Technological Forecasting & Social Change 151 (2020) 119794

Contents lists available at ScienceDirect

Technological Forecasting & Social Change

journal homepage: www.elsevier.com/locate/techfore

Matching the future capabilities of an artificial intelligence-based software for social media marketing with potential users' expectations

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A R T I C L E I N F O

Keywords:
Artificial intelligence
Machine learning
Social media marketing
Audience analysis
Image analysis
Sentiment analysis

A B S T R A C T

The increasing use of Artificial Intelligence (AI) in Social Media Marketing (SMM) triggered the need for this research to identify and further analyze such expectations of potential users of an AI-based software for Social Media Marketing; a software that will be developed in the next two years, based on its future capabilities.

In this research, we seek to discover how the potential users of this AI-based software (owners and employees from digital agencies based in France, Italy and Romania, as well as freelancers from these countries, with expertise in SMM) perceive the capabilities that we offer, as a way to differentiate our technological solution from other available in the market.

We propose a causal model to find out which expected capabilities of the future AI-based software can explain potential users' intention to test and use this innovative technological solution for SMM, based on integer valued regression models. With this purpose, R software is used to analyze the data provided by the respondents. We identify different causal configurations of upcoming capabilities of the AI-based software, classified in three categories (audience, image and sentiment analysis), and will trigger potential users' intention to test and use the software, based on an fsQCA approach.

1. Introduction

Artificial Intelligence (AI) technologies are highly effective in monitoring social media (Sterne, 2017) in order to get a complete picture of what people interacting on social networks are discussing about a brand in their posts and comments (sentiment analysis). They are useful as well to determine how they can be approached with personalized content (audience analysis) and how the images they share enable savvy marketers to recognize logos of brands or companies active in social media content (image analysis). The AI tools provide effective support to social media marketers in their tasks to optimize audience, image and sentiment analyses by identifying the branded-content that carries out high customer engagement with social media (Ashley and Tuten, 2015). Machine learning (ML), based on algorithms that enable specialized AI software to identify patterns within big data and classify it in categories, is perfectly adapted to deep analysis of social media content (Cambria et al., 2012).

To capture the value of Artificial Intelligence technologies' application in Social Media Marketing, this study explores the perceptions of 150 experts (owners and marketers of digital agencies and freelancers) from three countries (Romania, Italy and France) on twelve predefined capabilities of a future Artificial Intelligence-based software focused on Social Media Marketing analytics on audience, image and sentiment analysis and inspired by the principles characterized in previous approaches adopted by scholars in systematic literature reviews (Iqbal et al., 2018; Kurnia, 2018).

Specifically, the aim of this study is to address the following two research questions:

RQ1. Which are the variables associated to the respondents' profiles that explain their level of knowledge regarding the applicability of Machine Learning in Social Media Marketing?

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https://doi.org/10.1016/j.techfore.2019.119794
Received 5 June 2019; Received in revised form 25 September 2019; Accepted 23 October 2019
0040-1625/

RQ2. Which capabilities of the future Artificial Intelligence-based software, categorized in the three groups (audience, image and sentiment analysis) are more influential on the intention to test its features and how is their impact is perceived by the experts from Romania, Italy and France?

We begin by reviewing the literature related to the AI applications on Social Media Marketing (audience, image and sentiment analysis). We then focus on the methodological toolkit, able to provide relevant answers to the research questions. Based on the findings, we highlight the conclusions and come up with recommendations for the future AI-based software developers.

2. Theoretical background

2.1. Audience analysis

Numerous scholars have reffered to audience analysis as a fundamental pillar of Social Media Marketing strategies adopted by firms and supported by emerging AI technologies. In this age of AI, companies that develop social media strategies focused on audience analysis can control message content along with frequency and timing of publications in order to achieve marketing goals (Chen and Lin, 2019). As there are various social networks, each with different characteristics and audiences, social media marketers should answer the question of which social networks are more appropriate for their campaigns to get the maximum reach, based on the content they publish and the moment they make the content available (Tsimonis and Dimitriadis, 2014). Managing social interactions and creating a shared meaning of customer profiles are important to explain AI technologies' impact on social media audience analysis (Miller, 2018).

Companies have already begun to think about how to rely on virtual brand communities (Kaplan and Haenlein, 2010), where AI technologies are able to track their members' affinities and interests and group people with similar interests. Therefore, audience analytics tools provide visual reports on clusters of members belonging to a social community and enable their loyalty, which depends on the value gained from the community (Farquhar and Rowley, 2006).

