Associations between social media attributes for demand forecasting of new products

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***Abstract* — Data from social media is increasingly being utilized to better understand consumer preferences and prospective future demand. In this paper, the Decision Making Trial and Evaluation Laboratory (DEMATEL) and the Interpretive Structural Modeling (ISM) approaches are used to identify the interdependencies and cause-effect between social media attributes centered around better understanding the impact of attributes on product sales. The methodology is demonstrated on the social media and sales data from a large food and beverage company. Results show that the "followers" and "comments" are interdependent and influenced by the "posts", "impressions" and "videos". The ISM and DEMATEL results are validated with Pearson's correlation coefficient.**

***Keywords-* DEMATEL; ISM; Social media; Variable selection.**

I. INTRODUCTION

Social media (SM) platforms such as Facebook, Twitter and Instagram are untapped resources of information that could provide a deeper insight on actual customer demand for products. Some types of products are easily forecastable as they have very solid historical sales on which to build reliable forecasts, however there are many types of products that do not have reliable past sales such as promotional items, multi-generational products, products with intermittent demand or because of major unforeseeable events that changes the demand for the product.

Due to the lack of clear historical sales data, management is confronted with an increasingly difficult task of determining the demand for promotional items. Social media data is an underutilized resource that may be used to assess how user-generated content affects product sales and demand projections. This article uses interpretive structural modeling (ISM) to identify the most important social media elements and the Decision Making Trial and Evaluation Laboratory (DEMATEL) approach to examine the cause-and-effect interactions among these factors in order to solve this issue. A real-world example of a food and beverage firm that provides two promotional goods annually for a yearly special occasion is used to illustrate the efficacy of these techniques.

The rest of the article is organized as follows. Section 2 reviews the state of the art regarding the use of ISM and DEMATEL in the context of social media analytics, followed by the methodology in section 3. The findings of the methodological technique used in a real-world case study are given and discussed in Section 4. Conclusions and potential areas for more study are offered in the final section.

II. LITERATURE REVIEW

Social media networks can be an effective tool for companies to use in the sales of new products. Numerous studies on variable selection have been conducted [1], [2], but none have focused on choosing social media variables to predict the demand for new products. Badulescu et al. [3] explores the impact of social media sentiment and online user behavior on demand modelling and suggests a method for comparing and contrasting demand models using a variety of social media variables' clusters. In their research, they contrast other social media variable clusters that are chosen based on their commercial objectives or using machine learning with those that are chosen subjectively (engagement, awareness, consumer metrics and conversion). According to [4], statistical model selection was surpassed by forecast models that used human judgement to choose time-series characteristics. Cui et al. [5] utilize random forest to examine the use of social media variables for operational decision-making and its impact on performance. The authors find that firms that use social media information in their operations have a significantly higher performance than those who do not. They also find that the use of social media information leads to faster and more accurate decision making, improved customer service, and improved supply chain performance. Lehrer and Xie [6] examine the use of the least absolute shrinkage selection operator (LASSO) to select social media variables in forecasting box office revenue for Hollywood films. They compare the performance of models that use social media analysis with models that rely on traditional data sources and find that using social media data can significantly improve the accuracy of box office forecasts and help to reduce the uncertainty associated with box office predictions, which is particularly important for Hollywood studios that rely on box office revenue to finance their operations.

ISM [7], [8] and DEMATEL [9], [10] are two different methodologies used to analyze the relationship between social media platforms and their impact on decision making. Both methodologies can be used to analyze the impact of social media on decision making, but they focus on different aspects of the process. ISM focuses on the spread of information on social media and how it affects decision making, while DEMATEL focuses on the causal relationships between factors that influence decision making.

ISM is a technique for analyzing complex systems and identifying the relationships between their components. It was first introduced by [11] in the 1970's. The ISM method is based on the idea that complex systems can be represented as a network of interrelated components, and that the relationships between these components can be analyzed to understand the system as a whole. It is widely used in various fields such as decision making, management, engineering, public policy, and operations research to understand and organize complex systems. In recent years, ISM has been used to model a wide range of systems, including organizational structures, supply chains, transportation networks, and political systems. In [12], the authors used an ISM approach to identify the relationships between different factors that contribute to social networking service fatigue. The study surveyed a group of social media users to gather data on their social media usage habits, and then used the ISM approach to identify the factors that contribute to social networking service fatigue, and the relationships between them. The study found that the factors that were most strongly associated with social networking service fatigue were social pressure, addiction, and privacy concerns. The findings of this study suggest that interventions to address social media fatigue should focus on reducing social pressure, addressing addiction, and protecting user privacy. Agrawal and Narain (2021) [13] apply an ISM approach to identify the relationships between different factors that contribute to the digitalization of supply chain and identify the technological enablers (e.g., Internet of Things (IoT), blockchain, big data analytics, etc.) for the digitalization of supply chain. By using ISM, the authors identify the key factors that need to be addressed in order to successfully implement digitalization in supply chain. They show that the results of this study could be used to guide the design and implementation of strategies for digitalizing supply chains and achieving greater productivity and performance.

