Machine Learning and Artificial Intelligence
J.-L. Kim (Ed.)

doi:10.3233/FAIA230770

Social Web Analysis for Decision Support: A Case Study

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Abstract. In this study, we focused on analyzing customer-generated data on Facebook to explore how textual content on a social web can provide valuable information for decision support. To accomplish this goal, we used several techniques that included social network analysis (SNA), natural language processing (NLP), data mining (DM), and machine learning (ML), integrating them with artificial intelligence approaches. Our analysis aimed to harness the information generated during the Volkswagen pollutant emissions situation in a case study that was conducted using the textual content from 10,642 posts, that represented the interactions of 25,877 users over a span of twenty-two weeks. The results demonstrated that monitoring online social networks (OSNs) can significantly enhance decision-making processes and might help to mitigate potential damages to brands/businesses. By leveraging the proposed methodological approach, a set of orientations for decision-making was extracted, providing valuable guidance for brand management and reputation protection. Overall, this study highlights the importance of analyzing textual content on OSNs and leveraging advanced computational techniques to improve decision support.

Keywords. Social network analysis, natural language processing, data mining, decision support, machine learning, artificial intelligence.

1. Introduction to social web and data analytics

By monitoring the online social networks (OSNs), managers can gather real-time information into how their businesses are perceived by distinct stakeholders [1]. This enables them to identify both positive and negative sentiments, address customer concerns, and engage in meaningful interactions to build a strong brand reputation. Automated systems play a crucial role in capturing these interactions by analyzing customer needs and historical activity. Furthermore, the integration of social network analysis (SNA), natural language processing (NLP), Data Mining (DM) algorithms, and artificial intelligence (AI) brings additional benefits to OSN content analysis.

Following the Volkswagen (VW) pollutant emissions problem in Facebook, significant repercussions occurred. As a consequence, VW took decisive actions by dismissing key personnel involved in manipulating emissions measurements. This led to increased costs for the company, including legal fines and repairs. Negative information about auto brands spread quickly on OSN, and VW was no exception. Our study used SNA metrics and visualization techniques to show that impact. The objective was to understand user reactions and to develop indicators for monitoring online conversations. The main objective was to evaluate user opinions and VW's responsiveness, as well as to develop indicators that would enable the review and enhancement of strategies for managing the brand's image through SNA.

The remainder of the paper is structured as follows. To ensure self-containment, section 2 provides an overview of key concepts related to social web analysis, decision support, and relevant topics in SNA, DM, ML, and AI. Section 3 describes the case study conducted by using a high-volume of data. It also presents a discussion of obtained results. Finally, section 4 presents the conclusions drawn from the study.

2. Social web analysis studies and decision support

Social web analysis refers to a set of computational research methods and techniques that focus on various technical concepts and aspects of SNA, that can aid in decision-making through the capture, extraction, and interpretation of information from various sources, thus a focal point for business management [2].

The study conducted by Beck-Fernandez, Nettleton [3] not only provided a theoretical foundation, but also proposed a system for text processing and extraction, which further converted the extracted content into memes. The researchers employed semantic networks to condense and capture the essence of informal language messages, identifying the key themes as units of transmissible knowledge, namely memes. In a similar line, Biswas, Bordoloi [4] proposed an unsupervised method for extracting keywords from Twitter content by employing visualization techniques and SNA metrics. The researchers determined the importance of keywords by considering various factors such as frequency, centrality, position, and the influence of neighboring nodes. Conversely, Duari and Bhatnagar [5] focused on constructing semantic networks and identifying keywords by utilizing databases containing texts from scientific domains and online news articles. They adopted a supervised method by employing predefined and standardized lists of keywords for their analysis.

Freire, Antunes [1] conducted a comprehensive review of studies published in the past decade, focusing on social business decision support models and their application in SNA. Their analysis aimed to identify the variations and distinctions among these models. One important highlight was the growing importance of utilizing OSN data analysis as a decision support tool within organizational contexts. The authors also concluded that while some models provided theoretical frameworks, most of them are exploratory, relying on standardized approaches, and that the availability of data derived from online social media processing enables organizations to support timely, realistic, and well-informed decisions by leveraging the power of SNA.

