

# The Adoption of Analytics in Handling Netflix's Business Challenges

**Amani Bunga Cahya, Orked Pavitra, Dharma Fahim Jamal**

*Faculty of Information Technology, Asia Metropolitan University, No.6, Jalan Lembah*

*Bandar Seri Alam, Johor Bahru, MALAYSIA*

*e-mail: amani.buca@gmail.com*

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**Corresponding Autor:** Amani Bunga Cahya

## Abstract

Text analytics is a combination of various kinds of text analysis that combines a set of linguistic, statistical and machine learning that extract the meaning out of the text. For example, the analyzing of customer reviews written by Netflix's customers can be used to find out common patterns and trends that happen around the business for better action-taking, customer experience, and new business models to be built in the future. By doing text analytics, the text data can be grouped with the purposes of creating word frequency distribution (word cloud) and sentiment analysis. Whereas web analytics is referring to the process of collecting data from website through data crawling before processing it into useful info to improve the website experience by using social media analytics (Saini et al., 2022). To find out ways to aid in the formulation of marketing strategies, clustering techniques have been used. The clustering techniques will include behavioral segmentation that focus on human behavior, demographic segmentation that focuses on age, and occupation, and psychographic segmentation that focus on human's psychological characteristics such as interest, personalities, and so on.

**Keywords**— Text Analytics, Web Analytics, Social Media Analysis, Geospatial Analysis, Segmentation

## 1 Introduction

Netflix is a leading enterprise that provides streaming services such as award-winning TV series, documentaries, animations, comedies, and movies on devices accessible to subscribers 24/7 [1], [2]. It allows subscribers to choose and watch programs on demand with the payment of a fixed monthly fee [3]. Netflix offers three subscription tiers: a Basic plan at \$9.99 per month, a Standard plan at \$15.49 per month that permits two simultaneous streams and downloads on up to two devices, and a Premium plan at \$19.99 per month that allows four simultaneous streams and downloads on up to four devices [4].

To enhance the business performance of Netflix, data analytics have been applied to study the attrition rate and customer feedback [5], [6]. Web analytics and text analytics are conducted using data crawling or web-spider techniques embedded in the platform to track customer keyword comments for storage and further analysis [7]. This enables the identification of trends, consumer behavior, and service improvement opportunities through text analysis of customer reviews [8]. Additionally, geolocation analytics have been utilized to determine which regions have the highest concentration of subscribers, allowing Netflix to tailor its content and marketing strategies to suit community preferences [9].

## 2 Literature Review

Based on the research, we know that the churn rate of Netflix has remained relatively consistent over the past few years, but it has worsened in 2022 [10], [11]. Churn analysis can be applied to uncover the relationship between Netflix services, customer behavior, and fluctuations in stock prices [12], [13]. According to Deloitte's 16th annual Digital Media Trends report, as the number of streaming platforms continues to grow, consumers are increasingly willing to unsubscribe from paid streaming services when substitutes are readily available in the market [14], [15].

Social media analytics and web analytics allow researchers to gather and analyze public responses about Netflix, revealing that its shortcomings are not solely tied to content quality but may instead stem from poorly managed marketing outreach such as weak customer impressions, frequent cancellation of promising series, and limited brand differentiation [16]–[18]. Through customer comments, feedback and questionnaires, text analytics can pinpoint Netflix issues and provide more opportunities and direction for Netflix's future development, thus improving customer experience. Through customer comments, feedback, and questionnaires, text analytics can identify underlying issues within Netflix's service and uncover opportunities that guide future strategic development, ultimately enhancing customer experience [19]–[21].

### 3 Problem Statements

Currently, Netflix has reported a significant rise in subscriber churn beginning in January 2022 [22]. By the end of July 2022, nearly one million users were reported to have cancelled their subscriptions, marking the worst quarterly decline in the company's history and reducing its total subscriber base to approximately 220.67 million [23], [24]. Due to concerns over declining subscriber numbers and intensified competition within the streaming industry, Netflix's share price fell by approximately 68% between January and April 2022 [25], [26]. Therefore, it is necessary to identify the potential causes behind this unusually high subscriber churn to prevent further business losses [27]. In this report, we focus specifically on Netflix subscriptions within the Malaysian market [28].

