reveals structural variances across platforms, offering insight into the density, cohesion, and interaction style of each community.

Jobstreet exhibits a dense and centralized topology, characterized by a prominent core and multiple interlinked sub-clusters, indicating a vibrant and structured discourse. Dealls, by contrast, shows a sparse, radial network dominated by a single central actor, reflecting limited peer-to-peer interaction. Glints presents a hybrid structure—partially centralized with pockets of fragmented clusters—indicating moderate decentralization and sentiment diversity. These visual distinctions offer early indications of platform engagement styles and serve as a foundation for deeper analysis in subsequent sections.

3.4 Network Property Analysis

Following the initial network modeling process conducted in Gephi, this section elaborates on the structural characteristics of user interaction networks across three digital recruitment platforms: Jobstreet, Glints, and Dealls. Each platform was visualized as an undirected graph where nodes represent unique platform X users and edges represent reply to interactions. The summary of these properties is presented in Table 7.

Table 7. Comparison of Social Network Properties across Platforms

Property	Jobstreet	Glints	Dealls
Nodes	656	499	205
Edges	475	383	308
Average Degree	1.448	1.535	3.0
Average Path Length	2.834	3.192	2.378
Network Diameter	7	8	3
Modularity	0.840	0.804	0.089
Density	0.002	0.003	0.019

From the table, Jobstreet emerges as the most expansive network, with 656 nodes and 475 edges, representing the largest volume of user participation. This breadth of interaction reflects a wide reach of Jobstreet-related discussions on the X platform. However, its average degree of 1.448 suggests that, despite the high number of users, individual users tend to have fewer direct connections, pointing to dispersed interaction patterns. The average path length of 2.834 and network diameter of 7 indicate a moderately long communication chain, meaning that information diffusion requires several intermediate steps. Interestingly, Jobstreet also shows the highest modularity score (0.840), signifying the presence of well-defined user clusters, which may reflect topic segmentation, community grouping, or localized influence. This modularity is consistent with findings from Zhou & Liu, who assert that high modularity correlates with the presence of subcommunities and thematic divisions in social interaction networks [8]. However, its graph density (0.002) remains low, which is typical in large-scale social networks where not every user interacts with every other.

In contrast, Glints, while having fewer nodes (499) and edges (383), demonstrates a higher average degree of 1.535, suggesting that users on this platform tend to engage more frequently with one another. However, its average path length of 3.192—the highest among the three—suggests greater navigational distance within the network. This could imply less efficient communication flow or the presence of weakly connected clusters. Glints also maintains a high modularity score (0.804), reflecting strong community formation, though slightly less segmented than Jobstreet. Its density (0.003) is marginally higher, indicating a more tightly connected user base despite a smaller network size. This observation aligns with Hassan et al., who highlight that modest increases in density typically enhance responsiveness in clustered user interactions [10].

Meanwhile, Dealls presents a unique structural profile. With only 205 nodes, it features the smallest network, yet its average degree reaches 3.0, significantly higher than the other two. This suggests a concentrated interaction model, where users are highly engaged with a small circle, potentially indicating a more centralized or influencer-driven discourse. The short average path length (2.378) and smallest diameter (3) suggest that information can travel quickly and efficiently across the network. Dealls also demonstrates the highest density (0.019), which implies an unusually tight-knit community where users frequently engage with one another. However, this comes at the cost of low modularity (0.089), indicating that these interactions are not diversified across subgroups but instead centralized around a core actor or topic. As Samira et al. note, networks with high density but low modularity are often indicative of brand-dominated or administrator-centric interactions, where the dialogue is driven by one or a few dominant entities [6].

These results demonstrate that each platform's network structure reflects a distinct communication dynamic. Jobstreet operates as a broad, segmented network conducive to decentralized messaging strategies. Glints leans toward active intra-community engagement, while Dealls functions as a compact, centralized ecosystem ideal for focused influencer strategies.

3.5 Key Actor Identification Using Centrality Measures

The selection of central actors prioritized the highest degree centrality values, indicating users with the largest number of direct interactions. However, in line with the research design, the analysis deliberately excluded accounts identified as automated bots, organization-based accounts, or official recruitment platform handles. The purpose of these exclusions is to isolate perspectives originating exclusively from authentic users.