Several extensions and variations have been developed over the years to enhance the ISM method, such as the use of fuzzy logic [14], the integration of other methods like Analytic Network Process (ANP) [15] and Analytic Hierarchy Process (AHP) [16] and the application of ISM in specific domains like sustainability, healthcare, and education. The ISM method is also often used in conjunction with other multicriteria decision analysis techniques [17].

DEMATEL, on the other hand, is a method for analyzing causal relationships in complex systems, particularly in the field of decision making. It is first introduced by the Geneva Research Centre of the Battelle Memorial Institute [18] as a technique for evaluating decision-making problems, and it is commonly used in different fields, which can be seen in the review work of [19], such as management, engineering, and social science to identify the underlying causal relationships between different factors that influence a particular decision or outcome. The method is based on a multi-criteria decision-making approach and uses a combination of statistical and qualitative analysis to identify the most important factors and their causal relationships. In [9], the authors present a hierarchical DEMATEL approach that simplifies complex issues by dealing with numerous sorts of impacts via horizontal decomposition and the presence of hierarchy through vertical decomposition. The proposed technique is used to identify crucial elements in complex systems to both improve the quality of decision-making information and reduce the number of expert opinions. The study described in [20] applies the DEMATEL method to analyze the problem of social media addiction among an university students. They surveyed a group of students to gather data on their social media usage habits, and then used the DEMATEL approach to identify the factors that contribute to addiction, and the relationships between them. The study results showed that the factors that are most strongly associated with social media addiction are emotional dependence, self-esteem, and procrastination. The findings of this study suggest that interventions to address social media addiction should focus on reducing emotional dependence and increasing self-esteem, as well as addressing procrastination. The authors in [21] use the DEMATEL technique to investigate the influencing factors for visual perceptions and video communication in social media. The authors show that the results of this study could be used to better understand the factors that influence people's use of visual content and video communication on social media and could help guide the design of interventions to improve the sustainability of social media use.

DEMATEL and ISM are commonly used independently to analyze complex systems and identify hierarchical structures and causal relationships among factors with low computing overhead. However, because they share some traits, they can also be combined. Liu et al. [22] used the combined DEMATEL-ISM technique to assess the influencing elements of cross-border e-commerce supply chain resilience (CBSCR) in order to increase the competitiveness of a global supply chain. They created a system of CBSCR affecting elements and used the fuzzy DEMATEL-ISM technique to look at the causal links, degree of influence, and overall logical hierarchy among the components. The integrated two-stage DEMATEL-ISM approach was used by [23] to identify and assess significant barriers to Big Data Analytics implementation in manufacturing supply chains, providing insights into the interrelationships and intensities of the identified constructs to aid policy-makers in developing policies and strategies for improvement, and [24] uses the combined ISM and DEMATEL methods to establish the relationship among 13 key barriers and develop a conceptual framework for reducing the impact of adoption barriers against the integrated form of BLC-IoT in the food supply chain, highlighting the lack of government regulation and workers' low competency as significant influences.

While previous research has examined how social media affects consumer engagement and behavior across a range of industries, few studies have attempted to integrate various techniques and viewpoints in order to provide a thorough analysis of the underlying causal mechanisms. Moreover, the potential offered by the combination of factorial analysis techniques, such as ISM and DEMATEL, to identify the social media variables that contribute to estimate future product sales and the impact of their relationships has still to be identified and assessed. This paper develops a two-step approach to identify the interdependencies and cause-effect between social media attributes centered around better understanding the impact of attributes on product sales. The approach uses ISM as a first step and DEMATEL as a second step.

III. METHODOLOGY PROPOSED

The ISM and the DEMATEL approaches enable the identification of the attributes that most influence the other attributes. ISM represents the relationships between variables, whereas DEMATEL allows identifying the relationships between different factors (i.e., attributes) that contribute to social media use and how they influence each other.

