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Exploring Artificial Intelligence Techniques' Applicability in Social Media Marketing

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Abstract
The increasing interest in Artificial Intelligence (AI)'s impact on Social Media Marketing (SMM) creates new opportunities to be captured by software developers. Marketers become aware of AI powerful tools role in leveraging competitive advantage in social media campaigns. This study aims to test correlations between the experience in the field of SMM and the level of knowledge regarding the applicability of Machine Learning (ML) in SMM and the frequency of using of ML algorithms in SMM campaigns and to identify the perceptions of the potential users of an Artificial Intelligence (AI)-based software, which will embed deep learning algorithms and convolutional neural networks to recognize logos of brands or companies involved in social media content, regarding its proposed capabilities. The AI Media software capabilities were embedded into three clusters (audience analysis, image analysis and sentiment analysis), being assessed through a 3 points scale, revealing necessary vs. expected functionalities in the eyes of digital agencies' representatives of freelancers. The results outline a high interest and trust of potential users of AI Media software on its value proposition.

Keywords: Social Media Marketing, machine learning, deep learning, image analysis, audience analysis, sentiment analysis.

JEL classification: M31, C12.

1. Introduction

In the digital transformation age, companies have access to more information than ever about their customer behavior. One of the main challenges of social media marketing relates to anticipative capabilities regarding targeting people with content that they are interested in. Fortunately, machine learning (ML) algorithms has been developed to respond to online comments immediately using natural language, which enable online marketing to focus on strategy.

Based on machine learning algorithms, a computer can be trained by a Social Media Marketing specialist to recognize patterns in posts that match targeted posts within social networks, opening avenues for customized analysis categories.

As members of a research team, we are interested in designing and developing an Artificial Intelligence (AI)-based software, which will embed deep learning algorithms and convolutional neural networks to recognize logos of brands or companies involved in social media content.

The goal of this paper is to examine the correlations between the experience in social media marketing (SMM), the level of knowledge regarding the applicability of ML in SMM, the frequency of using of ML algorithms in SMM campaigns and the perceptions of the potential users of an Artificial Intelligence (AI)-based software on three pillars (audience analysis, sentiment analysis and image analysis) in the case of a sample of 100 respondents from worldwide digital agencies.

2. Theoretical background

Artificial Intelligence emerging technologies deal with consumer-generated content, being capable to provide compelling evidence of brand perceptions and attributes. The brand owner, therefore, has opportunities to adopt an Artificial Intelligence (AI)-based software to navigate the consumer-generated content to ensure that the fans remain as close as possible to the brand owner's desired promise (Singh and Sonnenburg, 2012). Knowing the content shared by people on a brand page can be a valuable input for machine learning algorithms involved in social media marketing (Cvijikj and Michahelles, 2011).

As consumers increasingly ignore conventional online marketing, emerging IT infrastructures based on machine learning algorithms contribute to social media predictive analytics development. Given these trends and the high potential of Artificial Intelligence tools for social media marketing, the key question for marketing managers became how to take full advantage of machine learning algorithms and find ways to train them for their specific objectives (Tsimonis and Dimitriadis, 2014). Using these tools, innovative managers are finding new ways of automatically collecting, combining, and analyzing data from social media to better understand customer behavior and effectively manage online marketing campaigns (Lee, 2018).

Machine Learning technologies, endowed with the capability to learn from social media data, identify patterns and make decisions with minimal human intervention, are frequently used to increase brand awareness and online reputation, promote customer engagement and loyalty, enable word-of-mouth communication about the brand, and drive traffic to a brand (Ashley and Tuten, 2015). Using the Machine Learning technologies as Marketing Intelligence tool could conceivably benefit both customers, who might receive social media content that better matches their preferences and companies, as they might be able to generate higher levels of customer satisfaction and loyalty (Lamberton and Stephen, 2016).

Deep learning algorithms and convolutional neural networks dealing with social media information allows the highly involved consumers to be identified and targeted using brand recognition based promotional methods, such as broadcast advertising, sales promotions, and events, in order to initiate communication (Kilgour et al., 2015).

