An Empirical Study of the Impact of Social Media Data Analytics on Marketing Strategy

Which Social Media Data Analytics Metrics to Select?

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Abstract: Social Media Data Analytics (SMDA) has emerged as a dynamic and growing field across various disciplines, including marketing. However, practitioners and researchers in the marketing domain have realized that harnessing the full potential of SMDA for guiding marketing strategies necessitates a clear understanding of the relevant SMDA metrics. A significant challenge lies in the lack of clear guidance on which SMDA metrics are most relevant for enhancing marketing strategies. This study aims to empirically evaluate the impact of SMDA on marketing strategies. To achieve this goal, the study carried out a questionnaire for data collection and employs an empirical investigation using the PLS-SEM methodology. The results show that the impact of SMDA on marketing strategy depends on SMDA metrics (data type, platforms and analysis methods) and also on marketing strategy type. The results suggest a valid conceptual model introducing novel metrics for the SMDA concept. These results present a broader perspective on how SMDA affects marketing strategies and suggest that future research should focus on a specific type of marketing strategy and study SMDA metrics in a different and more in-depth way.

Keywords: Social Media Data Analytics (SMDA), Marketing Strategies, Conceptual framework, Empirical study, PLS-SEM.

Introduction

The extensive usage of social media in our daily lives has resulted in the creation of large amounts of unstructured data (Stieglitz *et al.*, 2018). This data, gathered from social media platforms, is of value to analysts and specialists who aim to monitor and analyze various indicators related to business performance. Recently, the field of Social Media Data Analytics (SMDA) has emerged as a dynamic area spanning various disciplines, including marketing (Kaabi & Jallouli, 2019; Lee, 2018; Misirlis & Vlachopoulou, 2018). SMDA refers to the

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practice of collecting and analyzing social media data to assist decision-makers in addressing specific issues (Lee, 2018). The SMDA concept is built on Claude Shannon and Warren Weaver's Information Theory, which explores the utilization of information within a specific context (Ritchie, 1986). According to Misirlis & Vlachopoulou (2018), SMDA holds the potential to reshape marketing strategies within organizations and companies. However, realizing these opportunities requires both practitioners and researchers to increasingly examine data originating from social media platforms (Stieglitz *et al.*, 2018).

To effectively utilize this data for marketing insights, it is crucial to understand how to choose appropriate metrics and dimensions for SMDA (Misirlis & Vlachopoulou, 2018). Many researchers have explored the link between SMDA and marketing strategies, advocating for deeper investigation into different aspects of this relationship (Lee, 2018; Misirlis & Vlachopoulou, 2018; Rowley & Keegan, 2020). Earlier studies have also prompted a more detailed exploration of this relation by focusing on specific metrics (like data types, analysis methods, data sources, etc.) and emphasizing the need to choose suitable measurement scales to precisely outline the various dimensions of this connection (Campbell *et al.*, 2020; Stieglitz *et al.*, 2018; Saggi & Jain, 2018).

Consequently, there remains uncertainty in the literature regarding the selection of the most suitable metrics to guide marketing strategy. Furthermore, despite the increasing number of publications utilizing SMDA in the marketing field, there is a lack of comprehensive conceptual frameworks that thoroughly explore the process of using SMDA for marketing strategies (Lee, 2018; Stieglitz *et al.*, 2018; Saggi & Jain, 2018; Campbell *et al.*, 2020).

To bridge this gap, this article aims to empirically estimate the impact of SMDA on the marketing strategy concept. To do this, this research reports the results of a survey carried out to test the proposed model. PLS-SEM was used to analyse the data.

This study intends to assist both marketing researchers and practitioners by generating a guide, an overview, and a mapping that addresses the impact of SMDA and its metrics on various types of marketing strategies. Thus, the research questions of this research are:

- To what extent does the process of SMDA ensure benefits for marketing strategies?
- Which metric of SMDA guides marketing strategies?

The paper is organized as follows. The first section is intended to explore the literature related to marketing strategies and SMDA. The second section serves to introduce, drawing on the literature, a conceptual model that elucidates the relationship between the two concepts, SMDA and marketing strategy, along with their key dimensions. The third section outlines the methodology employed in the empirical study. The fourth section presents and discusses the main results of the data analysis process. Finally, the fifth section encompasses a concise

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conclusion, acknowledges limitations, and provides recommendations for prospective research endeavours.

Literature Review: SMDA to Guide Marketing Strategies

To investigate the impact of SMDA on marketing activities, Moe & Schweidel (2017) introduced a theoretical framework treating SMDA as a source of marketing information. Similarly, Misirlis & Vlachopoulou (2018) conducted theoretical research on SMDA metrics in the marketing domain, proposing that companies capable of gauging and harnessing the hidden potential of big data from social media could acquire insights to optimize product and service promotions, enhance targeting, foster brand loyalty, and elevate other marketing performance indicators. Considering intelligent tourism destinations, Vecchio et al. (2018) demonstrated what Social Big Data can bring to the value creation process. Verhoef & Bijmolt (2019) formulated a conceptual framework detailing how digital models and technologies influence markets and business performance. Likewise, Campbell et al. (2020) elucidated how the application of AI technology can enhance marketing planning and strategic approaches. By focusing on market performance, Gupta et al. (2020) endeavoured to explore the relation between big data predictive analytics and organizational performance. Benslama & Jallouli (2022) proposed a theoretical framework, through a systematic literature review of 120 articles published from 2015 to 2021, to delve into how SMDA can steer marketing strategies.

