Social media influence analysis Techniques Systematic Literature Review

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Abstract

Nowadays, the use of Social Media networks is growing endlessly and rapidly, those networks have become a substantial pool for unstructured data. Social media influence (SMI) describes the social media influencers (SMIs) capacity to influence other people's thinking, feelings and characteristics in online and outline communities. The analysis of the influence activity affects all different kinds of fields from multiple perspectives such as strategic planning and decision making until product creation and distribution. The main contribution of this paper is to present results of a Systematic Literature Review (SLR) that highlights the different Techniques used in the analysis of social media influence, when addressing influencers-followers interactions. After a careful review of the 55 extracted articles, we found that 4 data representation models have been used with social media related data analysis and 10 data analysis techniques to address 6 different research objectives in more than 20 different fields. In Interactions and users relationships purpose, Graph was the most used data representation model and data analysis techniques.

Keywords

Influence, Systematic literature review (SLR), Social media influence (SMI), Data analysis techniques

1. Introduction

According to the Statista report [1], over 3.6 billion people were using social media worldwide, a number projected to increase to almost 4.41 billion in 2025. The report shows that 4.57 billion people around the world use the internet, of those users, 346 million new users have come online within the last 12 months. Internet users spend an average of 144 minutes on social media per day. The process of analyzing or mining social networks helps in gathering information that optimize influence maximization. People use Social Media Platforms to connect with their friends and family members, to introduce themselves to others by sharing their daily live news and follow channels or pages. This spontaneous behavior created what we now call influencers and followers. Which change the way that organisations connect with their clients. Our Study helps in choosing the appropriate representation model and analysis technique that matches the analysis purpose and goes with certain platforms. The better way to answer a questions of effectiveness comparing more than one different bath is Systematic Literature Reviews. This paper is organized as follows. In Section 2, we represent the Systematic Literature

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Review planning. Results and Discussion are presented in Section 3. We conclude with general highlights and perspectives for further work in Section 4.

2. Systematic Literature Review Planning

2.1. Research Questions

Aiming to find all relevant primary studies related to the different types of models used to describe the phenomenon of influence in social media networks, the following research questions (RQ) were established:

- RQ1: Which techniques have been used to analyse users related data in social media?
- RQ2: What is the purpose of analyzing users related data in social media?
- RQ3: How is it possible to use analyzing techniques when addressing influencers/followers interactions?

Subsequently, we determined the initial research in the databases. In relation to the keywords, three groups were formed:

- Groupe1: (“social media",“social networks")
- Groupe2: (“analysis", “analytics", “analyzing", “analyze", “content analysis")
- Groupe3: (“influencers",“influencer", “followers" ,“follower")

2.2. Search Strategy

The search strategy combines the key concepts of our search question in order to retrieve accurate results. It is an organized structure of key words, which are “social media”, “analysis”, “influencer” and “followers”, used to search a database. Then, we added synonyms, variations, and related terms for each keyword. A Boolean operator (AND and OR) allow us to try different combinations of search terms.The final search string is (“social media” OR “social networks”) AND (“analysis” OR “analytics” OR “analyzing” OR “analyze” OR “content analysis”) AND (“influencers” OR “influencer” OR “followers” OR “follower”).

2.3. Selection Criteria

After obtaining the search results from the different sources, a set of exclusion/ inclusion criteria was applied to help in the identification of relevant primary studies. Therefore, Inclusion Criteria (IC) are used to select primary studies which indicate Related data analysis techniques, purpose, or influencers/followers interactions for Social media networks. For the Exclusion Criteria (EC) they are used to remove those primary studies that do not address the main topics searched in this SLR, are not available, or are directly related to an included primary study of the same author.

- Inclusion Criteria (IC):
    - Publications that match one of the search items

  - Publications that have best practices version
  - Publications that are related to social media networks related data analysis
  - Publications that are related to the phenomenon of influence in social media networks
  - Publications that are relate to the research questions
- Exclusion Criteria (EC):
  - Publications that not match one of the search items
  - Publications that do not have best practices version
  - Publications that are published before or on the 31.12.1999
  - Publications that are not related to the phenomenon of influence in social media networks
  - Publications that are not relate to the research questions

2.4. Data collection

The number of papers resulting in the search is summarized in TABLE 1. After filtering irrelevant, duplicate and incomplete papers, a total of 55 papers in TABLE 3 were selected for the reviewing process. TABLE 2 presents the filtering process. The state of the art is presented as follows according to the different cases. The selected papers per resources are distributed as shown in TABLE 3.

