DEVELOPING A STANDARDIZED FRAMEWORK FOR SOCIAL MEDIA ANALYTICS STRATEGY IMPLEMENTATION

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Abstract

There are several studies discussing social media analytics (SMA) frameworks with different stages and steps. These mainly include the Capture, Understand, and Present (CUP) stages (Fan & Gordon, 2014). However, these models often lack detailed implementation steps and focus on isolated aspects of the process. To address these gaps, this paper introduces an enhanced SMA framework, incorporating five stages: Identify, Capture, Understand, Present, and Evaluate (ICUPE). The Identify stage establishes objectives, scans the environment, and selects suitable SMA techniques. The Capture stage gathers and preprocesses social media data. The Understand stage applies advanced analytics, including sentiment and trend analysis, to extract insights. The Present stage visualizes findings through dashboards, ensuring effective communication. Finally, the Evaluation stage integrates feedback for continuous improvement. The proposed framework was refined using the Delphi technique (Fan & Gordon, 2014), incorporating feedback from industry experts to enhance its applicability and effectiveness. By addressing gaps in existing models, ICUPE provides a holistic and structured approach to SMA, enabling businesses to derive valuable insights, optimize decision-making, and improve operational strategies. Future work includes validating the framework through real-world applications and exploring its impact across various business domains.

Keywords: Framework, Data Mining, Delphi Technique, ICUPE

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1. INTRODUCTION

Technology is evolving rapidly, compelling companies to maintain efficiency in the global market. One of the most effective tools for competitiveness is social media, which has become essential in daily life. Social media platforms, blogs, wikis, and web services are part of Web 2.0,

an umbrella term describing applications that enable active user participation online (Sivarajah et al., 2015). Nearly 73% of marketers believe that their social media marketing efforts through analytics have been "somewhat effective" or "very effective" in achieving business objectives (American Marketing Association [AMA], 2024). These facilitate collaboration, networking, and customer interaction, allowing user-driven content and information sharing. Social media empowers individuals to express opinions, explore topics, and connect with others. Customers frequently discuss products and services, making their feedback crucial for businesses. Social networking platforms are expanding rapidly; for instance, Instagram has over a billion active users, Facebook has approximately 2,2 billion, and X/Twitter generates over 6,000 tweets per second (Garg & Sharma, 2020). This vast data source can offer valuable insights when properly analyzed.

Social media analytics (SMA) applies big data methodologies to collect and examine user-generated content, revealing patterns through statistical analysis, satisfaction scores, and text mining (Choi et al., 2020). Rathore et al. (2017) highlight SMA functions such as searching, filtering, summarizing, and visualizing, including sentiment analysis, conversation tracking, and engagement measurement. Techniques like opinion mining, sentiment analysis, and network analysis help extract business intelligence from social media data. This enables organizations to improve brand awareness, enhance marketing strategies, and boost customer satisfaction (Misirlis & Vlachopoulou, 2018). More importantly, SMA helps businesses connect with customers and refine their engagement strategies.

As social media platforms continue to generate massive volumes of data, businesses and researchers increasingly rely on SMA to extract meaningful insights that drive decision-making. Recent advancements in big data processing, artificial intelligence (AI), and deep learning have significantly enhanced the capabilities of SMA, enabling organizations to better understand user sentiment, detect emerging trends, and optimize marketing strategies. Kapoor et al. (2018) provide a comprehensive review of the evolution of social media research, emphasizing the growing role of analytics in strategic business planning. Furthermore, the rise of deep learning techniques, such as bidirectional encoder representations from transformers (BERT) and long short-term memory (LSTM), has improved the accuracy of sentiment analysis in social media data, allowing businesses to interpret consumer feedback with greater precision. Beyond business applications, SMA has also played a crucial role in addressing contemporary challenges such as misinformation and digital manipulation. For instance, during the COVID-19 pandemic, Ferrara et al. (2020) demonstrated how SMA frameworks helped detect the spread of misinformation and improve public communication strategies. These developments highlight the necessity for a structured and adaptive SMA framework that not only captures and analyzes data but also incorporates continuous evaluation to ensure accuracy and effectiveness. To address these gaps, this study introduces the Identify, Capture, Understand, Present, and Evaluate (ICUPE) framework, an enhanced SMA model that provides a comprehensive approach for organizations to optimize their social media strategies and drive informed decision-making. Moreover, some studies have proposed SMA frameworks, typically comprising the Capture, Understand, and Present (CUP) stages. However, existing frameworks lack detailed steps and implementation guidelines, focusing on limited aspects of the process. To address these gaps, it is essential to incorporate additional stages: Identify and Evaluate. The Identify stage helps companies scan the environment and set clear goals, while the Evaluate stage ensures feedback and continuous improvement. Few studies provide detailed insights into platform selection, tools, and techniques for each stage, or discuss practical applications of SMA.

Fan and Gordon (2014) introduced a widely used three-step SMA framework — CUP. However, this framework is broad and focuses on input-process-output methodology, requiring further implementation details. This research extends Fan and Gordon's model into a five-step process — ICUPE. This enhanced framework offers a comprehensive approach for organizations to leverage SMA effectively.

The main objective of this study is to develop a structured and actionable SMA framework by extending and enhancing the widely used Fan and Gordon (2014) model. This framework aims to cover the lack of previous studies that did not give details about the implementation steps and focus on only specific aspects of the process (e.g., capturing or understanding data), as well as many previous models (Fan & Gordon, 2014) only discuss three steps (CUP), ignoring critical stages such as identification of goals and evaluation of outcomes.

This paper is structured as follows. Section 2 provides the literature, Section 3 outlines the research methods used, Section 4 presents the results and discussion, and Section 5 is the conclusion of the work and the future direction.

2. LITERATURE REVIEW

Based on a wide review of related works, a cross-reference has been summarized in Table 1.