A. ISM Method

The ISM method consists of 3 main steps to follow (Figure 1):

1. Create the Self-Structural Interaction Matrix (SSIM).
2. Establish the Reachability Matrix.
3. Table allowing the breakdown the attributes by levels.

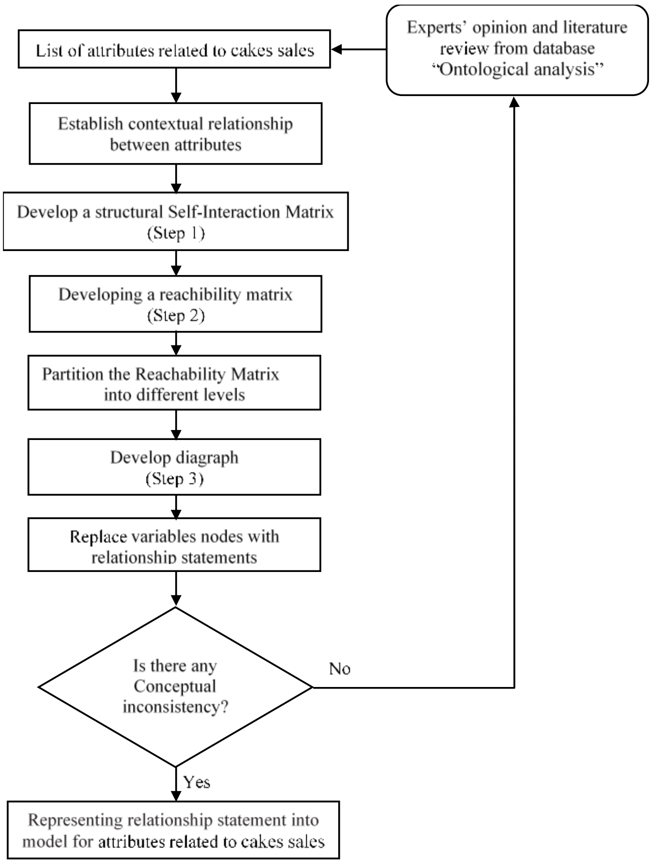

Figure 1. Flowchart of ISM methodology

The first step is to create the Self-Structural Interaction Matrix which is a matrix of size *n* attributes that allows to see the correlation between the different attributes. There are 5 different types of correlation:

- O → attribute without relations
- A → attribute *j* leads to attribute *i*
- V → attribute *i* leads to attribute *j*
- \- → between same attributes
- X → the attribute *i* and *j* will help each other to come true

The Reachability Matrix is created in the second stage to identify the traits that have a driving or dependency power. The transition from the Self-Structural Interaction Matrix (SSIM) to the Reachability Matrix is done with the following algorithm [25]:

- If the SSIM entry (i, j) is V, then the corresponding reachability matrix entry (i, j) is set to 1 and (j, i) is set to 0.
- If the SSIM entry (i, j) is A, then the corresponding reachability matrix entry (i, j) is set to 0 and (j, i) is set to 1.
- If the SSIM entry (i, j) is X, then the corresponding reachability matrix entry (i, j) is set to 1 and (j, i) is also set to 1.
- If the SSIM entry (i, j) is O, then the corresponding reachability matrix entry (i, j) is set to 0 and (j, i) is also set to 0.

The third step is to divide the attributes into tiers in order to identify the most significant elements. To do this, we will examine the reachability set, which corresponds to driving power, and the antecedent set, which corresponds to dependency power, for each attribute, and obtain the intersections between these two columns. The first level will be formed by the greatest common intersections between two attributes. After constructing the first level, the process is restarted to determine the attributes in the second level. The attributes defined in the first level must be deleted in the second iteration, and so on and so forth. The results are a hierarchy of attributes that enable the discernment of the attributes that have the greatest influence on the other attributes.

B. DEMATEL Method

The DEMATEL method is broken down into 6 stages (Figure 2):

1. Initialization of the direct relationship matrix: which allows to determine the influence between each attribute. This matrix assigns a numerical value to represent the degree of influence between each attribute, ranging from 0 to 4, where:
   - 0 indicates no influence;
   - 1 represents low influence;
   - 2 indicates medium influence;
   - 3 represents high influence; and
   - 4 represents very high influence.