Researchers analyze various textual feature representations of social media contents, coupled with machine learning algorithms and artificial neural networks applications, to explore in-depth the relationships between features of the contents and the opinions expressed by the persons engaged in social conversations related to a brand (Ghiassi et al., 2013).

Since the rise of social media marketing analytics, powerful tools have been built provided opportunities for marketers to track their brands on Facebook and Twitter. Most of these social media analytics dashboards simply aggregate text data from tweets and Facebook posts. In the past years, image recognition tools for Instagram and Pinterest have been adopted by digital agencies and online marketers, as logo recognition became a key pillar to brand analytics (Iandola et al., 2015).

Building upon the idea that social commerce led to an increased presence within social networks, AI-based analytics tools evolved to facilitate the social experiences of consumers, enabling alliances between e-retailers and social networking sites (Zhou et al., 2013).

Sentic Computing has been also developed as an approach to social media opinion mining and sentiment analysis that interrelates both computer and social sciences to better recognize and interpret opinions and sentiments over the social networks (Cambria et al., 2012).

Comparing to text information, the image related to a logo can be treated as a more reliable information during brand tracking in social media. In the case of images retrieved from microblogging sites, in addition to visual angle, marketers can analyze contextual information, which makes the problem different from the traditional logo detection/recognition task (Wang et al., 2016).
Logo or brand image recognition should be analyzed through brand post characteristics (e.g., vividness, interactivity), content of the brand post, tailored to the audience needs (e.g., information, entertainment), position of the brand post, and the valence of comments (sentiment analysis) on the brand post (De Vries et al., 2012).

3. Research methodology and hypotheses development

In line with the ambition of our future research, to an Artificial Intelligence based software, which will embed deep learning algorithms and convolutional neural networks to recognize logos of brands or companies involved in social media content, Yoo et al. (2018) proposed and implemented a system that analyze social media contents in real time to analyze and predict users' sentimental paths.
Machine Learning is perfectly adapted to unstructured data as social media posts, usually a mix of text, images, sounds, and video. The level of knowledge regarding the applicability of ML in SMM and the frequency of using of ML algorithms in SMM campaigns have been designed as dependent variables in the current research, while the experience in the field of SMM has been set as independent variable. Moreover, three clusters of analyses based on the future AI Media software (audience, image and sentiment) are considered target variables in the research conceptual model (Figure 1).