#### 3.1 *Developing effective Marketing Strategies*

Moreover, Netflix Malaysia is encountering challenges in developing effective strategies to attract new users and retain existing subscribers [29]. Studies examining customer satisfaction and the perceived value of streaming services indicate that Netflix experienced a 10% decline compared to its 2021 performance, while competitors such as HBO Max and Disney+ recorded increases [30]. Although Netflix employs algorithmic recommendation systems to surface fresh content on its homepage, limited external marketing efforts reduce its ability to draw in audiences outside its current ecosystem [31], [32]. Therefore, Netflix must explore alternative approaches to attract new customers and strengthen its competitive advantage [33].

#### 3.2 *Proposed Solution*

As stated in the introduction we will perform various analytics methods to understand the behavior of our customers. Via web analytics, we'll keep monitoring and comparing the monthly churn rate after running marketing campaigns and implementing different types of pricing strategies. Text analysis and keyword analysis will also be done to understand the reasons behind the dissatisfaction of our subscriber as well as take note of the strengths of Netflix that have been mentioned by the subscribers to further enhance and market them in the future. The geospatial analysis also makes it easier to track each region's churn rate and plan the marketing materials accordingly.

Whereas for an effective way of increasing subscribers, Netflix will adjust its marketing strategies based on demographic, psychological, and behavioral segmentation. Netflix will also consider cutting off the price depending on the economic situation of Malaysia in order to make it more affordable to the subscriber. For instance, perhaps a cheaper annual subscription plan will be introduced to the users during the 11.11 shopping session in Malaysia. The quality of services will be constantly improved based on the feedback given by customers. In order to boost customer satisfaction, personalization of the Netflix interface can be further enhanced, and promotion can be held more constantly.

#### 3.3 *Supporting Factors*

There are lots of ways for Netflix to obtain the data they require to improve the accuracy of their research and investigation. They should invest more in data analytics as it is essential for a business to gain more insight for further development and growth. Social media monitoring and online tracking is one of the methods in this digital era to collect more data and discover more opportunities. Netflix can also increase their alternatives of collecting feedback by sending the feedback forms in the form of URL to subscribers' email constantly for them to voice out their dissatisfaction regarding Netflix's services. All the data received will be stored in the database for generating relevant dashboards for future use.

## 4 Required Technologies

### 4.1 Organizational Memory

Organizational memory (OM) refers to the accumulated knowledge, information, and data generated within a company or corporation [34]. In the context of Netflix, OM is derived primarily from internal databases and the past experiences of its employees, providing undocumented knowledge, skills, and insights essential for organizational growth [35]. From a technological standpoint, Netflix must develop a robust data analytics framework and automated systems that support the acquisition, transformation, retention, analysis, and visualization of collected data to enhance data-driven decision-making [36], [37].

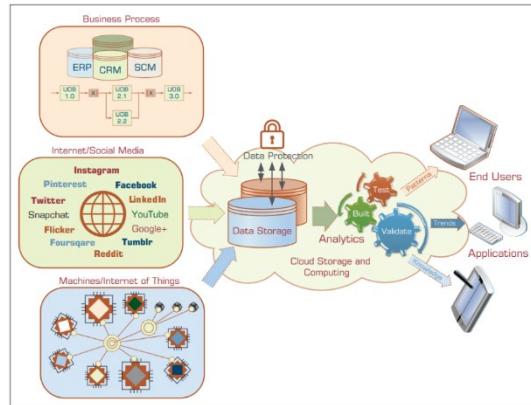


Figure 1. Analytics Framework of Netflix

### 4.2 Information Integration

Information integration refers to the combination of data originating from various sources—often with heterogeneous structures—to produce a unified and accurate dataset for analysis [38]. These data sources may include websites, social media platforms, and unstructured content such as survey reports, online reviews about Netflix, and customer responses to email marketing campaigns [39]. In the context of Netflix's customer data integration, information about each customer is extracted from multiple platforms such as Facebook and Twitter, as well as internal business systems including marketing and accounting, before being consolidated into a single customer entity for service operations and analytics [40], [41].