Melville et al. (2009) explored the Identify stage, emphasizing trend identification, key influencers, and relevant blogs, but focused solely on blogs rather than multiple social media platforms. Zeng et al. (2010) proposed a five-step framework: collect, monitor, analyze, summarize, and visualize — but lacked practical application. Etlinger and Li (2011) introduced a four-step model — strategy, metrics, organization, and technology — ideal for beginners but lacking depth in data collection and analysis. Mayeh et al. (2012) proposed a three-step framework: Capture, Analyze, and Act, based on qualitative research, extending beyond analytics to include actionable insights, though it focused only on customers. He et al. (2013) refined this by adding recommendations and actions and applying them to the tourism industry using Facebook and X/Twitter. Stieglitz et al. (2014) introduced a comprehensive framework incorporating various social media data sources but limited its scope to four use cases, omitting other potential applications. He et al. (2015) developed a competitive analytics framework using both qualitative and quantitative data, extracted via APIs from multiple social media platforms. Jimenez-Marquez et al. (2019) proposed a two-step framework — data preprocessing and analysis — focusing on big data but lacking a visualization component. Singh and

Verma (2020) enhanced the Understand stage by integrating machine learning techniques for better data classification and insights. Khan et al. (2021) devised a discovery, collection, preparation, and analysis framework, employing text mining and sentiment analysis for efficient data classification. Their model included data visualization, though it was not explicitly part of the framework.

Continuously, the study of Dwivedi et al. (2021) provided insights into the future of SMA, emphasizing AI-driven sentiment analysis and customer engagement models. It suggests new research directions, including ethical considerations in SMA.

The researchers categorized various SMA techniques, such as text mining and deep learning, while also identifying challenges in big data processing, such as real-time analytics and privacy concerns.

Some of the existing literature explored how AI-driven approaches improve the accuracy and efficiency of social media data analysis, particularly in sentiment analysis and consumer behavior prediction.

Table 1. State of the art: Social media analytics framework

Paper	*Purpose*	*Method*	*Data type*	*Framework*
Melville et al. (2009)	To extract and drive business insight	Data mining, social network analysis, and natural language processing (NLP)	Blogs	ICUP
Zeng et al. (2010)	To determine social media applications and challenges	By developing and evaluating informatics tools and frameworks	Social media	Collect, monitor, analyze, summarize, and visualize
Etlinger and Li (2011)	To provide a framework for social media monitoring and SMA	Interviews	Social media	Strategy, metrics, organization, technology
Mayeh et al. (2012)	To obtain and utilize external intelligence for business purposes	Scanning the external environment by using social media monitoring tools	Social media	Capture, analyze, act
He et al. (2013)	To show the importance of competitive social media and extract business value from social media data	Text mining	Social media (Facebook and X/Twitter)	Text preprocessing (capture), text processing (understand), actionable intelligence (present and act)
Stieglitz et al. (2014)	To produce an interdisciplinary approach for SMA and information systems	General	Social media	Track, model, analyze, and present
He et al. (2015)	To extract useful patterns and intelligence	Text mining and sentiment analysis	Application programming interface (API) from social media sites	Collect, monitor, and analyze
Jimenez-Marquez et al. (2019)	To propose a framework for big data social media content	Machine learning and NLP	Social media (Yelp)	Data preprocessing and data analysis
Singh and Verma (2020)	To present a fault-tolerant and parallelly framework for end-to-end analytics in real-time and batch processing	Machine learning in specific, naive Bayes and support vector machine	Social media (X/Twitter)	Data capturing, data preprocessing, data analytics, and dashboard
Khan et al. (2021)	To identify public engagement strategies	Text mining	Social media (X/Twitter)	Discovery, collection, preparation, and analysis

3. RESEARCH METHODOLOGY

Based upon a systematic review of different research approaches, theories, and media types, this paper presents and tests a framework for SMA by extending one of the most used frameworks developed by Fan and Gordon (2014). As well as exploratory research is used to identify or clarify a problem, to provide a better definition and understanding of it. It could also be the end of a research or the beginning of further research (Greener & Martelli, 2018). This research is also qualitative as qualitative techniques are used to describe, translate, decode, and reconcile the meaning through a list of techniques as opposed to the frequency of what is mostly a naturally prevailing phenomenon in the social world. Qualitative methods have several techniques, ranging from surveys and observations to interviews (Cooper & Schindler, 2014). Individual-depth interviews will be conducted through a Delphi method.

3.1. Social media analytics conceptual model

This study introduces the ICUPE framework, an extension of the widely used CUP framework by Fan and Gordon (2014). ICUPE enhances the original model by adding two critical steps: Identify at the beginning and Evaluate at the end. This five-step process provides a more structured and comprehensive approach to SMA.

The Identify stage ensures businesses define clear objectives, analyze their internal and external environments, and determine the most relevant SMA techniques. This step helps organizations recognize whether SMA will be used to solve a problem or identify new opportunities.

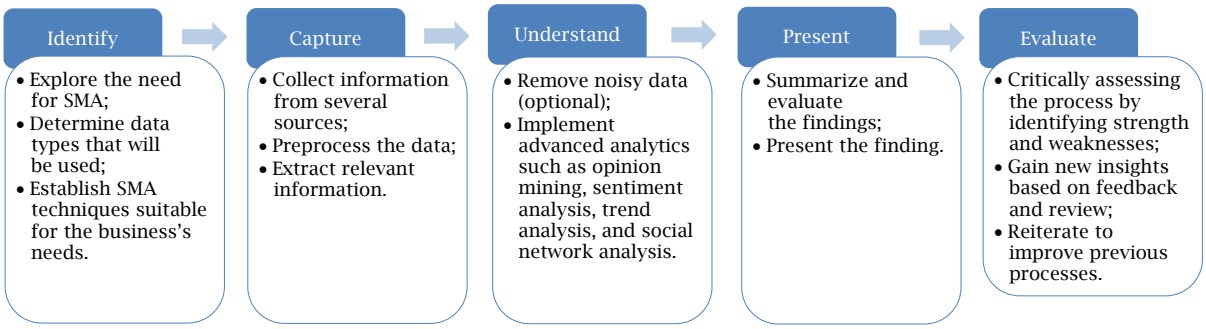
The CUP stages, inherited from the CUP framework, remain essential. Capture involves collecting and preprocessing social media data. Understands and applies analytics methods like sentiment analysis, trend detection, and network analysis to extract meaningful insights. Present ensures findings are effectively visualized through reports and dashboards to aid decision-making.

The evaluation stage is a key addition, allowing businesses to assess the efficiency and effectiveness of their SMA strategies. This phase enables continuous improvement by identifying strengths, weaknesses, and future opportunities.

By integrating the Identify and Evaluate stages, the ICUPE framework bridges gaps in previous models, offering organizations a holistic and iterative approach to SMA implementation. Future research should focus on validating this framework across different industries to enhance its adaptability and effectiveness.

