Applying Opinion Mining and Social Volume Analysis for Enhanced Visitor Relationship Management in A Museum: An Empirical Study

I-Hsien Ting[1] [0000−0002−6587−2438], Mei-Yun Hsu[2] [0000−0002−4496−953X], Chia-Sung Yen[3] [0000−0002−9021−9940], and Chian-Hsueng Chao[1] [2222−−3333−4444−5555]

[1] National University of Kaohsiung, Kaohsiung City, Taiwan iting@nuk.edu.tw
[2] National Museum of Taiwan History, Tainan City, Taiwan myhsu@nmth.gov.tw
[3] National Chinyi University of Technology, Taichung City, Taiwan csyen@ncut.edu.tw

Abstract. The management of museums is gradually shifting towards data-driven and digital governance approaches to enhance visitor relationship management and improve both operational efficiency and user experience. An essential part of effective visitor relationship management is the analysis of visitor data. In addition to data from physical visits to exhibitions, such as visitor numbers and survey responses, online discussions by visitors are increasingly valued.
This study conducts empirical research using opinion mining and sentiment analysis techniques to analyze online discussions about museums. After analyzing the data from April to June 2023, which includes discussions from 1,058 websites and 133,963 forum posts, the study offers recommendations for the future management of museums. The analyses include trend analysis of discussion volume, sentiment analysis, media analysis of discussion volume, and content keyword analysis.

Keywords: Visitor Relationship Management · Museum · Social Volume · Opinion Mining

1 Introduction

Opinion mining, social volume analysis, and public opinion analysis are becoming increasingly popular and are being applied across various fields. Opinion mining, also known as sentiment analysis, involves extracting and analyzing sentiments expressed in text to understand public attitudes and emotions. This technique is widely used in marketing, customer service, and political analysis to gauge public sentiment towards products, services, or political events [12].

Social volume analysis, on the other hand, measures the amount of content and interactions on social media platforms. By tracking the frequency of posts, comments, likes, and shares, organizations can assess the level of engagement and interest in specific topics or campaigns. This analysis helps businesses understand the reach and impact of their social media efforts and identify trending topics within their industry. Together, these techniques provide a comprehensive understanding of public sentiment and engagement, enabling organizations to make data-driven decisions and enhance their communication strategies [4]. As technology continues to advance, the integration and application of opinion mining, social volume analysis, and public opinion analysis are expected to grow, offering even deeper insights into the dynamics of public discourse [20].

Museums are increasingly recognizing the importance of opinion mining, public opinion analysis, and social volume monitoring. By leveraging these techniques, museums can gain valuable insights into visitor experiences, preferences, and overall sentiment towards their exhibits and services. Opinion mining, or sentiment analysis, allows museums to analyze feedback from visitors, whether it's through reviews, social media posts, or survey responses. This helps museums understand what aspects of their offerings are well-received and which areas may need improvement.

A recent empirical study conducted by the National Museum of Taiwan History serves as a prime example of how museums can utilize opinion mining, public opinion analysis, and social volume monitoring to better understand and engage with their visitors. In this study, the museum employed sentiment analysis to process and analyze thousands of online reviews, social media posts, and survey responses. By doing so, they were able to identify prevalent sentiments and key themes related to visitors' experiences.

Through public opinion analysis, the museum examined the broader perceptions of its exhibitions and programs. This analysis revealed valuable insights into how different demographic groups, such as local residents and international tourists, viewed the museum's offerings. For instance, the study found that while local visitors appreciated the historical accuracy and cultural relevance of the exhibits, international visitors were particularly impressed by the interactive and immersive displays.

Social volume monitoring played a crucial role in assessing the museum's digital outreach efforts. By tracking the frequency and context of social media interactions, the museum could measure the effectiveness of its online campaigns and identify which exhibits generated the most buzz. For example, a significant increase in social media activity was observed during the launch of a new exhibition on Taiwan's indigenous cultures, indicating high public interest and engagement.