Fedushko, Molodetska [6] proposed a model designed at securing user data, promoting sustainable communicative interaction for both managers and users. The authors presented a novel approach that focused on decision-making for online community administrators, specifically targeting antagonistic behavior prevalent in online services. Hasani, Sihotang [7] conducted a study with the aim of investigating decision support systems in social media. Their focus was to analyze the structural aspects and data techniques employed to extract valuable information, by conducting a comprehensive systematic literature review of existing decision support systems.

The research conducted by Dalal, Jain [8] emphasized the growing importance of ML and DL techniques in analyzing social data. By leveraging ML and DL algorithms, researchers could uncover hidden patterns, detect sentiment, and derive valuable information from social media content.

3. Related work and experimental evaluation

In this study, we implemented the Social Business Decision support Model (SBDSM), a proposed methodological approach introduced by Freire, Antunes [9], to retrieve, handle, organize, and examine data from OSNs. This approach, involving iterative procedures, merges SNA and DM techniques, emphasizing the crucial elements of human interaction and network configuration. To evaluate whether the SBDSM was suitable to support decision support in real brand image situations, we used a dataset collected in 2015 (in the midst of the September VW crisis). Previous studies [1, 9-13] allowed for the improvement of the model and its applicability in different scenarios, with varying levels of participation, but with small volumes of data.

In this case study, the focus of data analysis was to understand the impact of the VW pollutant emissions problem on the VWUK fan page (https://www.facebook.com/VolkswagenUK/, accessed in September 2015). We conducted the case study using textual content from 10,642 posts from the interaction of 25,877 users, during 22 weeks.

3.1. Social Business Decision Support Model (SBDSM)

In a nutshell, the SBDSM addresses a web discourse that comprises three primary components: user, post, and concept, which can be analyzed either individually or collectively. Each component can be converted into a square matrix, allowing for the depiction of discursive interactions, adjacency, and affiliation. When analyzing the three entities altogether within a network, a two-mode network is converted into a one-mode network [14, 15]. Leveraging these matrices, we constructed a multilevel matrix that formed the basis of the primary network (user|post|concept).

As depicted in Figure 1, the process can be summarized as follows: (i) data inputs encompassing information on communication patterns (GDF, CSV, TXT files); (ii) the inputs are subjected to processing and structuring in a network configuration, utilizing a graph database; (iii) the resulting representation captures the inferred social connections among users, along with the content they have posted online, enabling qualitative and quantitative information for decision support.

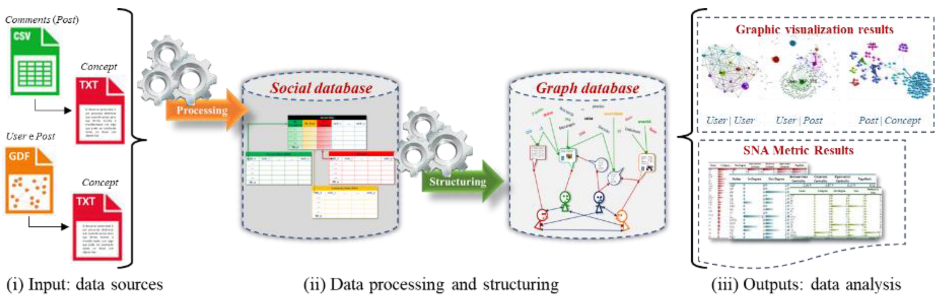


Figure 1. Overview of Social Business Decision Support Model (SBDSM) (available at https://link_1).

3.2. Data extraction

The data for this case study was collected over a timeline of 22 weeks from the VW institutional page. The situation came to light on the 18th of September of 2015, and data collection occurred on a weekly basis, spanning from the 31st of August of 2015 to the 31st of January 31 of 2016. This data compilation enabled the interconnection (using DM techniques) of multiple data sources, allowing the construction of various networks and the identification of the most discussed topics immediately after.