We will be discussing each stage's framework in detail below, which focuses on the theoretical and conceptual perspectives, as well as each stage's implementation strategies, which emphasize their operational and empirical aspects.

Figure 1. Proposed social media analytics framework



3.1.1. Phase 1: Identify

The Identify stage is a crucial first step in the ICUPE framework, ensuring companies define objectives and determine the best SMA techniques (Melville et al., 2009). Emphasize that businesses must identify relevant blogs, forums, and key influencers discussing their products or services. Additionally, detecting sentiment and emerging trends helps optimize SMA techniques such as sentiment analysis, content analysis, trend analysis, or social network analysis.

Mayeh et al. (2012) highlight the importance of environmental scanning to maintain a competitive edge. Organizations must continuously monitor market trends, competitors, and customer conversations on social media. Rather than relying on traditional surveys, listening to real-time social media data provides richer, unbiased insights that benefit various business functions, including marketing, sales, and supply chain management.

Supporting this perspective, Töllinen et al. (n.d.) argue that social media monitoring is more effective than word-of-mouth or surveys for decision-making. Their study found that 90% of marketers consider social media data essential for campaign strategy.

Furthermore, Etlinger and Li (2011) introduce the Social Media Measurement Compass, identifying five key objectives for SMA: brand health, innovation, customer experience, operational efficiency, revenue generation, and marketing optimization.

In summary, the Identify stage involves setting clear objectives based on a company's position and selecting the most effective SMA techniques to achieve business goals.

3.1.2. Phase 2: Capture

The Capture stage of the SMA framework is the process of gathering a massive number of social media data by monitoring various social media sources using crawler tools. This phase collects information from popular social media platforms such as Facebook, X/Twitter, LinkedIn, Pinterest, and Google+, as well as smaller and more specialized sources, including Internet Forums, blogs, Wikis, podcasts, and social bookmarking sites. Then, the relevant data are stored and archived. Moreover, the applicable information will be extracted. Following that, during the Understand stage, this data will be processed, and essential as well as relevant information will be excluded according to the company's needs, which are determined at the Identify stage. This process could be done by the company itself or outsourced to a third party (Andryani et al., 2019). Therefore, the Capture stage has two main tasks: collecting information and preprocessing data. Ayodeji and Kumar (2019) also further explored the activities that will be executed during the data preprocessing. Those activities are considered as preparation for the Understand stage. They include steps such as data modeling, data/record linking of data from different sources, stemming, part-of-speech tagging, feature extraction, and other syntactic and semantic operations that support analysis. Furthermore, pertinent information about users, user comments, user feedback, businesses, events, and other entities is also extracted to be used in the future for data analysis and analytical modeling. The most essential part of this process is to ensure there is inclusivity, input from various sources, and exclusivity of noisy and irrelevant information to produce data that would be needed for the Understand stage (Ayodeji & Kumar, 2019).

3.1.3. Phase 3: Understand

After collecting social media data in the Capture stage, the Understand stage focuses on analyzing and refining this data to generate meaningful insights. Andryani et al. (2019) highlight that this phase involves data cleaning, noise removal, quality selection, metric determination, and analytical processing. Since data originates from multiple users and platforms, it is often inconsistent and requires preprocessing techniques such as classifiers ranging from sophisticated machine learning models to rule-based text classifiers trained on labeled data to enhance accuracy. Once refined,

data undergoes analysis through a range of methods, including statistical techniques, opinion mining, network analysis, NLP, machine learning, and machine translation. Among these, sentiment analysis, topic analysis, social network analysis, and trend analysis are the most commonly applied techniques for extracting insights from social media data. According to Fan and Gordon (2014), these analytical techniques help businesses identify customer sentiment, detect emerging trends, and analyze user behavior. Insights derived from this stage can reveal consumer preferences, purchasing intentions, and engagement patterns, aiding businesses in optimizing their marketing campaigns and customer interactions. Additionally, businesses can extract useful metrics related to user demographics, interests, concerns, and relationship networks, providing valuable intelligence for strategic decision-making.

By leveraging these techniques, organizations can translate raw social media data into actionable insights, ultimately enhancing customer engagement, refining marketing strategies, and improving business operations.

3.1.4. Phase 4: Present

After analyzing data and gaining insights, it's integral to present the data in a visually appealing manner in order for the insights to be appropriately represented and to make it easier for decision-makers. Hence, the Present stage is a process to show or visually represent the information gathered and derived from the analysis stage (Andryani et al., 2019). The results are summarized, evaluated, and shown to the user or decision-maker in a relatively simple format. There are several different types of visualization techniques. Additionally, Fan and Gordon (2014) stated that one of the most popular types of data visualization is interactive dashboards. They are used to combine information from different sources and to visually present it. Moreover, sophisticated interactive dashboards not only present information but also provide customized views for a diverse range of users. Accordingly, depending on the level or role of the user, only specific information will be shown. Data visualization shows trends and patterns that humans may not notice; however, at this stage, data analysts or statisticians could provide further support and advice (Fan & Gordon, 2014). There are several other types of visualization according to Sadiku et al. (2016). Those include line graphs, which show relationships between items, bar charts to compare quantities of different categories, scatter plots, which are a two-dimensional plot that shows variations of two items, and pie charts to compare parts of a whole. However, a huge challenge of presenting the data is deciding on the best technique to use for the data (Sadiku et al., 2016). Presenting the data in a visual manner helps in several tasks, such as identifying trends, finding emerging market opportunities, optimizing operations, for instance, troubleshooting products and services, and showing insights regarding metrics such as churn rate prediction (Bikakis, 2018).

3.1.5. Phase 5: Evaluate

The last step in this extended social media framework is Evaluate. This is the process by which a company assesses the decisions and outcomes of the previous stages. At this stage, a company could compare social media techniques to view which is more efficient in order to enhance performance in future campaigns and processes. They could also assess the outcome or decision made from the SMA process to understand and examine if this process was successful. Moreover, they could identify key performance indicators (KPIs) to measure success. Furthermore, areas of improvement would be identified to reiterate and improve the previous steps further, such as capturing data from a specific platform, analyzing the data using a different SMA technique, and other more efficient methods to present the data. The previous stage would be evaluated in order to determine areas of strength and weakness, and thus optimize performance for future campaigns. Further confirming the importance of evaluation and recommendations is He et al. (2013), who proposed a text-mining process for social media content. At the end of the process, they concluded by doing a recommendations and actions stage to examine how the results could have been improved (He et al., 2013).