AI offers a wide range of appropriate analytics capabilities to social media audience analysis in terms of opportunity identification, sensemaking, insight generation, and decision making, by providing solutions to categorize social media posts according to their stage in the customer buying cycle (Holsapple et al., 2018). Real-Time Competitive Social Media Analytics, focused on the monitoring of prices and promotions, news alert, headlines and new product announcements, are considered appropriate for clustering social media posts, according to their stage in the customer buying cycle (Lee, 2018).

AI technologies use multiple types of customer-related data, such as purchases, sales or behavioural and demographic data. Moreover, they create opportunities to conduct social media monitoring and design a competitive analysis strategy, in order to come up with instant customer recommendations onthe right product to purchase (He et al., 2013). Bhimani et al. (2019)emphasize the role of AI-based social media strategies in yielding customer insights, co-creating ideas and concepts with customers, and suggesting new product launches and the right products to purchase.

2.2. Image analysis

Kaplan and Haenlein (2019) have classified Artificial Intelligence into three categories: *Analytical AI, Human-Inspired AI*, and *Humanized AI*. The first category, *Analytical AI*, refers to cognitive intelligence and it is said to create a "cognitive representation of the world" by using "learning based on past experience to inform future decisions" (pag. 18). The authors claim that the majority of AI systems used by companies belong to this category and encompass image recognition. At the same time, marketing literature observes that AI is employed to enhance personalized communication and to allow for improved targeting (Kosinski et al., 2013; Suwajanakorn et al., 2017).

Artificial Intelligence tools for brand logo recognition open avenues to analyse social media users' interests. For instance, photos people share on social networks strongly reflect connected behaviours, wants and needs that usually go unnoticed by marketers. However, images represent a category of social media data that has not been tapped into for large-scale social media marketing studies, while a billion of images are shared on the Internet every hour, making this type of rich media content an abundant source of data. Moreover, social media images can include additional data that could not be obtained from textual status updates (Garimella et al., 2016) and nowadays, it is feasible to automatically recognize items from images and create textual descriptions. For example, Garimella et al. (2016) explored if the content of images shared through Instagram could offer health-related information, and if machine-generated tags could in the same way add value over user-provided ones.

The employment of automatic image annotation tools may lead to many possible benefits, even for user expectations in Social Media Marketing. For instance, we can observe if the use of image recognition techniques may help in understanding a wide range of consumer expectation related issues.

Recently, automatic image annotation has significantly improved due to the enhancement in deep learning (Hinton et al., 2006). Image tagging (Karpathy and Fei-Fei, 2015) and object recognition (Wu et al., 2015) have become feasible thanks to studies' improvements as well. As some researches already utilize image results to identify and study, for example, food consumption (Kawano and Yanai, 2015), we conclude this can be usefully applied to any consumer behaviour marketing field.

Researchers as Bengio (2009) consider that social media marketers cannot unlock yet deep learning algorithms' full potential to discover the many visual and semantic concepts that seem to be necessary to interpret most images on social networks. To fill this gap, the future AI Media software we intend to develop will integrate deep learning algorithms to recognize images and detect objects for custom categories.

The capability of deep learning algorithms to find the connection between a brand logo in social media and the place and moment in which the represented product is consumed in real time has been addressed by researchers. A first attempt to correlate image recognition in social media to the analysis of user-generated content, aiming to identify places and moments of product consumption, has been made by Vázquez et al. (2014). The mediating effects of image recognition in social media and sales forecasting, considering the frequency with which a brand appears in social media photos, have been discussed by Lassen et al. (2017), who analysed the extent to which compelling brand-related photos shared by social media users can predict conversions and, implicitly, sales.

If a trained machine learning model is not able to understand the context in which an image is posted on a social network, the image recognition feature is not enough to predict any social media user behaviour. By using a Multimodal Recurrent Neural Network architecture, Karpathy and Fei-Fei (2015) prove that AI tools are able to generate natural language descriptions of images and provide their best results when they are trained in specific contexts. Contextual Intelligence fully captures the impact of users' engagement in social media softwares development, facilitating image recognition through analytics on posts (Jaakonmäki et al., 2017).

2.3. Sentiment analysis

Since the theoretical framework of 'sentiment analysis' has emerged, a rising amount of studies have as well concentrated on this topic. Cao et al. (2016) divide the research works on this topic in three levels: document level (Pang et al., 2002), sentence level (Wilson et al., 2004), and entity level (). However, in order to achieve better results many studies have combined the three levels and have applied their analysis to a specific field. For instance, Liu et al. (2007) have developed a sentiment model to forecast sales performances, while McGlohon et al. (2010) have used reviews' sentiment analysis in order to learn how to classify products and sellers.