Conceptual Framework

The referenced articles in the preceding section are fundamentally grounded in 'Information Theory', pioneered by Claude Shannon and Warren Weaver, delving into the use of information within a specific context (Ritchie, 1986). Furthermore, they evidence how an organization's internal operations pinpoint avenues for value creation, aligned with Michael Porter's Value Chain Theory (Porter, 1985).

Based on the studies discussed in the previous section, it can be expected that SMDA use can exert a positive impact on marketing strategies. Moreover, the in-depth study of the literature suggests that the dimensions and metrics of SMDA are not yet well studied by researchers nor tested empirically (Misirlis & Vlachopoulou, 2018; Benslama & Jallouli, 2022; Ramadeen & Oosterwyk, 2023).

According to Misirlis & Vlachopoulou (2018), in the field of marketing, the SMDA process is significantly impacted by two main dimensions: SMDA methods and social media platforms. Lee (2018) provided an overview of SMDA adoption for businesses, and highlighted the importance of the SMDA method, platforms, and data type. SMDA method, social media platform, and data type have also appeared in many studies as SMDA metrics (Batrinca &

Treleaven, 2015; Ghani *et al.*, 2019; Galetsi *et al.* , 2020). Therefore, SMDA relies on three main metrics: methods, platforms, and data type.

On the other hand, among the most important indicators contributing to the success of a marketing strategy is "the effectiveness" (DeLone & McLean, 1992). This indicator can be defined by the extent to which a strategy achieves the predefined objectives (Dean & Sharfman, 1996). Effectiveness is widely used by researchers and can be adapted depending on the context and the used concept (Wang & Byrd, 2017; Shamim *et al.*, 2019). Shamim et al. (2019) suggest that Big Data enables companies to improve the effectiveness of business strategies. In light of these arguments, this study proposes that the use of SMDA has a positive impact on the effectiveness of marketing strategy. Thus, the following hypothesis is proposed:

H1: SMDA has a positive impact on marketing strategy.

Moreover, regarding the marketing strategy concept, Benslama & Jallouli (2022) established a theoretical framework encompassing five primary strategies inspired by Leonidou et al. (2002), Armstrong et al. (2014), and Campbell et al. (2020), namely: Targeting and Positioning Strategy; Product, Service and Brand Strategy; Communication and Influence Strategy; Pricing Strategy; and Channel and Logistics Strategy.

Thus, this research considers that marketing strategy is reflected by six dimensions (Figure1). The linking of all the SMDA and marketing strategy dimensions leads to schematize the conceptual model shown in Figure 1.

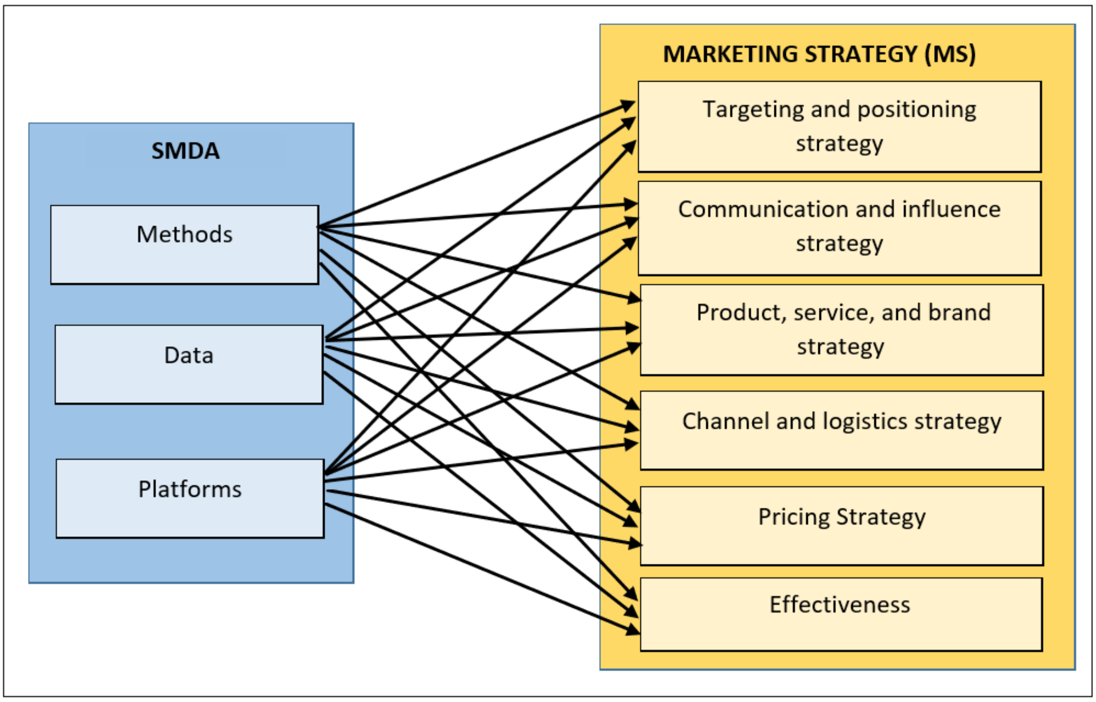

Figure 1. The conceptual model of the impact of Social Media Data Analytics on Marketing Strategies

