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TWITTER SOCIAL NETWORK INTERACTION AS CUSTOMER ENGAGEMENT IN COMPETITION FOR E-COMMERCE E-HEALTH PERFORMANCE IN INDONESIA

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Abstract
Background – *The presence of e-commerce e-health is a societal solution to health needs in the era pandemic. Social distancing rules cause considerable restrictions on community socialization, so they use social media alternatives to share experiences. That matter causes customers to talk about the performance of digital e-health services and create consumer engagement. Public opinion and ratings on social media become data information analyzed to improve service quality.*

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Aim – *This study aims to identify customer conversations on Twitter about e-commerce e-health to see its performance and compare e-health results networks in Indonesia.*
Design / Methodology / Approach – *The research method in this study is the Social Network Analysis (SNA) approach and descriptive meaning to get the results of the formulated goals.*
Findings – *The results of this study showed that pre-pandemic e-health users in Indonesia were more dominant in utilizing psychologist and psychiatric consultations and buying easy and practical medicines. During the pandemic, customers more often used doctor consultations related to symptoms and treatment of Covid-19, drugs and vitamins for self-isolation, supported by online payments.*
Conclusion - Judging from the proportion of network properties, Halodoc is superior to Alodokter because the number of Halodoc nodes and edges is far more weighted, both from the focus of consulting, medicine, and payments
Research implication – *This research contributes to e-health companies in Indonesia regarding suggestions for utilizing SNA through customer interaction on social media to improve the performance and competition of e-health services and determine superior strategies.*
Limitations – *This research explores data only from social media Twitter, based on the material for data visualization is only in text. The scope of the study is only in the health business, so it can further develop in other sectors.*

Keywords: *Customer, Engagement, E-Health, Social, Network, Twitter.*

Abstrak
Latar Belakang - Kehadiran *e-commerace e-health* merupakan solusi masyarakat sebagai pemenuhan kebutuhan kesehatan di masa pandemi. Aturan pembatasan sosial menyebabkan media sosial menjadi alternatif untuk berbagi pengalaman. Sehingga konsumen berbicara tentang kinerja layanan kesehatan digital dan menciptakan keterlibatan pelanggan. Opini publik dan penialaian di media sosial menjadi informasi data dapat dianalisis untuk meningkatkan kualitas kinerja pemasaran.

Tujuan – Penelitian ini memiliki tujuan mengidentifikasi pembicaraan pelanggan di twitter tentang e-commerce e-health untuk dilihat kinerjanya dan perbandingan jaringan hasil e-health di Indonesia.
Desain / metodologi / pendekatan – Penelitian ini menggunakan pendekatan *Social Network Analysis* (SNA) dan pemaknaan deskriptif untuk mendapatkan hasil dari tujuan yang telah dirumuskan. Pengambilan data bersumber pada data besar media sosial *twitter*, dengan hasil teks sebagai bahan analisis dan visualisasi data.
Temuan - Hasil penelitian ini menunjukkan bahwa pengguna *e-health* di Indonesia sebelum pandemi dominan memanfaatkan konsultasi psikolog dan psikiatri, pembelian obat yang mudah dan praktis. Selama pandemic, pelanggan lebih sering menggunakan konsultasi berkaitan gejala dan perawatan *covid-19* serta obat dan vitamin untuk isolasi mandiri yang didukung pembayaran online.
Keismpulan - Dilihat dari proporsi properti jaringan, Halodoc lebih unggul dari Alodokter karena jumlah node dan edge Halodoc jauh lebih berbobot, baik dari fokus konsultasi, kedokteran, maupun pembayaran.
Implikasi penelitian - Penelitian ini memberikan kontribusi terhadap perusahaan *e-health* di Indonesia mengenai saran untuk memanfaatkan SNA melalui interaksi pelanggan di media sosial agar dapat meningkatkan kinerja layanan dan daya saing *e-health* serta menetapkan strategi unggulan.
Batasan penelitian - Penelitian ini menggali data hanya dari media sosial Twitter, sehingga bahan untuk analisis dan visualisasi data hanya berupa teks. Ruang lingkup penelitian ini hanya pada bisnis kesehatan, dapat dikembangkan lebih lanjut pada sektor lain.

Kata Kunci : Keterlibatan, Konsumen, E-Health, Jaringan, Sosial, Twitter.

INTRODUCTION

Adopting technology in healthcare needs is familiar and has substantially provided good services. Electronic health (e-Health) uses information technology to solve health needs, from prevention to treatment (Crico et al., 2018). During the pandemic, the two most used e-health brands (Surahman et al., 2021). That makes it easier for consumers to get medicines at an appropriate distance, supported by payment services with various methods, such as e-wallets and mobile banking (Suzuki et al., 2020). During the COVID-19 pandemic, people's space for the movement was limited due to large-scale social restrictions (PSBB) to prevent the spread of the virus. The limitations of medical diagnosis are an obstacle due to misinformation about patient symptoms (Maeder et al., 2020). The existence of digital health services such as online doctor consultations, online pharmacies, and non-cash payments shows that digital e-health services are a solution to people's needs. Thus, e-health contributed significantly to many countries through the performance of its digital services during the covid-19 virus outbreak (Alonso et al., 2021).

Service delivery by e-health certainly raises user participation through customer-to-customer (C2C) interactions on social media that can support sustainable performance in business (Danarahmanto et al., 2020). Public opinion and assessment of user trust and convenience will create customer engagement (Srinanda et al., 2020) through reactions, interactions, and experiences such as shared uploads and comments (Mukherjee & Banerjee, 2019), (Alamsyah & Utami, 2018). With the number of interactions related to e-health on social media, it is not certain that digital e-health services are good in terms of performance. Therefore, careful analysis is needed to investigate social network interactions in performance services to get better results in the future (Carvalho & Medeiros, 2021). Social network analysis (SNA) explores user interaction relationships, such as uploading, replying, retweeting, and tagging other accounts (Mitei & Ghanem, 2020). Thus, this study uses an SNA approach to investigate customer-to-customer (C2C) interaction relationships by calculating network properties formed in conversations on social media. Collection of various kinds of database information gathered in big data. Social media platforms with big data include YouTube, Twitter, Instagram, and Facebook (Mai et al., 2020). However, the suitable social media for SNA is twitter, as the licensing process is uncomplicated and access-free, as well as the rapid spread of interactions (Fayjaloun et al., 2021). Tweet data is taken based on user-generated content (UGC), which is content data from interactions originating from users and contains creativity (Fayjaloun et al., 2021), (Saura et al., 2021). The determination of UGC in this study is about reviewing the use of consulting services, medicines, and payments on the Halodoc and Alodokter applications.