These analytical techniques not only helped the National Museum of Taiwan History understand visitor preferences and sentiments but also guided strategic decisions for future exhibitions and marketing initiatives. By leveraging data-driven insights, the museum was able to enhance the visitor experience, improve educational outcomes, and increase overall attendance. This study underscores the potential of modern analytical tools in transforming how museums connect with and serve their audiences.

The remainder of this paper is structured as follows: Section 2 provides a comprehensive literature review on social volume, opinion mining, social network analysis, and visitor relationship management. This section delves into the existing research and theoretical frameworks that underpin these fields, highlighting key findings and methodologies. Section 3 details the data sources and analytical methods used in this study, explaining the selection criteria for data collection and the specific techniques employed for analysis. Section 4 presents the empirical study conducted, with a focus on the National Museum of Taiwan History. This section illustrates how the museum applied these analytical tools to gain insights into visitor experiences and improve engagement strategies. Finally, Section 5 offers the conclusions drawn from the research, discussing the implications for future studies and suggesting potential areas for further investigation. This comprehensive approach ensures a thorough understanding of the subject matter and demonstrates the practical applications of these advanced analytical techniques in a museum context.

2 Literature Review and Related Works

2.1 Social Networks Analysis

The study of social network analysis has a rich history. As early as 1925, Lewin pioneered the interpretation of interactions among individuals using basic graphs of nodes and edges. In 1994, Wasserman and Faust laid the groundwork for the formal definition of social network analysis, viewing it as a sociological method. They suggested that social network analysis involves examining patterns of relationships and interactions among social actors to identify underlying social structures [25]. Consequently, numerous terminologies and concepts related to social network analysis have been established and are now widely applied in fields such as sociology, management, business, biology, and information science [11, **?**].

There are two influential books, "Social Network Analysis: A Handbook" and "Social Network Analysis: Methods and Applications," [18, **?**] offer thorough introductions to the essential concepts and techniques of social networks and their analysis. They cover definitions of different roles within social networks, as well as the definitions and calculations of relationships (such as centrality, closeness, betweenness, network clusters, network diameter, etc.). Additionally, these works discuss the positioning of nodes and structural holes within social network structures [2, **?**]. The well-established terminologies, methods, and metrics in social network analysis provided by these books form a robust foundation for researchers entering this field.

In the field of social network analysis within information science, the emphasis is on processing large volumes of data quickly and efficiently, while building on the foundations of traditional sociological approaches [26]. Two prevalent methods are the ego-centric and whole-network approaches. Currently, research in information technology for social network analysis prioritizes not only the comprehensive analysis of data-rich social networks but also the application of existing IT and data analysis techniques to this domain [15, **?**,**?**]. Techniques such as HITS (Hypertext Induced Topic Selection), the Semantic Web, and PageRank are notable examples. Matsuo and colleagues employed integrated techniques for analyzing web data and links [5, ?], including user interaction analysis, user description analysis, and web mining, to construct social networks [14].

In social network analysis and construction, data mining and web mining techniques are frequently used for data analysis and processing, leading to a close relationship between data mining and social network analysis [1]. Web mining is divided into three types based on the data it processes: web content mining, web usage mining, and web structure mining. In the analysis of online social networks, a key task is the classification or clustering of messages, where web content mining helps identify user preferences for certain messages. Web usage mining can convert usage patterns into relational data for building social networks [13]. Regarding the overall network structure, web structure mining can evaluate path lengths, reachability, and identify structural holes within the network.

2.2 Opinion Mining and Social Volume

With the rapid development of social networks and related discussion websites, a vast amount of user opinions and discussions have accumulated online. Scholars and experts in the field of information science and other related fields have recognized the value of this data. However, due to the large volume of data, extracting user opinions from the internet in an automated manner has become a hot research topic in recent years. Opinion mining, often referred to as Sentiment Analysis, is a significant application in the fields of Text Mining and Natural Language Processing (NLP) [9].