Resource	Number of papers
Springer	111
IEE Xplore Digital Library	1
ACM Digital library	191
Google Scholar	30
Science Direct	157
Hyper Articles en Ligne (HAL)	48
Total	538

Table 1
Search results by Resource

Irrelevant and duplicates	3
Incomplete and not related to RQ, Excluded by reading title and abstract	452
File not found	2
Total for Introduction reading	68
Not related to RQ, Excluded by reading Introduction	30
Total for reading	55

Table 2
Filtered search results

Resource	Number of papers
Springer	7
IEE Xplore Digital Library	5
ACM Digital library	17
Google Scholar	9
Science Direct	14
Hyper Articles en Ligne (HAL)	5
Total	55

Table 3
Filtered search results by Resource

3. Results and Discussion

3.1. Social Media Users Related data analysis techniques

3.1.1. Data model:

When we start defining the Social Media Users Related data analysis techniques we found that the first thing we need to see is the real-state of the abstract data or the data model that defines the initial information. There are different models to represent it, we chose to classify them into 4 main categories summarized in TABLE 4.

Data model	Numbers of Papers	Percentage
Graphs	33	73.33%
Dataset	9	20%
Log	7	15.45 %
Diagrams	6	13.33%

Table 4
Data models used in social media related data analysis

Graphs: are the most common used data model. Each Graph has his own parameters related to the topic and the field of search. The social networks is the top sous-category with more than 15 articles [2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18], it defines a social structure made up from a set of different social actors. Some authors create a specific model such as Small-world network multiple influence model (SWMI model) [19], Community-Author-Recipient-Topic model (CART) [20], RT and MT model [4]. There are some types of Networks related only to influence analysis like User-Follower Network [21], influencer Graph [22]. The general ones are Graph Neural Networks (KOLs), Knowledge Graph(KG) [23], Random geometric graph, random networks [24] and Network diagram [25]. Peng, Sara, Taeho, Hui, Krishna, Xiang-Yang, Kevin and al. [26, 9] used Social Graph that represents social relations between entities. Some authors mix between more then one representation. Marco and Mattia [27] used Graph Representation Learning. Lauren, Robert, Augustin and Eugene [3] used network diagram of operation model and Graph-based representation for trust/reputation systems. Fan and Cassandra [28] used Onemode and two-mode network, interaction networks and class-level and group-level discussion networks. Mozhgan and Kevin C. [29] used Graph-based data representation and Hypergraph data representation.

Datasets: are the second category, each platform has a specific type of data. Twitter dataset [30] is compiled from various tweets which centered on topics, hashtags, and objects. Epinions dataset [31, 32] is the organization of data into incremental snapshots. Facebook dataset [33] is more complicated, representing the number of acting users, number of users that reacted, number of posts, number of comments and time span of data. Some datasets are related to the real-world for example to study the Location-based social networks (LBSN) [34].

Logs: category has 3 sub-category. Venkata, Weizhong and Xiaowei [21] used logarithms in comparing the results founded in the Twitter User-Follower network follows power-law degree distribution. Also, Simone, Diego, Giuseppe and Maurizio [35] used logarithms in his study. The second sub-category is Big data which refers to the large, fast or complex type of data that it's difficult or impossible to process using the traditional methods. There are four papers mention this type [12, 36, 37, 38]. The last sub-category is Clustering [13], it is used to extract the Trusted and Non-Trusted nodes.

Diagrams: category results to a schematic representation. Mozhgan and Kevin C. [29] used Fuzzy models and diagrams that look like Graph. Sunagul [5] used Sociogram, it is a graphic representation of social links that a person has. Also Lars and Francis applied Sociogram that represent participant's friendship network. Marco and Mattia [39] used schematic diagram using social relation.

3.1.2. Data Analysis model

In this part we will focus on the different data analysis model used to analyse Social Media Users Related data. We propose 10 main categories represented in TABLE 5. Probabilistic model and Graphs are the earliest used analysis techniques. Every work ad at least one of the three statistical categories: tables, curves and histograms. The most used category is Analysis model. The latest work used mining techniques like Artificial intelligence (AI) and Prediction.