Table 8. Key Actors Based on Centrality Measures

Measures	Jobstreet	Glints	Dealls
Actor	Xaviernaxa	Xavytekniksipil	hrdbacot
Degree	23	18.0	2
Betweeness	275.0	64	1.0
Closeness	0.96	1.0	1.0
Eigenvector	0.055	0	0

As summarized in Table 8, the Jobstreet platform is dominated by the account @xaviernaxa, who achieved high scores across all four centrality measures: degree (23), betweenness (275.0), closeness (0.96), and eigenvector (0.055). This pattern demonstrates that the user is not only well-connected but also serves as a strategic bridge between clusters in the conversation network.

For Glints, the most central user is @xavytekniksipil, with a degree of 18.0 and betweenness of 64. While the account exhibits substantial reach and rapid access to the broader network (closeness: 1.0), its eigenvector score of 0 suggests minimal connectivity with other influential users. This implies that although the user is active, they may operate outside elite or highly connected subgroups, serving more as an entry-level hub than a core influencer within the network.

On the Dealls network, @hrdbacot was identified as the most interactive individual, with a degree of 2 and a betweenness of 1.0. Although relatively low, these values still reflect significance within a much smaller and denser network, where even minimal interactions can yield high visibility. Notably, Dealls' network structure is highly centralized with low modularity, and the centrality analysis reinforces this by showing that only a handful of nodes dominate the interaction space.

3.6 Lexicon-Based Sentiment Analysis

Table 9. Lexicon-Based Sentiment Distribution

Sentiment Category	Jobstreet	Glints	Dealls
Positive	32.2% (308)	29.3% (212)	53.7% (217)
Negative	22.5% (216)	21.9% (158)	25.5% (103)
Neutral	45.3% (434)	48.8% (353)	20.8% (84)

The distribution of sentiment categories across the three platforms is summarized in Table 9. From the results, Jobstreet displayed a balanced sentiment profile, with 32.2% positive, 22.5% negative, and the largest portion of 45.3% neutral tweets. This indicates a broadly discussed topic with mixed tones, possibly reflecting both praise and criticism of user experiences, recruitment outcomes, or platform reliability. The relatively high neutral sentiment suggests that many users are sharing informational or factual content rather than emotionally charged opinions.

In the case of Glints, neutral sentiment dominated (48.8%), followed by 29.3% positive and 21.9% negative tweets. This distribution implies that users are primarily exchanging objective, job-related content or inquiries, with less engagement in emotive expressions. The relatively lower share of polarized sentiment may reflect Glints' positioning as a professional platform geared toward younger, early-career job seekers, as supported by prior findings from Aribowo et al. regarding sentiment dilution in recruitment discourse [11].

Dealls recorded the highest proportion of positive sentiment (53.7%), significantly outweighing negative (25.5%) and neutral (20.8%) tweets. This result may reflect a more favorable brand perception or higher satisfaction with platform services among users. The sentiment structure aligns with the previously observed centralized network pattern, where a tight, positively engaged user group may amplify endorsement-oriented discourse. However, the relatively lower neutral count may also suggest that discussions around Dealls are more emotionally charged, either promotional or critical.

3.7 Integrated SNA and Sentiment Analysis

This section integrates centrality-based network findings with sentiment classification to examine the emotional influence of the most structurally central actors within each digital recruitment platform. While previous stages identified top actors through centrality metrics, this integration analyzes the sentiment expressed in their tweets, revealing not just *who* is central, but *how* they contribute to the tone and discourse.

To ensure interpretive relevance, bot-like accounts, base accounts, or official platform accounts were excluded from the sentiment mapping. This filtering guarantees that only authentic user perspectives are considered. Additionally, some top central actors identified earlier do not appear in the sentiment visualization. This is because certain users, despite being structurally central, did not post any original content, thus making it impossible to analyze their sentiment.

Figure 3 illustrates the sentiment distribution of the five most central users on each platform, combining social network centrality metrics with sentiment orientation to uncover both the structural and emotional influence of key actors. This integrated approach offers a layered perspective, highlighting not only who drives interaction within the network but also how they emotionally shape the discourse. While centrality identifies network prominence, sentiment reveals the tone of that influence, producing actionable insights for CRM responsiveness.

Additionally, the exclusion of bot-like accounts and platform-affiliated handles ensures that the analysis reflects authentic user-generated perceptions, enhancing the validity of the findings.