The limitations of the digital health business literature from interaction on social media became a gap in this study. Previous research has predominantly examined the influence of (Kalumata et al., 2021), determinants of e-health (Indriyarti & Wibowo, 2020), and analysis in terms of the quality of e-health applications (Chakraborty et al., 2021), not in terms of user interaction on social media. Likewise, the academic world is more interested in analyzing social networks from the element of financial business (Srinanda et al., 2020) and opinion in education (Lieharyani & Ambarwati, 2022); even so far, there has been no use of SNA in the field of digital health business. Thus, this study acts further as a filler for the shortcomings of the literature related to e-health in terms of user interaction networks formed on social media. It also is the novelty of research related to social network analysis methods in the field of health business.

The objectives of this study are twofold. The first goal is to identify the discussion of Twitter user interactions that focus on Halodoc and Alodokter based on consultation, medicine, and payment features. The hope is that as a supporter of e-health, companies evaluate the results of their marketing strategies through customer engagement to improve their services. Then, the second goal is to look for a comparison of the Halodoc and Alodokter social networks that were formed in two periods (before and during the pandemic). The comparative results of this social network study can be a reference and motivation for e-health

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companies to increase competitiveness and superior strategies. The problems investigated in this study are the interaction of discussion of e-health performance in social networks on Twitter and the comparison of e-health performance from networks formed before and during the pandemic.

LITERATURE REVIEW

Big Data

Big data is extensive information and complex amounts of data that cannot be managed and processed by traditional tools effectively. Big data has a volume at any time with variety and accurate information for further extraction. Thus, big data refers to big social data obtained from social networks (Abkenar et al., 2021).

Social Network Analyst *(SNA)*

Social Network Analysis (SNA) is part of the Social Computing technique for extracting information on big data, which studies human relations utilizing graph theory. SNA understands social by visually with connected nodes and link lines (edges) on an online social network (Prabowo, 2021).

Customer Engagement

Customer engagement is the result of relational value from the point of view of buyers and sellers, in this case, the extent of the customer's referral value, influence, and knowledge. Customer engagement can turn prospects on existing and valuable social networks, the results of ratings, comments, and reviews, and effective practical (Agnihotri, 2020).

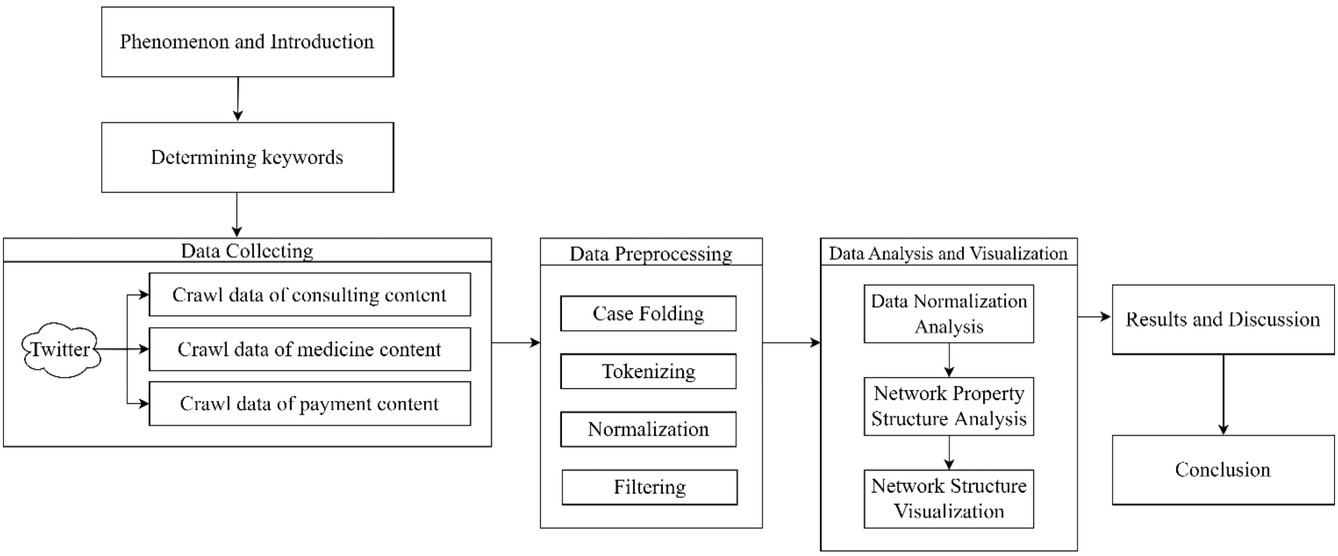

Figure 1. The concept of the research method

RESEARCH METHODS

This study uses a social networking analysis (SNA) approach in a qualitative descriptive research type. SNA is a form of social computing that extracts large volumes of data (E-commerce, 2018). The subject of this research is the Indonesian people as Twitter users. This study uses secondary data

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sources from tweets with Halodoc and Alodokter discussions before the 2017 to 2019 pandemic and during the 2020 to 2022 pandemic.

This study presents the results of the research and discussion. The results of the study are the results of a comparison of the calculation of the network property of each e-health and an figure showing the words that often appear in consumer engagement e-health on Twitter. For each discussion, there is an explanation of the results of this research and the literature from them. This study closes with conclusions, some implications and contributions for e-health companies, and suggestions for future research. Figure 1 shows the concept of the research method.

Before collecting data, this research examines the phenomenon of the reality of e-health that occurs in society and how marketing results through customer engagement and determines the formulation of the problem. Besides that, this study found a gap in the literature which became the novelty of this study. Data collection uses a Jupyter Notebooks by crawling the data with a certain coding formula. Jupyter Notebooks is an application that can insert text as explanations and results for narrative processing (Rule et al., 2019). It is within the scope of consultation (”*konsultasi*”) based on related queries, medicine (”*obat*”) content, and payment (”*pembayaran*”). All keywords in data withdrawal use Indonesian.

The data preprocessing, namely data processing, before analyzing data by carrying out the stages of case folding, tokenizing, normalization, and filtering. The tools used in this stage are the snscrape libraries, notepad++, and wordij. The analytical tool for processing research data is Gephi 0.9.2 Software. It is an analysis tool in the form of open-source software or application for social network analysis by exploring and analyzing big data in social networks. Gephi connects social network data to map and understand communities and networks (Zhang & Lan, 2022).

Data Collection

Data collection originates from social media Twitter as a forum for social interaction between e-health users with a discussion of Halodoc and Alodokter with the scope of three contents ; consultation (”*konsultasi*”), medicine (”*obat*”), and payment (”*pembayaran*”). The scrapping tool uses a jupyter notebook with the python programming language. They retrieve tweets using Indonesian by formulating ”id” in the query. The results of pulling the tweet data are in CSV format to enter the next processing stage. The results of collecting tweet data as a source in this study are in table 1. The table shows that the number of uses of each e-health increased during the pandemic. Its means from the tweets originating from consumers who tell on

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Twitter. Whereas the three years before the pandemic was the beginning of the emergence of e-health, this gives an understanding that when building a business, the number of users is still small because the company's brand awareness is still relatively small. So companies need to provide knowledge and education on the use of e-health. A pandemic moment has made e-Health take advantage of this period by advertising digitally, providing programs related to the covid pandemic theme, and campaigning for its products through influencers on social media, especially Twitter (Daragmeh et al., 2021).