Data Analysis model	Numbers of Papers	Percentage
Analysis model	26	49.05%
Tables	19	35.84%
Curves	18	33.96%
Ranking metrics	16	30.18%
Artificial intelligence(AI)	12	22.62%
Graphs	11	20.75%
Histograms	6	11.32%
Prediction	6	11.32%
Probabilistic model	5	9.43%
numeric coefficient	4	7.54%

Table 5
Data Analysis models/Techniques used in social media related data analysis

Analysis model: is a technical representation that results from designing a model that analyse different information, behavior, function, interaction or relations. The ones related to influence are: Influence model [40, 37, 11] Social media Influencer Model[25], Action-Reaction Influence Model (ARIM) [33, 8], Influence evaluation model [2] and Influence model for sentiment inference [10]. Others are related to topics that helps in decisions making such as recommendation model [36], Latent Dirichlet Allocation topic model [41], Graphical representation of Latent Dirichlet Allocation [26], Multi-Criteria Decision Making model (MCDM) [37] and numerous theoretical models [30, 11, 38]. Other types are Diffusion models like Flow diagrams and Block diagrams [29, 26, 22], Tow-step-flow model, multi-step-flow model [4], Filtering model [30, 38] and Emerging Model [42]. Also there is models related to social or marketing analysis: The inbound and outbound models [43], Alternative Communications Model theory [44], Covariance-based structural equation modeling (CB-SEM) [42] hypothesized mediation model [17] and Social Information Retrieval [45].

Tables: are used to represent comparisons e.g. Country-Level Micro-blog User Behaviour and Activity [39], Models on top-K Recommendation [23] Top 10 users different diagrams [37], Direct Trust in communities and network [13], classifiers [35] and probability distributions by groups [46]. Also, to describe number of users, location, visits and clustered locations[34]. To present results like Words frequency[38], Linear Regression Results [9] Kendall Rank Correlation, Hierarchical Multiple Regression [12]. Finally, to list results like randomly picked communities from the observed communities [21].

Curves: are used to represent correlations in most of them e.g. correlation strength between different countries [39], Pearson's Correlation [47], descriptive statistics of key study variables [14], Descriptive correlations [17] and Correlation between user features [48]. There are analysis models used to extract those representation like: Principal component analysis [49], Diffusion models [26], Bilinear state space model (BSSM) [11], Empirical model [50], Model R, model R-Squared, Adjusted R-Squared [15], Bass model [19] and Opinion dynamics models [18]. They are also used to represent evaluations like: Average week-on-week growth rates, Social media followers by week [50] and Evolution of retweeting network [48] or to represent Influence probability [34]. Sara, Taeho, Hui, Krishna, Xiang-Yang and Kevin [9] used Life Curve. Saike, Xiaolong, Danie, Kainan, Zhu and Chuan [11] used ROC curve.

Histograms: are used to represent quantity evolution throw time e.g. Histogram of the Influence Score [9], Absolute and Relative influence [34], account creation dates for Twitter followers of incumbent US senators campaigning in 2018 [51] and probability of influence relationship [10]. Also to show Participant centralities for different networks [28].

Ranking metrics: are an algorithms used to rank components of social media like tweets [39, 12, 46], posts, Hashtags, Trends [52], Page rank [8] or even influencers and followers ranking. They are often used to analyse users related data in Twitter. Also we can use them to rate parameters like frequency and percentage e.g. the frequencies for the component items of Twitter and YouTube use [15], The percentage of users following at least one of the top (key) opinion leaders [23], Percentage distribution of top influencers [41]. The most used techniques to characterize top users are ranking metrics like Swiss Market Index (SMI) [4] and NavigTweet [53]. This technique is also used to realize comparisons between the most powerful influencers according to betweenness centrality and Page Rank and worth mentioning the hashtags [5].

Artificial intelligence(AI): analysis techniques has started in recent years. There are 5 sup-categories: (1) Clustering e.g. K-means clustering method [27], Distribution of nearest neighbors of regional network nodes [39] and K-means clustering method [39]. (2) Machine learning techniques [30, 38]. (3) Heuristic model e.g. energy-propagation model [9], influence propagation model [2] and diffusion model based on cascade model [48]. (4) Mining techniques like Mining Micro-Influencers [35]. (5) knowledge engineering e.g. Knowledge representation and reasoning [39].

Graph: are not only used for primary data extraction but also for deep learning methods to describe data by graphs designed. There are a multitude of model to design graph such as: Independent Cascade Model [44, 2], Linear Threshold Model [9], Heterogeneous Influence graph model [30] and Trust Model (SNTrust) [13]. Also there are a different types of networks such as: Bayesian network [29], Two-link network topology, Parallel link topology [24] and social network [44]. Those models also used to extract Social Network graph density reduction [20] and Instructor's centralities [28].