The focus of the machine learning-based sentiment analysis research is shifting towards social media and mainly targeting Twitter (Kouloumpis et al., 2011) and Facebook (López et al., 2012), concentrating on experiments on unigrams, bigrams, part-of-speech tags, emoticons etc. (Habernal et al., 2013).

De Vries et al. (2012) argue that the process of sharing positive and negative comments is highly interconnected with brand post popularity; AI techniques lead to classifications and clusters of user-generated content based on variables such as tone, sentiment, or topic. Other researchers (Garimella et al., 2016) highlight the idea that social media marketers could seize the opportunity to track social media sentiments related to competing brands along with the reaction to new products launched in the market. Big data from social networks are extremely valuable to anticipate a potential image crisis by assessing the sentiments related to social mentions, as they are highly unlikely to be biased, as Mostafa (2013) suggests.

Even if text-based sentiment analysis has been deeply studied while image-centric sentiment analysis has attracted less attention, there is a particular scientific perspective that connects sentiment analysis and social media images (Wang et al., 2015; Yang et al., 2014;). Through the sharing of images, users can also express their sentiments and therefore, social media images can offer a rich and useful resource to identify and value users' sentiments.

This kind of results can be efficaciously employed in social media marketing, for instance, in social media recommendation tools or social media advertising. More specifically, studies on the topic are mainly divided in three categories. The first category of studies uses low-level visual attribute-based paths (Jia et al., 2012; Yang et al., 2014) while the second category uses mid-level visual attribute-based paths (Borth et al., 2013; Yuan et al., 2013). Finally, the third category of sentiment analysis for social media images uses deep learning-based paths (You et al., 2015). Ultimately, in order to leverage large-scale social media content for sentiment analysis, a particular study has used a consistent cross-modality regression model, which is able to use both the state-of-the-art visual and textual sentiment analysis paths (You et al., 2016).

3. Methodological approach

A multi-method approach was adopted for the purpose of providing an proper overview of the awareness of artificial intelligence usage among professionals in the digital marketing field based on three European countries (Romania, France and Italy). This geographical disparity was purposely chosen in order to include potential cross-cultural, economical, and technological differences. Our approach is based on two-steps methods: focus group conducted with professionals in the digital marketing field, and an online survey.

The purpose of the *focus groups with professionals of digital marketing* was to develop an understanding of artificial intelligence awareness from the perspective of such professionals by gathering insights from IT specialists. The focus-group discussions have become a major approach to the collection of qualitative data in social sciences (Barbour, 2008). Indeed, they provided valuable information from the interaction between participants (Brannen and Pattman, 2005). Based on the professional networks of some authors, six focus groups (two in each country) took place during 2018. In particular, a total of 30 experts in Social Media Marketing and Artificial Intelligence took part in these focus groups (10 experts per target country). This step allowed some crucial themes to emerge; for instance, a set of capabilities for the future AI-based software were proposed and discussed and they were used to design the subsequent online survey.

As surveys constitute one of the most popular research methods for obtaining data on behavior, interests and shared opinions (Engel and Schutt, 2012), we decided to complete our investigation by preparing and circulating an *online questionnaire*. Note in this regard that, as we faced a general lack of reliable information concerning artificial intelligence awareness from a cross-culture perspective, we designed our own survey instrument (partly based on the available literature and partly derived from information arisen from the focus groups). Hence, we decomposed our questions in three categories (audience, image and sentiment analysis) related to the proposed capabilities of the upcoming AI-based software. We also considered respondents' personal and professional profiles, as well as their level of knowledge of Machine Learning. The survey was pilot tested with 9 experts (3 per country) to check the clarity and suitability of the questions, evidenced by the respondents' interpretation of the logic behind the sequence of questions (Zikmund et al., 2003). Once their syntax was revised, we decided to conduct the survey by sending personalized invitations via e-mail to digital agencies' owners and social media marketers from Romania, Italy and France, obtained from https://www.topinteractiveagencies.com/, but also to freelancers from the same countries with expertise in AI and social media, whose contacts were obtained from https://www.freelancer.com/freelancers/. We received over 180 responses. After the elimination of inappropriate profiles or respondents who didn't answer to all questions, we selected a sample of 150 individuals (50 from each country).

Iterated Weighted Least Squares (IWLS), a standard method for fitting generalized linear models to data (Dutang, 2017) in R Statistical Computing Environment, was used to analyze the data regarding respondents' personal profiles (age, gender, and country of current professional implementation), their professional profiles (in the field of Social Media Marketing, based on job position and years of experience in the field, and their level of knowledge and frequency of use of Machine Learning technologies applied to Social Media Marketing. The model has been developed to offer relevant insights to first research question (RQ1).