To conduct the semantic analysis, the contents of the posts and their corresponding responses were extracted as plain text from the GDF and CSV outputs, ensuring that only the textual linguistic resources of communication were included in the analysis. The obtained lexical data was unstructured and needed processing, cleaning, and structuring to make it suitable for analysis. To achieve this purpose, we employed preprocessing methods such as normalization, lemmatization, and tokenization to create clean structured data.

3.3. Data processing and interpretation

In the first step, as data collections were carried out, the original unprocessed GDF-format data was imported into Gephi [16] for visualization. The graphical representations of the various snapshots assisted in the weekly interpretation of the networks. All constructed networks presented different characteristics. In an initial analysis, it was observed that there were significant differences between the layouts representing the 22 analyzed weeks. For instance, in the network representing the activity during the week of the event, when compared to the two previous weeks, in the week of the event (snapshot WK03), the number of new users on the VW fan page increased considerably. It went from 1,500 users in the snapshot, from the previous week, to 11,973. Additionally, the flow of information between shared links and created commented messages grew as people turned to social media to express their dissatisfaction. The connections increased from 1,546 to 15,212, and the posts from 160 to 2,212.

As can be observed in the graph of snapshot WK01, presented in Figure 2, several groups (orange, green, blue, etc.) were identified. In this network, following the graphical representation techniques of SNA, it was observed that users in examples C and D were key users, because if their connections ceased to exist, the network would divide into multiple isolated subnetworks. Furthermore, it was observed that there were irrelevant posts, such as those highlighted in A and B.

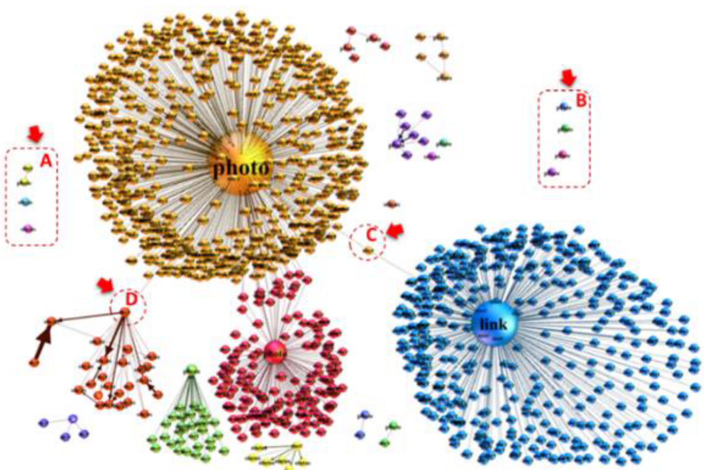


Figure 2. Graphic visualization to assist data mining (snapshot of WK01 available at https://Link_2).

After interpreting and storing the original data , attributes were created to establish connections between the various datasets. The data processing involved creating tables to store user information, message content (post and comment), and concepts. To achieve this objective, we leveraged a combination of relational and graph databases, DM techniques, as well as data quality and data validation methods.

The transformation of data from a relational model to a graph database model, with $n \times n$ relationships, was achieved using specifically defined attributes. The only pre-existing structured connections in the original raw data were the links between user entities and the initial post. The missing connections, required to structure the discourse, were inferred using various techniques, such as DM and entity matching, based on user IDs , post, and concept entities. Once all the data had been structured, it became feasible to construct two distinct types of semantic networks. The first type of network summarized the discourse exchanges, while the second type was based on keyword analysis.

3.4. Semantic processing

The SBDSM utilizes the bag-of-words model [17], specifically the term frequency-inverse document frequency (TF-IDF) representation, and additionally integrates a cleaning database, which can be continually updated with newly identified concepts in each context throughout the intermediate and recursive steps. To extract concepts from the post contents, the cleaning database and the designed algorithms were utilized. Additionally, the cleaning database was used to standardize and normalize the text, remove spaces, and eliminate irrelevant concepts.

The 22 initial data sets, snapshots, consisted of a total of 10,642 posts, of which 651 were initial posts and 9,991 were comments on those posts. From the data sources (GDF and CSV), messages containing pure text were selected, and semantic networks were created to summarize the discourse exchanges and identify keywords. The resulting valid data sets from the 22 snapshots, comprising 9,305 messages, were processed using Excel.

