Impact of Social Media Marketing on Business Performance: A Hybrid Performance Measurement Approach Using Data Analytics and Machine Learning

—ELIF KONGAR
University of Bridgeport, Bridgeport, CT 06604 USA

—OLUMIDE ADEBAYO
University of Bridgeport, Bridgeport, CT 06604 USA

(Corresponding author: Elif Kongar.)

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Abstract—*This article systematically applies machine learning and data envelopment analysis (DEA) to analyze Twitter messages, Twitter metrics, and organizational financial metrics to gain insights into impactful messaging typology on social media network. Automated machine learning is employed for the classification of tweets of select US Furniture Retail Stores while various DEA models are utilized to analyze multiple input metrics to obtain an efficiency ranking for the selected brands. Based on these analyses, the article discusses the implications of the findings for small and medium-sized enterprise marketing managers at the industry level. Recommendations for industry practice are also provided in addition to the directions regarding future research.*

Key words: AutoML, data envelopment analysis, performance evaluation, social media marketing, technology management

INTRODUCTION

A well-designed social media strategy that creates and curates engaging content helps organizations maintain competitiveness in today's dynamic business landscape [1]–[3]. Conventional marketing activities and strategies fall short in addressing specific requirements for efficient and effective social media marketing (SMM) operations because it seeks to sell through multiple means [4], in contrast to SMM which focuses on making individual connections and building long-lasting relationships. SMM customizes and personalizes marketing for a more meaningful and targeted marketing option [1].

As businesses incorporate and budget for SMM as part of their long-term corporate strategies, its return on investment (ROI) becomes questionable [5], [6]. According to a survey carried out by Headley [7], *measuring ROI* and *tying social activities to business outcomes* are the top two most challenging aspects of SMM. Traditional ROI appraisal techniques are not useful due to significant differences including cost structure and the external participant involvement that contribute to SMM activities. A systematic approach to relate SMM activities with revenue streams [8] makes the SMM investment justification nontrivial.

A handful of researchers have investigated SMM activities and their effects on firm performance but have taken a restricted view of the term organization performance. Kim and

Ko [9] evaluated a firm's performance solely on the basis of how many customers they are able to reach using social media network (SMN) compared to traditional marketing strategies. De Vries *et al* [10] and Öztamur and Karakadõlar [11] view firm performance strictly in terms of *likes, comments, retweets* while Constantinides *et al.* [12] view it as how engaged the SMN fan base is. These metrics are better referred to as *vanity metrics* (followers, views) or *actionable metrics* (retweets, comments, etc.) [7], [13], [14]. Öztamur and Karakadõlar [11] further captured the essence of the underlying problem with current research in SMM and organizational performance when they highlighted that companies should look beyond the retweets and likes noting that metrics such as the number of viewers, visitors, friends, or followers do not automatically translate to higher conversions, order value, or sales [11].

This article uses categorized Twitter messages, additional Twitter metrics, and other organizational financial metrics to gain insights into impactful messaging classification on SMN. Based on the collected furniture retail outlet data, the model evaluates firms for their SMM effectiveness. Automated machine learning (AutoML) is used for text classification.

The utilization of machine learning for SMM research is not new. The method has been extensively used for various analyses including engagement analysis [15], [16], sentiment analysis [17]–[19], and user classification [20]–[22]. Adding to the existing body of knowledge, this article introduces automated machine learning (AutoML) for investigating the performance of SMM via data envelopment analysis (DEA). The use of AutoML is novel in that it opens up social media big data research to nondata scientists enabling researchers to focus on domain knowledge instead of data science analytical modeling [23]. In addition, an evaluation of the performance provides insights into characteristics that may explain some of the performance outcomes. This information is valuable from a broader research perspective as it investigates and identifies factors that play predominate roles in addition to providing guidance for practice.

The remainder of the article is organized as follows. A background of related research in the literature is provided next. Following this, the proposed research and the methodologies that are utilized in the article are presented in detail. This is followed by a discussion regarding the conducted data analysis and the model results. The concluding remarks in addition to the directions for further research are provided in the last section.

Background

Significant research on social media big data utilization exists in communications [24], internal operations [25], risk management [26]–[29], education [28], [30], user engagement [31], [32], and user experience [30], [33]. The utilization of social networking sites to evaluate brand objectives is, however, quite limited [34]. Big data and data mining research naturally involve classifying tweets, comments, and various messages on social media networks. Data mining helps organizations discover hidden knowledge in large datasets [35]. Support vector machine (SVM), Bayesian networks (BN), and decision trees (DT) are the top three data mining techniques used by researchers in the area of social media text classification [58].