Fuzzy-sets Qualitative Comparative Analysis (fsQCA) methodology was employed to explore the capabilities of the upcoming Artificial Intelligence-based software; the objective was to understand how causal configurations of the proposed three clusters of capabilities (Integrated-in-Image analysis, Audience analysis and Sentiment analysis) lead to the outcome, defined as the potential clients' intention to use this software (second research question – RQ2). The premise of fsQCA is that the 150 cases (respondents' validated answers) can be viewed in terms of combinations of causally relevant conditions (Ragin and Fiss, 2008). This method relies on case comparisons in the three target countries (Romania, Italy and France), and the application of Boolean algebra to identify causal combinations of antecedent conditions (future AI software capabilities, clustered in audience, image and sentiment analysis) that systematically lead to the outcome (intention to test its features). With this focus on combinations of causal conditions, fsQCA is uniquely suited in order to seize complex complementarities within antecedent conditions (Khedhaouria and Thurik, 2017), as it is the case for our framework of proposed capabilities for the future AI software.

The AI Media software capabilities (Fig. 1) have been distributed in three clusters, as follows:

- Audience analysis (capability to categorize social media posts based on their stage in the customer buying cycle, capability to make recurrent decisions on which content and when to publish it 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 offering 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 to create custom categories,

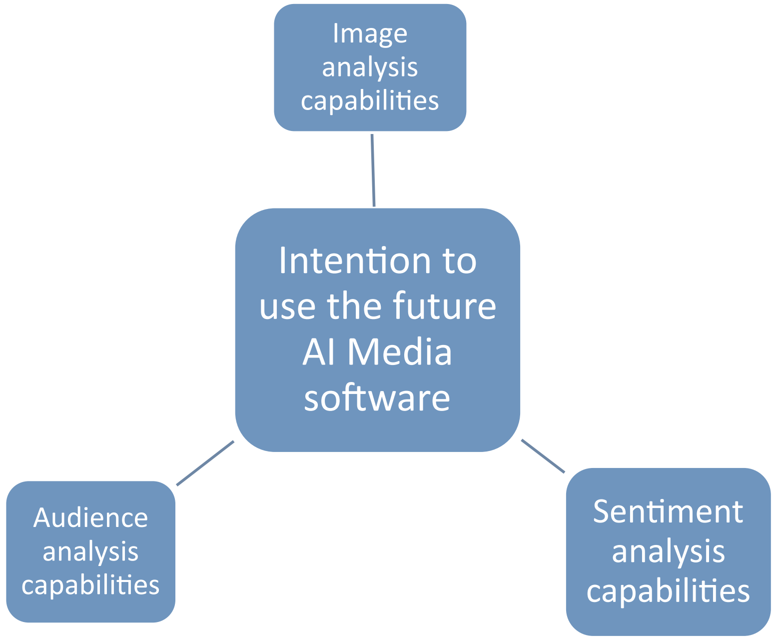

Fig. 1. Configurations of antecedent conditions (AI Media software capabilities) affecting the outcome.

capability of recognition, deep learning algorithms' capability to identify places and moments of product consumption, capability to correlate sales forecasting with the frequency with which a brand appears in photos from the social media and the 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, when reviewing a product/service, capability to track social media sentiments related to competing brands in order to unlock Competitive Intelligence mechanisms, capability to anticipate a potential image crisis by assessing the sentiments related to social mentions and capability to track the reaction to new products launched in the market and promoted on social networks).

Relationships between the variables are generally asymmetric because respondents' opinions from digital agencies in Romania, Italy and France vary. Therefore, alternative combinations of causal conditions can lead to the outcome. We transformed the values reflected in the scales we used in the questionnaire into fuzzy-set scores ranging from 0.10 to 1.00 (Table 1).

We established three qualitative anchors for the calibration: one to define full membership, a second anchor to define an almost complete lack of membership, and a crossover point.

4. Findings and discussions

Figs. 2–4 graphically outline the variables associated with the model developed for the *first research question*. Thus, we observe that more than 52% of participants are women. Almost one third of participants are less than 30 years old and the distribution of the country (of current professional establishment) is perfectly balanced between the three countries concerned (Romania, France and Italy). In addition, more than half of the participants are employees in a Digital Marketing agency, while less than 20% are freelancers and the rest are entrepreneurs. Note that the average number of years of experience of participants in the field of Social Media Marketing is estimated at 3.77, with a standard deviation of approximately 2.18.