Data Preprocessing

They were preprocessing to remove noise in tweet data, such as emotional symbols, hashtags, abbreviations, and informal words that are difficult for computers to understand (Lieharyani & Ambarwati, 2022). There are four sequences in this stage - the first is case folding functions to change the letters to lowercase. Second, tokenizing truncates sentences sourced from case folding stages based on each constituent word and eliminates noise. Thirdly, normalization is carried out to avoid repetition and standardize the document. After normalization, the dataset saves in CSV form. Finally, filtering with notepad++ removes punctuation marks such as quotation marks and slashes so that they become original words.

Data Analysis And Visualization

Normalization results are processed using word to retrieve important information from the dataset for analysis. The last stage is the utilization of gephi to develop a social network obtained from the phrase bigram to analyze the relationship between its words. In this study, gephi analyzes the value of the structure of the network of properties formed and visualizes it (Lieharyani & Ambarwati, 2022).

Table 1
Tweet data collection results

Brand e-health	Focus	Year	Number of tweets
Halodoc	Consultation (*"Konsultasi"*)	2017-2019	1.568
		2020-2022	7.259
	Medicine (*"Obat"*)	2017-2019	716
		2020-2022	1.979
	Payment (*"Pembayaran"*)	2017-2019	199
		2020-2022	1.056
Alodokter	Consultation (*"Konsultasi"*)	2017-2019	330
		2020-2022	1.804
	Medicine (*"Obat"*)	2017-2019	307
		2020-2022	468
	Payment (*"Pembayaran"*)	2017-2019	23
		2020-2022	178

Source : Output Jupyter Notebook

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RESULTS AND DISCUSSION

Analysis and Result

This study contains data that compares the results of Halodoc's marketing strategy with Alodokter through interactions on Twitter in consulting, medicine, and payment content. Researchers made the comparison because there was a drastic change in user interaction before and during the pandemic. The collection of tweet data based on queries related to consultation, treatment, and payments at Halodoc and Alodokter is in the preprocessing stage.

At this stage, it calculates the total number of words from each tweet and the unique words, as shown in Table 2. The tweet data will form a visualization that connects words in the dataset, and each word is called a node or word phrase. The number of words is the number of words appearing in data retrieval from e-health consumers through customer engagement on Twitter. The unique word is a word that has undergone a filter that comes from many words, in which there is no repetition of words that appear from consumers. The number of words generated from Halodoc consumers is more than Alodokter. It can be seen from the average that Halodoc produces is larger. Alodokter must provide information on advertising products and partnerships with other digital companies (Aisyah et al., 2023). Each node is interbond or connected, called an edge, which is represented in the form of a graph in the form of vertices and represents a bidirectional interaction (Azad & Devi, 2021). The frequency of words or nodes attached to edges (interlocking nodes) is called degrees. Identify network engagement through an undirected graph (interlocking node), the frequency of bigram phrases with thematic word repetitions in different locations, such as A-B and B-A (Hou et al., 2019). Data processing forms a network with property values to make comparisons through ranking order between Halodoc and Alodokter. The results of the consulting property network are in table 3 during the pre-pandemic period.

Networks with more bindings per node lead to further and faster penetration (Muller & Peres, 2019). Halodoc has the most nodes and edges, meaning that Halodoc consultation deployment data is better, as evidenced by many Halodoc user interactions, than Alodokter. The average degree describes the ratio of the overall number of network ties to the sum of all possible bonds. The more connected the network, the higher the performance growth (Muller & Peres, 2019), The superior average degree is Halodoc. Then, the average weight degree shows the average number of link weights Halodoc is superior in this property. Network diameter symbolizes the mileage in the network Halodoc and Alodokter have the same long distance. The magnitude of the modularity value of Alodokter is better, which illustrates the strength of the group

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formed. Finally, the middle-length path that Halodoc has is better.

From table 3, it can be seen that the number of Halodoc consumers is greater than that of Alodokter. So the amount of Halodoc consumer information is greater, placing Halodoc in the first rank. The higher the number of degrees, diameters, and modularity, the amount of consumer information dissemination is large (Chandra & Henriette Pattyranie Tan, 2022).

Table 4 shows that Haodoc's drug, node, and edge content networks are more numerous and frequently discussed by Twitter users. Halodoc's average degree is most extensive, and Halodoc's drug content spreads faster. The best average weight degree is Halodoc, indicating a more robust Halodoc link weight. Halodoc and Alodokter's network diameter reaches the same number. The modularity of the Alodokter network indicates the formation of more solid groups. A minor average path is in Alodokter, where the average mileage is shorter and faster. Halodoc forms a superior consumer information network with lots of consumer information and many words through customer engagement. Halodoc consumers subscribe to medicine features more than medicine on Alodokter, even though both have the same network diameter (Mochammad Aldi Kushendriawan et al., 2021). It's just that the amount of information from Alodokter is smaller.

The payment content network can be seen in table 5, showing that most nodes and edges are in Halodoc. Halodoc's average degree is more extensive and faster in the distribution of information. The enormous average weight degree is on Halodoc, meaning it has the most average link weight. The network diameter of Alodokter is the smallest. Hence the information step time is faster. Halodoc's modularity is outstanding, indicating the more vital groups formed in the network. The small size of the average path of length belongs to Alodokter, with a faster average distribution time. From the network properties that formed payment content before the pandemic, it shows that Halodoc has a higher superiority than Alodokter. It is factored into the number of payment methods in each e-health. Halodoc has collaborated with digital payment providers and additional programs such as discounts and promos so that Halodoc's customer engagement value is higher than Alodokter. As for Alodokter, when he was building a brand, there needed to be more cooperation with influencers and digital advertising in social media so that consumers could become more familiar with it (Ningsih, 2020).

The property values in table 6 show that nodes and edges are more Halodoc and frequently discussed and interconnected, plus the pandemic. Halodoc's average degree is more extensive, meaning information dissemination is the fastest. Halodoc's most

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enormous average weight degree indicates that the weight of the links formed on the network is more robust than Alodokter's. Halodoc's shortest diameter network property has at least the time to disseminate information. The modularity that Alodokter showed was more significant, and the groups formed were densest. Halodoc's average path length is smaller, meaning that the average information dissemination is faster than Alodokter's. A pandemic has increased the amount of e-health consumption in society (Rahmawati et al., 2023). However, Halodoc remains superior in terms of marketing results. Because Halodoc already had high brand awareness before the pandemic, so with this momentum, Halodoc only needs to provide additional education to the public, plus a collaboration program with other platforms (Sutarsa et al., 2020).