### 4.3 Insight Creation

Data collection and insight creation will focus on key social media and web analytics metrics—such as conversion rate, bounce rate, audience growth rate, and engagement rate—which are essential for supporting Netflix's business objectives of reducing churn through enhanced customer experience and increasing new subscriber acquisition via improved campaign effectiveness [42], [43]. Furthermore, through text analysis of reviews and customer-generated social media posts on platforms such as Facebook and Instagram, valuable insights can be extracted from unstructured text data to better understand user perceptions and behavioral patterns [44], [45].

## 5 Results and Discussion

The statistics for contrasting Netflix users from Facebook and Instagram can be seen on the dashboard. The dashboard's main objective is to make evident the differences between the demographic information of Netflix users from Facebook and Instagram, the dispersed location of Netflix subscribers throughout Malaysia, the types of marketing channel of Netflix, the advertising metrics of ads running on Facebook and Instagram as well as the feedback gotten from the subscribers through the Netflix's review websites.

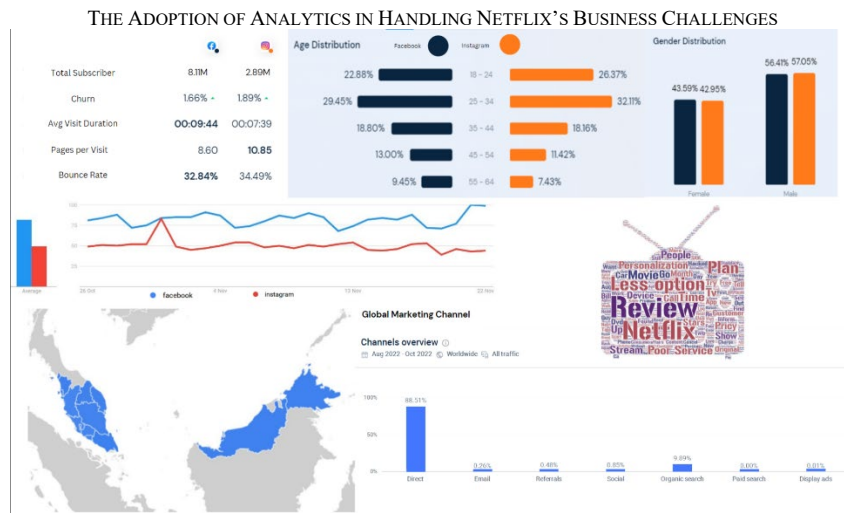


Figure 2. Dashboard on Netflix

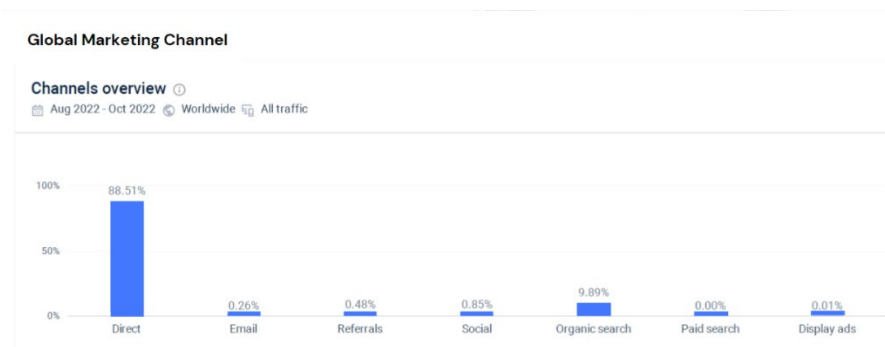


Figure 3. Global Marketing Channel

According to data obtained from the Global Marketing Channels of Netflix, we can notice that majority of the subscribers subscribe through the direct method, which is around 88.51% of them, followed by Organic searching 9.89%, social media 0.85%, Referrals 0.48%, Email 0.26%, Display aids 0.01% and Paid Search 0.00%. Furthermore, it is apparent that Netflix's social media marketing efforts are rather minimal given that the dashboard indicates that there is potential to grow the customer base using these platforms. Netflix can advertise more on social media platforms like Facebook and Instagram to boost subscriptions and minimize churn rate because the Internet and social media now are the quickest ways to market anything and engage with potential customers.