Finally, to describe the participants ' report with the Machine Learning, we considered two variables:

- Self-assessment of the level of knowledge of the applicability of the Machine Learning in their professional field: It is measured by using a scale of Likert ranging from 1 to 4 (1 = Excellent or Very Good, 2 = Adequate, 3 = Needs improvement, and 4 = Needs considerable improvement)
- The level of use of software based on " Machine Learning algorithms " in their profession activities, measured through a scale of Likert ranging from 1 to 5 (1 = Most of the time, 2 = Often, 3 = Sometimes, 4 = Rarely et 5 = Never)

Thus, it is noted that almost 5% of participants are almost permanent users of software based on Machine Learning algorithms and more than 60% of participants almost never used this kind of software. In addition, 64% of participants argued that their level of knowledge regarding the role of the Learning Machine in their professional field was rather low.

Next, we define the auto-evaluation of level of knowledge regarding the applicability of Machine Learning in the professional field as variable Y. Note that Y belongs to the family of ordinal variables: the ranking between different levels is significant. The aim of the following

Table 1
Calibration of scales.

Scale point		Fuzzy-set value	Membership
Expected/Very probably	5	1	Fully in
Rather expected/Probably	4	0.75	More in than out
Great to have/Possibly	3	0.5	Cross-over (neither in nor out)
Rather necessary/Probably not	2	0.25	More out than in
Necessary/Definitely not	1	0.1	Fully out

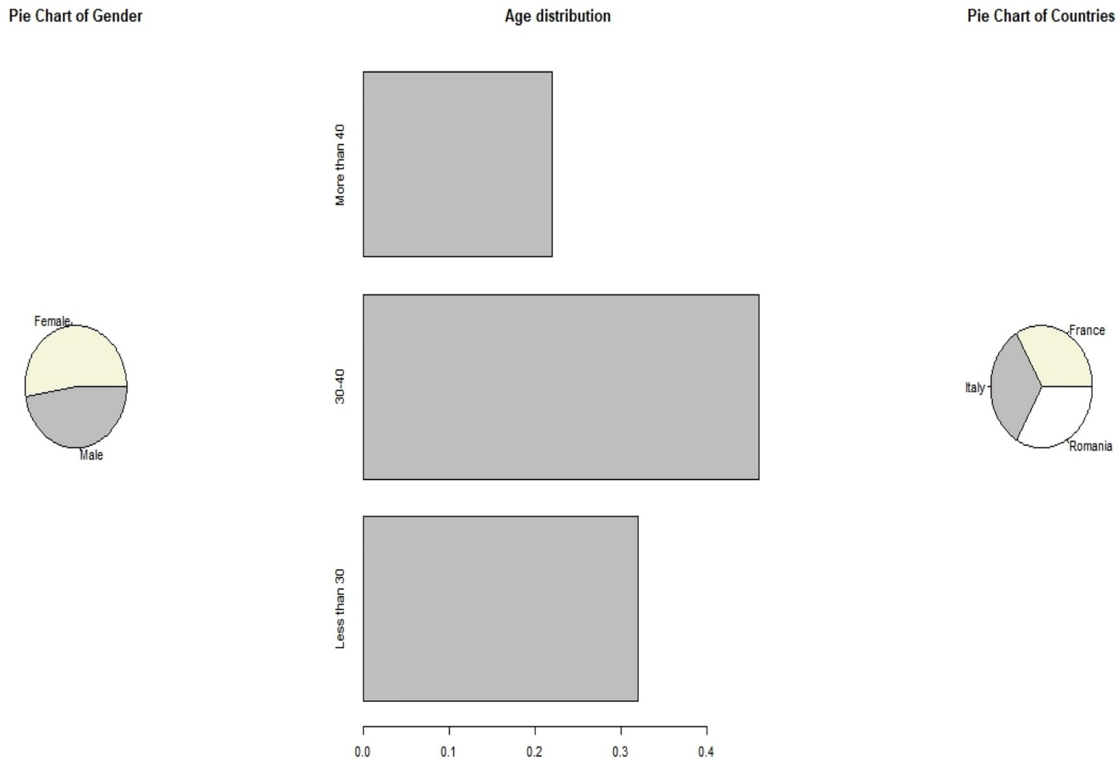

Fig. 2. Plot of personal profile variables.

part is to determine the link between Y, the so-called dependent variable, and the following explanatory variables (which are the other considered variables related to the profile of the participants): Gender, Age, Country, Current position, Years of experience, and Frequency of use. The *question sheet* is created in a way that all considered variables are categorical. With regards to the explanatory variables, we adopt a 'dummy coding' system: a categorical variable for which m levels are transformed into $m-1$ dummy variables (with binary levels: ``0", ``1"). Table 2 shows variables after the dummy coding process for the explanatory variables. The variables with "$" have been kept as fixed and variables with ``O" have been removed. Therefore, 13 explanatory variables are fixed.