The drug network in Table 7, where most of the nodes and edges are present in Halodoc, is based on many drug interactions. The average degree of Halodoc is most remarkable, so the distribution of drug contents is fast. The superior average weight level is on Halodoc, where Halodoc link weight is most robust. Halodoc has a network with a diameter, which means that the distribution of drug information on Halodoc is fast. Halodoc's more excellent modularity value means more solid group formation. The average path length is minor in Halodoc, where the average information travel distance is fast. In terms of drug network properties during a pandemic, Halodoc has the overall advantage. It was because of the marketing programs offered by Halodoc, such as drug delivery in collaboration with certain hospitals during the pandemic. Discounts on buying vitamins and supplements to prevent the covid-19 virus (Lenardi et al., 2020). Alodokter also carries out a marketing program for medicinal properties, and it's just that there must be more collaboration programs with other platforms or influencers.

The payment network in Table 8 shows the nodes and edges generated by Halodoc. The average degree is more comprehensive, meaning that the dissemination of information on payment content is fast. Its considerable average weight level has the most average (edge) link weight. At least the halodoc information step time or network diameter is short, and information dissemination related to Halodoc payments is fast. Alodokter's modularity is outstanding, indicating the strength of the groups formed in the payment network. The small average path length in Halodoc indicates a faster average spread time. In payment marketing content, Halodoc is superior to Alodokter. It was because Halodoc added many payment methods that are mutually bound, also holding discount and voucher programs with certain payments. When people need online health services, Halodoc and Alodokter offer e-

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health features. It's just that Halodoc's marketing program is more intense than Alodokter, causing the small value of Alodokter's customer engagement (Tarmidi et al., 2021).

Table 2
Tweet data retrieval results

Content focus	Year	Number of words	Unique word	Average
Halodoc Tweets				
Consultation (*"Konsultasi"*)	2017-2019	15.200	789	19,26
	2020-2022	74.146	2.593	28,59
Medicine (*"Obat"*)	2017-2019	7.753	555	13,97
	2020-2022	22.787	1.302	17,50
Payment (*"Pembayaran"*)	2017-2019	2.058	200	10,29
	2020-2022	11.442	704	16,25
Alodokter tweets				
Consultation (*"Konsultasi"*)	2017-2019	2.816	211	13,35
	2020-2022	20.303	1.101	18,44
Medicine (*"Obat"*)	2017-2019	1.303	116	11,23
	2020-2022	4.931	446	11,06
Payment (*"Pembayaran"*)	2017-2019	151	23	6,57
	2020-2022	1.550	173	8,96

Source : Output Jupyter Notebook

Table 3
Pre-pandemic Consultation ("Konsultasi") network properties

Network properties	Value of Consultation		Ranking
	Halodoc	Alodokter	
Node	111	62	1. Halodoc 2. Alodokter
Edge	652	200	1. Halodoc 2. Alodokter
Average degree	11,748	6,452	1. Halodoc 2. Alodokter
Average weight degree	194,901	65,226	1. Halodoc 2. Alodokter
Network diameter	4	4	-
Modularity	0,169	0,271	1. Alodokter 2. Halodoc
Average path length	1,999	2,249	1. Halodoc 2. Alodokter

Source : Output Jupyter Notebook

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Table 4
Pre-pandemic Medicine ("Obat") network properties

Network properties	Value of Medicine		Ranking
	Halodoc	Alodokter	
Node	92	48	1. Halodoc 2. Alodokter
Edge	399	115	1. Halodoc 2. Alodokter
Average degree	8,674	4,792	1. Halodoc 2. Alodokter
Average weight degree	86,739	39,125	1. Halodoc 2. Alodokter
Network diameter	5	5	-
Modularity	0,133	0,148	1. Alodokter 2. Halodoc
Average path length	2,188	2,089	1. Alodokter 2. Halodoc

Source: Output Jupyter Notebook

Table 5
Pre-pandemic Payment ("Pembayaran") network properties

Network properties	Value of Payment		Ranking
	Halodoc	Alodokter	
Nodes	76	23	1. Halodoc 2. Alodokter
Edges	191	11	1. Halodoc 2. Alodokter
Average degree	2,230	0,957	1. Halodoc 2. Alodokter
Average weight degree	35,158	4,957	1. Halodoc 2. Alodokter
Network diameter	7	3	1. Halodoc 2. Alodokter
Modularity	0,328	0,162	1. Alodokter 2. Halodoc
Average path length	2,855	1,636	1. Halodoc 2. Alodokter

Source: Output Jupyter Notebook

Table 6
Property Consultation ("Konsultasi") network during the pandemic

Network properties	Value of Consultation		Ranking
	Halodoc	Alodokter	
Nodes	155	105	1. Halodoc 2. Alodokter
Edges	2.224	717	1. Halodoc 2. Alodokter
Average degree	28,697	13,657	1. Halodoc 2. Alodokter
Average weight degree	632,632	212,895	1. Halodoc 2. Alodokter
Network diameter	2	3	1. Halodoc 2. Alodokter
Modularity	0,130	0,221	1. Alodokter 2. Halodoc
Average path length	1,814	1,974	1. Halodoc 2. Alodokter

Source: Output Jupyter Notebook

Table 7
Property Medicine ("Obat") network during the pandemic

Network properties	Value of Medicine		Ranking
	Halodoc	Alodokter	
Nodes	126	102	1. Halodoc 2. Alodokter
Edges	898	271	1. Halodoc 2. Alodokter
Average degree	14,254	5,314	1. Halodoc 2. Alodokter
Average weight degree	159,413	39,588	1. Halodoc 2. Alodokter
Network diameter	3	4	1. Halodoc 2. Alodokter
Modularity	0,219	0,206	1. Halodoc 2. Alodokter
Average path length	1,912	2,144	1. Halodoc 2. Alodokter

Source: Output Jupyter Notebook

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Table 8
Property Payment ("Pembayaran") network during the pandemic

Network properties	Value of Payment		Ranking
	Halodoc	Alodokter	
Nodes	105	42	1. Halodoc 2. Alodokter
Edges	544	90	1. Halodoc 2. Alodokter
Average degree	10,362	4,286	1. Halodoc 2. Alodokter
Average weight degree	126,571	24,619	1. Halodoc 2. Alodokter
Network diameter	5	8	1. Halodoc 2. Alodokter
Modularity	0,176	0,448	1. Alodokter 2. Halodoc
Average path length	2,069	2,908	1. Halodoc 2. Alodokter

Source: Output Jupyter Notebook

Visualization between node relationships in this network using ForceAtlas2. ForceAtlas2 is a layout algorithm that accelerates graphics to be force-oriented (Lieharyani & Ambarwati, 2022). The researcher chose it because of the use of indirect graphs. The results of network visualization related to Halodoc's e-health before the pandemic is in Figure 2 and figure 3. Visualization of Alodokter's network data before the pandemic through Figure 4 and Figure 5.