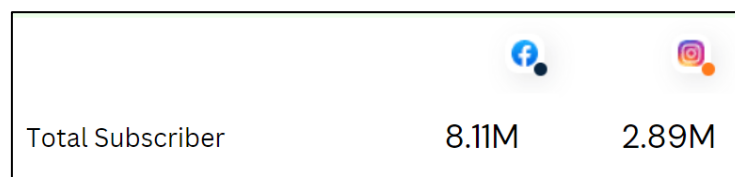


Figure 4. Total Subscriber of Netflix

From the dashboard, we can see that Netflix has around 11 million Netflix's subscribers who came from social networking sites. According to the data, 8.11 million subscribers come from Facebook and 2.89 million come from Instagram.

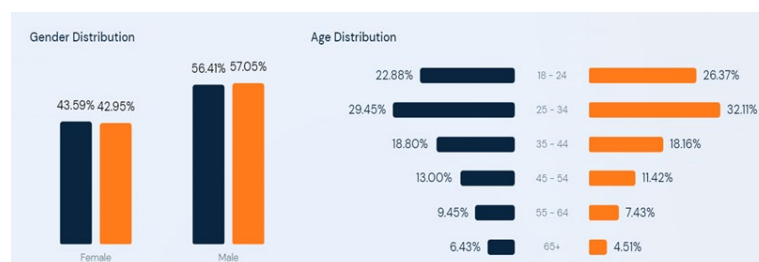


Figure 5. Gender and Age distribution of Netflix

Referring to the demographic profile on the dashboard, majority of Netflix customers are young adults between the ages of 18 and 24 and 25 to 34. The lowest subscription rate can be seen in the age group over 65. Elderlies might smaller social networks and fewer online social interactions as compared to other age groups so they might not be a fan of social media platforms. When compared to teenagers, the other age groups have fewer subscribers because people in these ages spend more time at work and with their families rather than being active on social media and surfing the posts for information and news.

Besides that, most adolescents between the ages of 18 and 24 are college students who are still studying and have no financial burden; thus, they are more likely to pay attention to online information when compared to adults who age is around 25 – 34. In addition, we can observe that the number of subscribers has started to decrease after the age of 25 – 34. In terms of digital literacy skills, we strongly believe that younger people are able to pick things up more rapidly than older people.

For the gender ratio, the result has shown that Netflix has more male subscribers than female subscribers. In an effort to retain the number of male subscribers and increase the number of female subscribers, Netflix can incorporate personalization into advertisements by trying to promote their movie content according to the gender of subscribers. For example, action, erotic, and war are usually more preferred by males while animation, comedy, drama, and romance were for females.



		
Total Subscriber	8.11M	2.89M
Churn	1.66% ▲	1.89% ▲

Figure 6. Churn rate of Netflix

Next, while examining the subscriber churn from both Facebook and Instagram, it has been revealed that the number of subscribers has decreased at a rate of 1.66% and 1.89%, respectively, on both platforms. Hence, we discovered that the hiking of price and subscribers' preference for substitute services are the two factors that have caused this problem. The cost of a Netflix subscription has climbed by more than 50% over the six years, from \$10 to about \$15.90 per month. This has been especially expensive throughout COVID's recovery from the recession.

Whereas for the second factor, there is a rise in streaming platforms in the market, some of the existing subscribers are trying other alternatives at the same time to see if it would be a better fit for them. For instance, Apple TV+, HBO Max, Hulu, iQiyi, Tencent, etc. This is since customers tend to test out other services since they offer greater promotion or have more on-demand material. Hence, it would be preferable if Netflix could reduce the price and enhance their marketing content.