Text classifiers can be categorized into lexicon-based and machine learning approaches [36]. Lexicon-based text classification is more dominant in sentiment analysis or opinion analysis where the text is mostly classified into two or three buckets [37]. The accuracy of classifiers is one of the major driving forces behind the shift from lexicon-based classifiers to machine learning. Human classification accuracy is rated at around 0.84 [19]. In other words, humans, at first parse, will classify 84% of given texts correctly. With this in mind, any algorithm that can achieve a similar or better accuracy is considered acceptable. While there are many classes of machine learning algorithms, this article concerns itself only with supervised learning. Supervised learning algorithms are set of algorithms that rely on training datasets. They commonly employ three sets of data known as training, validation, and test datasets to learn the contextual relationships between the data and the target labels, a.k.a., classes. The training set is used to learn and fit parameters for the classifier; the validation set is used to fine tune what was learnt, and the test set is used to assess the performance of the classifier [38]. Given sizable training data, many machine learning algorithms can achieve or exceed acceptable accuracy levels [39]. In the area of machine learning, deep neural network (DNN) is a class of machine learning algorithms that is more prevalent in social media text classification [40], [41]. This research utilizes the Google AutoML, which is also based on convolutional neural network (CNN), a DNN class of machine learning algorithm [42].

Data Envelopment Analysis (DEA) has—over the years—become a popular analytical tool for performance measurement [43]. DEA has been commonly employed in evaluating the efficiencies of various decision making units (DMUs) in fields such as software development and project management [44]–[47], human resource management [48], [49], telecommunication services [50], and manufacturing [51]–[53].

To measure the effect of the adoption of technological advances across multiple countries, Shao *et al.* [50] applied DEA to construct a total factor production performance metric. Schmidt and Hazõr [45] applied a variable return to scale DEA model to capture the complex relationship between total cost of a project and its completion time to generate a robust schedule that takes multiple factors into consideration similar to a DEA-based resource allocation model proposed by Lee *et al.* [51] for allocating emissions permit. To gain insight regarding the role of technical experience and task complexity in the efficiency of software development personnel, Otero *et al.* [48] applied DEA to calculate the efficiencies of personnel at a leading software engineering organization. In addition, Talluri and Sarkis [53] show that DEA can be used in identifying alternative high performing solutions by applying cross efficiency analysis to the work of Shafer and Bradford [52].

DEA method is proven to be effective in the evaluation of the efficiency and performance of DMUs when multiple input and output parameters being considered simultaneously. This overcomes a major limitation of other popular efficiency evaluation methods such as stochastic frontier analysis [48]. Another plausible alternative for DEA is the ordinary least squares regression analysis (RA), which can be used either jointly with DEA or individually to assess the comparative performance of such DMUs. However, RA lends itself as a model of choice when comparing the performance of DMUs using a single input or to secure a single output [54]. According to Otero *et al.* [48], considering multiple performance measures simultaneously provides a more thorough evaluation process that structures the decision problem more accurately for practical purposes.

One of the most relevant studies that utilized DEA is proposed by Martő́nez-Núñez and Pérez-Aguiar [43]. The authors employed a multilayered DEA model to measure the relative efficiencies of information technology (IT) firms in Spain similar to an earlier study on productive efficiency and innovation in the Spanish wood industry [55]. The authors explored whether the possession of a web2.0 technology such as blogs, Facebook, YouTube, and Twitter has a direct impact on the efficiency of a particular IT firm. The study, however, did not attempt to quantify Web 2.0 technology utilization. Given that the possession of a social network account alone does not serve as a reliable performance metric, this article aims at filling this gap by demonstrating the utilization of related social media platforms on organizational performance. In this regard, similar to [71], this article employs a multilevel DEA model to determine the relative efficiencies of selected furniture retail stores in the United States.

The main contribution of this article is the development of a multilayer, multivariable framework that employs autoML and DEA in order to identify constantly evolving SMM messaging trends. The method is based on the continuous categorization of social media messages using autoML coupled with periodic analysis of business and social metrics using multiple DEA algorithms to rank the efficiencies of selected firms. To the best of our knowledge, there is no study in the relevant literature that utilizes autoML for message classification along with DEA for performance indexing with the aim of identifying message typologies with their impact on organizational performance.

Methodology

Brand Selection Approaching SME as a whole is a daunting task to say the least. This article focuses primarily on medium sized organizations rather than small organizations due to the availability and adequacy of data. The criteria for selecting an industry was due to its: i) its wide representation in the USA; ii) strong social media presence; and iii) the availability of organizational financial data. Wide representation is crucial to avoid clustered industries such as mining and agriculture. A strong presence of Twitter in the selected industry was also another factor that played a role in this selection. Finally, evolving data privacy rules dictate that the industries with complex and stringent privacy laws surrounding their data were avoided. Satisfying these conditions, two potential industries were identified for possible research—construction and retail trade. The availability of data within retail trade helped support our decision toward the selection of the furniture industry.

