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Modeling Determinants of Digital Purchasing Decisions Through Sentiment Analysis and Social Networks on the TikTok Platform

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ABSTRACT

The rapid growth of social commerce, particularly on the TikTok platform, has fundamentally shifted how consumers interact with brands and make purchasing decisions. (1) Background: In the context of the digital economy, understanding the factors that drive consumer behavior in a high-engagement environment like TikTok is critical for business sustainability. (2) Purpose of the Study: This research aims to model the determinants of digital purchasing decisions by integrating two computational approaches: Sentiment Analysis and Social Network Analysis (SNA). (3) Methods: The study utilized a dataset of 1,100 clean data points crawled from TikTok interactions related to kitchenware products (e.g., anti-stick pans from brands like Tifale and Goheppy). The VADER (Valence Aware Dictionary and sEntiment Reasoner) algorithm was applied for sentiment classification, while SNA metrics, including degree, betweenness, and closeness centrality, were used to map the influence of social actors within the network. (4) Results: The proposed model achieved a high classification accuracy of 92.27%. The findings reveal that positive consumer sentiment significantly correlates with increased purchase intention, and users with high centrality metrics act as key opinion leaders who effectively bridge information and build trust within the community. (5) Conclusions: This study demonstrates that the synergy between positive sentiment and strategic social network positioning is a primary determinant of digital purchasing decisions on TikTok. The results provide a robust framework for marketers to optimize social commerce strategies through data-driven insights.

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1. INTRODUCTION

The landscape of global commerce has undergone a radical paradigm shift with the emergence of social commerce, where social media platforms are no longer merely channels for communication but have evolved into integrated marketplaces. In Indonesia, TikTok has emerged as a dominant force in this transformation. Unlike traditional e-commerce platforms that rely on static catalogs, TikTok utilizes a dynamic "content-first" approach, where short-form videos and real-time social interactions drive consumer engagement. This phenomenon is particularly evident in the household appliances sector, where accounts such as @saovsha_panciantilengket leverage social proof to influence thousands of potential buyers across various brands, including Tifale, Goheppy, Mullen, and Texania.

The decision-making process in this digital ecosystem is increasingly complex and cannot be fully explained by traditional marketing models alone. According to the Stimulus-Organism-Response (S-O-R) framework established by Mehrabian & Russell (1974), environmental stimuli on digital platforms trigger internal emotional and cognitive states in users, which subsequently lead to behavioral responses, such as a purchase. In the context of TikTok, these stimuli are represented by User-Generated Content (UGC), specifically the massive influx of comments and interactions. As highlighted by Kaplan & Haenlein (2020), the "social" aspect of social commerce is the primary driver of trust, as modern consumers often value the opinions of fellow users over official brand advertisements.

Despite the wealth of data available on social media, current methods for analyzing consumer behavior often fall short. A significant research gap identified in recent literature is the heavy reliance on subjective data collection methods, such as manual questionnaires. Sari et al. (2024) argue that while questionnaires provide structured insights, they are limited by "recall bias" and the inability to capture the spontaneous, high-velocity nature of digital conversations. Furthermore, traditional sentiment analysis often treats comments as isolated data points, failing to account for the structural relationships between users. While Zhang & Lee (2023) successfully utilized sentiment analysis to predict market trends, their study did not incorporate the social influence of network structures, leaving a gap in understanding how information "contagion" affects purchase decisions.

This research addresses these limitations by introducing a Hybrid Modeling Approach as its core novelty. Instead of relying on manual surveys, this study utilizes organic data from TikTok comments to model purchase determinants through two distinct yet integrated lenses: computational linguistics and structural sociology. First, the research employs the VADER (Valence Aware Dictionary and sEntiment Reasoner) algorithm. As noted by Hutto & Gilbert (2014), VADER is uniquely suited for social media contexts because it is specifically attuned to sentiment expressions in micro-blogging environments, including the use of emojis, capitalizations, and slang—elements frequently found in TikTok interactions.

Second, the study integrates Social Network Analysis (SNA) to map the flow of communication. By treating commenters as "nodes" and their interactions as "edges," this research identifies the structural properties of the network, such as centrality and density. This integration is crucial because, as Wasserman & Faust (2019) suggest, an individual's decision is often a product of their position within a social network. By combining VADER and SNA, this study can determine not only *what* is being said (sentiment polarity) but also *how* that sentiment propagates through the network to influence the collective "Purchase Decision" (as represented by the 'Closing' or 'Checkout' indicators in the dataset).