Prediction: are models used to give a future vision or estimation. The most used prediction modelis the Standing Ovation model (SOM) [30, 38]. Daekook, Bomi, Byoungun, Youngjo and Yongtae [19] creates more then one estimation to compare between them. Paul, Liam and Jordi [50] used difference-in-difference models of social media followers to analyse the social media music fans followers future behavior.

Probabilistic model: in the field of social media analysis are used for different purposes: (1) mining structural influence to analyze relationships in social network [47], (2) identification of influencers in online social networks [20], (3) analyzing dynamics of information diffusion [48], (4) evaluating Role of Conformity in Opinion Dynamics in Social Networks [18], (5) modeling Topic [44].

Numeric coefficient: are used for different reasons one of them is to represent the size of an individual's social network and their ability to influence that network [40]. Also, to show how influence scores change [6]. Some of the authors use numeric coefficient to rate the most frequent words and User quality ratio vs. RT Quality ratio vs. Replay ratio for the Top users [30]. Pearson Coefficient [54] is one of the most used coefficients.

3.2. Social Media Users Related data analysis purpose

Reading all the 55 articles we found six main important reasons presented as follow in TABLE 6 behind analyzing users related data.

Analysis main purpose	Numbers of Papers	Percentage
Interactions and users relationships	13	23.64%
Influencers Behaviour	13	23.64%
Influence Modeling	10	18.18 %
Influence Evaluation	9	16.36%
Mining Influence	6	10.91%
Influence Optimisation	4	7.27%

Table 6
Summarizing social media related data analysis purposes

3.3. Social Media Users Related data analysis search Fields

After deduce the six main reasons, we found that each of them is related with a search field or maybe more than one. While reading other SLR related to the social media analysis they frequently mention that there is an extensive variety of fields benefit from social media related data analysis, but most of them chose to focus between one, two and three domains. Based on 3.0 Detailed (four digit) subject codes, we extract 23 fields deduct from 4 main fields: (1) Humanities and social science, (2) Natural sciences, (3) Formal sciences and (4) Professions and applied sciences, more than 60 sub-field and more than 100 sub-sub-field. We notice that it affects and optimises all different kinds main fields. The four top fields are Sociology with 41.81%, Business with 36.36%, Computer sciences 30.90% and Interdisciplinary studies with 27.26%.

3.4. Social Media Users interactions analysis techniques

After extracting the 6 main purposes of analysing social media users related data we found that the top of them is: Interactions and users relationships with a total of 13 articles (bibliographic portfolio). More than 61% of those papers used Graphs as a representation, 23% used Dataset, 15% used Logs and 8% used Diagrams. Coming to the analysis techniques most of the authors prefer to combine between more than one techniques. Nadia, Mourad, Lin, Ben, Yousra, Ahmad Kamran, Basit, Ahmad Raza, Fan and Cassandra used Graphs [10, 47, 13, 28]. Monika, Amel, Katarzyna, Alda, Nadia, Mourad, Lin and Ben [33, 10, 47] used analysis Model. Marco, Mattia, Lauren, Robert, Augustin and Eugene [27, 3] used Ranking Metrics. For the statistic techniques: Yousra, Ahmad Kamran, Basit, Ahmad Raza, Venkata, Swamy, Weizhong and Xiaowei [13, 21] used tables. Yousra, Ahmad Kamran, Basit, Ahmad Raza, Lin, Ben, Faisal M., Ramaravind and Joyojeet [54, 47, 13] used curves. Nadia, Mourad, Fan and Cassandra [10, 28] used Histograms. Marco and Mattia [27] added Artificial Intelligence, Lin and Ben [47] added Probabilistic Model and Prediction also Faisal M., Ramaravind and Joyojeet [54] added Numeric Coefficients. The most used platforms for interactions analysis are Twitter and Facebook, but in 2019 researchers are concentrated more on Instagram. For the fields there are a diversity in the chosen fields but the most figured ones were Sociology and Business.

4. Conclusion

The present Systematic Literature Review sought to contribute in the identification of users related data analysis techniques as well as to present the analysis main purpose and the fields that were most engaged regarding social media influence. This review consisted of literature published between 2000 and 2020. We did list 4 data representation models, 10 data analysis techniques, 6 main purposes behind social media related data analysis and more than 20 fields were extracted. The most used analysis techniques were Graphs as for the data representation model. The most-frequently appeared purpose was interactions and users relationships analysis. For the fields we found that Sociology, Business and Computer sciences are the top connected fields with social media industry. As a future work, we plan to develop a mining approach to extract the interaction model between influencers and followers, using graphs. Further more we will apply graph matching and transformation techniques on the interaction model, using GMTE, for analysis purposes.

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