While this article opted for furniture and home furnishings stores, some of the other interesting subsections under this industrial sector include motor vehicle and parts dealers, building material and garden equipment and supplies dealers, food and beverage stores and health and personal care stores, just to list a few. The industry lends itself strongly to medium sized organization status firms and any of the listed subsectors could have been easily picked for a reasonable research study.

Brands were systematically selected via two searches in the Nexis Uni[1] database maintained by LexisNexis. Both searches were limited to US-based firms. The first search was for

[1]LexisUni Database maintained by Lexis-Nexis: https://www.lexisnexis.com/en-us/products/nexis-uni.page

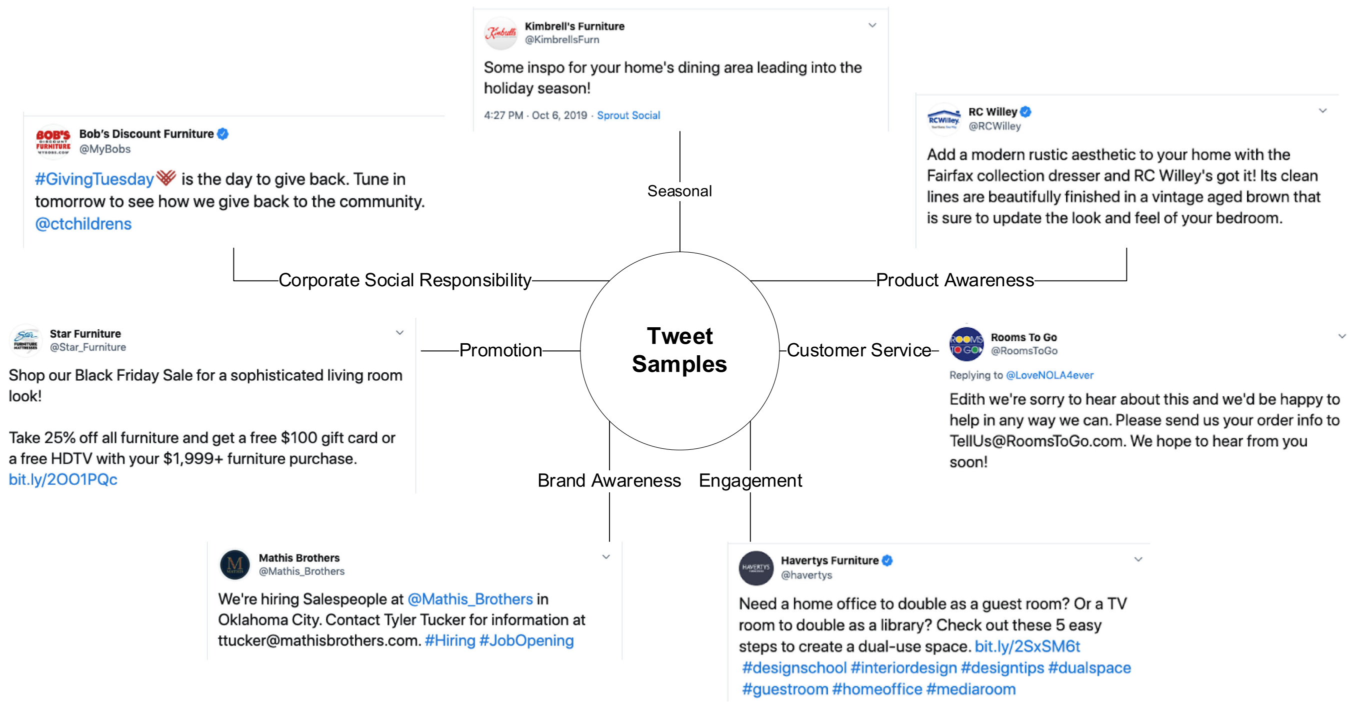

Figure 1. Categorical tweet samples.

firms with the identified North American Industry Classification System (NAICS[2]) Code 442110 (furniture stores) and the second search was for firms with the identified SIC[3] Code 5712 (furniture store). 2849 firms overlapped in both sets with 3148 unique firms across both sets. The 3148 were further filtered by dropping records without revenue information and records where either the SIC code or the NAICS was not designated as primary, bringing the number of potential brands down to 192. Out of these 192, 90 firms had Twitter accounts while only 70 have tweeted in 2019. The organizations that provided complete financial data were then selected leaving 43 companies in the dataset. Out of the 43, 20 firms were identified as SMEs, with the remaining 23 being classified as large-sized enterprises (LGEs).

Data Collection Twitter is recognized as the most popular source for social big data research both in academia and industry [56]. Today, even though Facebook still ranks #1 among social media sites due to its extensive utilization for sales, marketing, and customer service by many organizations, it does not lend itself readily to educational research. Twitter, however, is considered to be research-friendly with its application programming interfaces (APIs) that make harvesting larger datasets more efficient [57]. 1.122 random tweets were collected for training the AutoML model, while 9700 tweets collected across 70 brands selected for this article.