Methodology

The relations and hypotheses presented in our conceptual model are drawn from existing literature. This study seeks to empirically validate these relations, so this study follows a positivist epistemology that favours the application of quantitative methods to test causal relationships (Creswell, 2003).

Given the absence of geographical boundaries in our study, we opted for online questionnaire dissemination (via email, Facebook, Messenger, LinkedIn). Google Forms was adopted due to its cost-effectiveness and practicality for information collection (Bhattacherjee, 2012).

We employed a convenience sampling method, due to the limited nature of our targeted population (professionals knowledgeable in both SMDA and marketing strategy). The measurement scales were identified based on previous research. Tables A1 and A2 in the Appendix provide a summary of the main measurement scales, items and sources for SMDA and Marketing Strategy variables that were included in the questionnaire (such as Blankson & Kalafatis (2004); Filipe Lages et al. (2008); and Slater & Olson (2001)).

To ensure questionnaire clarity, a pretest was conducted involving a small subset of targeted individuals to gather their feedback (Jolibert & Jourdan, 2011). To this end, our questionnaire was distributed to 30 individuals. This pretest facilitated the incorporation of valuable insights (for instance, four respondents recommended adding the LinkedIn platform due to its perceived professional significance).

The questionnaire was distributed to 600 professionals, resulting in 317 collected responses, of which only 132 reported the utilization of SMDA in their enterprises. It is worth noting that the questionnaire was launched on December 20, 2021, and concluded on July 4, 2022.

The descriptive analysis of our sample reveals that most of the surveyed businesses are small and medium-sized enterprises (63.5%). Respondents primarily belong to the following departments within their companies: the IT department (39.4%); marketing department (11%); and production department (10.1%). Most companies in our sample are located in Tunisia (61.5%), followed by France (18%) and Mexico (7.6%). Regarding the sectors of these businesses, the predominant ones are technology (37.8%), automotive industry (11.2%), and education/culture (7.4%).

Following data collection and descriptive analysis, we proceeded to the application of statistical tests to evaluate the validity of our proposed model and to test the reliability of the variables, dimensions, and measurement instruments. The data analysis process consists of two basic steps: the first step involves exploratory factor analysis, while the second step aims to test the relationships between variables and examine the study's structural model.

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For the exploratory factor analysis, we started by determining the main factors of each variable. We thus applied the Principal Component Analysis method (PCA), which represents the most commonly used method (Carricano *et al.*, 2010). Then, we assessed reliability to examine the internal consistency of measurement scales by using "Cronbach's Alpha".

To evaluate the model's validity, we employed the Structural Equation Modelling (SEM) method. Specifically, we applied the Partial Least Squares-SEM (PLS-SEM) method. The PLS-SEM, renowned for its capacity to address various research types (confirmatory, predictive, exploratory, etc.) (Benitez et al., 2019), and its robustness in dealing with non-normally distributed data, demonstrates its effectiveness, even when applied to small sample sizes, as in our specific case (Hair *et al.*, 2011).

Main results and Discussion

Exploratory factor analysis of the SMDA variable

The proposed conceptual model breaks down the SMDA variable into three factors: "Data", "Methods" and "Platforms". These three factors encompass a total of 21 items. To conduct factor analysis on the SMDA variable, we performed PCA on all 21 items. The KMO test produced a value of 0.853, which is considered excellent and indicates that the data can be factored (Pett *et al.*, 2003).

The PCA with Varimax rotation generated six factors, ensuring a good representation quality for all the items (with loadings >0.5) (Evrard *et al.*, 2009) and capturing 74.5% of the total variance.

In our conceptual model, the SMDA variable encompasses three factors. Based on the PCA results, only the "Methods" factor is retained. For the other two factors, Varimax rotation classified them into sub-factors: "Data" was divided into two sub-factors, the first encompassing three data types — text, image, and video — while the second included likes, comments, hashtags, and ratings. Regarding the "Platforms" factor, it was divided into three dimensions: the first comprised Twitter, Facebook, and Instagram; the second encompassed YouTube and LinkedIn; and the third included platforms like TripAdvisor, Yelp, Weibo, and Booking that pertain to specific domains, activities, or subjects. As such, we replaced the three factors from our conceptual model with the six factors from the PCA results, since we found this arrangement meaningful and useful. Thus, the "Methods" factor remains unchanged; the "Data" factor resulted in two distinct dimensions. "General Data" (composed of three items) and "Specific Data" (composed of three items). The "Platforms" factor yielded three different dimensions, which we named "General Platforms" (composed of three items), "Specific Platforms" (composed of four items) and "Professional Platforms" (composed of two items).