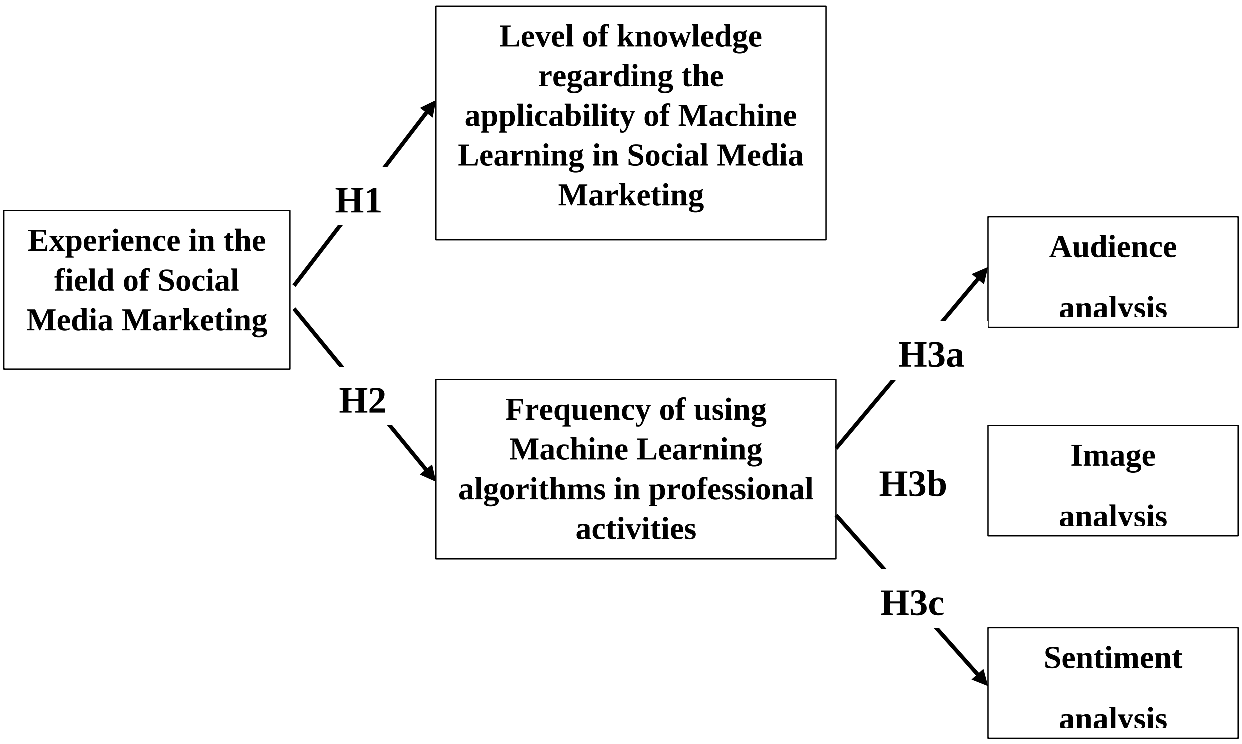

Figure 1 – Conceptual model of the research

We have designed and applied an online questionnaire on a convenience sample of 100 respondents (owners of digital agencies, social media marketers and freelancers from all

continents – Figure 2) in order to assess their perceptions regarding the ranking process of the forthcoming AI Media software capabilities on a pre-defined scale from 1 to 3: 1 (necessary) - 2 (great to have) - 3 (expected/by default).
The AI Media software capabilities have been distributed in three clusters, as follows:

- **Audience analysis** (capability to categorize social media posts by their stage in the customer buying cycle, capability to make recurrent decisions on which content to publish at what time in order to get the maximum reach, capability to provide instant customer recommendation of the right product to purchase and guide him/her to the store with the lowest price and capability to track affinities and interests in a social network and to generate a visual report grouping people with similar interests);
- **Image analysis** (deep learning algorithms trained capabilities to recognize images/detect objects for custom categories, capability recognition deep learning algorithms' capability to identify places and moments of product consumption, capability to correlate sales forecasting with the frequency a brand appears in social media photos and capability to correlate image recognition with contextual intelligence);
- **Sentiment analysis** (capability to classify each user-generated content based on variables such as tone, sentiment, or topic, while reviewing a product/service, capability to track social media sentiments related to competing brands in order to enable Competitive Intelligence mechanisms, capability to anticipate potential image crisis by assessing the sentiments related to social mentions and capability to track the reaction to new products launched on the market and promoted on social networks).

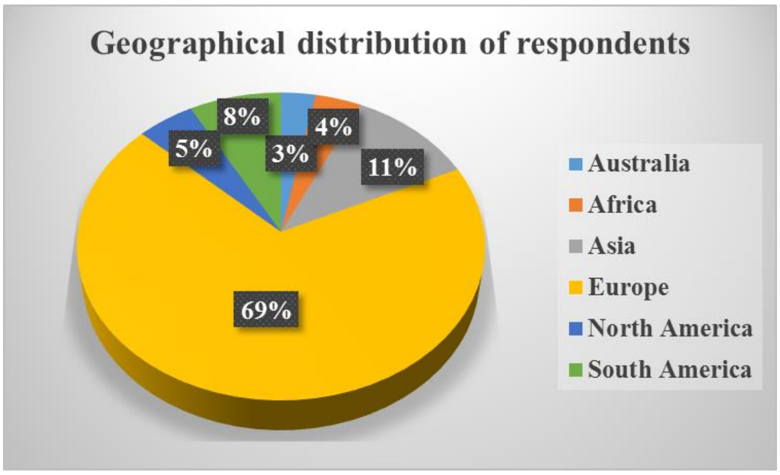

Figure 2 - Geographical distribution of respondents

Three hypotheses have been designed:
H1: The experience in the field of SMM influences in a larger extent the level of knowledge regarding the applicability of ML in SMM
H2: The experience in the field of SMM influences in a larger extent the frequency of using of ML algorithms in SMM campaigns
H3: The frequency of using of ML algorithms in SMM campaigns positively relates with respondents' perceptions on future capabilities of the AI Media Software (at the level of audience analysis – H3a; image analysis – H3B and sentiment analysis – H3c).
The statistical methods employed to test the hypotheses are chi-square, Pearson's R and Spearman coefficients of correlation. Chi-square test has been applied in the case of H1 and