Classification of SMM Messages There are seven broad categories for classifying SMM messages [58], [59]. These categories include brand awareness, corporate social responsibility, customer service, [User] engagement, product awareness, promotional, and seasonal—see Table 1 for definitions.

Table 1. Definitions of the Tweet Categories.

Category	Definition
Brand Awareness	Tweets that provide information regarding the organizational activities such as hires, location openings, celebrity visits, etc.
Customer Service	Tweets that attempt to resolve customer issues.
Corporate Social Responsibility	Tweets that mention charity, goodwill or social consciousness.
Product Awareness	Tweets that draw attention to specific products, product attributes or instructions.
Promotion	Tweets that mention giveaways, contests, sweepstakes, coupons, and reduced rates.
Seasonal	Tweets that mention periodic events such as holidays.
Engagement	Tweets that do not fit into the above six categories.

[2]North American Industry Classification System: https://www.naics.com/
[3]Standard Industrial Classification: https://www.osha.gov/pls/imis/sicsearch.html

Vargo [60] extended these classifications specifically for Twitter, creating relevant subcategories in the process. Figure 1 gives a graphical example of these classes and tweets that might fall under each category.

Implementing a deep learning text classifier model from scratch comes with a steep learning curve for a nondata scientist. To make ML more accessible to nondata scientists, cloud-based companies have been promoting automated machine learning (autoML) platforms. AutoML attempts to construct machine learning programs without human assistance and within limited computational budgets [61]. References [61]–[64] give a state-of-the-art review of autoML and the inner workings of a cloud-based autoML. For this research, Google Cloud AutoML [65] is utilized. Figure 2 provides the overall flow of the tweet acquisition and classification process.

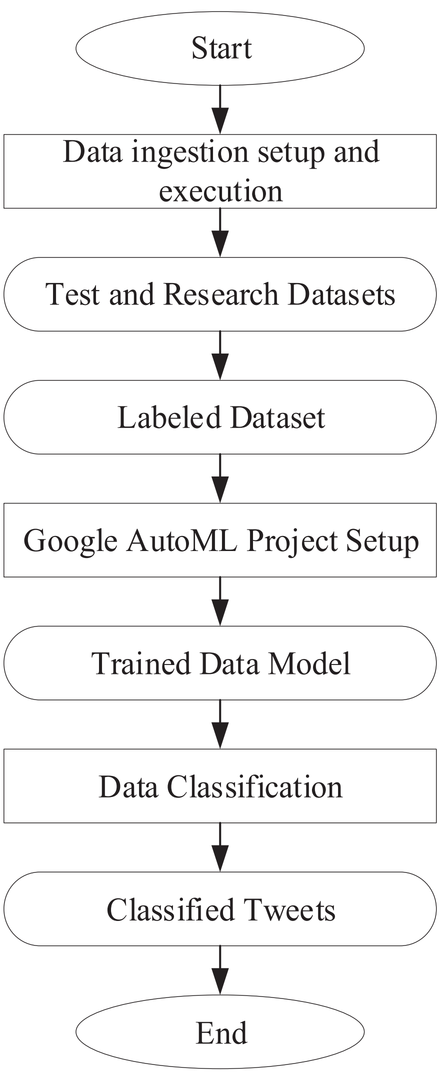

Figure 2. The Tweet classification process.

When assessing the quality of information retrieval systems, *precision* and *recall* are the two most prevalent performance measures used [66], [67]. Precision is the percentage of relevance. Recall is the percentage of correctness. Even though achieving a high precision and an equally high recall is appealing, it is not always achievable in nontrivial (binary, true/false) cases. A mid-range threshold or confidence level of 0.5 was selected in order to achieve a balanced precision and recall. A higher confidence level of say, 0.8, will result in a much higher precision but lower recall unless the model has been trained with a far much higher amount of training data. The evaluation of the Google Cloud AutoML model is shown in Table 2, which validates the reliability of results. Here, the confidence level indicates the level of confidence a model must have in its ability to correctly determine that a record/ document/tweet belongs to a class prior to class assignment.

The accuracy of the classifier can be calculated in terms of its precision and recall as the F1 score [68]:

$$F1 = \frac{2}{\left(\left(\frac{1}{\text{precision}}\right) + \left(\frac{1}{\text{recall}}\right)\right)} = \frac{2(\text{precision} * \text{recall})}{\text{precision} + \text{recall}}. \quad (1)$$

Solving (1) using the data in Table 2 provides a classifier accuracy of 82%. The accuracy of the classifier can be improved further by a larger training dataset.