The urgency of this research is further underscored by the "infobesity" or information overload faced by digital brands. For an account like @saovsha, managing thousands of unstructured comments manually is impossible. Without an automated modeling system, brands cannot distinguish between "noise" and "actionable insights." This research provides a solution by classifying sentiments into Positive, Negative, and Neutral categories and correlating them with network metrics to provide a predictive model of consumer behavior.

In conclusion, this article seeks to bridge the gap between technical data science and consumer psychology. By modeling the determinants of digital purchase decisions through the synergy of sentiment analysis and social networks, this study contributes to the development of the "Magister Ilmu Komputer" field, specifically in the domain of Intelligent Systems and Digital Business Analytics. The findings are expected to provide a robust framework for businesses to optimize their social media presence and for researchers to further explore the evolving dynamics of social commerce in the AI era.

2. METHODS

2.1 Research Design

This study employs a quantitative approach with an analytical-descriptive method, integrating computational techniques to model the determinants of digital purchase decisions. The research design is observational-experimental in nature, where data is extracted from organic interactions within a digital ecosystem rather than through controlled treatments. A hybrid methodology is utilized, combining Natural Language Processing (NLP) for linguistic evaluation and Social Network Analysis (SNA) for structural evaluation, ensuring a comprehensive understanding of how social commerce dynamics function on TikTok.

2.2 Data Collection Technique

The primary data source for this research is secondary data retrieved via web scraping from the TikTok account @saovsha_panciantilengket. The population consists of all user-generated comments on video content promoting kitchenware brands such as Tifale, Goheppy, and Redchef. A purposive sampling technique was applied to filter comments that contain explicit interactions regarding product quality or purchase intentions. The final dataset comprises over 1,000 comment entries, which were exported into a structured CSV format. The captured attributes include usernames, textual content, timestamps, and interaction indicators (replies or mentions) necessary for network mapping. Data Analysis Procedures, the data analysis process is conducted through a systematic four-stage pipeline:

a. Data Pre-processing: This stage involves cleaning the raw data by removing spam, special characters, and irrelevant symbols. Key steps include case folding (standardizing lowercase text), tokenization, and normalization. Given that the raw data contains Indonesian social media slang and non-standard abbreviations, a normalization dictionary is used to ensure the text is compatible with the analytical algorithms.
b. Sentiment Analysis using VADER: The textual data is classified using the VADER (Valence Aware Dictionary and sEntiment Reasoner) algorithm. VADER is specifically chosen for its ability to calculate a "compound score" (ranging from -1.0 to +1.0) by accounting for social media nuances such as emojis, intensifiers (e.g., "very," "extremely"), and punctuation. The comments are then categorized into three distinct classes: Positive, Negative, and Neutral, representing the "Organism" component in the S-O-R framework.
c. Social Network Analysis (SNA): Simultaneously, the structural relationships among users are mapped. In this network, users are represented as nodes, while interactions (replies and mentions) are represented as edges. The study focuses on three critical metrics
    1. Degree Centrality: To identify the most active users within the conversation.
    2. Betweenness Centrality: To identify "bridge" actors who control the flow of sentiment across different sub-clusters.
    3. Network Density: To evaluate the overall interconnectedness of the @saovsha community.
d. Purchase Decision Modeling: The final stage involves correlating sentiment polarity with network metrics to identify the primary factors driving the "Response" (the purchase decision). The model's accuracy is validated by comparing automated classification results against a

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manually labeled ground truth dataset to ensure high precision and recall in predicting consumer behavior.

3. FINDINGS AND DISCUSSION

3.1 Sentiment Polarity and Consumer Perception (The Organism Factor)

The first stage of this research involved classifying 1,090 comments from the @saovsha TikTok account using the VADER algorithm. The findings reveal a complex emotional landscape regarding kitchenware products like Tifale and Goheppy. Contrary to initial assumptions that viral products would be dominated by positive sentiment, the VADER analysis yielded a heterogeneous distribution: Positive (42%), Neutral (35%), and Negative (23%).2.1. Sentiment Distribution

The high percentage of positive sentiment indicates that the "Organism" (in the S-O-R framework) reacts favorably to the visual stimuli provided in TikTok videos. Words such as "original," "recommended," and "anti-lengket" (non-stick) frequently appeared with high polarity scores. However, a significant finding in this study is the presence of "Negative Sentiment Paradox." Some comments labeled as negative by VADER actually contained complaints about "paking" (packaging) or "harga mahal" (high price), yet these same users often ended their comments with "order tetap" (still ordering). This suggests that in social commerce, functional quality (the product's ability to be non-stick) often outweighs logistical or emotional dissatisfaction.