H2 to test significant differences between the expected and observed frequencies of the datasets. The correlation coefficient Pearson's R is a useful descriptor of the degree of linear association between two variables, having two key properties of magnitude and direction. When it is near zero, there is no correlation, but as it approaches -1 or +1 there is a strong negative, respectively positive relationship between the variables. The sign of the Spearman correlation indicates the direction of association between the independent variable and the dependent variable. If the dependent variable tends to increase when the independent variable increases, the Spearman correlation coefficient is positive; otherwise, the Spearman correlation coefficient is negative. Pearson R and Spearman have been used in the H3a, H3b and H3c.
The process of performing analyses on the three key pillars included in the conceptual model (experience in the field of Social Media Marketing, level of knowledge regarding the applicability of Machine Learning in Social Media Marketing and frequency of using Machine Learning algorithms in professional activities) reveals that Cronbach's Alpha value is **0.834**, which indicates a high level of internal consistency for the scales (Table 1).

Table 1 - Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
,834	,845	3

The correlation between a particular item and the sum of the rest of the items outlines that the best item included in the conceptual model appears to be the second (level of knowledge regarding the applicability of Machine Learning in Social Media Marketing), with an item-total correlation of r = .857. The item with the lowest item-total correlation is the first one (experience in the field of Social Media Marketing) (r = .551). Analyzing “Cronbach’s Alpha if item deleted" column, we observe that none of the values is greater than the current alpha of the whole scale: .834. This means that no item has to be removed from the conceptual model (Table 2).

Table 2 - Item-Total Statistics

	Scale Mean if Item Deleted	**Scale Variance if Item Deleted**	**Corrected Item-Total Correlation**	**Squared Multiple Correlation**	**Cronbach's Alpha if Item Deleted**
Experience in the field of Social Media Marketing	5,21	5,440	,551	,309	,824
Level of knowledge regarding the applicability of Machine Learning in Social Media Marketing	4,68	2,947	,857	,764	,592
Frequency of using Machine Learning algorithms in professional activities	4,73	2,543	,829	,752	,647

4. Findings

The experience in the field of Social Media Marketing has been related to the period of time respondents have been involved in SMM activities (less than 1 year, 1 to 3 years, more than 3 years), while the level of knowledge regarding the applicability of Machine Learning in SMM has been measured on a five item scale: needs considerable improvement, needs improvement, adequate, very good, excellent.

The distribution of research results corresponding to the first hypothesis involves the design of a contingency table with double entry, which allows the classification of the observed frequencies (Table 3).

Table 3 – Contingency table related to H1

		Level of knowledge regarding the applicability of Machine Learning in Social Media Marketing					**Total**
		needs considerable improvement	needs improvement	adequate	very good	excellent	
Experience in the field of Social Media Marketing	less than 1 year	8	8	1	0	0	**17**
	1 to 5 years	9	23	10	13	1	**56**
	more than 5 years	0	5	5	16	1	**27**
Total		**17**	**36**	**16**	**29**	**2**	**100**

The results corresponding to the test of the first hypothesis, based on respondents' answers, exported into a SPSS database, are revealed in Table 4.

Table 4 - Chi-Square Tests (H1)

	Value	Degrees of freedom	Asymptotic Significance (2-sided)
Pearson Chi-Square	33,085	8	0,000059
Likelihood Ratio	38,726	8	0,000006
Linear-by-Linear Association	29,957	1	,000
N of Valid Cases	100		

In this case, the value associated to the Asymptotic significance (0,000059) is under the level of significance (0,05) and the Pearson Chi-Square value (33,085) is superior to the Chi-Square value reflected by Chi Square Distribution Table for eight degrees of freedom (15,51), so we can state that there is a strong correlation between **the experience in the field of SMM and the level of knowledge regarding the applicability of ML in SMM (H1 supported).**

The second hypothesis emphasizes the cross-tabulation between the experience in the field of Social Media Marketing and the frequency of using Machine Learning algorithms in professional activities, assessed by the respondents on the following scale (Never; Rarely; Sometimes; Often; Usually/Most of the time) – Table 5.