Table 3 provides the categorical and utility distribution of the 1122 *training dataset.* The rows depict the category breakdown by count of tweets while the columns show the number of tweets involved in each phase of the training process. Training an autoML model is a three-stage process—training, validation, and testing. The *training* column shows how much of the training dataset—in number of data points used—to actually fit the classifier model. The *validation* column is how much of the training dataset is used for tuning the classifier. The *test* column tells us how much of the training data are used to provide an unbiased evaluation of the final model. It is important to have a balanced spread across all classes within each stage of the training process in order to avoid an overfitted or biased classifier.

Data Envelopment Analysis Following the collection and the classification of tweets, the sample companies are evaluated using data envelopment analysis (DEA) [69]. DEA models measure the performance of a homogenous set of entities also known as decision making units (DMUs), using multiple input and output factors. DMUs in this article represent firms. DEA does not assume a parametric relationship or distribution [70]. The performance of each entity is defined by their technical efficiency, which can be calculated as the ratio between the weighted outputs and inputs [71]. Generally, input factors are the variables that are subject to minimization, whereas, output factors are the ones that are subject to maximization.

Table 2. Statistical Analysis Results of the Google Cloud AutoML Model.

Statistics	Value
Confidence Level	0.5
Test Items	989
Precision	86.91%
Recall	76.85%

The technique is nonparametric because it can provide a quantitative evaluation score for each entity without assuming a parametric relationship between the criteria. DEA uses mathematical programming optimization approach, while statistical methods rely on a maximum likelihood approach with some parametric distribution and relationship among the data [70]. The general consensus is that DEA models best perform when there is sufficient number of DMUs in relation to the total number of input and output factors [72]–[74] and often require the number of DMUs to be at least twice the total number of input and output variables.

A basic DEA model allows for the introduction of multiple inputs and multiple outputs by obtaining an "efficiency score" of each DMU with conventional output/input weighted productivity ratio analysis. Basic efficiency is the ratio of weighted sum of outputs to the weighted sum of inputs. The relative efficiency score of a test DMU i can be obtained by solving the following DEA ratio model (CCR) proposed by Charnes *et al.* [69]

$$E_i = \sum_{k=1}^{K} u_k y_{ki} \Big/ \sum_{h=1}^{H} v_h x_{hi},$$

where E_i is the efficiency score of DMU i

s.t.

$$\begin{aligned} &\sum_{k=1}^{K} u_k y_{kp} \Big/ \sum_{h=1}^{H} v_h x_{hp} \le 1 \ \forall p \\ &u_k,\ v_h\ \ge 0\ \forall\ k,\ h \end{aligned} \tag{2}$$

where
i = index of DMU,
y_{ki} = amount of output k for DMU i,
x_{hi} = amount of input h for DMU i,
y_{kp} = amount of output k for DMU p,
x_{hp} = amount of input h for DMU p,
v_h = weight of input h,
u_k = weight of output k.

The linearized version of (2) can be mathematically be expressed as follows:

$$\max E_i = \sum_{k=1}^{K} u_k y_{ki}$$

s.t.

$$\begin{aligned} &\sum_{h=1}^{H} v_h x_{hi} = 1, \\ &\sum_{k=1}^{K} u_k y_{kp} - \sum_{h=1}^{H} v_h x_{hp} \le 0 \forall p, \\ &u_k, v_h \ge 0 \forall k, h. \end{aligned} \tag{3}$$

Solving (3) provides the relative efficiency score of DMU i relative to the remaining DMUs. A DMU i with an efficiency score of 1 is considered to be efficient whereas any score other than 1 implies that the DMU i is inefficient.

A variant of DEA, DEA with cross-efficiency measurement [75], allows the ranking of DMUs [76] and hence is mostly utilized for peer evaluation; the CCR model usually results in multiple efficient units with a score of 1 and it is difficult to discriminate among those DMUs. In addition, the method also eliminates unrealistic weight schemes since it does not require unrealistic weight restrictions [76]–[78]. Doyle and Green [79] formulated the method as

$$\begin{aligned} &\min \sum_{k=1}^{K} u_k \left(\sum_{j=1, j\neq i}^{F} y_{kj} \right) \\ &\textit{or} \max \sum_{k=1}^{K} u_k \left(\sum_{j=1, j\neq i}^{F} y_{kj} \right) \end{aligned} \tag{4}$$

s.t.

$$\begin{aligned} &\sum_{h=1}^{H} v_h \left(\sum_{j=1, j\neq i}^{F} x_{hj} \right) = 1 \\ &\sum_{k=1}^{K} u_k y_{ki} - E_i \sum_{h=1}^{H} v_h\, x_{hi} = 0 \\ &\sum_{k=1}^{K} u_k y_{ki} - \sum_{h=1}^{H} v_h\, x_{hi} \le 0, \\ &j = 1, 2, \ldots, F \ \text{ and } \ j \neq i, v_h, \\ &u_k \ge 0 \quad \forall k, h. \end{aligned}$$

When the objective function is to minimize, (4) provides the *aggressive* cross-efficiency DEA formulation and aims at minimizing the sum of weighted outputs. When the objective function is to maximize, the equation is defined as a *benevolent* cross-efficiency formulation and aims at maximizing the sum of the weighted outputs [80]. In addition to the CCR model, this article utilizes the benevolent cross-efficiency formulation to obtain the set of the optimal weights. By applying the cross-efficiency DEA, all the DMUs are assessed by the weights of target DMU i. Following this, the average value is calculated. The cross-efficiency score of the jth DMU can be calculated as

Table 3. Model Training, Validation, and Test Dataset Distribution.