3.2. Evaluation of the proposed framework

The Delphi technique was chosen for its ability to gather expert opinions systematically and refine insights through multiple rounds of feedback. Unlike traditional survey methods or focus groups, Delphi ensures:

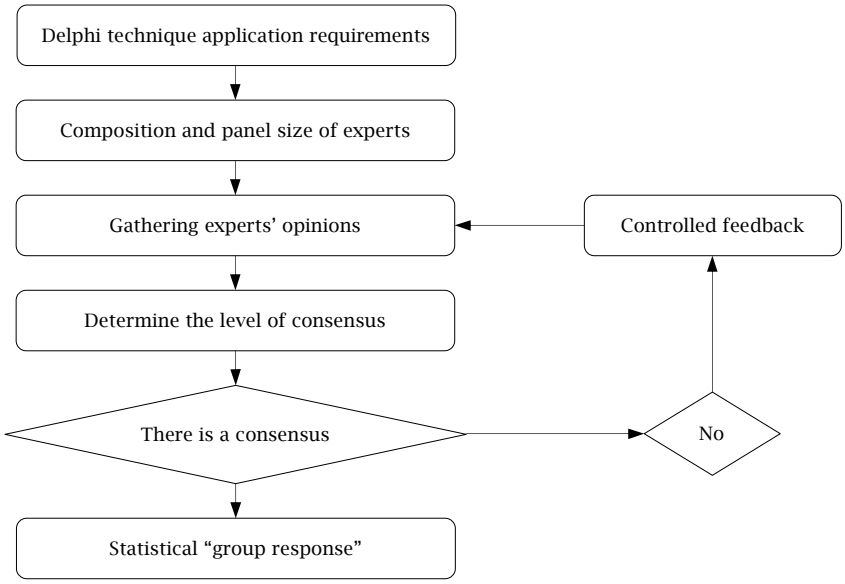
1. Anonymity and reduced bias: Experts provided their opinions without the influence of dominant voices, leading to more independent and unbiased evaluations.
2. Consensus building: Through iterative rounds, the method allowed experts to refine their views based on group feedback, ensuring well-rounded insights.
3. Handling complexity: SMA involves multi-dimensional aspects (data collection, processing, business strategy, and visualization). Delphi helped structure diverse expert perspectives into a cohesive framework.

The Delphi technique is used as a means of consensus in cases where differences in opinion exist about similar situations and where decisions are likely to be influenced by strong groups. The process of structured communication takes place through the gathering of a group of experts' opinions on a complex problem. The Delphi technique is a process that consists of identifying the problem, selecting the expert panelists, and conducting the interviews. The key success factor, however, for the Delphi technique is the choice of relevant experts in the field in order to increase the validity of the research (Yıldırım & Büyüköztürk, 2018). Habibi et al. (2014) also added that there are some essential requirements for conducting the Delphi technique such as group consensus to achieve the results, anonymity in data collection, a complex, multidimensional, and interdisciplinary problem, imperfect knowledge, dispersion of experts, no time limitation, and lack of cost-effective method (Habibi et al., 2014).

In this study, the Delphi technique occurs as follows. Firstly, interview questions regarding the research were developed. Secondly, experts in the area of research of data analytics were identified and selected. The in-depth interviews were then

conducted by introducing the concepts and asking the initial questions to the expert panel. Moreover, the results were then analyzed. Accordingly, the results were analyzed, and the framework was revised. Furthermore, the expert's evaluation and interview were conducted again on the adjusted framework. Finally, the results and findings are reported. Figure 2 below indicates the process that took place.

Figure 2. Delphi technique model



3.2.1. Instrument

In our application of qualitative research and the Delphi method, interviews were used to collect information from experts. Interviews are a technique used to collect primary data in qualitative methodologies. They usually differ according to factors such as the number of people being interviewed together, the proximity of the interviewer to the interviewee, the structure level, and the number of interviews done during the research period (Cooper and Schindler, 2014). The structure level of this interview is semi-structured as it will start with some specific questions and follow-up questions according to the interviewee's answers. The structured questions were divided into primary and technical perspectives. The primary perspectives included general questions about the company for which they work and their position and role in it. Those questions are shown in the Appendix. The technical questions were related to discussing the framework and asking the experts for their recommendations. Accordingly, the framework was updated and revised. Then, the second round of interviews was conducted to gather the final opinions of the experts.

3.2.2. Expert selection

The number of experts or professionals involved in the Delphi technique varies depending on factors such as the availability of time and money, the topic itself, and the nature of different viewpoints, according to Habibi et al. (2014). Moreover, they also recommended that researchers should use a heterogeneous group with a combination of individuals with multiple specialties rather than a homogeneous group. The group should also be highly trained and competent in this specialized area of knowledge (Habibi et al., 2014). Accordingly, the Delphi panel for this research included four experts in the data analytics and social media field. The selection of four experts was justified based on:

1. Balancing depth and manageability: A panel of four allowed for in-depth discussions while maintaining an efficient and manageable review process. Larger panels can introduce logistical challenges and diminishing returns on additional feedback.
2. Saturation of insights: The responses reached a point where additional experts were unlikely to introduce significantly new perspectives, aligning with the principle of data saturation in qualitative research.
3. Expert availability and engagement: The selected experts actively engaged in multiple rounds of feedback, ensuring high-quality iterative validation without dropout concerns common in larger Delphi panels.

The interviewees were carefully selected according to their background and experience in the field. Furthermore, we used a variety of the roles of our experts in the field as well as a variety in the size of the company they are currently working for, ranging from big multinational companies to small startups. We reached out to them through LinkedIn, and due to the difficulty of face-to-face meetings with COVID-19 restrictions, the interviews were conducted virtually. The first expert is the country manager of IQVIA Egypt. IQVIA is a multinational company leading the market in the usage of data, technology, advanced analytics, and expertise to help customers drive healthcare forward. They currently have over 100 branches with around 700,000 employees, according to our expert. Therefore, it's considered a large enterprise. For our second expert, we interviewed a Data & AI specialist at Microsoft. Microsoft is also a multinational technology company that is the leader in the market with computer software, consumer electronics, and operating systems. They also specifically have

computer software that specializes in data analytics and data visualization, which is named Power BI. Our expert panel specializes in that software. Additionally, our third expert is also a program manager at Microsoft; however, she's also a PhD researcher at the University of Liverpool, and she has a master's degree in data science. Lastly, our final expert is the chief executive officer (CEO) of Your EMMA, which is a startup company that was initiated in 2014. Your EMMA is an aspiring small enterprise that sells modest clothes and scarves in the retail industry. Their current growth rate is around 30% and increasing each year, according to our expert. They are also influential on social media, with around 350 followers on Instagram and around 500,000 followers on Facebook. All our experts were notified of key concepts and an overview of the paper.