We considered YouTube as a professional platform, since the majority of its users are liberal professionals (artists, businesses, educators, etc.) (Firat, 2019; Costa-Sánchez, 2017).

The Cronbach's alpha of the overall SMDA variable was estimated, yielding a reliable value surpassing the empirical threshold (0.894), with acceptable correlations (> 0.3) (Zalma *et al.*, 2015) among the elements of this variable. In a second step, we proceeded with the reliability analysis for each SMDA dimension separately. The results displayed in Table 1 demonstrate that internal consistency reliability is maintained for all dimensions (>0,6) (Evrard *et al.*, 2009).

Table 1. Internal consistency test for the SMDA variable

Dimension	Cronbach's alpha	Average correlation (r)
General Data (GD)	0.795	0.569
Specific Data (SD)	0.819	0.599
General Platforms (GPL)	0.664	0.40
Specific Platforms (SPL)	0.919	0.746
Professional Platforms (PPL)	0.648	0.480
Methods (METH)	0.862	0.512
The global variable: SMDA	**0.894**	**>0.3**

Exploratory factor analysis of the Marketing Strategy variable

The PCA with six factors without rotation displayed a good representation quality for all items and indicated that both the KMO test and the Bartlett's test of sphericity (p=0.000) are significant for the marketing strategy variable. Moreover, the results showed the absence of multicollinearity with a non-zero determinant (2.127E-023) and demonstrated acceptable correlations between items.

Moving forward to the application of PCA with rotations, we obtained a relevant structure identical to our conceptual model with six factors. Varimax rotation described 70.8% of the explained total variance; and produced a KMO test value of 0.918; a significant Bartlett's sphericity test (p=0.000); a non-zero determinant; and a good quality of representation and factor contributions for all items.

Factor F1 included four items corresponding to the "Effectiveness" dimension. The second factor, F2, consisted of 14 items related to the "Targeting and Positioning Strategy" dimension. The third factor, F3, encompassed nine items describing the "Communication and Influence Strategy" dimension. The fourth factor, F4, referred to the "Product, Service, and Brand Strategy" dimension with its eight items. The fifth factor, F5, related to the "Channel and Logistics Strategy" dimension with five items. Finally, the sixth factor, F6, included six items describing the "Pricing Strategy" dimension.

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The internal consistency is ensured for all factors as well as for the global variable "Marketing Strategy", as the application of the reliability test on this scale yields an excellent Cronbach's alpha value (0.970) and an average correlation among elements of 0.410 (Table 2).

Table 2. Internal consistency test for the Marketing Strategy variable

Dimension	Cronbach's alpha	Average correlation (r)
Effectiveness (EFF)	0.921	0.746
Targeting and Positioning Strategy (TPS)	0.952	0.606
Communication and Influence Strategy (CIS)	0.934	0.614
Product, Service, and Brand Strategy (PSBS)	0.926	0.584
Channel and Logistics Strategy (CLS)	0.898	0.638
Pricing Strategy (PS)	0.922	0.664
The global variable: Marketing Strategy	**0.970**	**0.410**

PLS-SEM method: model testing and validation

The measurement reliability analysis reveals that both Twitter and Sentiment Analysis indicators exhibited low loadings (<0.7), which affected their constructs' reliability; therefore, we removed these two items (Hair *et al.*, 2011). After removing Twitter and Sentiment Analysis, the results indicate that the correlations between the indicators and their constructs exceed (or are close to) the threshold of 0.7 (Henseler *et al.*, 2009), ensuring indicator reliability.

Table A3 in the Appendix shows that the Cronbach's α values are acceptable (> ≈0.6), and the obtained values for composite reliability and Rho (A) adhere to the recommended threshold of 0.7.

The results indicate that the AVE (Average Variance Extracted) for each construct meets the required threshold (AVE > 0.5 as per Fornell & Larcker (1981)). This implies that convergent validity is ensured. Using the HTMT (Heterotrait-Monotrait) method, all HTMT correlation values are below the threshold of 0.85 (Henseler *et al.*, 2015), demonstrating that discriminant validity is confirmed.

To validate the structural model, we began by checking for multicollinearity issues: all VIF (Variance Inflation Factor) values were found to be below 5 for each construct, indicating no multicollinearity issues (Akter *et al.*, 2016). We then proceeded to estimate the effect size f^2 and the coefficient β to assess the significance of relationships in the internal model using the Bootstrapping PLS-SEM algorithm (Hair *et al.*, 2017). The results show that twelve relationships are significant at the 0.05 threshold and have an acceptable effect size f^2 (>0.02) (Figure 2).