Unlike traditional topic detection, opinion mining does not focus on specific topics and keywords but rather on the expression of sentiments such as good and bad, beautiful and ugly, happy and angry. These sentiments are analyzed through adjectives with emotional connotations in text mining. Therefore, the primary task of sentiment analysis is to extract information with emotional significance from texts, converting unstructured documents into structured formats that are easier for computers to recognize and process. This process further classifies the sentiment as positive, negative, or neutral [24] , or even into more nuanced multi-scale sentiment classifications [16]. Besides the mentioned scale-based sentiments, some literature also views sentiments as continuous ranges to assess the degree of emotion in documents [19] [23].

In the field of opinion mining, there are two primary methods for extracting sentiment information from documents: corpus-based and thesaurus-based approaches [17]. Current research indicates that thesaurus-based methods can provide more precise sentiment polarity judgments for keywords, making it the mainstream approach in sentiment analysis. Generally, opinion mining consists of four steps: extracting attribute words, extracting opinion words, determining the polarity of opinions, and associating opinion words with attribute words. Following these steps allows for the analysis and judgment of opinions and sentiments in documents [10].

Social volume is considered as one application of opinion mining. Social volume refers to the cumulative amount of content generated and shared across social media platforms and online communities. This includes posts, comments, likes, shares, and other interactions that occur within digital networks. Social volume is a key indicator of the level of engagement and activity within a given topic, brand, or event. It provides valuable insights into public opinion, trends, and the overall impact of social media campaigns. By analyzing social volume, researchers and marketers can gauge the reach and influence of their content, identify emerging trends, and understand the sentiment and behavior of their audience. This metric is crucial for strategic planning, real-time decision-making, and measuring the effectiveness of online initiatives [21].

2.3 Visitors Relationship Management

In [8], the authors propose an innovative concept known as Visitor Relationship Management (VRM), which is an extension of Customer Relationship Management (CRM) theory. This research introduces a comprehensive model that integrates VRM with Knowledge Management (KM). The theoretical framework of this model is depicted in Figure 1.

In this model, the central focus is on the visitors, emphasizing three core components of visitor relationship management: marketing, services, and content. The process begins with knowledge acquisition, where relevant information is gathered to support visitor relationship management. The next step is knowledge storage, which involves systematically organizing the acquired knowledge within a knowledge base. This stored knowledge is then distributed, ensuring it is effectively shared and accessible. The final step focuses on the practical application of this knowledge, enabling museums to enhance their management of visitor relationships. This structured approach ensures that the information is not only collected and stored efficiently but also utilized effectively to improve visitor engagement and satisfaction, thereby fostering a more dynamic and interactive museum experience.

3 Data Sources and Analyses

In the empirical study, data are gathered from a diverse array of sources. These sources are categorized into five main groups: Comments, Social Websites, Discussion Boards, News, and Blogs. The Comments category includes feedback from platforms such as Google Maps, various mobile apps, and podcasts. Social Websites encompass major platforms like Facebook, Instagram, and YouTube. The Discussion Boards category features popular forums like Ptt, Dcard, and Mobile01. Additionally, the News category covers numerous news websites, while Blogs include a wide range of individual and group blog sites. Altogether, the dataset encompasses approximately 1056 websites and 133,963 channels.

In the empirical study, three keywords have been established: "Taiwan History Museum," "Taiwan History," and "Museum." Various analyses have been conducted, including "Volume," "Media," "Activities," and "Sentiment Analysis."

"Volume" refers to the frequency with which the set keywords are discussed. "Media" indicates the sources from which this volume is derived. "Activity" measures the exposure rate, specifically the ratio of social media (S) mentions to news (N) mentions (S/N).

In the sentiment analysis, natural language processing is utilized to evaluate the sentiment of the volume. This analysis categorizes the mentions into three sentiment types: "Positive," "Negative," and "Neutral."