3.2.3. Procedure

As previously stated in Figure 2, we conducted two rounds of interviews. We first reached out to 10 potential experts through LinkedIn; however, only five responded. Out of those five, we chose three experts who specialize in the data analytics of social media data. The first and second rounds of interviews were both conducted virtually due to the circumstances of the lockdown due to the COVID-19 virus, and there was a distance limitation; therefore, it was more suitable for the interviews to take place through online platforms. The Delphi panel was given an overview of the purpose of our research and the conceptual model. Moreover, there were initial questions regarding the company, its role, and its current social media processes and operations. Next, there were follow-up questions, and their views regarding the proposed framework were asked. Afterward, in round two, we followed up with two of the experts via email to get further validation on the finished framework and findings.

3.2.4. Findings

Findings from interviews following the Delphi study, all the panel members participated in interviews conducted over Microsoft Teams; they were recorded and transcribed. Interviews followed the protocol shown in Appendix. After each interview, notes and transcripts were reviewed to identify potential challenges or problems. The interviews' results showed that there is a clear consensus that the proposed framework is a comprehensive representation of the essential steps needed to conduct SMA.

• *Phase 1: Identify.* To start with, all of the members of the panel agreed that the first step of conducting SMA is identifying business objectives. Our first interviewee, a solution sales specialist in the Department of Data & AI at Microsoft, specifically stated that: "*A discussion has to be made beforehand regarding AI and analytics for the organization to be data-driven. A business problem has to be identified and, according to the suitable social media tool, will be determined*" (personal communication, March 23, 2023).

This corroborates our proposed framework with the Identify stage starting with an organization determining the need or business problem and then determining the appropriate social media technique to be used. He also added an example of a recent project at Mercedes-Benz where they identified a low churn rate. The company first sat down with the management to determine how they measure churn rate, as well as how it is defined. They then collected data from customer service and social media to capture complaints and analyze them to determine and solve the problem.

Our second interviewer, a program manager at Microsoft United Kingdom with a PhD in data science from the University of Liverpool, also further added that competitor intelligence and environment scan should be part of the first stage: "*Sometimes customers are not sure what they want, they want to be ahead of the market, but they do not know how to. Therefore, external environment scanning has to be conducted before going with social media analytics*" (personal communication, March 23, 2023).

This further proves the importance of conducting external scanning in order to identify trends in the competitors' products, trends, and campaigns. Business departments should identify scenarios that competitors do and be able to improve or lead the market accordingly. In addition, if a company is multinational or sells products abroad, it should also conduct market research or environmental scanning of the abroad market. Another situation that has also been added to our attention is conducting internal scanning and investigating business processes and operations to determine how to improve current business processes and identify business problems. This has been mentioned by our third interviewee, the information director and country manager at IQVIA Egypt: "*Conducting market research is an integral part of the social media analytics process. Market research could help a company determine current trends in the market and recognize what their customers are interested in*" (personal communication, March 23, 2023).

Lastly, our fourth interviewee is the CEO at EMMA Scarves. EMMA Scarves is a start-up launched in 2016. Their main product is luxurious scarves for modest wear. EMMA Scarves grew online at a rate of 22% in the last year, being a market leader in the retail industry of scarves. Their marketing campaigns have a high reach, with around a million views per post. They use SMA to identify potentially new demographics, maintain relationships with current customers by offering personalized messaging with them, extracting insights on customer feedback from marketing campaigns, and using their platform to further grow the brand "*The link to a successful data analytics project is to link the right tool with the right platform with the relevant business problem to solve business objectives*" (personal communication, March 23, 2023).

• *Phase 2: Capture.* For this stage, all of our interviewers agreed that this stage includes capturing data from several sources. Our first interviewee gave a further example of an infamous retail company that collected data from Facebook: "*Mansour Group, for instance, conducts data analytics using two forms: once using transactional data and secondly using social media data extracted from Facebook*" (personal communication, March 23, 2023).

Therefore, in this stage, the Capture stage is responsible for collecting data from various sources such as transactional data, historical data, and social media data. Social media data could be extracted from different platforms such as Facebook, X/Twitter, Instagram, Google+, Pinterest, or web

blogs and forums. Our fourth interviewee further stated that social media platforms are the most common way to collect information: "*Most of our customers use Facebook and Instagram as a method to collect information about their customers to determine what they want, what they don't want, and their feedback on their newest marketing campaigns*" (personal communication, March 23, 2023).

Furthermore, one of the Delphi panel experts stated that the information collected is based on three types, which are internal smart media (SM) data of employees, external SM data of customers, or a hybrid SM model of both. This is determined according to the business problem or opportunity decided on by the stakeholders in the previous stage of Identify. Additionally, the most common trend of collecting data is through manual methods, such as downloading, or through automated methods such as API, rich site summary (RSS), or hypertext markup language (HTML) parsing.

• *Phase 3: Understand.* In our proposed framework, the Understand stage includes two essential stages. Firstly, data must be preprocessed. Data from social media is usually unstructured, with various types, forms, and contexts. This makes the data more difficult to analyze and extract insights from, which is what makes the preprocessing and cleaning stage consequential. For instance, our interviewees stated: "*The biggest challenge in social media data is preprocessing. The data is highly unstructured and is usually of high volume*" (Solution sales specialist, personal communication, March 23, 2023).

"*Social media data is captured in many forms, hashtags, emojis, text, images, and sometimes even video which is why it's difficult to clean and difficult to determine the right technique to analyze it with*" (Program manager, personal communication, March 23, 2023).

"*A factor that needs to be taken into consideration is a company has to have a high computing power and a specialized team with high skills to be able to pre-process the data*" (Information director and country manager, personal communication, March 23, 2023).