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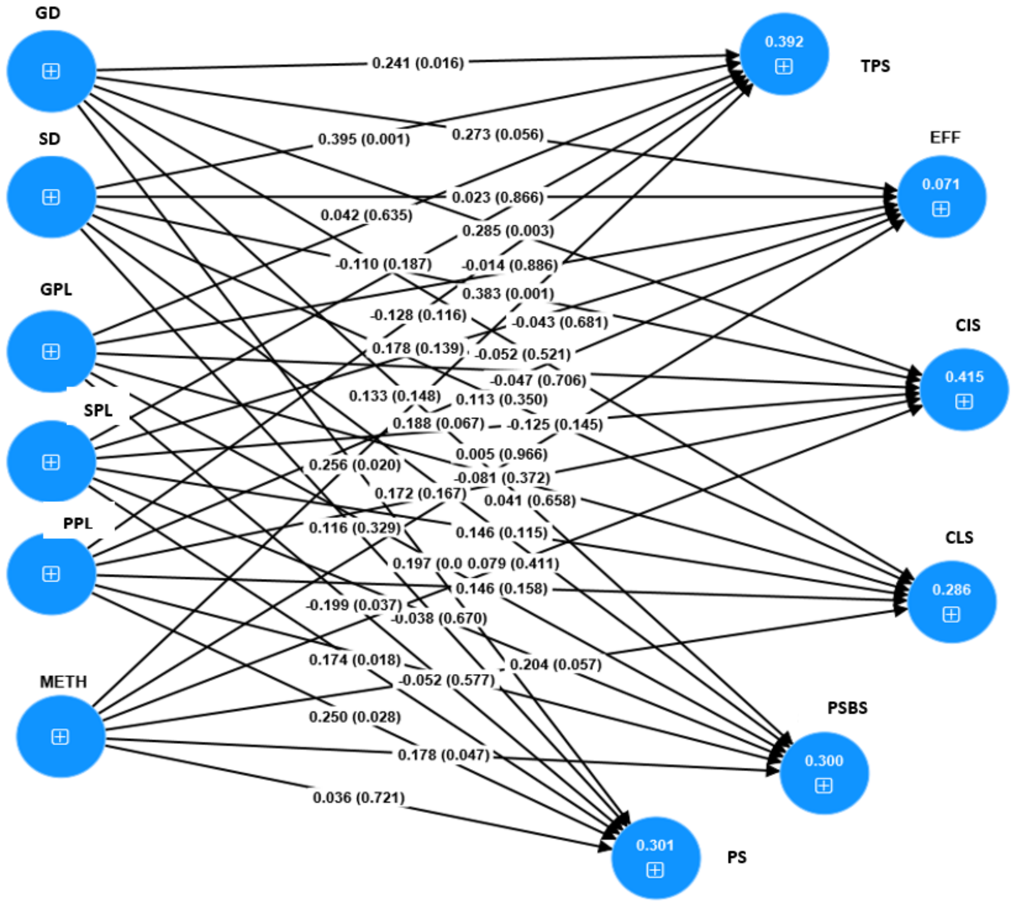

Figure 2. Internal model estimation

The predictive and explanatory power of the model can be assessed through two coefficients, R^2 and Q^2 (Hair *et al.*, 2017). Table 3 shows that all R^2 values obtained are acceptable as they exceed 0.1 (Falk & Miller, 1992). These values suggest that the model is primarily explained by "Communication and Influence Strategy" and "Targeting and Positioning Strategy", and that the explanatory power of our structural model is moderate and acceptable (Chin, 1998). By examining the Q^2 coefficient, we can assess the predictive power of each construct (Table 3). A positive Q^2 value indicates that the predictive relevance of the construct is confirmed (Geisser, 1974; Stone, 1974). Note that the highest predictive relevance is presented for the dimensions "Communication and Influence Strategy" and "Targeting and Positioning Strategy". Furthermore, the results showed the absence of predictive relevance for the "Effectiveness" dimension.

Table 3. R^2 and Q^2 coefficients generated by the PLS-SEM algorithm

	R-squared	Q^2predict	Results
Effectiveness	0.109	-0.034	no predictive relevance
Communication and Influence Strategy	0.513	0.345	strong predictive relevance
Channel and Logistics Strategy	0.353	0.193	moderate predictive relevance
Targeting and Positioning Strategy	0.503	0.321	strong predictive relevance

	R-squared	Q²predict	Results
Pricing Strategy	0.402	0.216	moderate predictive relevance
Product, Service, and Brand Strategy	0.359	0.214	moderate predictive relevance

On the basis of all statistical analysis results presented above (exploratory factor analysis, external and internal model assessment), the final structure of our model is shown in Figure 3.