   We will then sum each row and keep the highest value (Z).
2. Normalization of the direct relation matrix: which is divided by Z to yield the matrix Y.
3. Estimation of the total relationship matrix:
   - Creation of an identity matrix (matrix I)
   - Calculation of I-Y
   - Do the inverse of the I-Y matrix
   - Final matrix = $Y(\mathrm{inv}(I-Y))$
   - Sum the rows (R_i) and columns (C_i) of the final matrix
4. Build a direct / indirect relationship matrix T of attributes
   - Add and subtract these sums ($R_i + C_i$ and $R_i - C_i$)
   - When $R_i - C_i$ is negative, the attribute is an effect
   - When $R_i - C_i$ is positive, the attribute is a cause
5. Determining the threshold value
   - Average the values of the final matrix (= threshold

value)
- Identify the values that are greater than this threshold value

6. Formation of the causal digraph
   - Read each line and as soon as the value is greater than the threshold value connected the two attributes by an arrow.
   - Do the same for the columns [25].

IV. APPLICATION CASE OF THE APPROACH IN THE FOOD INDUSTRY

The application of the methodology was illustrated through a case study of a food and beverage company that has a substantial Facebook following of more than 400,000 accounts. The company supplies its own restaurants and stores in commercial shopping malls, equaling to over 55 locations. Additionally, it directly caters to customer orders by providing fresh and frozen products, and also supplies supermarkets as a B2B service. The study specifically focuses on the analysis of new products introduced during an annual special event that spans over a period of two to three weeks. The dataset used for analysis includes 19,307 datapoints derived from 23 explanatory variables, gathered from January 2017 to July 2019, from the company's Facebook page. All data is aggregated on a daily timescale.

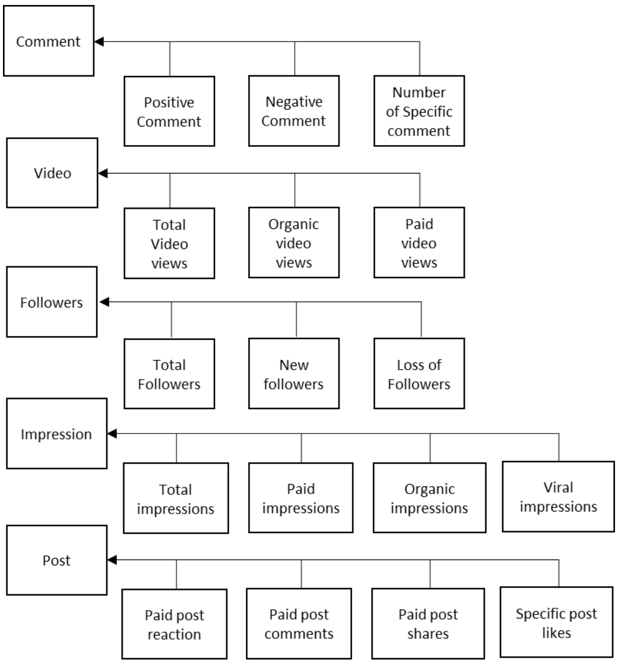

Figure 2. Ontological analysis

Before being able to perform the two methods, it was necessary to reduce the number of social attributes. At first, this database contained about 24 attributes, which for both methods were far too many. For example, for the DEMATEL method, without having reduced the number of attributes, it would have been necessary to determine the influence between each attribute on a 24X24-24 matrix, i.e., approximately 552 elements to be determined. To reduce the number of attributes, an ontological analysis is performed and shown in Figure 3 to group the different attributes into five "attribute types": followers, comments, videos, impressions, and posts.

The ISM approach is performed on the data and the attributes are classified under two levels as in Figure 3. The graph represents the contextual relationships between attributes. Level 1 consists of the most important attributes according to the ISM approach, which is this case are "comments" and the "followers". These attributes have an impact on each other represented by the arrows. The second level consists of the "posts", "impressions" and "videos" which contribute to increasing the number of "comments" and "followers". These have arrows pointing to the level 1 attributes showing that the attributes of level 2 impact those in level 1.

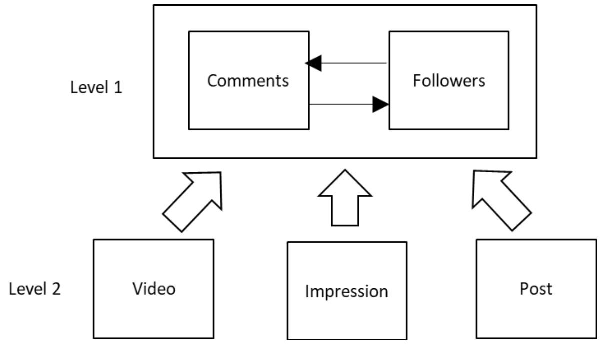

Figure 3. Results of the ISM method

The DEMATEL technique makes it possible to determine how the traits relate to one another. It is firstly necessary to determine the level of influence between all the attributes with different levels using the scale 0 to 4 described in step 1 shown in Table 1. The evaluation is conducted by a decision-maker which is an expert forecaster.