The comprehensive analysis provides insights into the public's engagement and perception of the keywords across various media platforms. By examining the volume, the study identifies the prominence and reach of the keywords. The media analysis reveals the distribution of discussions across different platforms, highlighting where the most engagement occurs. Activity analysis helps in understanding the relative influence and spread of information on social media compared to traditional news outlets. Sentiment analysis, through natural language processing, further enhances the understanding by categorizing the emotional tone of the discussions, thereby identifying the overall public sentiment towards the keywords. This multifaceted approach enables a thorough understanding of the public discourse surrounding "Taiwan History Museum," "Taiwan History," and "Museum."

4 The Empirical Study

In the empirical study, data were collected over a three-month period, from April 1, 2023, to June 30, 2023. During this timeframe, extensive data were gathered from various sources to ensure a comprehensive analysis. The collection period was strategically chosen to capture a diverse range of interactions and discussions relevant to the study's focus.

4.1 Social Volume

The social volume of the three keywords is detailed in Table 1. The social volume for "Taiwan History Museum" is 1,769, representing 0.3% of the total volume. For "Taiwan History," the social volume is 335,728, accounting for 66.63% of the total. Finally, the social volume for "Museum" is 170,453, which constitutes 32.92% of the total.

These figures highlight the relative prominence and public interest in each keyword during the data collection period. The significant disparity in volume indicates a much higher level of discussion and engagement surrounding "Taiwan History" compared to "Taiwan History Museum" and "Museum." This suggests that the broader topic of Taiwan's history resonates more with the public compared to the more specific focus on museums or a particular museum.

Understanding these volumes is crucial for analyzing the reach and impact of each keyword within the social discourse. The high volume for "Taiwan History" can be indicative of a strong public interest or ongoing discussions about historical events, cultural heritage, or educational content related to Taiwan's history. Meanwhile, the lower volumes for "Taiwan History Museum" and "Museum" might reflect more specialized or niche conversations. This distribution of social volume provides valuable context for interpreting the results of the study's sentiment analysis and other metrics.

Table 1. The table of social vloume of the three keywords

	Social Volume	Percentage
Taiwan History Museum	1769	0.3%
Taiwan History	335,728	66.1%
Museum	170,453	33.6%

4.2 The Source Media of Social Volume

Table 2. The Source Media of Social Volume

	News	Social	Board	Comment	Blogs
THM	618	1061	60	1	29
TH	115,197	200,991	13,839	153	5,548
Museum	36,805	119,440	7,073	2,623	4,512
Total	152,620	321,492	20,972	2,777	10,089

From the table 2, it can be seen that the sources of volume for each topic are primarily social websites, followed by news, discussion forums, blogs, and comments. Overall, social websites account for approximately 321,492 instances of volume, making up about 63%. News accounts for 152,620 instances of volume, representing 30%.

Regarding this distribution, news media still holds a significant position. It seems to confirm that while social media continues to expand, the volume of news media remains substantial and noteworthy. This trend indicates that despite the rapid growth and dominance of social platforms, traditional news media continues to be a crucial source of information and discussion. The consistent presence of news media volume highlights its ongoing relevance and influence in shaping public discourse, even as social media platforms increasingly become the primary venues for public interaction and engagement. This dual presence of both social and news media underscores the multifaceted nature of modern information consumption and dissemination.

4.3 Activity

From Figure 3, we can see that the activity level of social media volume is highest for "Museum" at 4.5, while it is lowest for "Taiwan History Museum" at 1.97.

The disparity in these proportions is more than twofold. This indicates that the Taiwan History Museum could focus on improving its social media engagement to reduce reliance on general news exposure.