These variables are denoted by $X_1, \ldots, X_{13}$ for the purposes of this study. Using a latent variable, denoted Y_*, we can express:

$$Y = \begin{cases} 1 & \text{if} \quad Y_* \in \,]\, a_0;\; a_1] \\ 2 & \text{if} \quad Y_* \in \,]\, a_1;\; a_2] \\ 3 & \text{if} \quad Y_* \in \,]a_2;\; a_3] \\ 4 & \text{if} \quad Y_* \in \,]\, a_3;\; a_4[\end{cases}$$

where $a_0 = -\infty$, $a_4 = +\infty$, and a_1, a_2, a_3 are three unknown coefficients. We can model Y_* by using a multiple linear regression: $Y_* = \beta_0 + \beta_1 X_1 + \ldots + \beta_{13} X_{13} + \delta$, where $\beta_0, \beta_1 \ldots \beta_{13}$ are a set of unknown coefficients and δ is a random variable that has a symmetric

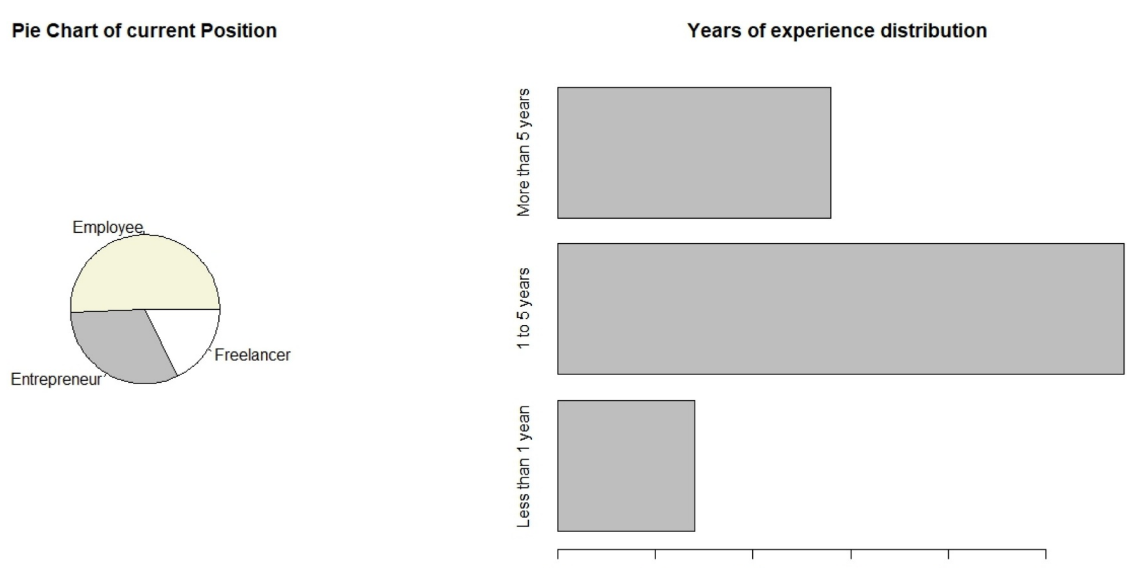

Fig. 3. Plot of professional profile variables.