Table 1 Direct Relationship Matrix

	Comments	Video	Followers	Impression	Posts	**SUM (Z)**
Comments	0	1	2	1	1	**5**
Video	4	0	4	1	1	**10**
Followers	1	1	0	1	1	**4**
Impression	1	1	4	0	1	**7**
Posts	4	1	4	1	0	**10**

The direct relation matrix is normalized by dividing by Z to yield the matrix Y (step 2), which is then subtracted from the identity matrix I to generate the final matrix $Y(\mathrm{inv}(I\text{-}Y))$.

Final matrix with summed columns (C_i) and rows (R_i) in bold =

$$\left(\begin{array}{c|c} \begin{array}{ccccc} \mathit{Comments} & \mathit{Video} & \mathit{Likes} & \mathit{Impression} & \mathit{Post} \\ 1.25 & 0.22 & 0.51 & 0.22 & 0.22 \\ 0.74 & 1.23 & 0.89 & 0.32 & 0.32 \\ 0.31 & 0.20 & 1.31 & 0.20 & 0.20 \\ 0.40 & 0.26 & 0.75 & 1.17 & 0.26 \\ 0.74 & 0.32 & 0.89 & 0.32 & 1.23 \\ \mathbf{2.44} & \mathbf{1.22} & \mathbf{3.36} & \mathbf{1.22} & \mathbf{1.22} \end{array} & \begin{array}{c} R_i \\ \mathbf{1.43} \\ \mathbf{2.49} \\ \mathbf{1.22} \\ \mathbf{1.83} \\ \mathbf{2.49} \\ \end{array} \end{array}\right)$$

C_i labels the last row.

The fourth step consists of summing and subtracting the columns (C_i) with the rows (R_i). As mentioned in the methodology, if R_i - C_i is negative, the attribute is considered an effect and if R_i - C_i is positive, the attribute is a cause.

Table 2: Direct / Indirect relationship matrix T for the identification of cause or effect attributes

Attribute	R_i	C_i	$R_i + C_i$	$R_i - C_i$	Cause or Effect?
Comments	1.43	2.44	3.86	-1.01	Effect
Video	2.49	1.22	3.72	1.27	Cause
Followers	1.22	3.36	4.58	-2.13	Effect
Impression	1.83	1.22	3.06	0.61	Cause
Posts	2.49	1.22	3.72	1.27	Cause

The fifth step is to calculate the threshold value of the matrix *Y* which is taken as the average of the values. The threshold value for our case is 0.38. The values highlighted in bold in matrix *Y* are above the threshold value and indicate the strength of the cause-effect relationship between attributes.

$$Y = \begin{array}{r} \\ \textbf{Comm.} \\ \textbf{Video} \\ \textbf{Follow} \\ \textbf{Impre.} \\ \textbf{Posts} \end{array} \begin{array}{ccccc} \textbf{Comm.} & \textbf{Video} & \textbf{Follow} & \textbf{Impres.} & \textbf{Posts} \\ \end{array}$$

$$\begin{pmatrix} 0.25 & 0.22 & \mathbf{0.51} & 0.22 & 0.22 \\ \mathbf{0.74} & 0.23 & \mathbf{0.89} & 0.32 & 0.32 \\ 0.31 & 0.20 & 0.31 & 0.20 & 0.20 \\ \mathbf{0.40} & 0.26 & \mathbf{0.75} & 0.17 & 0.26 \\ \mathbf{0.74} & 0.32 & \mathbf{0.89} & 0.32 & 0.23 \end{pmatrix}$$

The causal digraph in Figure 4 is built based on the values in matrix *Y* above the threshold value which indicates which attributes are linked, and on the direct / indirect relationship matrix *T* to indicate the direction of causality. It is observed that many arrows are connected to "followers" and "comments". These two attributes are then the most important ones.