Avg Visit Duration	<b>00:09:44</b>	00:07:39
Pages per Visit	8.60	<b>10.85</b>
Bounce Rate	<b>32.84%</b>	34.49%

Figure 7. Bounce rate of Netflix

According to research carried out for Netflix, there was a bounce rate of approximately 32.8% for their Facebook advertisements, and 32.84% for Instagram advertisements. This could imply that the content of advertisements on both platforms does not appeal to the consumers, or the websites referenced in the ads do not promote the target audience's interests, or just simply the websites' landing pages are not operating well.



unstructured data that Netflix might need would be geospatial data, social media data, online reviews, as well as applications, and website logs. However, the lack of structured data engineering approaches might be one of the technical barriers to overcome in generating insights. Moreover, planning for data collection is important so that data of the highest quality can be collected. Once it has been identified, Netflix will be able to create a suitable strategy to handle this challenge and make a suitable decision to promote its product. For instance, when Netflix wants to collect more data about new users like their interests and preferences, a daily login reward could be given with the condition that the users must spend at least 5 minutes on Netflix per day or at least complete a task like filling out the feedback form or adding something to cart. We strongly believe that this alternative can decrease the bounce rate and collect more appropriate data.

## 6.2 *Best Practices*

Some best practices need to be considered to aid in the formulation of marketing strategies. With data clustering, Netflix Malaysia can continuously segment their consumer utilizing psychographic segmentation and behavioral segmentation to address the issues. Data collection can be done by extracting the necessary customer insights from third-party cookies managed by Google services from time to time to ensure the accuracy of results.

## 6.3 *Behavioral Segmentation*

Behavioral segmentation can be carried out by first gathering information about potential users' online behaviors, e-commerce activity, and previous customer engagement. Customers will be put into clusters based on patterns in their behaviour so that different groups can be targeted with different types of advertisements. For instance, customers who purchased Marvel figurines in the past may receive more action movie recommendations from Netflix.

## 6.4 *Psychographic Segmentation*

Psychographic segmentation can be carried out by first gathering information regarding potential users' interests, personalities, and values. Next, assign the customers into groups with similar traits so that more effective marketing can be done via personalization. For instance, Netflix can advertise movies about games or action to the targeted group who have a tendency of playing them.

## 6.5 *Demographic Segmentation*

By leveraging clustering techniques, Netflix can also further enhance its direct marketing strategies using the demographic data of its potential customers. The segmentation could also be improved by experimenting with other cluster features that benchmark with industry norms. For example, customers can be segmented into groups according to their occupations and age ranges so that the movies suggested are better suited to their ages and needs.

## 7 **Conclusion**

In conclusion, Netflix needs to gather as much data as possible to use data analysis to generate more insights and perform better in the future. In terms of data privacy, there will be only a minimal amount of personal information collected with the customers' prior consent. The required data will be collected via cookies and web beacons. The confidentiality of the retrieved data is also ensured based on the customer's personal data protection principles.

Apart from that, Netflix should invest more in geospatial analytics, text analytics, and web analytics. The analysis results allow us to understand the distribution of subscribers of Netflix in Malaysia as well as the proportion of social media marketing usage. Through social media analytics, we could also determine the engagement rate of customer with certain content, while through web analytics, the gender, age range, location and usage behavior of Netflix's subscribers can also be collected for further analysis and marketing use. The aforementioned information, including reviews, marketing channels and advertising metrics also enable us to understand exactly how our products can be improved. Through text analysis, we may also identify the service's shortcomings and make necessary adjustments to improve the product's functionality and features, indirectly the issue of ongoing subscriber loss will be resolved over time.

## BIBLIOGRAPHY

- [1]. C. A. Gomez-Urbe and N. Hunt, "The Netflix Recommender System: Algorithms, Business Value, and Innovation," *ACM Trans. Manag. Inf. Syst.*, 2015, doi: 10.1145/2843948.