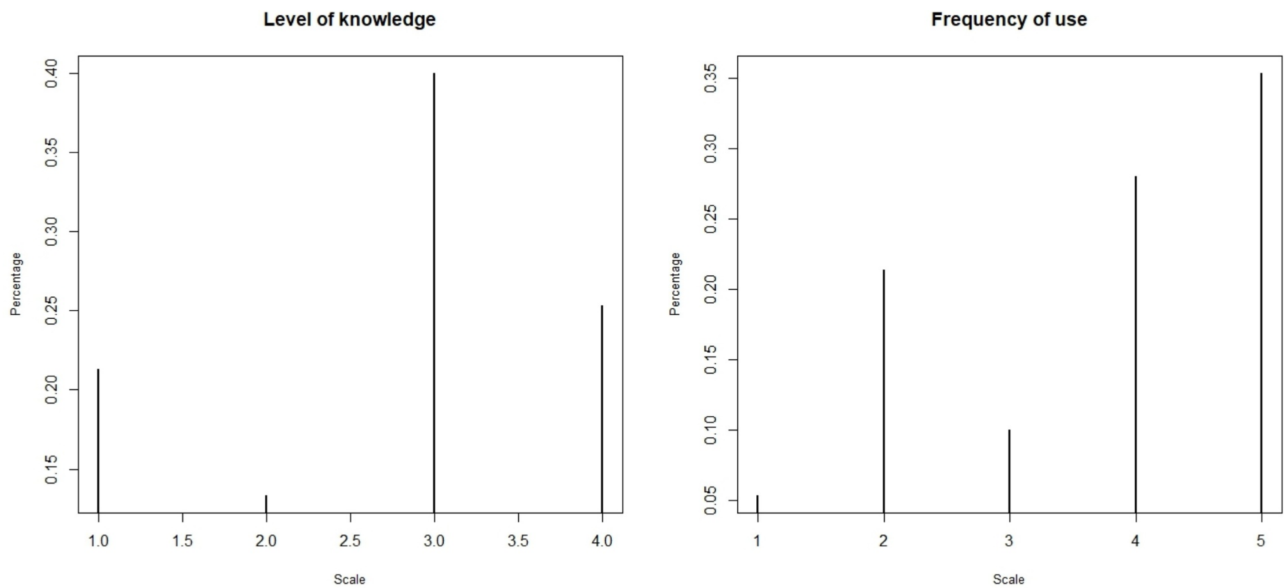

Fig. 4. Plot of variables related to the relationship with professional activities and Machine Learning.

Table 2
Variables after the dummy coding for the explanatory variables.

Variable	Coding
$ Y	Factor w/ 5 levels ``1″,``2″,``3″,``4″
O Gender_F	Factor w/ 2 levels ``0″,``1″
$ Gender_M	Factor w/ 2 levels ``0″,``1″
O Age_A1	Factor w/ 2 levels ``0″,``1″
$ Age_A2	Factor w/ 2 levels ``0″,``1″
$ Age_A3	Factor w/ 2 levels ``0″,``1″
O Country_C1	Factor w/ 2 levels ``0″,``1″
$ Country_C2	Factor w/ 2 levels ``0″,``1″
$ Country_C3	Factor w/ 2 levels ``0″,`` 1″
O Position_P1	Factor w/ 2 levels ``0″,``1″
$ Position_P2	Factor w/ 2 levels ``0″,``1″
$ Position_P3	Factor w/ 2 levels ``0″,``1″
O Exper_E1	Factor w/ 2 levels ``0″,``1″
$ Exper_E2	Factor w/ 2 levels ``0″,``1″
$ Exper_E3	Factor w/ 2 levels ``0″,``1″
O Use_U1	Factor w/ 2 levels ``0″,``1″
$ Use_U2	Factor w/ 2 levels ``0″,``1″
$ Use_U3	Factor w/ 2 levels ``0″,``1″
$ Use_U4	Factor w/ 2 levels ``0″,``1″
$ Use_U5	Factor w/ 2 levels ``0″,``1″

distribution close to zero. We then use an ordinal regression based on the above linear model. Further details on this model are given by Winship and Mare (1984) and McCullagh (1980). Using the latent variable Y_* and considering that $(X_1 \ldots X_{13}) = (x_1, \ldots, x_{13}) = x$, we assume that the probability that $Y = k$, with $k \in \{1, \ldots, 4\}$ is given by

$$\begin{aligned} P_k(x) &= \quad P(\{Y = k\}|\{(X_1 \cdots X_{13}) = x\}) \\ &= F_\delta(a_k - (\beta_0 + \beta_1 x_1 + \cdots + \beta_{13} x_{13})) \\ &\quad - F_\delta(a_{k-1} - (\beta_0 + \beta_1 x_1 + \cdots + \beta_{13} x_{13})), \end{aligned}$$

$\mathbb{P}(\cdot|\cdot)$ denotes the conditional probability and F_δ denotes the cumulative distribution function of the random variable δ. For the purposes of this study, we assume that δ follows the logistic distribution. Next, we estimate the unknown coefficients: $a_1 - \beta_0$, $a_2 - \beta_0$, $a_3 - \beta_0$, $\beta_1, \ldots, \beta_{13}$ by using a likelihood estimation method. Numerical values are obtained via the IWLS algorithm from the software R.

These estimations are given in the column ‘value’ of Table 3 (note that column ‘Std. Error’ gives the standard deviation of the estimators. Wald tests that study the significance of the explanatory of the variable

Table 3
Estimation results of unknown parameters of the model.