Figure 2 presents data visualization of content about consultation, medicine, and payment. In part of the consultation that users more frequently discuss the features and benefits received regarding doctor consultations, such as the emergence of "chat", "doctor", "psychology", "psychiatrist", and "specialist" nodes. Before the pandemic, consumers are more dominant in their psychological health talks. "Easy" and "helpful" nodes become supporters if consumers are receptive and enthusiastic about the performance provided by Halodoc. Part of the medicine's content is users discussing more satisfaction in purchasing drugs, such as "prescription", "delivered", "message", "direct", and "consultation." The emergence of supporting nodes such as "practical", "easy", and "helpful" indicates if the performance of online pharmacy features is acceptable to consumers. Furthermore, Halodoc customers are talking more about the payment experience, such as "gopay", "discount", "wallet", and "debit" when before the pandemic. The performance of payment services as a support for consultation features and online pharmacies. However, nodes such as "truncated", "failed", and "transaction" also

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appear if there are problems experienced related to the service.

The visualization results of Alodokter's network before the pandemic are in Figure 3, where the direction of customer conversations is more about the benefits provided, such as "chat", "doctor", "booking", "friendly", and "fast" at consulting content. Show if the Alodokter consultation feature based on performance is quite good because customers seem satisfied with the service, convenience features, and communicative doctor integration. As for the drug network, users on Twitter are still talking a little about drug content, but some users are talking about drugs with disease names such as "wounds", "tightness", and "eczema". Before the pandemic, the performance of the Alodokter online pharmacy feature needed improvement, and this was due to the need for more branding in the time bracket. In figure 3, Alodokter users talk less about payment content, but there is one talk related to payment: "gopay". That means Alodokter is only integrated with gopay e-wallets and still needs to complete payment features.

Figure 4 shows the consultation, medicine, and payment network generated by Halodoc during the pandemic. User discussions are more suggestive of pandemic disease conditions and Halodoc as a solution with the nodes "doctor", "chat", "fever", "flu", "help", "check", and "online", illustrating that customers are pretty satisfied with the performance of Halodoc during the pandemic. The results of the drug network show users sharing the experience of drug features with the emergence of "covid", "pharmacy", "prescription", "isoman", "delivered", and "vitamin" nodes. E-health help customer during the pandemic and even the number of users has increased drastically. Then there is support for payment services to make users share their transaction stories, such as the "gopay", "shopeepay", "discount", "cheap", and "balance" nodes. This node shows that if the more complete and easy payment becomes an attraction for customers, even payment methods with e-wallets get promos and discounts.

The visualized data from figure 5 shows that the discussion of features and benefits received (value) consultation related to the consultation is more dominant related to the pandemic, such as "doctor", "chat", "help", and "fast", which shows that during the pandemic, Alodokter contributed through the performance of digital health services. The Alodokter drug network in figure 5 discusses the experience of purchasing drugs accompanied by pandemic diagnoses as shown in the nodes "isoman", "cough", "delivery", prescription", and "covid". The nodes indicate that they use alodokter's online pharmacy feature to buy medications with symptoms of covid-19-related illnesses. Then, network with a discussion of Alodokter payments and is more focused on

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the completeness of payment methods like "gopay", "shopeepay", "cashback", and "savings". Unlike the pre-pandemic period, fewer networks formed than this time. So the complete payment will trigger the number of users and interactions.

Discussion

Halodoc and Alodokter applications integrate with official health professionals who provide online doctor consultation services. Based on the visualization of "consultation" content before and during the pandemic shows the intensity of related discussions, meaning that responses to consultation content often appear and relate. Of the two e-health, before the pandemic, more often appeared "psychologist" and "psychiatrist" nodes, meaning that consumers tended to take advantage of e-health for consultations with psychologists and psychiatrists in that year. So, research states that people feel great benefits regarding online consultations (e-health), especially mental health, through psychiatrists or psychologists (Alonso et al., 2019).

As for the visualization during a pandemic, the nodes "covid" and "symptoms" often appear, which means that many consumers take advantage of online consultations to check their health regarding the symptoms and treatment of Covid patients. Research states that e-health is one of the solutions used by people in several countries during the pandemic to fight Covid-19 (Alonso et al., 2021). Research that states that there is a feature to check or check the symptoms of contracting the coronavirus (Tebeje & Klein, 2021) is also a factor that e-health users utilize.

Digitalization is causing consumer demand to facilitate the purchase of drugs, both in terms of distance, speed, and completeness. Visualizations of "drug" content before and during the pandemic show the intensity of related discussions, meaning that responses to drug content often appear and relate.

Visualization with the appearance of "easy", "practical", and "sent" nodes means that users take advantage of the feature to buy drugs delivered with straightforward and practical reasons to the nearest location. A line that provides convenience and speed and determines the closest location to consumers will be a consumer strategy through user experience (Gucen & Hamzah, 2020). As for the visualization during a pandemic, the nodes "pandemic", "vitamins", and "covid" appear. That is that year consumers took advantage of buying medicines during the pandemic to buy vitamins as a form of prevention against the Covid-19 virus, which means e-health is one of the solutions people use during the pandemic (Bokolo, 2021).

Technology demands every start-up to be more efficient in payments. Halodoc and

Alodokter complete the payment needs because there are payments in various methods, both offline and online. Visualizations of "payment" content before and during the pandemic illustrate a response to emerging and related payment content but less consulting and drug content. For pre-pandemic visualizations, users take advantage of online payment features because they are easy, cheap, and discounted by digital wallet partners. Digital payments are more effective and efficient because there are rarely admin fees. However, there are cheaper than directly (Purba et al., 2021).

It is the same with visualization during the pandemic but with more user interaction. Like the previous year, users took advantage of the payment feature with easy excuses and promos from partners. During this period, there is further cooperation with shopeepay and an increasing number of e-health users because of the more complete payment partners. Cashless transactions through ease of use significantly influence people's consumption behaviour intentions (Daragmeh et al., 2021).