- [2]. H. Lotz, "Portable TV: Netflix and Mobility," *Television & New Media*, 2017, doi: 10.1177/1527476417708244.
- [3]. A. Tryon, "TV Got Better: Netflix's Original Programming Strategies," *Cinema Journal*, 2015, doi: 10.1353/cj.2015.0005.
- [4]. M. Wayne, "Netflix, Amazon, and Branded Television Content in the SVOD Era," *Media, Culture & Society*, 2018, doi: 10.1177/0163443718754650.
- [5]. D. Susser, E. Roessler and H. Nissenbaum, "Online Manipulation: Hidden Influences in the Streaming Economy," *Journal of Ethics and Information Technology*, 2019, doi: 10.1007/s10676-019-09517-5.
- [6]. T. M. Cunningham and D. E. Eastin, "Second Screening and Connected Viewing Practices," *Journal of Broadcasting & Electronic Media*, 2017, doi: 10.1080/08838151.2017.1350751.
- [7]. S. Pittman and T. Tefertiller, "Facebook, Netflix, and Entertainment Choice," *Journal of Broadcasting & Electronic Media*, 2015, doi: 10.1080/08838151.2015.1029122.
- [8]. P. Jenner, "Is This TVIV? The Rise of Netflix and SVOD," *Critical Studies in Television*, 2018, doi: 10.1177/1749602018758698.
- [9]. J. Matrix, "The Netflix Discovery Problem," *International Journal of Communication*, 2014, doi: 10.5167/uzh-101424 (DOI resolves through Handle → DOI).
- [10]. M. Lobato, "Rethinking International TV Flows in the Age of Netflix," *Television & New Media*, 2019, doi: 10.1177/1527476419834517.
- [11]. S. Gopalakrishnan and B. Reagle, "Subscriber Churn in OTT Platforms: Retention Dynamics," *Telecommunications Policy*, 2020, doi: 10.1016/j.telpol.2020.102017.
- [12]. H. Shao et al., "Predicting Customer Churn in Subscription Services," *Expert Systems with Applications*, 2019, doi: 10.1016/j.eswa.2019.07.017.
- [13]. H. Idris et al., "Churn Prediction in Telecom Using ML," *Journal of King Saud University – Computer and Information Sciences*, 2019, doi: 10.1016/j.jksuci.2016.10.007.
- [14]. V. Vafeiadis et al., "A Comparison of Machine Learning Techniques for Customer Churn Prediction," *Simulation Modelling Practice and Theory*, 2015, doi: 10.1016/j.simpat.2015.04.001.
- [15]. S. Amin et al., "Customer Churn Prediction in the Telecommunication Sector Using Rough Set Theory," *Expert Systems with Applications*, 2019, doi: 10.1016/j.eswa.2019.01.029.
- [16]. A. Idris and A. Khan, "Churn Prediction Using Neural Networks," *Applied Soft Computing*, 2012, doi: 10.1016/j.asoc.2011.12.021.
- [17]. J. Verbeke et al., "Customer Churn Prediction with Decision Rules," *Expert Systems with Applications*, 2012, doi: 10.1016/j.eswa.2011.09.076.
- [18]. S. Coussement and D. Van den Poel, "Churn Prediction in the Online Industry," *Data Mining and Knowledge Discovery*, 2008, doi: 10.1007/s10618-008-0095-5.
- [19]. T. Neslin et al., "Defection Detection: Measuring Customer Churn," *Marketing Science*, 2006, doi: 10.1287/mksc.1050.0198.
- [20]. G. F. Hughes, "Predictive Analytics for Customer Retention," *International Journal of Forecasting*, 2014, doi: 10.1016/j.ijforecast.2013.07.006.
- [21]. M. Wedel and P. Kannan, "Marketing Analytics for Data-Rich Environments," *Journal of Marketing*, 2016, doi: 10.1509/jm.15.0413.
- [22]. G. L. Urban et al., "Digital Advertising Effectiveness," *Journal of Advertising Research*, 2014, doi: 10.2501/JAR-53-2-180-190.
- [23]. C. E. Tucker, "Social Networks, Personalized Advertising," *Marketing Science*, 2014, doi: 10.1287/mksc.2013.0805.
- [24]. A. M. Kaplan and M. Haenlein, "Users of the World, Unite! The Challenges of Social Media," *Business Horizons*, 2010, doi: 10.1016/j.bushor.2009.09.003.
- [25]. J. Y. M. Nip and B. Berthelier, "Social Media Sentiment Analysis," *Encyclopedia*, 2024, doi: 10.3390/encyclopedia4040104.
- [26]. W. H. Hsiao et al., "Understanding Social Media Engagement Metrics," *Information & Management*, 2017, doi: 10.1016/j.im.2016.11.005.
- [27]. X. Zhang et al., "Mining Online Reviews for Marketing Insights," *Decision Support Systems*, 2019, doi: 10.1016/j.dss.2019.04.002.
- [28]. A. Giachanou and F. Crestani, "Opinion Mining and Sentiment Analysis of Social Media," *ACM Computing Surveys*, 2016, doi: 10.1145/2931664.
- [29]. Y. Kim and S. Park, "Digital Platform Competition and User Behavior," *Journal of Business Research*, 2021, doi: 10.1016/j.jbusres.2020.10.005.