Before optimizing the cleaning database, the messages from the 22 snapshots contained a total of 256,395 concepts, which were reduced to 88,209 after removing irrelevant data. Around 66% of the concepts were discarded as irrelevant, yet their removal did not compromise the meaning of the obtained final summaries. The outputs with semantic data in graph database format were used to construct the web discourse networks.

For aggregating the three levels of web discourse, we transformed two-mode networks into a single one-mode network. This produced networks that encompassed the three analyzed components (user, post, and concept). Creating these networks involved aggregating user data, post data, and textual content from the posts.

3.5. Web discourse and semantic networks

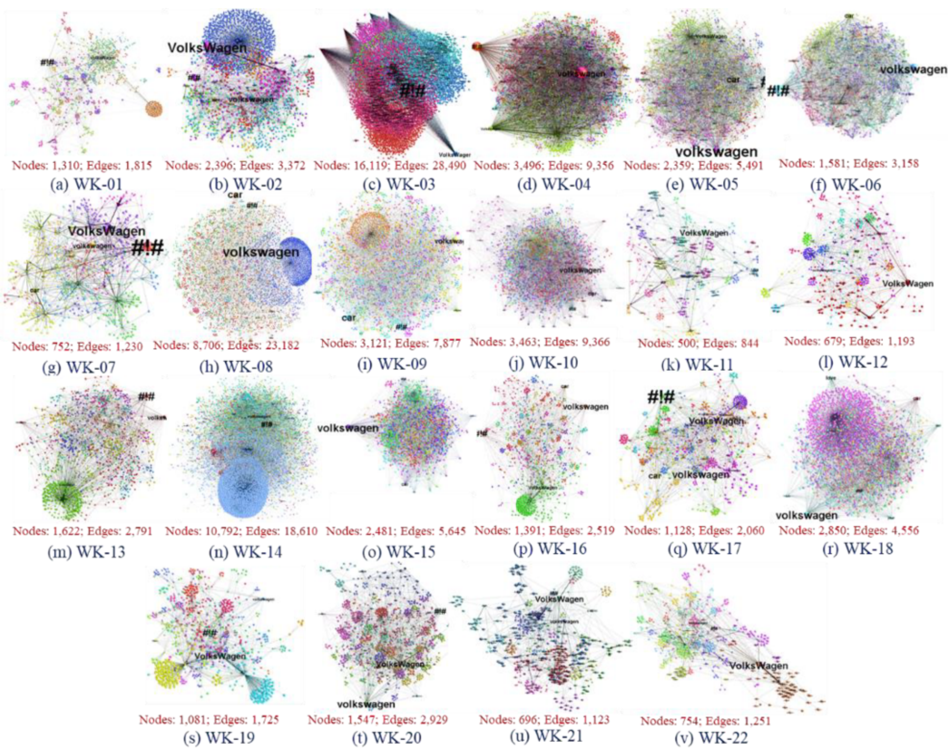
After the final processing, data was explored and interpreted in Gephi to visualize and manipulate the various networks more easily and to apply SNA representation techniques. A total of 15 users consistently participated in the OSN over the course of 22 weeks. It was observed that some individuals were very active users of the fan page. This type of indicator is important because such users have more power and tend to influence others positively or negatively.

The user centrality metrics for VW fan page owner, summarized in Table 1, allowed to identify the users' activity and control over the flow of information. In Week 03, for instance, the in-degree centrality (representing the count of posts or comments published on the VW Facebook account) and the out-degree centrality (representing the number of responses provided by VW) reached their peak values. As for the other metrics, the highest values for betweenness centrality, PageRank, and eigenvector centrality were observed in snapshot Week 01. The highest value for the closeness centrality metric was recorded in snapshot Week 09. These indicators, supported by SNA, highlighted the user's ability to attend to and respond to users (both customers and non-customers).

Table 1. User VW SNA metrics (available at https://Link_3).