Furthermore, this stage includes the data analysis. Our paper focused on four different social media analysis techniques, which are sentiment analysis, trend analysis, content analysis, and social network analysis. Our expert panels also suggested that another essential technique is using NLP first as a method to understand the data and then using other techniques such as sentiment analysis and text mining.

"*NLP is commonly used for social media data as it has the highest accuracy, and easier to validate. Following that, according to the business objective, the appropriate technique could be used such as sentiment analysis, content analysis, video analytics, and image processing*" (Solution sales specialist, personal communication, March 23, 2023).

"*The most important step in conducting the analysis is determining the entities that the data would be focused on*" (Solution sales specialist, personal communication, March 23, 2023).

Furthermore, the data storage type should also be determined in this stage, as suggested by one of the Delphi experts. Firstly, a decision must be made on how the data will be stored, whether in a structured, unstructured, or semi-structured form. Then, the storage type, such as on the cloud, in a server, or hybrid, should also be determined.

• *Phase 4: Present.* Moreover, for the Present stage, this proposed framework identified this stage with summarizing and reporting the data and then presenting the findings in the form of dashboards or reports. All our experts agreed on the essential tasks for this stage.

"*Visualizing the data is how the insights gathered are truly unlocked. Presenting the data in an easy-to-read, simple, visual, and colorful manner makes it easier for managers to take decisions according to that data*" (CEO, personal communication, March 23, 2023).

"*Our clients (business managers) rarely have the time to hear scenarios and stories, they need quick, accurate, and easy-to-read facts and graphs to base their decision on*" (CEO, personal communication, March 23, 2023).

"*Choosing the best way to visualize the data, whether it's through pie charts, line graphs, bar graphs, or other methods should depend on the type of data and the desired result or business objective*" (Information director and country manager, personal communication, March 23, 2023).

"*The most common platforms of data visualization are Tableau, Microsoft Power BI, or Zoho Analytics*" (Program manager, personal communication, March 23, 2023).

This further proves the tasks proposed in this paper for the Present stage, with the addition of providing platforms to present the insights on such as Tableau, Microsoft Power BI, and Zoho. Those platforms provide visualization tools that require zero to a few years of experience for people to use. They also provide different charts and recommended metrics to be used according to the type of data, whether textual or numerical.

• *Phase 5: Evaluate.* Finally, the last stage of this framework is Evaluate. In this stage, our research paper proposed that its main responsibility is to identify the weaknesses and strengths of the process. This ensures continuous improvement of the framework and constant feedback on whether the process is efficient and effective or not. This is also further proved by one of our interviewees: "*Nowadays, the need to work in an Agile way is in every company. It advocates adaptive planning, evolutionary development, early delivery, and continual improvement, and it encourages flexible responses to change. In the area of social media analytics in particular, this is extremely important as social media is volatile and fast paced*" (personal communication, March 23, 2023).

Another interviewee also stated that examining the process could also help to identify other stakeholders that could further help with the SMA process, such as departments in the company, such as finance, supply chain, and human resources (HR). Those departments could also add input on their views of how to further use SMA.

Additionally, another issue brought to our attention by our panel is investigating the areas affected by the insights gathered. As stated by one of our Delphi panel, "*a client of ours in the automobile industry conducted social media analytics to identify feedback of their recent product launch. Even though the feedback was 80% positive, there were issues with some of the car parts and the repair services that customers complained about. Some customers even had ideas on how to improve it. The company then acted fast and reported those issues to the Research & Development department which then improved the car parts for the next model*" (personal communication, March 23, 2023).

The above is an example of a company that acted fast to identify trends and capture customer insights, as well as used those insights to improve their product development for the future. This task could then also be placed in the Evaluate stage.

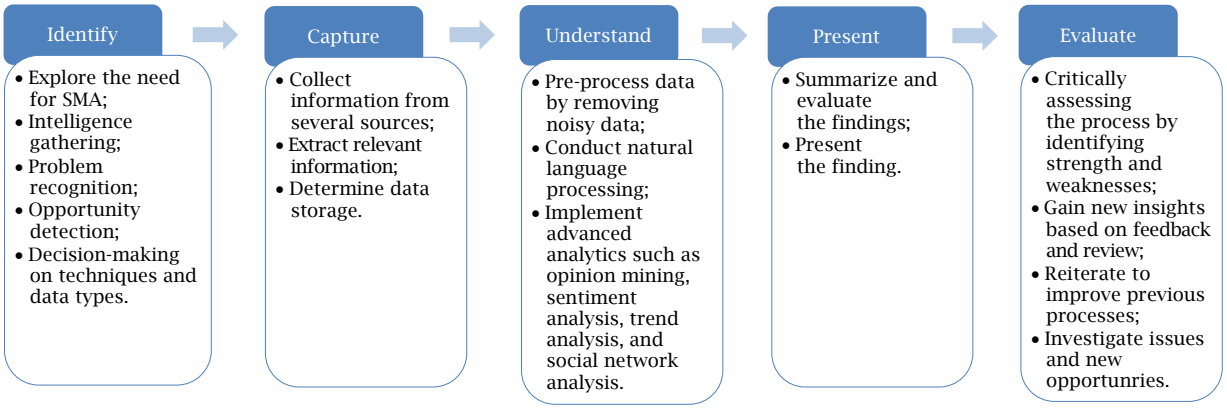
4. RESULTS AND DISCUSSION

The evaluation of the ICUPE framework was conducted using the Delphi technique, incorporating insights from experts in data analytics and social media. The findings from this evaluation confirm the relevance and applicability of the proposed framework while also highlighting areas for refinement and further.

4.1. Effectiveness of the ICUPE framework

The ICUPE framework presents a structured and comprehensive approach to SMA, covering the five essential stages: Identify, Capture, Understand, Present, and Evaluate. Each stage plays a critical role in ensuring that businesses can systematically collect, analyze, and leverage social media data for strategic decision-making. The expert panel affirmed the necessity of integrating all five stages, particularly the Identify and Evaluate phases, which were absent in previous models. The additional stages enhance the strategic depth and iterative improvement of SMA processes.

Figure 3. Adjusted social media analytics framework



4.2. Identify phase

Experts unanimously agreed that the Identify stage is fundamental for defining business objectives, scanning the environment, and selecting appropriate SMA techniques. This phase ensures that companies align their social media strategies with their overarching business goals. Notably, experts suggested incorporating opportunity detection as an additional task in this phase, enabling businesses to proactively identify emerging market trends and customer needs.