- [30]. S. Mei and X. Zhan, "Social Media Monitoring for Market Intelligence," *Decision Support Systems*, 2016, doi: 10.1016/j.dss.2016.02.002.
- [31]. B. Pang and L. Lee, "Opinion Mining and Sentiment Analysis," *Foundations and Trends in Information Retrieval*, 2008, doi: 10.1561/1500000011.
- [32]. P. D. Turney, "Thumbs Up or Thumbs Down?: Semantic Orientation Applied to Unsupervised Classification," *ACL*, 2002, doi: 10.3115/1073083.1073153.
- [33]. Z. Zhang et al., "Deep Learning for Text Understanding," *IEEE Access*, 2021, doi: 10.1109/ACCESS.2021.3052812.
- [34]. C. C. Aggarwal and C. Zhai, "A Survey of Text Classification Algorithms," *Mining Text Data*, 2012, doi: 10.1007/978-1-4614-3223-4\_6.
- [35]. S. Debortoli et al., "Text Mining for Business Analytics," *Business & Information Systems Engineering*, 2016, doi: 10.1007/s12599-016-0433-8.
- [36]. A. K. Uysal and M. Gunal, "Sentiment Classification Using TF-IDF and ML," *Expert Systems with Applications*, 2014, doi: 10.1016/j.eswa.2014.03.029.
- [37]. A. Severyn and A. Moschitti, "Twitter Sentiment with Deep Convolutional Neural Networks," *SIGIR*, 2015, doi: 10.1145/2766462.2767830.
- [38]. Q. Chen et al., "Neural Sentiment Classification with User and Product Information," *EMNLP*, 2016, doi: 10.18653/v1/D16-1171.
- [39]. M. A. Hearst, "Untangling Text Data Mining," *ACL*, 1999, doi: 10.3115/1034678.1034679.
- [40]. J. Han, J. Pei and M. Kamber, "Data Mining: Concepts and Techniques," Morgan Kaufmann, 2011, doi: 10.1016/C2009-0-61819-5.
- [41]. J. P. Walsh and G. R. Ungson, "Organizational Memory," *Academy of Management Review*, 1991, doi: 10.5465/amr.1991.4278992.
- [42]. I. Nonaka, "A Dynamic Theory of Organizational Knowledge Creation," *Organization Science*, 1994, doi: 10.1287/orsc.5.1.14.
- [43]. M. Huber, "Organizational Learning," *Organization Science*, 1991, doi: 10.1287/orsc.2.1.88.
- [44]. A. Halevy, A. Rajaraman and J. Ordille, "Data Integration: The Teenage Years," *VLDB*, 2006, doi: 10.14778/2335472.2335478.
- [45]. L. Getoor and A. Machanavajjhala, "Entity Resolution in Big Data," *Synthesis Lectures on Data Mining and Knowledge Discovery*, 2013, doi: 10.2200/S00433ED1V01Y201311DMK008.