SNA metrics	WK 01	WK 02	WK 03	WK 04	WK 05	WK 06	WK 07	WK 08	WK 09	WK 10	WK 11	WK 12	WK 13	WK 14	WK 15	WK 16	WK 17	WK 18	WK 19	WK 20	WK 21	WK 22
Degree	264	87	**1,735**	323	215	100	35	1,179	317	346	45	45	148	228	119	75	201	90	107	44	60	1,483
In-Degree	222	35	**1,563**	212	152	66	0	1,117	292	285	0	0	115	182	78	31	173	55	53	5	18	1,424
Out-Degree	42	52	**172**	111	63	34	35	62	25	61	45	45	33	46	41	44	28	35	54	39	42	59
Closeness	0.711	0.711	0.799	0.639	0.650	0.800	0.754	0.851	**0.875**	0.849	0.778	0.718	0.683	0.869	0.717	0.779	0.765	0.804	0.812	0.760	0.797	0.738
Betweenness	**0.009**	0.001	0.001	0.004	0.003	0.001	0.000	0.001	0.001	0.002	0.000	0.000	0.002	0.002	0.003	0.001	0.001	0.002	0.001	0.001	0.002	0.001
PageRank	**0.037**	0.002	0.014	0.007	0.008	0.005	0.001	0.016	0.011	0.009	0.001	0.001	0.009	0.008	0.007	0.003	0.008	0.007	0.004	0.001	0.004	0.019
Eigenvector	**1.000**	0.028	0.277	0.188	0.166	0.144	0.000	0.208	0.178	0.174	0.000	0.000	0.175	0.208	0.175	0.115	0.101	0.247	0.177	0.026	0.162	0.200

Initially, through visual analysis of the networks, it was observed that three networks exhibited high density and contained substantial amounts of information. By using Gephi and zooming in on the layouts, it became easier to identify distinct posts and the concepts they contained. The application of the modularity class algorithm enabled grouping of concepts within the same post, treating them as distinct subgroups [16].



Nodes: 1,310; Edges: 1,815 (a) WK-01
Nodes: 2,396; Edges: 3,372 (b) WK-02
Nodes: 16,119; Edges: 28,490 (c) WK-03
Nodes: 3,496; Edges: 9,356 (d) WK-04
Nodes: 2,359; Edges: 5,491 (e) WK-05
Nodes: 1,581; Edges: 3,158 (f) WK-06
Nodes: 752; Edges: 1,230 (g) WK-07
Nodes: 8,706; Edges: 23,182 (h) WK-08
Nodes: 3,121; Edges: 7,877 (i) WK-09
Nodes: 3,463; Edges: 9,366 (j) WK-10
Nodes: 500; Edges: 844 (k) WK-11
Nodes: 679; Edges: 1,193 (l) WK-12
Nodes: 1,622; Edges: 2,791 (m) WK-13
Nodes: 10,792; Edges: 18,610 (n) WK-14
Nodes: 2,481; Edges: 5,645 (o) WK-15
Nodes: 1,391; Edges: 2,519 (p) WK-16
Nodes: 1,128; Edges: 2,060 (q) WK-17
Nodes: 2,850; Edges: 4,556 (r) WK-18
Nodes: 1,081; Edges: 1,725 (s) WK-19
Nodes: 1,547; Edges: 2,929 (t) WK-20
Nodes: 696; Edges: 1,123 (u) WK-21
Nodes: 754; Edges: 1,251 (v) WK-22

Figure 3. keyword networks (available at https://Link_4).

Unlike the networks depicted in Figure 3, where individual posts were linked to sub-networks, the keyword network differed by connecting each post directly to the global semantic network. In this type of network, discursive exchanges between users were structured to create semantic networks of keywords. The objective was to identify keywords, both to populate the cleaning database and to identify useful information for decision support.

In the networks depicted in Figure 3, node and label size were based on the out-degree metric, which aided in identifying the concepts that were most frequently utilized. Using a thorough textual analysis, a comprehensive list of the most frequently used keywords was generated and categorized. Given space constraints, it is not feasible to depict and analyze here all the networks generated in this particular case study. Therefore, Figure 4 shows only the three keyword networks corresponding to snapshots with the highest flow and volume of information: (a) Week 03, (b) Week 08, and (c) Week 14. This graphical representation offers a comprehensive overview of the content within discursive exchanges and facilitates the identification of the most prevalent concepts. The analysis of semantic content and the identification of keywords such as "emissions", "problem", and "affected", provided valuable knowledge and information on the most frequently discussed topics. Interestingly, as depicted in the figure, these snapshots also highlighted the inclusion of unexpected keywords like "love" and "nice".