Table 3. The Activity of the three keywords

	Social	SRatio	News	NRatio	S/N
THM	1,769	66.31%	596	33.69%	1.97
TH	240,715	71.46%	96,133	28.54%	2.5
Museum	140,063	81.82%	31,123	18.18%	4.5
Total	382,547	74.95%	127,852	25.05%	2.99

This significant difference suggests that the Taiwan History Museum has considerable room for growth in its social media presence. By enhancing its social media strategies, the museum can increase its visibility and engagement with the public. This could involve creating more interactive and engaging content, leveraging popular social media platforms, and actively participating in relevant online discussions. Improving social media engagement not only helps in reaching a wider audience but also in building a more connected and engaged community. Furthermore, a stronger social media presence can complement traditional news coverage, providing a balanced approach to public outreach. This dual strategy can help the Taiwan History Museum become more prominent in both the digital and traditional media landscapes.

4.4 Sentiment Analysis

From table 4 and figure 4, we can clearly see the sentiment volume for each topic:

The sentiment volume for both "Taiwan History Museum" and "Museum" is predominantly positive, with P/N (Positive/Negative) values greater than 2. The P/N value for "Taiwan History Museum" even surpassed 3, while the P/N value for "Museum" slightly decreased.

The proportion of significant sentiment volume, from most to least, is in the order of "Taiwan History," "Museum," and "Taiwan History Museum", accounting for approximately 45%, 35%, and 31, respectively.

Table 4. The Activity of the three keywords

	P	PRatio	N	NRatio	Ne	P/N
THM	426	24.08%	115	6.5%	1,228	3.7
TH	55,104	16.41%	95,366	28.41%	185,258	0.58
Museum	40,866	23.97%	18,646	10.94%	110,941	2.19
Total	96,396	18.98%	114,127	22.47%	297,427	0.85

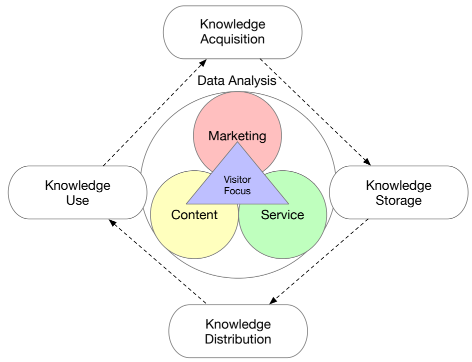

Fig. 1. A combined model with knowledge management and visitor relationship management. [8]

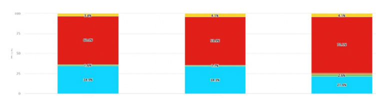

Fig. 2. The Source Media of Social Volume

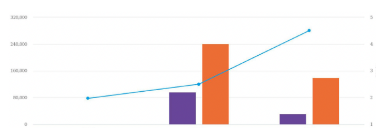

Fig. 3. The Histogram of The Activity of the three keywords

Fig. 4. The Histogram of Sentiment Analysis

This analysis highlights the overall positive reception of museums and the Taiwan History Museum, suggesting successful engagement and public relations efforts. The increased P/N value for the Taiwan History Museum in Q2 is a particularly encouraging sign, indicating improved public perception and sentiment. Conversely, the lower P/N value for "Taiwan History" suggests a growing amount of negative sentiment, which could be due to ongoing debates or controversies surrounding historical topics.

The distribution of sentiment volumes emphasizes the importance of continuing to foster positive interactions and addressing any negative perceptions proactively. For the Taiwan History Museum, this could involve creating more educational and engaging content to further enhance its positive image. Meanwhile, addressing the concerns contributing to the negative sentiment around "Taiwan History" could help balance public perception and improve overall sentiment.

5 Conclusion

This study provides a comprehensive analysis of online discussions surrounding "Taiwan History Museum," "Taiwan History," and "Museum" from April 1, 2023, to June 30, 2023. By employing opinion mining and sentiment analysis techniques, we have been able to capture and understand the volume, media sources, activities, and sentiment of public discourse related to these topics. The results show that while "Taiwan History" garners the highest social volume, it also attracts a significant amount of negative sentiment. Conversely, "Taiwan History Museum" and "Museum" generally receive positive sentiment, though their social media activity levels differ markedly.