4.3. Capture phase

The Capture phase involves data collection from various social media platforms. The experts confirmed the importance of choosing the right data sources and tracking methods, such as API extractions and web crawlers. One suggested refinement was to explicitly differentiate between structured, semi-structured, and unstructured data sources, as this distinction impacts subsequent analytical processes. Additionally, it was recommended that the decision-making process regarding data storage — whether on cloud, on-premises, or hybrid — be included in this phase.

4.4. Understand phase

The Understand phase is crucial for analyzing collected data and deriving actionable insights. The experts emphasized the importance of preprocessing data to eliminate noise, inconsistencies, and irrelevant information. One of the key recommendations was to include NLP as a fundamental technique before applying sentiment analysis, content analysis, or trend analysis. This approach improves the accuracy and contextual understanding of textual data. Furthermore, experts highlighted the need for domain-specific analytics to cater to different industries, ensuring that insights are relevant and actionable.

4.5. Present phase

In the Present phase, findings are visualized through dashboards, reports, and alerts. Experts reaffirmed the significance of effective data presentation for decision-making. They suggested that businesses adopt dynamic and interactive visualization tools such as Tableau, Power BI, and Zoho Analytics, which allow for customized reports based on different user needs. Additionally, they recommended including best practices for data storytelling to enhance the interpretability of insights.

4.6. Evaluate phase

The evaluation phase facilitates the continuous improvement of the SMA process by assessing its effectiveness and identifying areas for refinement. Experts acknowledged the value of incorporating performance metrics and KPIs to measure the impact of SMA. A noteworthy recommendation was to expand this phase by investigating cross-departmental benefits, such as how insights from SMA can inform marketing, product development, and customer service strategies. Moreover, an agile approach to evaluation was suggested to ensure flexibility and responsiveness to rapidly evolving social media trends.

4.7. Comparative analysis with existing frameworks

The ICUPE framework addresses critical gaps identified in previous models, such as the three-stage Fan and Gordon's (2014) framework (CUP). Unlike earlier frameworks that focused primarily on data processing, ICUPE incorporates strategic planning (Identify) and iterative assessment (Evaluate), making it more robust for real-world applications. Furthermore, the integration of advanced techniques such as NLP, dynamic visualization, and industry-specific analytics enhances its practical value.

4.8. Challenges and limitations

Despite its advantages, the ICUPE framework presents several challenges:

- Data privacy and ethical concerns: Social media data collection must comply with regulations such as the General Data Protection Regulation (GDPR) and the California Consumer Privacy Act (CCPA). Future implementations of the framework should incorporate ethical considerations and best practices for data privacy.
- Computational requirements: The processing of large-scale social media data requires significant computational resources. Businesses may need scalable cloud-based solutions to effectively implement the framework.
- Customization for different industries: While ICUPE provides a general approach, industry-specific adaptations may be necessary for optimal effectiveness. Future research should explore how the framework can be tailored to different sectors, such as healthcare, finance, and retail.

5. CONCLUSION

The ICUPE framework offers a structured and comprehensive approach to conducting SMA. The Delphi study confirmed its relevance, while expert recommendations led to refinements that enhanced its applicability. By integrating strategic planning, data-driven analysis, and iterative evaluation, the ICUPE framework provides businesses with a robust methodology for leveraging social media insights. Future research and real-world applications will further establish its effectiveness across different industries.

To further validate the ICUPE framework, future research should focus on: empirical validation through case studies, implementing the framework in real-world business settings to assess its practical effectiveness, integration with AI and machine learning, and exploring how AI-driven analytics can enhance the automation and accuracy of SMA processes. Cross-industry applications: examining how the framework can be customized for specific industry needs and regulatory environments. As well as the paper's findings also open multiple avenues for future research in the following key areas, like empirical validation in real-world applications and integration of advanced AI and machine learning in SMA.

In addition, future studies could customize the ICUPE framework for different sectors, exploring industry-specific requirements such as regulatory compliance in healthcare or consumer behavior analysis in retail.

Our research was aimed at reaching five or more experts; however, we were only able to interview four. Therefore, this was a limitation of the current research paper. Nevertheless, we were able to maintain a variety of roles and companies, as well as the backgrounds of our experts. Another limitation is that we would have preferred to implement the framework at a company and then measure the success rate. However, this was not possible due to time limitations, as well as the situation of the lockdown, where most companies are currently closed off for the safety of their employees. Nonetheless, we believe we gained enough perspectives from our experts to know how their operations are conducted.

REFERENCES

American Marketing Association (AMA). (2024, January 5). *Social media marketing platforms to consider for businesses in 2024.* https://www.ama.org/marketing-news/social-media-marketing-platforms/

Andryani, R., Negara, E. S., & Triadi, D. (2019). Social media analytics: Data utilization of social media for research. *Journal of Information Systems and Informatics, 1*(2), 193–205. https://doi.org/10.33557/journalisi.v1i2.23

Ayodeji, O. G., & Kumar, V. (2019). Social media analytics: A tool for the success of online retail industry. *International Journal of Services Operations and Informatics, 10*(1), 79–95. https://doi.org/10.1504/IJSOI.2019.100630

Bikakis, N. (2018). Big data visualization tools. In S. Sakr & A. Zomaya (Eds.), *Encyclopedia of big data technologies* (pp. 1–6). Springer. https://doi.org/10.1007/978-3-319-63962-8_109-1

Choi, J., Yoon, J., Chung, J., Coh, B.-Y., & Lee, J.-M. (2020). Social media analytics and business intelligence research: A systematic review. *Information Processing & Management, 57*(6), Article 102279. https://doi.org/10.1016/j.ipm.2020.102279

Cooper, D. R., & Schindler, P. S. (2014). *Business research methods* (12th ed.). McGraw-Hill.