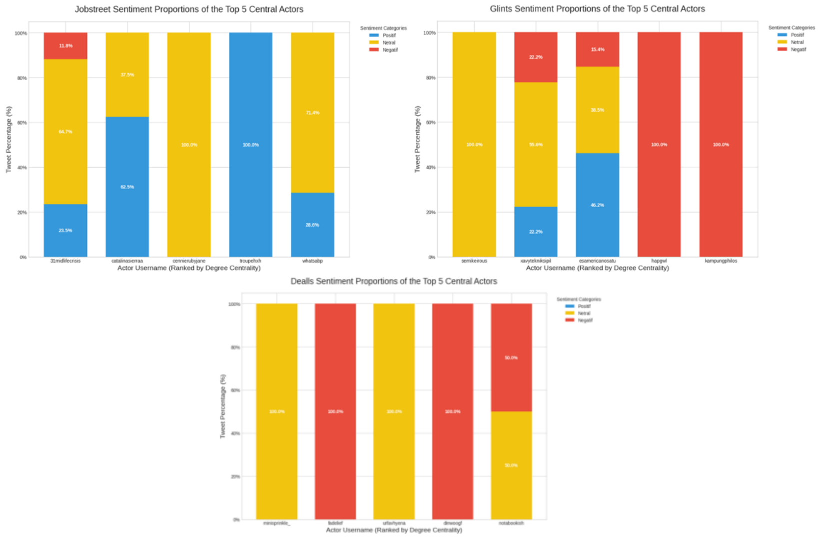

Figure 3. Sentiment Proportion from Centrality Actor for Jobstreet, Glints and Dealls

Jobstreet demonstrates a stable and trust-enhancing ecosystem, where most central users exhibit favorable sentiment tendencies. Accounts such as @troupehxh and @cennierubyjane posted entirely positive and neutral tweets, respectively. Others, like @catalinasieraa (62.5% positive) and @whatsabp (28.6% positive), further reinforce the constructive atmosphere. Only a minor trace of negativity was evident from @31midlifecrisis, whose overall sentiment remained predominantly neutral. These findings suggest that Jobstreet not only fosters interaction through high-connectivity actors but also benefits from an emotionally supportive discourse.

On the other hand, Glints and Dealls exhibit more concerning emotional dynamics. Glints' network features highly polarized sentiments, with actors like @hapgwl and @kampungphilos expressing 100% negativity, while others show varying neutrality or mild positivity. Dealls, on the other hand, shows the most skewed sentiment pattern: three of its five key actors voiced intense negativity, and none expressed positive sentiment. This imbalance signals reputational vulnerability, with critical voices occupying structurally central positions. For both platforms, the absence of tweet data from certain key actors also explains their exclusion from this sentiment mapping. These accounts may still receive attention but contribute no measurable emotional stance. From a CRM system standpoint, Glints may require targeted sentiment mitigation and user reassurance campaigns, while Dealls needs to rebuild emotional engagement through transparent communication and community repair strategies.

3.8 Insight Interpretation

The integration of social network structures, user centrality, and sentiment classifications provides a multifaceted understanding of how discourse and emotional dynamics arise on digital recruitment platforms. Jobstreet, Glints, and Dealls display unique patterns in their interaction structures and user sentiments, highlighting their distinct digital cultures that influence CRM adaptation practices. While structural properties, such as modularity and average path length, describe how users cluster and communicate, sentiment proportions from central actors reveal the prevailing emotional atmosphere that shapes user perception and loyalty.

Jobstreet is distinguished by its clear and supportive interaction ecosystem. With 656 nodes and a modularity score of 0.84, its network forms well-defined community clusters. Its top central users predominantly express neutral or positive sentiment, such as @troupehxh and @cennierubyjane, which suggests the presence of emotionally supportive interaction hubs. This blend of network cohesion and positive sentiment indicates that Jobstreet has effectively developed a user base that promotes both high engagement and organically generated positive narratives. In comparison, Glints displays a more polarized environment, with a higher average path length (3.192) and structurally significant users such as @hapgwl and @kampungphilos expressing exclusively negative sentiments. This indicates an emotionally fragmented user base where dissatisfaction may be amplified by influential nodes, warranting closer strategic listening.

Dealls presents the most critical case, both structurally and emotionally. With only 205 nodes and the lowest modularity (0.089), Its interaction clusters are sparse and unstable, but sentiment among key actors is largely negative. Influencers such as @fadelief and @dinwoogf dominate the space with unfavorable expressions, which could jeopardize brand perception if left unmanaged. Moreover, several high-centrality accounts were excluded from sentiment analysis due to the absence of original tweets, emphasizing an important divide between visibility and expressive involvement. This asymmetry reinforces the need for CRM strategies that differentiate between structurally central users and actual sentiment drivers. Among the platforms, Jobstreet emerges as the most trustworthy, with strong community cohesion and a prevalence of emotionally positive interactions, positioning it as the most stable and credible recruitment platform during the observed period.