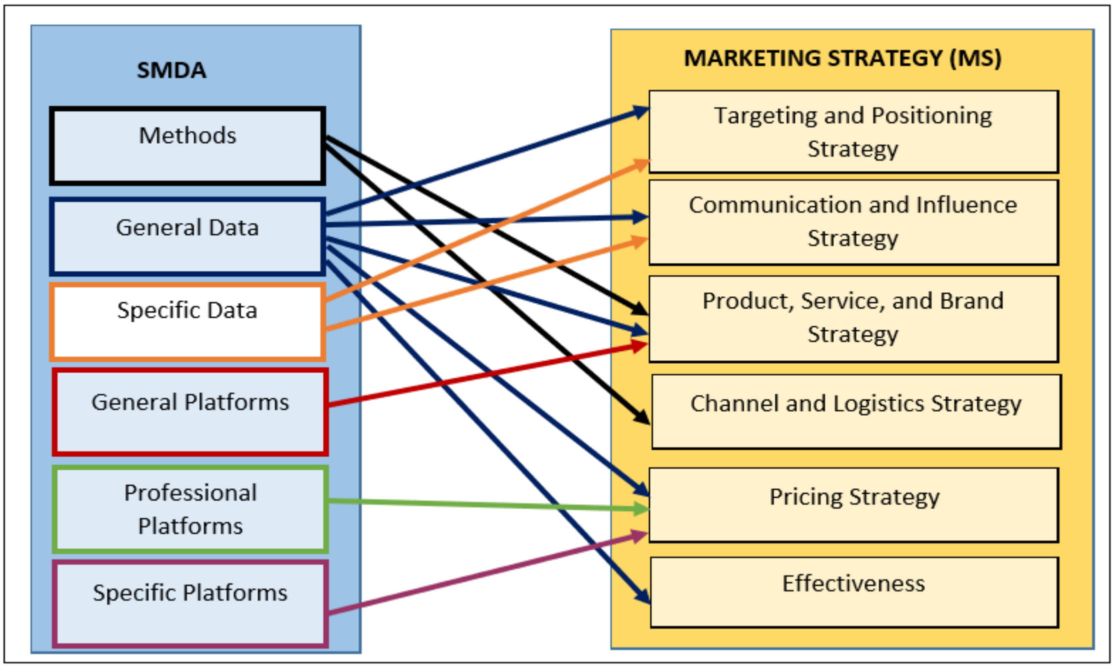

Figure 3. Impact of SMDA metrics on marketing strategies (framework with confirmed hypotheses)

The conceptual model evaluation, using SMART-PLS-4, with the new metrics derived from the exploratory factor analysis demonstrated that SMDA has a partial positive impact on marketing strategy. Moreover, the empirical study showed that the use of text, image, and video data in SMDA has a positive impact on all marketing strategies (except Channel and Logistics Strategy) and also on Marketing Strategy Effectiveness. In contrast, the use of data types, such as hashtags, ratings, number of likes, and comments, has a direct positive impact only on Targeting and Positioning Strategy and Communication and Influence Strategy. Additionally, the empirical results revealed that analyzing platforms like Facebook and Instagram can positively influence Product, Service, and Brand Strategy, while analyzing platforms like LinkedIn, YouTube, Tripadvisor, Yelp, Weibo, and Booking can guide Pricing Strategy. The results also demonstrated that adopting methods, such as statistics, artificial intelligence, coding and modelling, data mining, and/or visualization, in the SMDA process can yield several advantages for Channel and Logistics Strategy and Product, Service, and Brand Strategy.

Furthermore, the evaluation of the structural model using the Bootstrapping algorithm confirmed that, among all dimensions of SMDA, Specific Data (hashtags, ratings, the number of likes, comments, etc.) are the most likely to positively influence Targeting and Positioning Strategy and Communication and Influence Strategy. Thus, analyzing Specific Data is recommended for the development of these two strategies. The second dimension of SMDA that has a strong impact on both Targeting and Positioning Strategy and Communication and Influence Strategy is the "General Data" dimension, which encompasses textual data, images, and videos. Therefore, we can generally consider the primary SMDA metric that practitioners should focus on to guide these two types of strategies is the type of data to analyze.

Additionally, the test of the explanatory and predictive power of the global model demonstrated that the model is primarily explained by Targeting and Positioning Strategy and Communication and Influence Strategy, which also exhibited strong predictive relevance. followed by Pricing Strategy, Product, Service, and Brand Strategy, Channel and Logistics Strategy, and, finally, the Effectiveness variable with a low R^2 value of 0.109. This indicates that Targeting and Positioning Strategy and Communication and Influence Strategy are more influenced by SMDA than other types of strategies.

Results also show that SMDA has a very weak positive impact on strategy effectiveness, and also indicate the absence of predictive relevance for the "Effectiveness" dimension. This result can be explained by the early stage of SMDA adoption (the majority of companies that participated in the survey indicated that they had started adopting SMDA technology within the last two to five years). Indeed, SMDA technologies require experimentation time to implement suitable analysis strategies that can improve the effectiveness of marketing strategies (Jabado & Jallouli, 2023).

It should be Highlighted that the measurement reliability analysis obtained using SMART-PLS led to eliminating the Twitter platform and the Sentiment Analysis method from the analysis due to their low saturation. It is possible that the weak correlation between the "Twitter" indicator and its "General Platforms" construct goes back to the lack of resemblance of Twitter to the two platforms Facebook and Instagram (remembering that Instagram belongs to the Facebook company). For example, posts on Facebook and Instagram are unlimited and permanent. Conversely, with Twitter posts limited to 140 characters, the lifespan of posts is very short and the functions are also limited (Surbhi, 2017). Regarding the "Sentiment Analysis" method, its low saturation may be due to the presence of the Artificial Intelligence method among the analysis methods, since many analysts consider Sentiment Analysis to be just a tool, or a special case, of Artificial Intelligence that works with Natural Language Processing to provide sentiment-based knowledge (Lee, 2018).