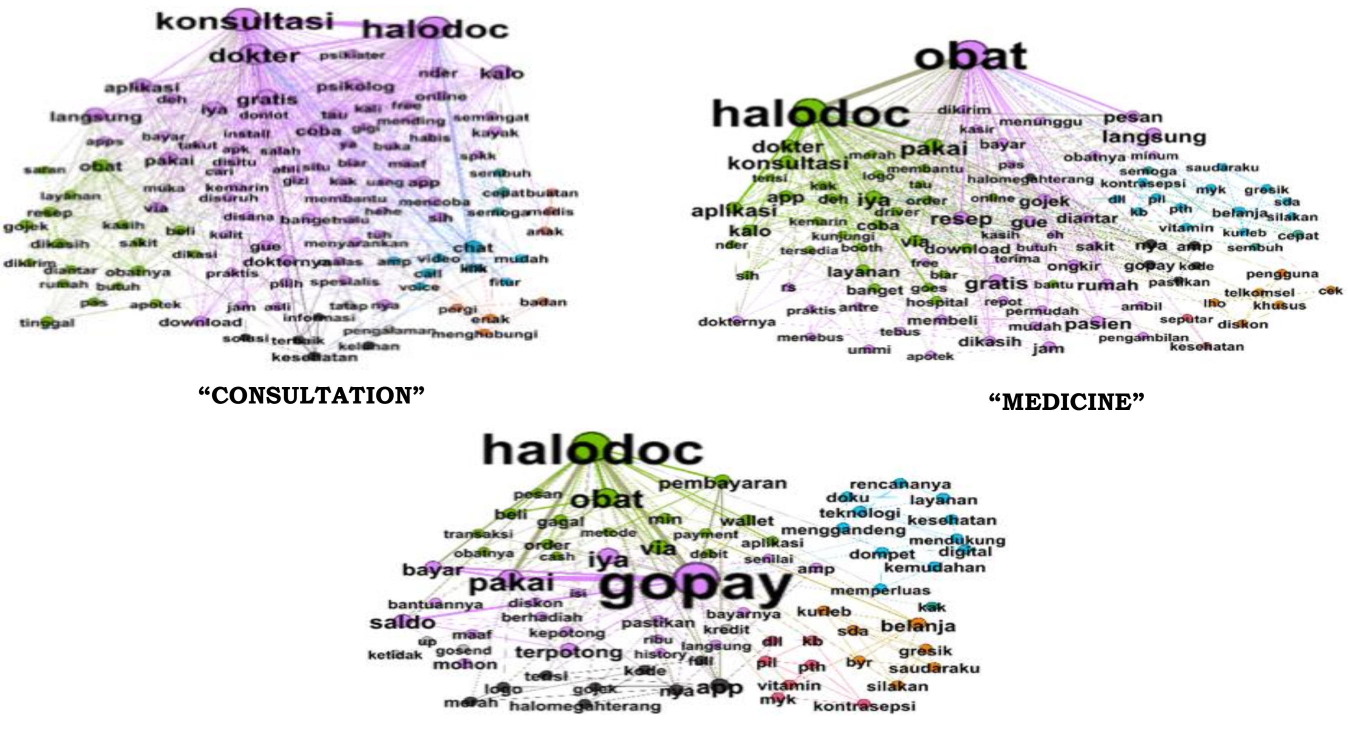

Figure 2. Visualization of Halodoc's network before the pandemic

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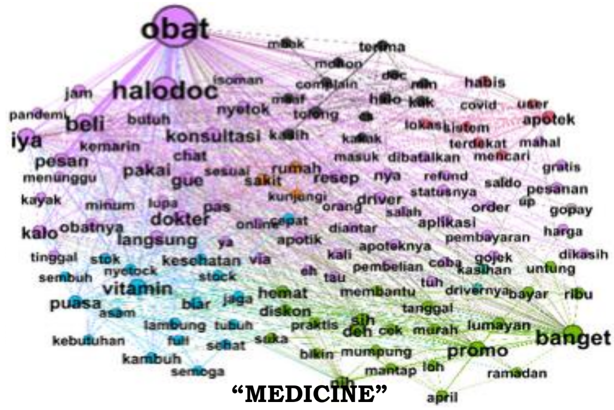
"CONSULTATION"

"MEDICINE"

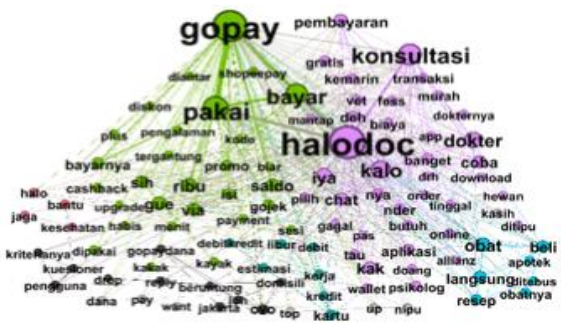
"PAYMENT"

Figure 3. Visualization of Alodokter's network before the pandemic

"CONSULTATION"



"MEDICINE"



"PAYMENT"

Figure 4. Visualization of Halodoc's network during the pandemic

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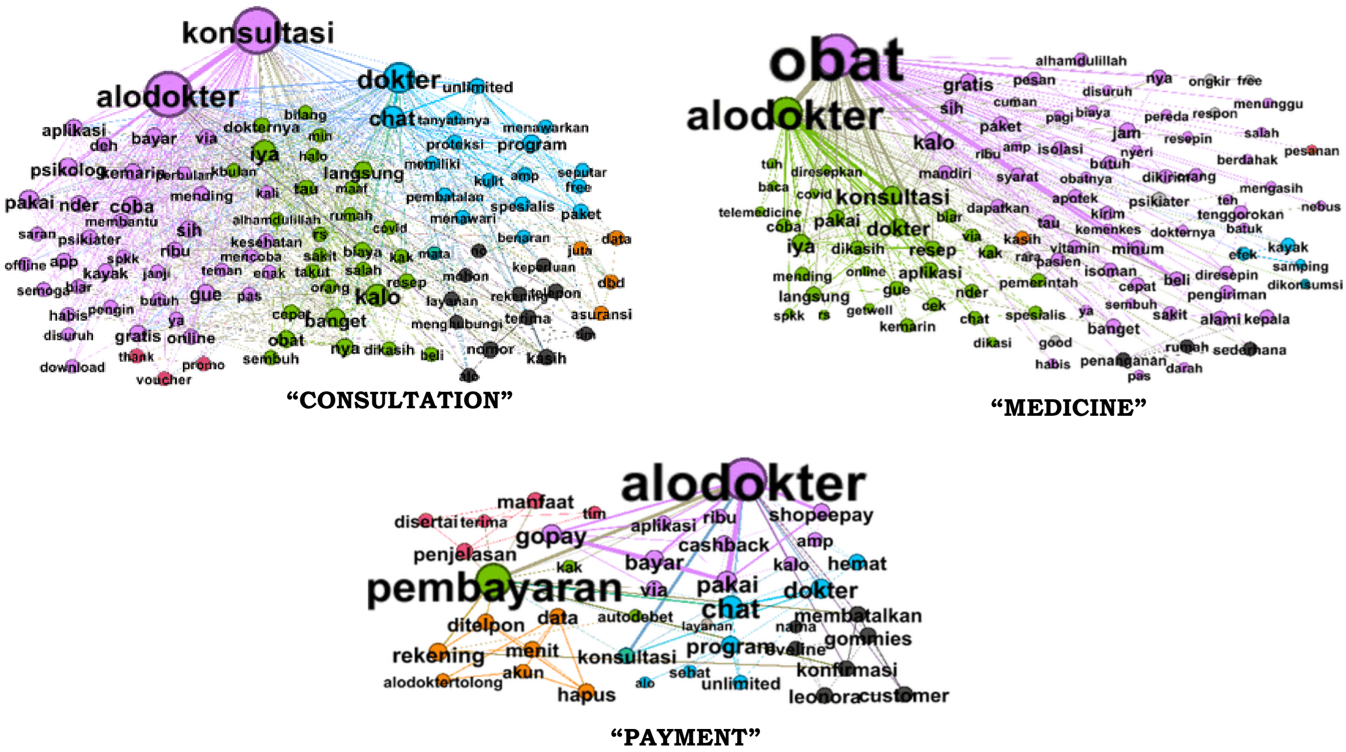