3.9 Social CRM Strategy Recommendations

To address the observed sentiment patterns and network dynamics across Jobstreet, Glints, and Dealls, strategic Social CRM interventions must be tailored based on the integrated findings of actor centrality and sentiment orientation. This research analyzes the emotional attitudes of prominent influencers, providing a major opportunity to create trust-based engagement strategies supported by evidence. Prior studies suggest that social CRM is most effective when it harnesses not only transactional data but also emotional and relational signals from user interactions on social media platforms [14].

For Jobstreet, which is defined by a predominance of neutral to positive sentiments among central actors, a strategic focus should be placed on amplifying success stories created by users and highlighting content from positively influential users. Research by Cahyani et al. shows that central actors in social networks can shape collective behavior, making their recognition a powerful tool to enhance user participation [15]. Similarly, Al-Rubaiee and Alomar emphasize that engaging such key users enhances brand credibility and fosters a community-oriented environment conducive to sustaining positive narratives [16]. Since these central figures often act as social validators, leveraging their positive sentiment through emotionally resonant storytelling can drive advocacy, deepen trust, and reinforce long-term brand loyalty.

On the other hand, Glints' sentiment landscape, which features a fragmented mix of both highly positive and strongly negative central users, requires a dual-track sentiment management strategy. This approach involves segmenting user groups based on sentiment polarity and delivering communication tailored to each segment. For users expressing negative sentiment, direct and empathetic engagement, such as public responses, community moderation, or feedback loops, can help reduce dissatisfaction and rebuild trust. This is supported by Malki et al., who emphasize that encouraging active two-way communication and collaborative interactions through social CRM greatly enhances customer satisfaction, which in turn boosts loyalty and reduces disengagement [17]. At the same time, positively influential users can be supported through recognition, collaborations, or spotlight features to strengthen positive narratives. Prior research confirms that tailoring CRM strategies to different user segments based on sentiment polarity improves both engagement and perception across digital communities [18]. This provides further evidence that the proposed dual-track strategy is not only theoretically sound but also practically valid and applicable.

For Dealls, where sentiment among central figures is predominantly negative or neutral, there is an urgent need for a social CRM strategy focused on brand sentiment recovery. To rebuild user trust, empathy-driven campaigns should be implemented that not only acknowledge past service flaws but also respond in a timely and emotionally attuned manner to user concerns. Al-Rubaiee and Alomar emphasize that integrating real-time sentiment from social media into CRM systems enables emotionally responsive interventions that restore customer confidence [16]. Similarly, Sun et al. highlight that transparent engagement can significantly influence community sentiment dynamics, while Pos Indonesia's case illustrates how timely CRM responses on Instagram helped shift public perception toward neutral or positive [15], [19]. Recognizing emerging neutral-to-positive actors is also vital, as Ba et al. point out the importance of network structures in sustaining long-term behavioral change in digital communities [20]. Altogether, these insights confirm that this recovery-oriented strategy is both theoretically grounded and practically effective.

In sum, Social CRM strategies must be tailored to each platform's sentiment and network dynamics. Amplifying positive voices, managing polarity with targeted engagement, and restoring trust through empathy are key approaches. Supported by both analysis and literature, these strategies offer a practical, evidence-based path to building stronger, trust-driven digital recruitment communities.

4. Conclusion

This study concludes that integrating Social Network Analysis (SNA) and lexicon-based sentiment analysis provides a comprehensive framework for optimizing Social CRM strategies on Indonesian digital recruitment platforms. By analyzing user interactions and sentiment distributions on Jobstreet, Glints, and Dealls, the research reveals how network structure and emotional tone influence public perception. Jobstreet emerged as the most trusted platform, supported by neutral and positive sentiment from central actors, while Dealls exhibited greater emotional vulnerability. These findings provide not only practical insights for platform-specific CRM improvements but also theoretical contributions to the field of user engagement analytics. The proposed approach—employing Python-based preprocessing, Gephi for SNA, and lexicon classification—can be adapted for broader digital ecosystem management. Future work may expand into deeper emotion classification and real-time monitoring to support emotionally responsive engagement strategies in Indonesia's evolving digital workforce landscape.

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