Based on the findings, the Taiwan History Museum should focus on enhancing its social media engagement to bridge the activity gap with general "Museum" discussions. Developing more engaging and interactive content, such as virtual tours, live Q&A sessions, and user-generated content campaigns, can boost social media presence. Collaborating with social media influencers and partnering with other cultural institutions can expand reach and visibility. Actively monitoring social media channels for feedback and promptly responding can improve public perception and foster a positive community around the museum.

Future research should explore the following areas to build on the current study's insights. 1) Conducting a longitudinal study over a more extended period can help identify long-term trends and seasonal variations in public sentiment and engagement. 2) Analyzing sentiment and engagement across different demographic segments, such as age, gender, and geographic location, can provide more targeted insights for improving visitor relationship management. 3) Comparing the sentiment and engagement metrics of the Taiwan History Museum with other similar institutions globally can highlight best practices and areas for improvement. 4) Assessing the impact of specific marketing and outreach campaigns on public sentiment and engagement can offer actionable insights for future strategies.

By addressing these areas, future research can further enhance the understanding and management of public engagement and sentiment in the context of cultural and historical institutions.

References

1. Agrawal, R., Rajagopalan, S., Srikant, R., & Xu, Y. (2003). Mining Newsgroups Using Networks Arising From Social Behavior. World Wide Web 2003 Conference, 529–535.
2. Burt, S. P. (1992). Structural Holes. Harvard University Press.
3. Cai, M., Luo, H., Meng, X., & Cui, Y. (2022a). Differences in Behavioral Characteristics and Diffusion Mechanisms: A Comparative Analysis Based on Social Bots and Human Users. Frontiers in Physics, 10. https://doi.org/10.3389/fphy.2022.875574
4. Chao, C. H., Ting, I. H., Tsai, T. H. and Chen, M. C. "Opinion Mining and the Visualization of Stock Selection in Quantitative Trading," 2019 International Conference on Technologies and Applications of Artificial Intelligence (TAAI), Kaohsiung, Taiwan, 2019, pp. 1-6, doi: 10.1109/TAAI48200.2019.8959875.
5. Dingt, C. H., Zha, H., Husbands, P., & Simont, H. D. (2004). Link Analysis: Hubs and Authorities on the World Wide Web. SIAM Review, 46(2), 256–268.
6. Godbole, N., Srinivasaiah, M., & Skiena, S. (2007). Large-Scale Sentiment Analysis for News and Blogs. Proceedings of ICWSM 2007.
7. Goodreau, S. M. (2007). Advances in exponential random graph (p *) models applied to a large social network. Sociological Methodology, 29(39), 231–248. https://doi.org/10.1016/j.socnet.2006.08.001
8. Hsu, MY., Ting, IH. (2023). Applying a Combination Model of Knowledge Management and Visitor Relationship Management in the Study of the Visitors of Historical Museum. In: Uden, L., Ting, IH. (eds) Knowledge Management in Organisations. KMO 2023. Communications in Computer and Information Science, vol 1825. Springer, Cham. https://doi.org/10.1007/978-3-031-34045-1_23Hsu, MY., Ting, IH. (2023). Applying a Combination Model of Knowledge Management and Visitor Relationship Management in the Study of the Visitors of Historical Museum. In: Uden, L., Ting, IH. (eds) Knowledge Management in Organisations. KMO 2023. Communications in Computer and Information Science, vol 1825. Springer, Cham. https://doi.org/10.1007/978-3-031-34045-1_23
9. Hu, M., & Liu, B. (2004). Mining and Summarizing Customer Reviews. In KDD 2004 (pp. 168–177). Seattle, Washington, USA.
10. Jakob, N., & Gurevych, I. (2010). Using Anaphora Resolution to Improve Opinion Target Identification in Movie Reviews. In Proceedings of the 2010 ACL Conference (pp. 263–268). Uppsala, Sweden.
11. June, T., Kim, J., Kim, B. J., & Choi, M. Y. (2006). Consumer Referral in A Small World Network. Social Networks, 28(3), 232–246.
12. Kumaresan, A., Liberona, D. (2018). A Case Study on Challenges and Obstacles in Transforming to a Data-Driven Business Model in a Financial Organisation. In: Uden, L., Hadzima, B., Ting, IH. (eds) Knowledge Management in Organizations. KMO 2018. Communications in Computer and Information Science, vol 877. Springer, Cham. https://doi.org/10.1007/978-3-319-95204-8_23
13. Lento, T., Welser, H. T., Gu, L., & Marc, S. (2006). The Ties that Blog: Examining the Relationship Between Social Ties and Continued Participation in the Wallop Weblogging System. Proceedings of the 15th International World Wide Web Conference, 23.