Figure 5. Visualization of Alodokter's network during the pandemic

CONCLUSION

Of the three focuses, there is a significant difference; the number of interactions during the pandemic has increased dramatically and has become necessary during the pandemic. Remote regulations have also been the trigger for the high number of e-health users. This is evidenced by the number of nodes and edges that have increased dramatically during the pandemic. Judging from the proportion of network properties, Halodoc is superior to Alodokter because the number of Halodoc nodes and edges is far more weighted, both from the focus of consulting, medicine, and payments. The collaboration between Halodoc and Gojek makes Halodoc more exist, especially promo hunters who tweet on Twitter. That is, the effect of collaboration can increase the number of subscribers.

However, this research has limitations related to data sources because of only user perceptions on Twitter media. Twitter is just one of the social media that people are interested in. So the researchers suggest other data sources. Then, further research can focus on sectors other than the health business, such as sports, games, public services, etc.

RESEARCH IMPLICATIONS

This research implies that the e-health start-up business industry needs to increase size through active users on Twitter and strengthen customer engagement for feature performance. So that it can be a strategy to develop and grow the e-health business through customer engagement, the existence of SNA analysis and its visualization can determine customer response so that companies can improve what they demand and get good feedback.

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REFERENCE

Abkenar, S. B., Kashani, M. H., Mahdipour, E., & Jameii, S. M. (2021). Big data analytics meets social media: A systematic review of techniques, open issues, and future directions. *Telematics and Informatics*, *57*, 101517.

Agnihotri, R. (2020). Social media, customer engagement, and sales organizations: A research agenda. *Industrial Marketing Management*, *90*(July), 291–299. https://doi.org/10.1016/j.indmarman.2020.07.017

Aisyah, P., Ika, N., & Wardhani, K. (2023). *(Studi Pada Pt . Victory International Futures Kota Optimizing the Benefits of Digital Marketing Using Tiktok Social Media At Pt . Victory (Study At Pt . Victory International Futures City)*. *3*(1), 5–10.

Alamsyah, A., & Utami, A. (2018). Social network performance analysis and content engagement on Indonesia's E-commerce: Case studies Tokopedia and Bukalapak. *2018 6th International Conference on Information and Communication Technology, ICoICT 2018*, *0*(c), 464–469. https://doi.org/10.1109/ICoICT.2018.8528729

Alonso, S. G., de la Torre Díez, I., & Zapiraín, B. G. (2019). Predictive, Personalized, Preventive and Participatory (4P) Medicine Applied to Telemedicine and eHealth in the Literature. *Journal of Medical Systems*, *43*(5). https://doi.org/10.1007/s10916-019-1279-4

Alonso, S. G., Marques, G., Barrachina, I., Garcia-Zapirain, B., Arambarri, J., Salvador, J. C., & de la Torre Díez, I. (2021). Telemedicine and e-Health research solutions in literature for combatting COVID-19: a systematic review. *Health and Technology*, *11*(2), 257–266. https://doi.org/10.1007/s12553-021-00529-7

Azad, S., & Devi, S. (2021). Tracking the spread of COVID-19 in India via social networks in the early phase of the pandemic. *Journal of Travel Medicine*, *27*(8), 1–9. https://doi.org/10.1093/JTM/TAAA130

Bokolo, A. J. (2021). Application of telemedicine and eHealth technology for clinical services in response to COVID- 19 pandemic. *Health and Technology*, *11*(2), 359–366. https://doi.org/10.1007/s12553-020-00516-4

Carvalho, R. C. de, & Medeiros, D. D. de. (2021). Assessing quality of air transport service: a comparative analysis of two evaluation models. *Current Issues in Tourism*, *24*(8), 1123–1138. https://doi.org/10.1080/13683500.2020.1765750

Chakraborty, I., Ilavarasan, P. V., & Edirippulige, S. (2021). Health-tech startups in healthcare service delivery: A scoping review. In *Social Science and Medicine* (Vol. 278). Elsevier Ltd. https://doi.org/10.1016/j.socscimed.2021.113949

Chandra, A., & Henriette Pattyranie Tan, P. (2022). Analysis of Factors Affecting E-Loyalty With E-Trust and E-Satisfaction as Mediation Variables on Halodoc Application Users in Indonesia. *Quantitative Economics and Management Studies*, *3*(6), 983–997. https://doi.org/10.35877/454ri.qems1272

Crico, C., Renzi, C., Graf, N., Buyx, A., Kondylakis, H., Koumakis, L., & Pravettoni, G. (2018). mHealth and telemedicine apps: in search of a common regulation. *Ecancermedicalscience*, *12*.

Danarahmanto, P. A., Primiana, I., Azis, Y., & Kaltum, U. (2020). The sustainable performance of the digital start-up company based on customer participation, innovation, and business model. *Business: Theory and Practice*, *21*(1), 115–124. https://doi.org/10.3846/btp.2020.11053

Daragmeh, A., Lentner, C., & Sági, J. (2021). FinTech payments in the era of COVID-19: Factors influencing behavioral intentions of “Generation X” in Hungary to use mobile payment. *Journal of Behavioral and Experimental Finance*, *32*, 100574. https://doi.org/10.1016/j.jbef.2021.100574

E-commerce, S. M. B. (2018). *Social network analysis untuk analisa interaksi user dimedia sosial mengenai bisnis e-commerce*. *2*(2), 107–115.

Fayjaloun, R., Gehl, P., Auclair, S., Boulahya, F., Guérin-Marthe, S., & Roullé, A. (2021). Integrating strong-motion recordings and twitter data for a rapid shakemap of macroseismic intensity. *International Journal of Disaster Risk Reduction*, *52*, 101927. https://doi.org/10.1016/j.ijdrr.2020.101927

Gucen, M. R., & Hamzah, H. (2020). Verbal Representation Analysis of Meaning in Gojek and Grab TV Commercials. *English Language and Literature*, *9*(2), 349. https://doi.org/10.24036/ell.v9i3.113897

Hou, Z., Cui, F., Meng, Y., Lian, T., & Yu, C. (2019). Opinion mining from online travel reviews: A comparative analysis of Chinese major OTAs using semantic association analysis. *Tourism Management*, *74*(March), 276–289. https://doi.org/10.1016/j.tourman.2019.03.009

Indriyarti, E. R., & Wibowo, S. (2020). Bisnis Kesehatan Berbasis Digital: Intensi Pengguna Aplikasi Digital Halodoc. *Jurnal Pengabdian Dan Kewirausahaan*, *4*(2).