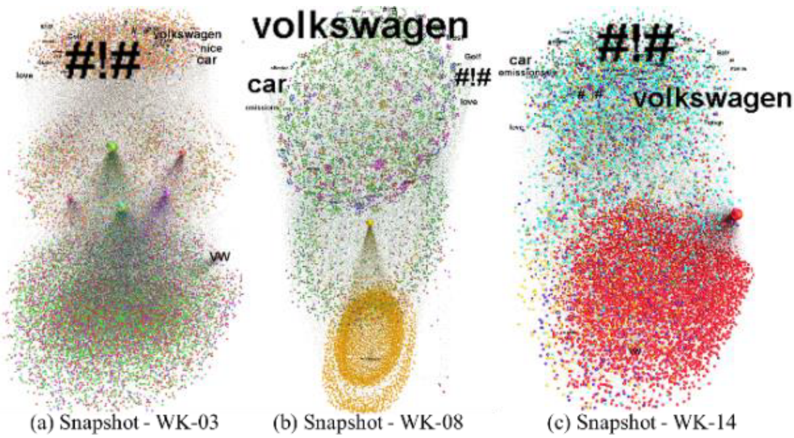


Figure 4. Graphical representation of the 3 weeks with the highest flow of communication (available at https://Link_5).

Upon examining the layouts in Figure 4, an intriguing observation was made regarding the frequent usage of exclamation points. Although not representing specific concepts or words themselves, the inclusion of character sequences like "!!!!", "???", and "..." served the purpose of emphasizing ideas. In this analysis, their presence shed light on the degree of satisfaction or dissatisfaction expressed by users. The significant adoption of exclamation points by users, represented in the figure as the sequence #!#, swiftly conveyed their discontent and dissatisfaction towards pollutant emissions. In line with the defined model, the character sets ".", "?", and "!" were uniformized replaced with the standardized terms #.#, #!#, and #?#, respectively.

4. Validating the results: strengthening the findings

To reinforce the validity of our findings, we validated the results of the case study by conducting a thorough comparison with actual outcomes, with a particular focus on the number of vehicles sold and the percentage variation in sales from one year to the next. To achieve this, we collected and analyzed data from VW's annual reports, covering the sales performance from 2014 to 2022[1].

As illustrated in Figure 5, our analysis reveals that the sales in the European market remained unaffected, showing a consistent increase over the years. In the Europe/Other markets region, in 2015, unit sales demonstrated growth, with an increase of 2.1% to 4.5 million vehicles. However, in the South American region, we observed a decrease in unit sales by -32.0%, due the deterioration of the economic environment [18].

	(a) VEHICLE SALES									(b) % more VEHICLE SALES in the year before							
Thousand vehicles	2014	2015	2016	2017	2018	2019	2020	2021	2022	2015	2016	2017	2018	2019	2020	2021	2022
Europe/Other markets	4,430	4,524	4,635	4,731	4,739	4,856	3,929	3,727	3,495	2.1%	2.5%	2.1%	0.2%	2.5%	-19.1%	-5.1%	-6.2%
North America	879	941	968	992	925	956	744	805	868	7.1%	2.9%	2.5%	-6.8%	3.4%	-22.2%	8.2%	7.8%
South America	794	540	421	526	596	607	471	503	487	-32.0%	-22.0%	24.9%	13.3%	1.8%	-22.4%	6.8%	-3.2%
Asia-Pacific	4,114	4,005	4,367	4,527	4,640	4,538	4,012	3,540	3,632	-2.6%	9.0%	3.7%	2.5%	-2.2%	-11.6%	-11.8%	2.6%
Volkswagen Group	**10,217**	**10,010**	**10,391**	**10,777**	**10,900**	**10,956**	**9,157**	**8,576**	**8,481**	**-2.0%**	**3.8%**	**3.7%**	**1.1%**	**0.5%**	**-16.4%**	**-6.3%**	**-1.1%**