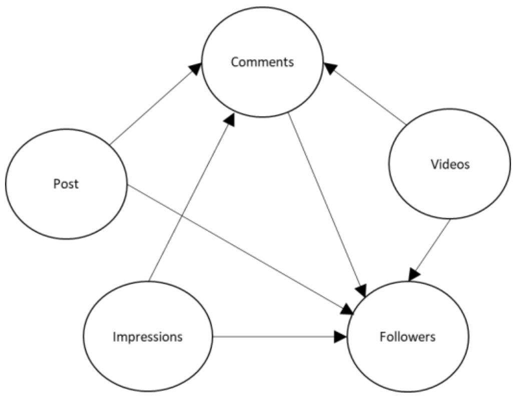

Figure 4. DEMATEL Digraph showing cause-effect relationships amongst social media attributes

C. *Validation of methodology and discussion of results*

The results from the proposed approach are validated against the Pearson's correlation coefficient (r) between the attributes and sales and the normalised values of r shown in Table 3. These values are compared against R_i - C_i from the DEMATEL approach which are also normalised to compare with r. The results show that r values are aligned with R_i - C_i in that they show a negative correlation for "comments" (r= -0.15, R_i-C_i= -1.01) and "followers" (r= -0.35, R_i-C_i= -2.13) which are the two 'effect' attributes and positive correlation for the rest, which are 'cause' attributes. The positive or negative sign of r is also aligned with the levels of influence using the ISM method with "comments" and "followers" in level 1 (Figure 3), followed by the other attributes in level 2.

Moreover, when normalizing the values (norm(r) and norm(R_i - C_i) to make them equal 1 in order to compare the strength of their correlations. "Impressions" has the strongest correlation r value with norm(r)=0.33, followed by "video" (0.28) and "followers" (0.20). Both "comments" (0.09) and "posts" (0.10) have the weakest correlations with the sales. Conversely, R_i - C_i have "followers" (norm(R_i - C_i)=0.34) as their strongest association followed equally by "video" (0.20) and "posts" (0.20), showing that the magnitudes of the associations with respect to the sales between the two methods are different. Although the direction of their associations (either cause/effect or positive/ negative) are aligned.

Table 3: Comparison between correlation coefficient and R_i - C_i from DEMATEL approach

	r	**norm(*r*)**	$\boldsymbol{R_i - C_i}$	**norm ($\boldsymbol{R_i - C_i}$)**
Comments	-0.15	0.09	-1.01	0.16
Video	0.48	0.28	1.27	0.20
Followers	-0.35	0.20	-2.13	0.34
Impressions	0.56	0.33	0.61	0.10
Posts	0.17	0.10	1.27	0.20

Both ISM and DEMATEL identify the "followers" and "comments" attributes as the most interactive with other attributes, however, these are not two attributes that necessarily result in more sales. In fact, the calculation of r shows that these two attributes are negatively correlated to the sales. These two attributes are those which are most influenced by the other attributes, namely "posts", "impressions" and "videos". As more social media users view "videos", or the company content of their feed ("impressions") or like one of their "posts", the number of "followers" and "comments" are increased. The ISM and DEMATEL approaches demonstrate the influence of these variables on the number of "comments" and "followers".

The combined ISM-DEMATEL approach provides a more comprehensive analysis of the cause-effect relationships among attributes beyond simply measuring the correlation, r, between them. It allows for a systematic evaluation of the strength and direction of the relationships among attributes and identifies key attributes that have the most significant impact on the overall system. Additionally, the ISM-DEMATEL approach can also identify feedback loops and potential areas of improvement in the system, which cannot be achieved by simply computing the correlation coefficient. Although computing the correlation coefficient may be computationally efficient, it may not provide a complete understanding of the underlying relationships and dynamics in the system.

V. Conclusion

Social media information is increasingly being used to understand consumer needs and potential future purchases. This paper uses both ISM and DEMATEL to better understand the relationships between the social media attributes from the Facebook page of a large food and beverage company with the purpose of correctly utilizing them, and potentially avoid multicollinearity, in demand forecasting for new products.

The results from both ISM and DEMATEL approaches identify the "followers" and "comments" social media attributes as interdependent and influenced by the "posts", "impressions", and "videos". The DEMATEL approach also calculates the strength of the associations between the attributes and identifies whether the attributes have more causality on, or have more of an effect by, the other attributes.

The integrated ISM-DEMATEL approach provides a novel detailed analysis of the social media landscape in the food and beverage industry, identifying the key variables impacting consumer behavior and engagement. This study advances the field of social media research and provides valuable insights into the complex nature of social media, making it an important contribution to academic literature with practical implications for marketers and managers seeking to improve their social media strategies and customer engagement in this industry.

Future research directions will consider the relationship between SMD on product sales and the development of demand forecasting techniques that use the most appropriate SMD variables.

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