Kalumata, E. M., Waleleng, G. J., & Kalangi, J. S. (2021). Pengaruh Penggunaan Aplikasi Halodoc Terhadap Pemenuhan Kebutuhan Informasi Kesehatan Di Kelurahan Paniki Bawah Kecamatan Mapanget Kota Manado. *Acta Diurna Komunikasi*, *3*(4).

Lenardi, C., Studi, P., Komunikasi, I., Ilmu, F., & Fish, H. (2020). *REPRESENTASI NILAI PERSATUAN DALAM IKLAN # DIRUMAHAJA HALODOC : KAJIAN DIMENSI KULTURAL Unity Value Representation in Halodoc ' s Ad # diRumahAja : A Cultural Dimension Study*. *1*(September), 71–84.

Lieharyani, D. C. U., & Ambarwati, R. (2022). Visualisasi Data Tweet di Sektor Pendidikan Tinggi Pada Saat Masa Pandemi. *Building of Informatics …*, *4*(1), 116–123. https://doi.org/10.47065/bits.v4i1.1551

Maeder, A., Bidargaddi, N., & Williams, P. (2020). Contextualising Digital Health Contributions to Fighting the COVID-19 Pandemic. *Journal of the International Society for Telemedicine and EHealth*, *8*, 1–5. https://doi.org/10.29086/jisfteh.8.e3

Mai, M., Leung, C. K., Choi, J. M. C., & Kwan, L. K. R. (2020). Big Data Analytics of Twitter Data and Its Application for Physician Assistants: Who Is Talking About Your Profession in Twitter? *Studies in Big Data*, *65*, 17–32. https://doi.org/10.1007/978-3-030-32587-9_2

Mitei, E., & Ghanem, T. (2020). Leveraging Social Network Analysis to Explore Obesity Talks on Twitter. *Proceedings - 2020 IEEE International Conference on Big Data, Big Data 2020*, 3563–3572. https://doi.org/10.1109/BigData50022.2020.9377798

Mochammad Aldi Kushendriawan, Harry Budi Santoso, Panca O. Hadi Putra, & Martin Schrepp. (2021). Evaluating User Experience of a Mobile Health Application 'Halodoc' using User Experience Questionnaire and Usability Testing. *Jurnal Sistem Informasi*, *17*(1), 58–71. https://doi.org/10.21609/jsi.v17i1.1063

Mukherjee, K., & Banerjee, N. (2019). Social networking sites and customers' attitude towards advertisements. *Journal of Research in Interactive Marketing*, *13*(4), 477–491. https://doi.org/10.1108/JRIM-06-2018-008

Muller, E., & Peres, R. (2019). The effect of social networks structure on innovation performance: A review and directions for research. *International Journal of Research in Marketing*, *36*(1), 3–19. https://doi.org/10.1016/j.ijresmar.2018.05.003

Ningsih, D. R. (2020). Peran Financial Technology (Fintech) Dalam Membantu Perkembangan Wirausaha UMKM. *Prosiding Seminar Nasional Program Pascasarjana Universitas PGRI Palembang*.

Prabowo, N. (2021). Social Network Analysis for User Interaction Analysis on Social Media Regarding E-Commerce Business. *IJIIS: International Journal of Informatics and Information Systems*, *4*(2), 95–102. https://doi.org/10.47738/ijiis.v4i2.106

Purba, J. T., Samuel, S., & Budiono, S. (2021). Collaboration of digital payment usage decision in COVID-19 pandemic situation: Evidence from Indonesia. *International Journal of Data and Network Science*, *5*(4), 557–568. https://doi.org/10.5267/j.ijdns.2021.8.012

Rahmawati, W., Putri, W. F., Azhari, D. W., Asbari, M., Novitasari, D., Widodo, A., & Wiyono, N. (2023). Penerapan Aplikasi e-Health sebagai Media Online Konsultasi Kesehatan di Masa Pandemi Covid-19. *Journal of Community Service and Engagement*, *3*(2), 1–7.

Rule, A., Birmingham, A., Zuniga, C., Altintas, I., Huang, S. C., Knight, R., Moshiri, N., Nguyen, M. H., Rosenthal, S. B., Pérez, F., & Rose, P. W. (2019). Ten simple rules for writing and sharing computational analyses in Jupyter Notebooks. *PLoS Computational Biology*, *15*(7), 1–8. https://doi.org/10.1371/journal.pcbi.1007007

Saura, J. R., Reyes-Menéndez, A., Dematos, N., & Correia, M. B. (2021). Identifying startups business opportunities from ugc on twitter chatting: An exploratory analysis. *Journal of Theoretical and Applied Electronic Commerce Research*, *16*(6), 1929–1944. https://doi.org/10.3390/jtaer16060108

Srinanda, D., Sisilia, K., & Perangingangin, Y. (2020). Analisis Promosi Penjualan Gopay Dengan Menggunakan Social Network Analysis Di Media Sosial Twitter. *Journal Of Applied*

P-ISSN : 2354-8592
E-ISSN : 2621-5055

Business Administration, *4*(2), 163–170.

Surahman, M., Widiyasono, N., & Gunawan, R. (2021). Analisis Usability Dan User Experience Aplikasi Konsultasi Kesehetan Online Menggunakan System Usability Scale Dan User Experience Questionnaire. *Jurnal Siliwangi Seri Sains Dan Teknologi*, *7*(1).

Sutarsa, N., Astuti, P. A. S., Choy, M., & Moore, M. (2020). COVID-19 Pandemic: Opportunity to Accelerate e-Health in Indonesia. *Public Health and Preventive Medicine Archive*, *8*(1), 1–3. https://doi.org/10.15562/phpma.v8i1.259

Suzuki, T., Hotta, J., Kuwabara, T., Yamashina, H., Ishikawa, T., Tani, Y., & Ogasawara, K. (2020). Possibility of introducing telemedicine services in Asian and African countries. *Health Policy and Technology*, *9*(1), 13–22. https://doi.org/10.1016/j.hlpt.2020.01.006

Tarmidi, D., Mardhatillah, S., Masripah, F., Febriyanto, D., & Pribadi, T. A. (2021). The Influence Of Product Innovation And Price On Customer Satisfaction In Halodoc Health Application Services During Covid-19 (Survey Of Halodoc App Users In Bandung In 2021). *Turkish Journal of Computer and Mathematics Education*, *12*(11), 1084–1091.

Tebeje, T. H., & Klein, J. (2021). Applications of e-Health to Support Person-Centered Health Care at the Time of COVID-19 Pandemic. *Telemedicine and E-Health*, *27*(2), 150–158. https://doi.org/10.1089/tmj.2020.0201

Zhang, M., & Lan, B. (2022). Detect Megaregional Communities Using Network Science Analytics. *Urban Science*, *6*(1), 12. https://doi.org/10.3390/urbansci6010012