Tweet Category	Training	Validation	Test	Total
Brand Awareness	97	29	30	156
Corporate Social Responsibility	101	27	31	159
Customer Service	101	31	31	163
Engagement	101	31	31	163
Product Awareness	101	31	31	163
Promotion	100	31	31	162
Seasonal	101	24	31	156

$$CE_j = \frac{\sum_{i=1}^{F} E_{ij}}{F} = \frac{\sum_{i=1}^{F}\left(\frac{u_1^i y_{1j} + u_2^i y_{2j} + \ldots + u_K^i y_{Kj}}{v_1^i x_{1j} + v_2^i x_{2j} + \ldots + v_H^i x_{Hj}}\right)}{F} \quad (5)$$
$$i = 1, 2, \ldots, F.$$

The ranking of each DMU can then be obtained via its cross-efficiency (CE_j) score since higher values of (CE_j) indicate higher efficiency and vice versa. The R package "deaR" version 1.1.0 is utilized for the calculations using RStudio Version 1.2.1335 by RStudio, Inc.

Case Study Analysis and Results

Assessing social media activity impact on corporate goals is challenging due to complexities associated with lack of visibility, unclear relationship to corporate investment, and a time lag between the efforts and their market results.

We use six DEA cross-efficiency measurement models to rank furniture stores. These six models together constitute an incremental multistage DEA model [43] providing a detailed analysis of business and SMM performance. The quantitative input and output data for the DEA models are obtained from Twitter [81], the US Manufacturer Survey [82], and D&B Hoovers [83].

The SMM evaluation includes data such as the number of tweets, fans, and followers. Corporate success is measured using organizational and financial data. The selection of input and output variables are based on whether the factor was a response or an operational measure. For instance, the number of tweets is considered an input variable since tweets are initiated by the organization, whereas the number of likes derive from customers and hence is classified as an output variable [43]. The complete list of input and output variables utilized in this article are summarized in Table 4. Each of the factors have been utilized by other studies and the references are provided. A unique factor in this article is list count. List count indicates the number of lists a user belongs to and is included in the model since it is a reliable indicator of engaged Twitter users.

Table 5 provides a summary of the SME and LGE tweet data based on each category. The values in Table 5 demonstrate the significant difference among the related business and SMM indicators in relation to the quantity of tweets.

Not surprisingly, LGEs demonstrate more activity compared to their SME counterparts. Note that *engagement* represents the category with the largest number of tweets. This result is expected given that customer engagement is a precursor to brand loyalty [92]. *Product awareness* is also popular. One significant difference between company size categories is *customer service* tweets. LGEs (65.70) put more effort on these tweet types than do SMEs (3.45). A reason for this is a proactive approach by LGEs to address and resolve customer issues; dedicating resources to handle these complaints online and in real-time. Fewer *customer service* tweets for SMEs may also be attributed to their relatively smaller customer segment and fewer resources.

There are three sets of incremental multistage DEA models employed in the article. The first pair of DEA models include all companies (SMEs and LGEs). The DEA I model measures business efficiency and considers only overall business data. In DEA I, the number of employees and total assets are considered as input variables whereas the annual sales is the output variable. DEA II model introduces social media related variables and includes the number of tweets as an additional input variable whereas the numbers of likes, followers, friends, and list count are added as other output variables.

An aggressive cross-efficiency DEA models aim at obtaining a maximum simple efficiency score for a particular DMU while determining a set of weights that will minimize the aggregate output of other DMUs. Alternatively, benevolent DEA models aim at maximizing the aggregate output and is more appropriate for this article. One additional benefit of using the benevolent formulation arises from the fact that the aggressive formulation may cause too much input and output information loss in the efficiency assessment [93]. Therefore, this article considers the results of the benevolent formulation

Table 4. Input and Output Variables for the DEA Models.

DEA Model	Reference	Business Efficiency	Social Media Marketing (SMM) Efficiency
Inputs			
Number of employees	[43], [84]–[86]	√	√
Total assets	[43], [84], [87], [88]	√	√
Tweets	[43], [84]		√
Outputs			
Annual sales	[43]	√	√
Likes	[84], [89]		√
Followers	[43], [90], [91]		√
Friends	[43]		√
List count			√

to be more accurate and reliable. Descriptive summary statistics of the six DEA models are provided in Table 6.