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Conclusion, Implications and Perspectives

This study aimed to propose a reliable conceptual model through empirical evidence concerning the relation between SMDA and marketing strategy. To the best of our knowledge, this study is the first to provide empirical evidence regarding the impact of SMDA and its dimensions on various marketing strategies.

The exploratory analysis conducted in this study validated the reliability of the following six dimensions for marketing strategy: Targeting and Positioning Strategy; Product, Service, and Brand Strategy; Pricing Strategy; Channel and Logistics Strategy; Communication and Influence Strategy; and Effectiveness (Armstrong *et al.*, 2014; Campbell *et al.*, 2020; Shamim *et al.*, 2019). It also confirmed the reliability of considering the following six dimensions of SMDA: Methods, General Data, Specific Data, General Platforms, Specific Platforms, and Professional Platforms. This classification allowed for distinguishing between different types of data and platforms, emphasizing that social media data and platforms should not be treated as a homogeneous group. Instead, adapting approaches to each group can enhance the expected marketing analysis outcomes.

This research explored the relationship between SMDA and marketing strategy, developing an empirical model that positions SMDA as a key driver of value creation for companies in shaping their marketing strategies. Furthermore, the empirical study supported the reliability and validity of the proposed framework.

In summary, based on all the results of the empirical analysis, we can conclude that SMDA does not always guarantee improvement in marketing strategy. It is essential to carefully select, depending on the nature of the marketing strategy to be developed, the most appropriate SMDA metrics (platform type, method, and data type). For example, the results showed that analyzing Professional Platforms is more suitable for guiding Pricing Strategy than analyzing General Platforms. Thus, it is crucial to specify the most important metric to focus on before starting the analysis. Results also show that the Channel and Logistics Strategy is only impacted by the use of analysis methods, so practitioners should give higher importance to the choice of analysis method rather than other metrics or dimensions.

This article represents a significant advancement in Value Chain Theory and information theory by shedding light on how SMDA metrics affect marketing strategies, and by defining six key metrics of SMDA applied to marketing strategies. By detailing these metrics, the article provides an essential conceptual framework for comprehending and measuring the impact of SMDA metrics on strategic marketing decisions.

The originality of this research lies in addressing the literature and industry's need for a comprehensive, reliable, global, and valid conceptual framework to guide both researchers and practitioners in the SMDA process for developing marketing strategies. Furthermore, this study provides numerous reliable measurement scales adopted and used for the first time in a context different from their original design.

Regarding the practical contribution of this research, it presents and discusses various SMDA solutions, aiding decision-makers in selecting the right combination of different SMDA components and metrics based on their marketing requirements and needs to extract insights for their marketing strategies. Thus, based on this study, marketing researchers and practitioners can quickly select the most suitable social media platform, data type, and analysis method. Moreover, this research has provided results that offer a roadmap for describing the relationships between research concepts in a comprehensive way, likely to inspire researchers and practitioners to explore and experiment with different possible combinations of social media platforms, data types, and analysis methods, depending on the targeted marketing strategies, within specific industries through surveys, case studies and qualitative research.

This study has thus addressed the call made by Misirlis & Vlachopoulou (2018) and Jallouli & Kaabi (2022) highlighting the need for a conceptual framework encompassing social media, analytics, and marketing. Furthermore, it contributes to the enhancement of prior research efforts (such as Stieglitz *et al.*, 2018 and Galetsi *et al.*, 2020) aimed at providing a more thorough explanation and understanding of the SMDA process and its impact on marketing strategy. Unlike previous studies that focused on specific industry domains, single data types, or particular platforms/methods of analysis (such as Benslama & Jallouli, 2020 and Chebil *et al.*, 2021), this study explored a large set of SMDA metrics, offering insights into the SMDA framework for marketing strategies.

Finally, this study has certain limitations, including the small sample size in the questionnaire. It is highly recommended to conduct a study with a larger sample size for more robust results. Additionally, the research model treats the research concepts in a general and global manner, and tests only direct effects. To enhance the depth of understanding, it would be beneficial to explore the subject in more specific contexts and incorporate other mediating or moderating variables, a consideration for future research endeavours.