Table 5 - Contingency table related to H2

		Frequency of using Machine Learning algorithms in professional activities					**Total**
		never	rarely	sometimes	often	usually/most of the time	
Experience in the field of Social Media Marketing	less than 1 year	11	5	1	0	0	**17**
	1 to 5 years	14	19	7	12	4	**56**
	more than 5 years	1	4	5	16	1	**27**
Total		**26**	**28**	**13**	**28**	**5**	**100**

The results corresponding to the test of the second hypothesis, based on respondents' answers, exported into a SPSS database, are revealed in Table 6.

Table 6 - Chi-Square Tests (H2)

	Value	Degrees of freedom	Asymptotic Significance (2-sided)
Pearson Chi-Square	35,178	8	0,000025
Likelihood Ratio	38,988	8	0,000005
Linear-by-Linear Association	26,464	1	,000
N of Valid Cases	100		

In this case, the value associated to the Asymptotic significance (0, 000025) is also under the level of significance (0,05) and the Pearson Chi-Square value (35,178) is superior to the Chi-Square value reflected by Chi Square Distribution Table for eight degrees of freedom (15,51), so we can state that there is a strong correlation between **the experience in the field of SMM and the frequency of using Machine Learning algorithms in professional activities (H2 supported).**

The cross-tabulation between the frequency of using Machine Learning algorithms in professional activities and respondents' perceptions on the capability of a future AI Media software to categorize social media posts by their stage in the customer buying cycle led to the design of the contingency table related to H3a (Table 7).

Table 7 - Contingency table related to H3a

		Perception on the capability of a future AI Media software to categorize social media posts by their stage in the customer buying cycle			Total
		necessary	great to have	expected/by default	
Frequency of using Machine Learning algorithms in professional activities	never	9	4	13	**26**
	rarely	10	6	12	**28**
	sometimes	4	4	5	**13**
	often	10	5	13	**28**
	usually/most of the time	2	1	2	**5**
Total		**35**	**20**	**45**	**100**

The results of the H3a hypothesis testing process are revealed by Pearson's R and Spearman correlation coefficients: their values (-0,025, respectively -0,027 – Table 8) are negative, but situated near zero, emphasizing the lack of correlation between the independent variable (the frequency of using Machine Learning algorithms in professional activities) and dependent variable (respondents' perceptions on the capability of a future AI Media software to categorize social media posts by their stage in the customer buying cycle) – Table 8.

Table 8 - Symmetric Measures (H3a)

		Value	Asymptotic Standard Error	Approximate T	Approximate Significance
Interval by Interval	**Pearson's R**	**-,025**	,101	-,245	,807
Ordinal by Ordinal	**Spearman Correlation**	**-,027**	,101	-,269	,789
N of Valid Cases		100			

Another cross-tabulation between the frequency of using Machine Learning algorithms in professional activities and respondents' perceptions on the capability of a future AI Media software to recognize images/detect objects for custom categories led to the design of the contingency table related to H3b (Table 9).

Table 9 - Contingency table related to H3b

		Perception on the capability of a future AI Media software to recognize images/detect objects for custom categories			Total
		necessary	great to have	expected/by default	
Frequency of using Machine Learning algorithms in professional activities	never	12	5	9	**26**
	rarely	13	5	10	**28**
	sometimes	6	1	6	**13**
	often	7	10	11	**28**
	usually/most of the time	1	1	3	**5**
Total		**39**	**22**	**39**	**100**

The values of Pearson's R and Spearman correlation coefficients (0,151, respectively 0,146 – Table 10) are positive, but also situated near zero, outline the lack of correlation between the independent variable (the frequency of using Machine Learning algorithms in professional activities) and dependent variable (respondents' perceptions on the capability of a future AI Media software to recognize images/detect objects for custom categories) – Table 10.