Table 7 provides an ordered rank of DMUs based on their business and SMM efficiencies. The findings indicate that, when the business performance of SMEs and LGEs are evaluated collectively, the top ten firms are evenly distributed as SMEs and LGEs. When SMM metrics are introduced into the evaluation, LGEs constitute 70% of the overall set of the top 10 in rank. One plausible explanation for this result is that LGEs have a significantly higher number of Tweets indicating stronger presence in social media. LGEs are also associated with a significantly higher number of likes caused by their dominating presence.

Comparing the business effectiveness of SMEs in their own class—Models DEA III and IV in Table 2—show the top ten SMEs within their groups. The remaining lower scored five firms that are characterized by a large number of employees with larger assets. The top ten firms have relatively small total assets and number of employees indicating better utilization of business resources. When SMEs are evaluated for SMM effectiveness, the organizations with strong assets but weaker social media presence are replaced in the top ten rankings by those organizations with higher numbers of follower and friend—despite their relatively limited resources.

Evaluation of LGEs among their own size of firms—represented by models DEA V and VI in Table 7—include the top five companies that were in the industry-at-large comparison in the DEA I model results. The remaining five organizations in the top ten for DEA V have similar financial standing and are primarily characterized by high annual sales. Introducing SMM metrics—DEA VI model—results in companies with high sales being replaced with organizations that have strong SMM presence; indicated by higher number of Tweets and other related measures such as the number of followers.

When we consider the tweet typologies of the top SME firms, it helps to provide a picture of where the top performers are focused. The top four SME performers in terms of business efficiency (DEA I and DEA III) all show a strong focus on engaging users on social media—an engagement typology—accounting for well over 50% of their Twitter activities. They also have a very small footprint for *promotional and product awareness* dimensions. Four other SME DMUs show an interest in engagement along with promotional and product awareness dimensions but are not highly ranked. The key difference between them being that the lower ranked DMUs have few employees. This potentially could be

Table 5. Descriptive Statistics of Tweet Data Based on Each Category.

SMEs	Ave.	Std. dev.	Range	Min.	Max.	Total
Product Awareness	17.75	30.41	106	0	106	355
Promotional	9.30	18.46	70	0	70	186
Brand Awareness	14.80	17.09	60	0	60	296
Seasonal	5.50	7.90	26	0	26	110
Engagement	38.65	43.66	160	0	160	773
Customer Service	3.45	12.73	57	0	57	69
Corporate Social Responsibility	1.00	2.08	9	0	9	20
LGEs	**Ave.**	**Std. dev.**	**Range**	**Min.**	**Max.**	**Total**
Product Awareness	29.83	28.18	117	0	117	686
Promotional	21.65	27.28	130	0	130	498
Brand Awareness	26.04	22.07	95	1	96	599
Seasonal	16.65	13.05	46	0	46	383
Engagement	70.91	41.11	152	3	155	1631
Customer Service	65.70	90.80	260	0	260	1511
Corporate Social Responsibility	4.09	6.53	27	0	27	94

Table 6. Summary Results of the DEA Models.

Perspective	Business			SMM		
DEA Formulation	CCR	Agg	Ben	CCR	Agg	Ben
SMEs+LGEs	DEA I			DEA II		
Average Efficiency	0.41	0.31	0.32	0.72	0.30	0.39
Standard Deviation	0.29	0.22	0.23	0.30	0.16	0.20
# Efficient DMUs	3	0	0	16	0	0
% Efficient DMUs	6.98%	0.00%	0.00%	37.21%	0.00%	0.00%
Max. Efficiency	1.00	0.92	0.95	1.00	0.63	0.81
Min. Efficiency	0.02	0.02	0.02	0.10	0.03	0.04
SMEs	DEA III			DEA IV		
Average Efficiency	0.52	0.37	0.39	0.87	0.33	0.58
Standard Deviation	0.31	0.22	0.23	0.21	0.12	0.22
# Efficient DMUs	3	0	0	13	0	0
% Efficient DMUs	15.00%	0.00%	0.00%	65.00%	0.00%	0.00%
Max. Efficiency	1.00	0.93	0.97	1.00	0.56	0.88
Min. Efficiency	0.04	0.02	0.03	0.40	0.10	0.21
LGEs	DEA V			DEA VI		
Average Efficiency	0.41	0.32	0.33	0.72	0.31	0.46
Standard Deviation	0.32	0.25	0.26	0.31	0.19	0.26
# Efficient DMUs	3	0	0	11	0	0
% Efficient DMUs	13.04%	0.00%	0.00%	47.83%	0.00%	0.00%
Max. Efficiency	1.00	0.91	0.95	1.00	0.78	0.93
Min. Efficiency	0.02	0.02	0.02	0.14	0.04	0.08

a function of the quality of the engagement where the employees are not social media savvy, or a distraction created with a multifocused social media messaging campaign. All top ten SMEs barely register on the *seasonal* and *corporate social responsibility* dimensions and as such, we can assume those typographies have no direct impact on the business efficiency rankings.