14. Matsuo, Y., Mori, J., & Hamasaki, M. (2006). POLYPHONET: An Advanced Social Network Extraction System from the Web. Proceedings of 2006 International World Wide Web Conference.
15. Mika, P. (2005). Flink: Semantic Web Technology for the Extraction and Analysis of Social Networks. Web Semantics, 3(2–3), 211–223.
16. Pang, B., Lee, L., & Vaithyanathan, S. (2002). Thumbs up?: sentiment classification using machine learning techniques. In Proceedings of the ACL-02 conference on Empirical methods in natural language processing - Volume 10 (pp. 79–86). Stroudsburg, PA, USA.
17. Rao, D., & Ravichandran, D. (2009). Semi-supervised Polarity Lexicon Induction. In Proceedings of the 12th Conference of the European Chapter of the Association for Computational Linguistics (pp. 675–682). Stroudsburg, PA, USA.
18. Scott, J. (2000). Social Network Analysis: A Handbook. SAGE Publication.
19. Thelwall, M., Buckley, K., Paltoglou, G., Cai, D., & Kappas, A. (2010). Sentiment strength detection in short informal text. Journal of the American Society for Information Science and Technology, 61(12), 2544–2558.
20. Ting, I. H. Special Issue: Applications and Management Aspects of Social Networks Research. Rev Socionetwork Strat 16, 571–572 (2022). https://doi.org/10.1007/s12626-022-00130-y
21. I-Hsien Ting and Hao-Ting Kao (2017) “Spatial Analysis of Social Volume of Crime Issues Based on Social Media Data”, In Proceedings of MISNC 2017, Bangkok, Thailand, July 17-19, 2017
22. Ting, I. H., Zhang, Z. and Wang, L. S. L. 2016. A Study of The Effect of Spiral of Silence between Different Social Networking Platforms. In Proceedings of the The 3rd Multidisciplinary International Social Networks Conference on SocialInformatics 2016, Data Science 2016 (MISNC, SI, DS 2016). Association for Computing Machinery, New York, NY, USA, Article 55, 1–5. https://doi.org/10.1145/2955129.2955183
23. I-Hsien Ting and Chia-Sung Yen (2012). Opinion Groups Identification in Blogsphere based on the Techniques of Web and Social Networks Analysis. In The 4th International Conference on Machine Learning and Computing. Hong Kong, China.
24. Turney, P. D. (2002). Thumbs up or thumbs down?: semantic orientation applied to unsupervised classification of reviews. In Proceedings of the 40th Annual Meeting on Association for Computational Linguistics (pp. 417–424). Stroudsburg, PA, USA.
25. Wasserman, B., & Faust, K. (1994). Social Network Analysis: Methods and Applications. Cambridge University Press.
26. Wellman, B. (1982). Studying Personal Communities. In M. P. & L. N. (Eds.), Social Structure and Network Analysis (pp. 61–80). SAGE Publication.
27. Wellman, B., & Berkowitz, S. D. (1988). Social Structures: A Network Approach. Cambridge University Press.
28. Wilson, D. S. (1989). Levels of Selection: An Alternative to Individualism in Biology and the Human Science. Social Networks, 11(3), 257–272.