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Appendix

Table A1. SMDA variable measurement scales

Dimension	ITEMS	SOURCE
Platforms	Twitter Facebook Instagram TripAdvisor YouTube Yelp Weibo Booking LinkedIn	Choudhury & Harrigan (2014); Benslama & Jallouli (2022)
Data	Text Image Video Number of (likes, comments, etc.) Hashtags Rating	Gupta & George (2016); Vitari & Raguseo (2020); Benslama & Jallouli (2022)
Methods	Sentiment analysis Artificial intelligence Data mining Statistical Visualization Coding and modelling	Gupta & George (2016); Vitari & Raguseo (2020); Benslama & Jallouli (2022)

Table A2. Marketing strategy variable measurement scales

Measurement scale of the Targeting and Positioning strategy	
ITEM	**SOURCE**
Top of the range, product/service range	Blankson & Kalafatis (2004)
Reliability	Blankson & Kalafatis (2004)
Attractiveness	Blankson & Kalafatis (2004)
Country of origin	Blankson & Kalafatis (2004)
Product positioning	Filipe Lages *et al.* (2008); Benslama & Jallouli (2022)
Market segmentation	Slater & Olson (2001); Benslama & Jallouli (2022)
Evaluate which market to target	Slater & Olson (2001); Benslama & Jallouli (2022)
Focus on specific segments	Slater & Olson (2001); Benslama & Jallouli (2022)
Search for customer information	Al-Surmi *et al.* (2020); Olson *et al.* (2005); Narver & Slater (1990); Benslama & Jallouli (2022)
Customize offers	Jayachandran *et al.* (2005); Benslama & Jallouli (2022)
Identify your best customers	Jayachandran *et al.* (2005); Benslama & Jallouli (2022)
Analyze competitive advantages/disadvantages	Al-Surmi *et al.* (2020); Olson *et al.* (2005); Narver & Slater (1990); Benslama & Jallouli (2022)
Increase consumer engagement, satisfaction and retention	Cao *et al.* (2019); Benslama & Jallouli (2022)
Attract new customers and sales	Slater & Olson (2001); Benslama & Jallouli (2022)
Measurement scale of the Communication and Influence strategy	
ITEM	**SOURCE**
Digital communications marketing	Cao *et al.* (2019); Benslama & Jallouli (2022)
Direct marketing	Yaa *et al.* (2011); Smith *et al.* (1997)
Sponsorship and events	Yaa *et al.* (2011); Smith *et al.* (1997); Benslama & Jallouli (2022)
Advertising strategy management	Filipe Lages *et al.* (2008); Slater & Olson (2001); Benslama & Jallouli (2022)
Brand image	Cao *et al.* (2019); Benslama & Jallouli (2022)
Promotion strategy	Filipe Lages *et al.* (2008); Benslama & Jallouli (2022)
Public relations	Filipe Lages *et al.* (2008); Slater & Olson (2001)
Sales force management	Filipe Lages *et al.* (2008)
Media allocation	Filipe Lages *et al.* (2008)

Measurement scale of the Product, Service and Brand strategy	
ITEM	**SOURCE**
Characteristics	Filipe Lages *et al.* (2008)
Brand name	Filipe Lages *et al.* (2008); Filipe Lages & Montgomery (2004)
Design	Filipe Lages *et al.* (2008)
Product/Service Quality	Filipe Lages *et al.* (2008); Benslama & Jallouli (2022)
Product labelling and packaging	Filipe Lages *et al.* (2008)
Brand reputation	Chaudhuri (2002); Chaudhuri & Holbrook (2001); Benslama & Jallouli (2022)
Brand awareness	Chaudhuri (2002); Chaudhuri & Holbrook (2001); Benslama & Jallouli (2022)
Brand loyalty	Chaudhuri (2002); Chaudhuri & Holbrook (2001); Benslama & Jallouli (2022)
Measurement scale of the Channel and Logistics strategy	
ITEM	**SOURCE**
Logistics and channel improvements	Chen *et al.* (2015)
Warehousing, inventory, stock optimization	Chen *et al.* (2015)
Channels and distribution network	Filipe Lages & Montgomery (2004)
Transport strategy	Filipe Lages & Montgomery (2004)
Budget for distribution	Filipe Lages & Montgomery (2004)
Measurement scale of the Pricing strategy	
ITEM	**SOURCE**
Wholesale price	Filipe Lages *et al.* (2008)
Retail price	Filipe Lages *et al.* (2008)
Pricing method	Filipe Lages & Montgomery (2004)
Profit margins	Filipe Lages *et al.* (2008)
Sales terms	Filipe Lages *et al.* (2008)
Customer credit	Filipe Lages *et al.* (2008)
Measurement scale of Effectiveness	
ITEM	**SOURCE**
I believe that we make good marketing strategies.	Visinescu *et al.* (2017)
The marketing strategies we make result in the desired outcomes.	
I am satisfied with the outcomes of our marketing strategies.	
Our marketing strategies improve organizational performance.	

Table A3. The internal consistency reliability and convergent validity indices

	Cronbach's alpha	**Composite reliability Rho (A)**	**Composite reliability**	**AVE**
GD	0.798	0.811	0.805	0.580
SD	0.817	0.827	0.821	0.605
EFF	0.921	0.939	0.922	0.750
METH	0.855	0.860	0.851	0.537
GPL	0.758	0.786	0.768	0.626
PPL	0.649	0.649	0.709	0.580
SPL	0.922	0.929	0.922	0.749
CIS	0.935	0.942	0.932	0.610
CLS	0.898	0.904	0.894	0.632
TPS	0.956	0.958	0.956	0.611
PS	0.922	0.924	0.922	0.665
PSBS	0.923	0.928	0.922	0.600

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