These initial findings mean that SMEs *engaging* users on social media might be more valuable than inducing them with promotional offerings as long as the firm can support the engagement with enough manpower. This inference cannot be made for LGE data. LGEs likely have the resources and wherewithal to engage on multiple social channels. This may mean that a more holistic SMM typology is needed when considering LGEs.

The results indicate that DEA results are clearly sensitive to the SMM metrics they employ; they do provide some initial exploratory results that can link the multitude of performance measures. Tying rapidly changing social media data—operational data—to longer term financial indicators provides insights than if separately evaluated would be missed. These models and this methodology allow for dynamic and timely measurement of SMM performance.

DISCUSSION

This article evaluates social media activities—in particular t*weets*—of US-based furniture retail stores. The findings include the relative performance measures of businesses using business and SMM perspectives. Currently, no studies have directly related and integrated online social media activities to firm performance using a novel combination of autoML and DEA, especially in the retail industry which is dominated by SMEs. We provide a methodology that allows companies and researchers to complete these evaluations. These issues are important because significant resources are being dedicated to social media marketing. Whether the returns are acceptable and what characteristics make them more acceptable are important areas of research. This article provides methods for stronger inferencing that can be made as to which typologies provide more value for organizations and which ones are not economically productive.

Tying SMM activities to company financial performance is a challenging task. Data would make it possible to map users on social channels to economic transactions taking place offline at retail stores. The probability of such data existing however is difficult to acquire due to the desire to remain anonymous or the tendency to use false identities online.

MANAGERIAL IMPLICATIONS

A managerial implication from the results and discussion is the need for SMEs to closely monitor the social media network channels they utilize and be agile enough to quickly adapt when trends change. It is clear that the types of messaging are significant and managers need to be adept at aligning their marketing campaigns to impactful classes of SMM messages as trends change. Social media network users are quite fluid and easily influenced by current social event or culture. Unlike traditional marketing channels, social media network trends have the ability to change rapidly and it is imperative for managers and organizations to be constantly aware of this situation. The success of a marketing campaign will be greatly enhanced if it employs impactful messaging classes. The whole organization needs to be aware that their products and reputation can be greatly affected by how they are viewed and shared on social media.

The results equally imply the need for managers to be aware of leaders in their space. Keeping track of the top performers in their industry is a precursor to being able to adapt to changing messaging trends. In the SME segment where resources and publicly available business data are limited, the methodology put forward in this research presents a viable way to rapidly identify industry leaders and

Table 7. Top Ten Benevolent Cross Efficiency Results of the DEA Models.

SMEs+LGEs				SMEs				LGEs			
Business (DEA I)		SMM (DEA II)		Business (DEA III)		SMM (DEA IV)		Business (DEA V)		SMM (DEA VI)	
DMU	Eff.	DMU	Eff.	DMU	Eff.	DMU	Eff.	DMU	Eff.	DMU	Eff.
35	0.95	37	0.81	14	0.97	5	0.88	35	0.95	33	0.93
37	0.93	33	0.73	12	0.70	13	0.87	37	0.93	37	0.89
14	0.78	5	0.72	15	0.67	14	0.86	21	0.69	30	0.81
21	0.67	7	0.70	13	0.66	15	0.84	24	0.61	24	0.80
12	0.64	36	0.66	11	0.66	3	0.76	36	0.57	40	0.79
24	0.62	24	0.66	5	0.51	7	0.76	30	0.39	38	0.63
15	0.56	3	0.65	19	0.40	19	0.75	25	0.38	32	0.59
36	0.56	40	0.65	6	0.35	11	0.74	33	0.34	36	0.58
11	0.54	35	0.62	4	0.34	2	0.72	34	0.32	35	0.54
13	0.49	30	0.59	16	0.33	12	0.64	40	0.32	31	0.51

also play a competitive role in how to present and respond to product issues faced by an organization. The leaders represent what is tested and proven at any given point in time, without which, it will be much of a guessing game.

The methodology may not be easy to apply for an SME without the necessary skills in their organization. In this case, hiring outside expertise may be valuable in the long run to be able to access this type of information. But in some industries, even a little more information as well as image management can allow companies to build some competitive advantages. This methodology can also enable organizations to manage this performance.

CONCLUSION

While this article integrates various disciplines including data mining, social media marketing, and performance evaluation—there are limitations and opportunities for further research. This research was based on limited data from a single Social Media Network, Twitter. Twitter is a good case example for a proof of concept; but it provides only a certain type of information. Further research would benefit from including a larger dataset and other competing Social Media Networks.

Overall, given the pervasiveness and growth of SMM, more and better methodologies are needed for managerial and research investigations. This article adds to the discourse and helps build additional foundation for further investigation.

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