Dwivedi, Y. K., Ismagilova, E., Hughes, D. L., Carlson, J., Filieri, R., Jacobson, J., Jain, V., Karjaluoto, H., Kefi, H., Krishen, A. S., Kumar, V., Rahman, M. M., Raman, M. M., Rauschnabel, P. A., Rowley, J., Salo, J., Tran, G. A., & Wang, Y. (2021). Setting the future of digital and social media marketing research: Perspectives and research propositions. *International Journal of Information Management, 59*, Article 102168. https://doi.org/10.1016/j.ijinfomgt.2020.102168

Etlinger, S., & Li, C. (2011, August 10). *A framework for social analytics: Including six use cases for social media.* Altimeter Group. https://ru.scribd.com/document/808208034/a-framework-for-social-analytics

Fan, W., & Gordon, M. D. (2014). The power of social media analytics. *Communications of the ACM, 57*(6), 74–81. https://doi.org/10.1145/2602574

Ferrara, E., Cresci, S., & Luceri, L. (2020). Misinformation, manipulation, and abuse on social media in the era of COVID-19. *Journal of Computational Social Science, 3*, 271–277. https://doi.org/10.1007/s42001-020-00094-5

Garg, N., & Sharma, K. (2020). Machine learning in text analysis. In A. Solanki, S. Kumar, & A. Nayyar (Eds.), *Handbook of research on emerging trends and applications of machine learning* (pp. 383–402). IGI Global.

Greener, S., & Martelli, J. (2018). *An introduction to business research methods* (3rd ed.). Bookboon.

Habibi, A., Sarafrazi, A., & Izadyar, S. (2014). Delphi technique theoretical framework in qualitative research. *The International Journal of Engineering and Science, 3*(4), 8–13. https://surl.lu/ainoua

He, W., Wu, H., Yan, G., Akula, V., & Shen, J. (2015). A novel social media competitive analytics framework with sentiment benchmarks. *Information & Management, 52*(7), 801–812. https://doi.org/10.1016/j.im.2015.04.006

He, W., Zha, S., & Li, L. (2013). Social media competitive analysis and text mining: A case study in the pizza industry. *International Journal of Information Management, 33*(3), 464–472. https://doi.org/10.1016/j.ijinfomgt.2013.01.001

Jimenez-Marquez, J. L., Gonzalez-Carrasco, I., Lopez-Cuadrado, J. L., & Ruiz-Mezcua, B. (2019). Towards a big data framework for analyzing social media content. *International Journal of Information Management, 44*, 1–12. https://doi.org/10.1016/j.ijinfomgt.2018.09.003

Kapoor, K. K., Tamilmani, K., Rana, N. P., Patil, P., Dwivedi, Y. K., & Nerur, S. (2018). Advances in social media research: Past, present, and future. *Information Systems Frontiers, 20*, 531–558. https://doi.org/10.1007/s10796-017-9810-y

Khan, M. L., Ittefaq, M., Pantoja, Y. I. M., Raziq, M. M., & Malik, A. (2021). Public engagement model to analyze digital diplomacy on Twitter: A social media analytics framework. *International Journal of Communication, 15*, 1741–1769. https://ijoc.org/index.php/ijoc/article/view/15698/3411

Mayeh, M., Scheepers, R., & Valos, M. (2012). Understanding the role of social media monitoring in generating external intelligence. In *23rd Australasian Conference on Information Systems*. SciSpace. https://scispace.com/pdf/understanding-the-role-of-social-media-monitoring-in-2q3suhr106.pdf

Melville, P., Sindhwani, V., & Lawrence, R. D. (2009). *Social media analytics: Channeling the power of the blogosphere for marketing insight*. CiteSeerX. https://surl.li/kfomwh

Misirlis, N., & Vlachopoulou, M. (2018). Social media metrics and analytics in marketing — S3M: A mapping literature review. *International Journal of Information Management, 38*(1), 270–276. https://doi.org/10.1016/j.ijinfomgt.2017.10.005

Rathore, A. K., Kar, A. K., & Ilavarasan, P. V. (2017). Social media analytics: Literature review and directions for future research. *Decision Analysis, 14*(4), 229–249. https://doi.org/10.1287/deca.2017.0355

Sadiku, M. N. O., Shadare, A. E., Musa, S. M., & Akujuobi, C. M. (2016). Data visualization. *International Journal of Engineering Research and Advanced Technology, 2*(12), 11–16. https://ijerat.com/index.php/ijerat/article/view/191/197

Singh, A., Shukla, N., & Mishra, N. (2018). Social media data analytics to improve supply chain management in food industries. *Transportation Research Part E: Logistics and Transportation Review, 114*, 398–415. https://doi.org/10.1016/j.tre.2017.05.008

Singh, R. K., & Verma, H. K. (2020). Redis-based messaging queue and cache-enabled parallel processing social media analytics framework. *The Computer Journal, 65*(4),843–857. https://doi.org/10.1093/comjnl/bxaa114

Sivarajah, U., Irani, Z., & Weerakkody, V. (2015). Evaluating the use and impact of Web 2.0 technologies in local government. *Government Information Quarterly, 32*(4), 473–487. https://doi.org/10.1016/j.giq.2015.06.004

Stieglitz, S., Dang-Xuan, L., Bruns, A., & Neuberger, C. (2014). Social media analytics: An interdisciplinary approach and its implications for information systems. *Business & Information Systems Engineering, 6*, 89–96. https://doi.org/10.1007/s12599-014-0315-7

Töllinen, A., Järvinen, J., & Karjaluoto, H. (n.d.). *Opportunities and challenges of social media monitoring in the business to business sector*. CiteSeerX. https://surl.li/jgqjvm

Yıldırım, H., & Büyüköztürk, Ş. (2018). Using the Delphi technique and focus-group interviews to determine item bias on the mathematics section of the level determination exam for 2012. *Kuram ve Uygulamada Eğitim Bilimleri, 18*(2), 447–470. https://files.eric.ed.gov/fulltext/EJ1201840.pdf

Zeng, D., Chen, H., Lusch, R., & Li, S.-H. (2010). Social media analytics and intelligence. *IEEE Intelligent Systems, 25*(6), 13–16. https://doi.org/10.1109/MIS.2010.151

APPENDIX. INTERVIEW QUESTIONS

Primary questions:

1) What is the nature of the company's operations?
2) What industry is the company operating in?
3) What is the size of the company?
4) What is your role in the company?
5) Are you familiar with social media data analytics?

Technical questions:

1) Does your company have social media accounts?
2) If yes, what value does social media bring to your company?
3) Does your company currently conduct social media analytics?
4) What projects did you work on regarding social media analytics?
5) What are the processes currently undergone to conduct social media analytics?
6) In your opinion, what should be the first stage of conducting social media analytics?
7) In your opinion, what should be the last stage of conducting social media analytics?
8) Are there any current data analytics or machine learning techniques being used to produce value from social media data?