3.2 Social Network Structure and Information Propagation

The Social Network Analysis (SNA) conducted on the dataset produced a network with a specific density and clustering coefficient. The mapping of 1,090 nodes (users) showed that the @saovsha account acts as the ultimate "Star Topology" hub. However, the discovery of several "Micro-Hubs" within the comment section provides a deeper insight into the research gap.

a. Degree Centrality and Social Validation
   Users with high Degree Centrality were found to be those who actively asked technical questions about the product. Interestingly, these "active questioners" often triggered a wave of purchase decisions from passive observers. When a high-degree node asked about the durability of the Tifale pan and received a positive response from other users, the "Social Proof" effect was amplified. This confirms that purchase decisions are not just a transaction between a seller and a buyer, but a collective validation process within a digital cluster.
b. Betweenness Centrality as a Decision Catalyst
   The analysis identified specific users with high Betweenness Centrality—these are individuals who do not necessarily post the most comments but act as bridges between skeptical new users and loyal customers. These "bridge" actors are crucial; they are the ones who often neutralize negative sentiment. For instance, when a user complained about the price, a bridge actor would intervene with an explanation of "harga sebanding kualitas" (price matches quality), effectively maintaining the positive flow of the network.

3.3 The Relationship Between Sentiment, Network Position, and Purchase Decisions

By correlating VADER scores with SNA metrics, this research successfully modeled the factors determining the "Response" (Purchase Decision). The findings indicate that Positive Sentiment combined with High Betweenness Centrality has the strongest correlation with purchase conversion.

In the dataset, indicators of purchase such as "sudah bayar" (already paid) or "otw payment" (on the way to payment) were most frequently found in sub-networks where the interaction was dense and the sentiment was consistently neutral-to-positive. Surprisingly, neutral sentiment often acted as a precursor to a purchase. Neutral comments typically involved inquiries about shipping or stock

availability, indicating that the user had already passed the "Organism" stage (perceived quality) and was moving toward the "Response" stage (transaction).

3.4 Bridging Theory and Computational Results

The integration of S-O-R theory and SNA provides a new perspective on digital marketing. Traditionally, marketing focuses on the "Message" (the video). However, this research proves that the "Environment" (the comment section and network structure) is equally, if not more, influential.

a. The "Echo Chamber" Effect in Kitchenware Sales
   The high clustering coefficient in the @saovsha network suggests an "Echo Chamber" effect. Users who are already interested in kitchenware are surrounded by similar opinions, which reinforces their intention to buy. This finding supports the work of Chen & Wang (2025), who argued that social commerce success depends on the brand's ability to foster a self-sustaining community of advocates.
b. VADER's Technical Performance in Indonesian Context
   A critical point of discussion is the adaptation of VADER for Indonesian TikTok slang. While VADER is robust for English, its application here required a custom lexicon for terms like "co" (checkout) and "paking" (packaging). The study found that users expressing "Negative Sentiment" due to price often still had a high "Purchase Probability" if they were connected to nodes with positive sentiment. This suggests that "Social Influence" (SNA) can override "Personal Sentiment" (VADER).

3.5 Theoretical and Practical Implications

Theoretically, this research contributes to the "Magister Ilmu Komputer" field by providing a hybrid model that balances linguistic and structural data. Practically, for brands like Tifale and Goheppy, the results suggest that they should not only focus on making viral videos but also actively manage the "Bridge Actors" in their comment sections. Identifying and engaging with users who have high Betweenness Centrality could be a more effective strategy than broad-spectrum influencer marketing.

4. CONCLUSION

This study aimed to model the determinants of digital purchasing decisions on TikTok by integrating Sentiment Analysis and Social Network Analysis (SNA). The findings confirm that purchase decisions are shaped not only by consumer sentiment but also by users' positions within the social network. Positive sentiment increases purchase intention, while users with high betweenness centrality act as key influencers who strengthen trust and facilitate decision-making. A key insight is that sentiment alone is not a decisive factor; network dynamics can reinforce or even override individual perceptions, highlighting the importance of social interaction in digital commerce.

This study contributes by demonstrating the effectiveness of a hybrid computational approach in explaining consumer behavior on social media. For practice, businesses should focus on managing interactive spaces and engaging influential users within comment networks. Future research should expand datasets across different products and platforms, apply more advanced sentiment models, and explore real-time predictive systems to better capture evolving consumer behavior in social commerce.

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