Table 10 - Symmetric Measures (H3b)

		Value	Asymptotic Standard Error	Approximate T	Approximate Significance
Interval by Interval	**Pearson's R**	**,151**	,096	1,513	,134
Ordinal by Ordinal	**Spearman Correlation**	**,146**	,097	1,460	,147
N of Valid Cases		100			

The last cross-tabulation between the frequency of using Machine Learning algorithms in professional activities and respondents' perceptions on the capability of a future AI Media software to classify each user-generated content based on variables such as tone, sentiment, or topic, while reviewing a product/service led to the design of the contingency table related to H3c (Table 11).

Table 11 - Contingency table related to H3c

		Perception on the capability of a future AI Media software to classify each user-generated content based on variables such as tone, sentiment, or topic, while reviewing a product/service			Total
		necessary	great to have	expected/by default	
Frequency of using Machine Learning algorithms in professional activities	never	8	7	11	**26**
	rarely	11	7	10	**28**
	sometimes	6	2	5	**13**
	often	14	5	9	**28**
	usually/most of the time	1	1	3	**5**
Total		**40**	**22**	**38**	**100**

The values of Pearson's R and Spearman correlation coefficients (-0,061, respectively -0,070) are negative, but also situated near zero, outline the lack of correlation between the independent variable (the frequency of using Machine Learning algorithms in professional activities) and dependent variable (respondents' perceptions on the capability of a future AI Media software to classify each user-generated content based on variables such as tone, sentiment, or topic, while reviewing a product/service) – Table 12.

Table 12 - Symmetric Measures (H3c)

		Value	Asymptotic Standard Error[a]	Approximate T[b]	Approximate Significance
Interval by Interval	**Pearson's R**	**-,061**	,100	-,603	,548[c]
Ordinal by Ordinal	**Spearman Correlation**	**-,070**	,100	-,697	,487[c]
N of Valid Cases		100			
a. Not assuming the null hypothesis.					
b. Using the asymptotic standard error assuming the null hypothesis.					
c. Based on normal approximation.					

The H3a, H3b and H3c hypotheses have been rejected, outlining different opinions on the ML applicability at the level of audience, image and sentiment analyses.

5. Conclusions, implications, limitation and further research

As social media has been widely adopted by customers, it became imperative for Social Media Marketing experts to leverage AI tools tailored to social media platforms to boost competitiveness in the global economy. Machine learning relies on trained algorithms for audience, image and sentiment analyses, so Social Media Marketing experts are able to capture opportunities to analyze and categorize posts and conduct thorough analyses of consumer opinions on products and services they are promoting on social networks.

This article presented the results of an exploratory research on Social Media Marketing experts (digital agencies' owners, marketers and freelancers) that assessed some of the forthcoming AI Media software capabilities, based on social media analytics reflecting audience, image and sentiment analyses. The goal of this paper was not to analyze the ranking of the future AI Media software capabilities, as they were perceived by the target public, but to test correlations between the experience in the field of SMM and the level of knowledge regarding the applicability of ML in SMM, on the one hand, and the frequency of using of ML algorithms in SMM campaigns, on the other hand.

Since engagement of Social Media Marketing experts in learning how to adopt AI technologies is a key benefit for their companies or projects they are working for, decision-makers should encourage investments in technologies such the future AI Media software, in a way that leads not only to more short-term tangible benefits in terms of profits, but on long term, on behalf a better understanding of online customer experiences.

This study is just a preliminary attempt to understand how potential users of the AI media software, an outcome of the FutureWeb research project, expect to benefit from its capabilities. Given the quantitative nature of the present study and the fact that the distribution of respondents in countries from worldwide is random, findings should be considered as exploratory.

As further research, we intend to integrate the ranking results of the future AI Media software capabilities in a paper considered for the 4th International Conference on Marketing, Business and Trade (ICMBT 2019), which will be held in Tokyo, Japan, in January 2019. We have also in mind the opportunity to test causal recipes for audience, image and sentiment analysis in a research paper, tailored to a Journal of Business Research special issue: Artificial Intelligence and the Shaping of Business Contexts.

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