(c) Volkswagen Group

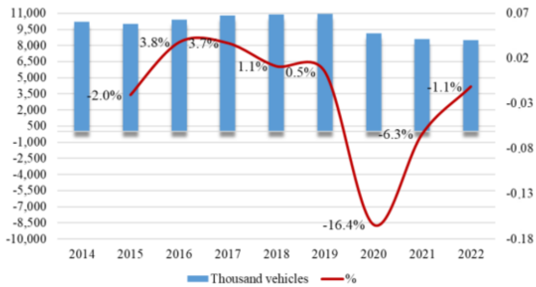


Figure 5. Key Figures by market (available at https://link_6)

Furthermore, according to VW's reports [18, 19], fiscal years 2015 and 2016 were particularly impacted by the diesel issue, leading to additional charges due to legal risks and expenses associated with technical modifications, repurchases, and legal risks related to the diesel matter. Afterward, as shown in figure 5 (c), in 2020, an obvious decline occurred due the COVID-19 pandemic and had a strong impact on the VW Group [20].

Data plays a central role in understanding how customers, stakeholders, and competitors perceive a brand. Brand perception is a multifaceted concept that comprises various aspects, including reviews, reputation, customer experience, advertising, social engagement, and customer purchase. As part of our study, we focused on the volume of vehicle units sold and the percentage increase in vehicles sold from one year to the next as measures of the brand's reputational risks. This analysis was important as companies rely on OSN as a communication strategy to support their brand and sales strategies [21]. These metrics served as key indicators to assess the impact of the brand's image on consumer behavior and market performance.

[1] Data available at https://annualreport2015.volkswagenag.com, https://annualreport2017.volkswagenag.com/, https://annualreport2019.volkswagenag.com/, https://annualreport2021.volkswagenag.com/, https://annualreport2022.volkswagenag.com/.

Significantly, the increase in the volume of vehicle units sold serves as evidence of the effective management of the brand's reputational risks by the company. This validation process reinforces the credibility of our research findings and further supports the implications of our proposed SBDSM for real-world decision-making scenarios. By incorporating this validation, we ensure that our research is anchored in real-world outcomes and offers practical insights to decision support.

5. Conclusions

This study highlighted the significant role of methods and techniques from AI in SNA and its transformative impact on understanding and leveraging social web interactions. Through the integration of SNA, NLP, DM, and ML techniques, we have demonstrated the power of these methods in extracting valuable knowledge and information from OSN.

In the case study we focused on the VW pollutant emissions problem expressed in VW's Facebook, by applying the SBDSM. The analysis of semantic content and identification of keywords provided valuable information on the impact on the company's reputation. We observed that the event story was pervasive, and the analysis highlighted both negative and positive concepts. The findings of this study emphasize that the timely analysis of social web data can provide numerous benefits to companies, including improved decision-making regarding products/services, and cost reduction management.

The results of the VW case study analysis offer valuable insights for decision support in diverse areas. For instance, in brand reputation management, understanding the reactions on Facebook page helps to improve the brand image and address concerns. In customer engagement, analyzing user interactions helps identify key influencers and adapt communication strategies. For crisis management, real-time monitoring of OSN data allows quick responses to protect brand reputation. In improving sales performance, OSN data provides insights into customer behavior and preferences, leading to targeted sales strategies. These examples show how social web analytics support informed decision making by aligning with customer expectations and market demands.

After thorough validation, our findings confirm the robustness of the conclusions, highlighting the resilience of VW's sales in specific markets despite the challenges faced due to the pollutant emissions issue. This validation strengthens the effectiveness of our decision support model in real-world scenarios.

In summary, the combination of SNA, NLP, DM, and ML techniques, powered by AI, provides comprehensive methods and techniques for analyzing social web data and extracting valuable knowledge and information.

Acknowledgments

The research leading to these results received funding from the Portuguese Foundation for Science and Technology under project UIDB/00308/2020 and project UIDB/05037/2020.

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