Variable	Value	Std. error	T value	*P* value
Gender_M	−0.06036358	0.3884569	−0.1553932	8.765113e-01
Age_A2	−0.34301280	0.4686368	−0.7319373	4.642068e-01
Age_A3	−0.46626440	0.5805808	−0.8030999	4.219170e-01
Country_C2	−0.34899743	0.4965503	−0.7028441	4.821529e-01
Country_C3	1.33756694	0.5052142	2.6475245	8.108348e-03
Position_P2	−0.21249008	0.4785861	−0.4439955	6.570459e-01
Position_P3	−1.03617394	0.5386846	−1.9235261	5.441402e-02
Exper_E2	−1.39282690	0.6022609	−2.3126638	2.074113e-02
Exper_E3	−1.87550878	0.7253583	−2.5856309	9.720097e-03
Use_U2	−5.14854705	0.7075393	−7.2766938	3.421006e-13
Use_U3	−1.52986482	0.5523978	−2.7694985	5.614266e-03
Use_U4	−0.74878490	0.4890075	−1.5312340	1.257116e-01
Use_U5	1.88160961	0.5168648	3.6404292	2.721839e-04
1|2	−5.94023229	0.9381329	−6.3319733	2.420454e-10
2|3	−3.68525445	0.7980551	−4.6177942	3.878406e-06
3|4	0.42595307	0.7137400	0.5967902	5.506474e-01

on Y are performed. The column ‘t-value’ shows the associated statistics tests and the ‘p value’ column is showing the associated p-values) Residual Deviance and AIC are respectively 212.3966 and 244.3966. The last three rows contain estimations for $a1 - \beta 0$, $a2 - \beta 0$, and $a3 - \beta 0$, which are respectively −5.94023229, −3.68525445 and 0.42595307. Thus, we can deduce that the most significant variables are: frequency of use of software based on Machine Learning algorithms, years of experience in the Social Media Marketing field, and country of current professional establishment.

The estimation results are based on the fixed variables shown in Table 2 (when using the dummy coding system, modalities of variable became indicator variables).

Thereafter, exact Fisher tests were performed to highlight the dependency relationship between Y and each of the above fixed variables. Crossed results from the survey are shown in Tables 4–6. Hence, we can find for each test that the p-value is $< 10^{-3}$, which confirms the high level of dependency between Y and the fixed variables. Furthermore, note that, byusing Spearman's rank correlation test, we can observe that there exists a significant link between Y and the frequency of use of software based on Machine Learning algorithms (p-value $<$ 2.2e–16).

As a concluding remark, we can find that respondents with a high level of knowledge regarding the applicability of Machine Learning in Social Media Marketing are those who frequently make use of software

Table 4
Contingency matrix for Y and Country.

	Romania	France	Italy
1	13	18	3
2	9	7	4
3	19	17	24
4	9	8	19

Table 5
Contingency matrix for Y and Years of experience.

	Less than 1	Between 1 and 5	More than 5
1	0	16	18
2	1	12	7
3	9	42	9
4	11	17	8

Table 6
Contingency matrix for *Y* and frequency of use.

	1	2	3	4	5
1	6	32	8	6	6
2	2	6	7	11	2
3	0	2	7	28	23
4	0	0	1	5	30

based on Machine Learning algorithms in their professional activities.

The approach of the *second research question* implies the test of two propositions:

P1. The configurations of antecedent conditions (capabilities of the future AI software which are grouped into three categories: audience, image and sentiment analysis) show equifinality with regards to the interest to test the upcoming software features.

P2. The causal recipes that lead to the highest interest to test the AI software features are shown to be different in Romanian, French and Italian sub-samples.

We have defined a new variable AIS through the computation of the fuzzy-set values of the antecedent conditions in the conceptual model (capabilities distributed in the three analytical categories), achieved by using fsQCA software: AIS = fuzzyand(Audience, Image, Sentiment).

Then, we analyzed the consistency and the coverage scores on the fuzzy-set XY plots (Figs. 5–7, revealing Romanian, French and Italian sub-samples).

The results of the graphical distribution of the observed cases within Romanian, French and Italian sub-samples suggest that antecedent conditions are enough to achieve the outcome in all target countries, due to the position of the majority of cases above the diagonal in the XY plots. We could observe a few exceptions in each sample with the corresponding cases positioned on the diagonal in the XY plot.

Regarding the Romanian sub-sample (Fig. 5), the consistency score is 1, and the coverage score 0.201. These scores imply that the distribution of fuzzy sets is largely consistent with the starting assertion previously explained, which is that respondents' perceptions on the capabilities of the future AI software represent a subset of the outcome (interest to test the software). Antecedent conditions' coverage of the outcome is 20.1%.

Regarding the French sub-sample (Fig. 6), the consistency score is 1, and the coverage score is estimated at 0.151. These scores reveal that the distribution of fuzzy sets in this sub-sample is largely consistent with the initial assertion here made, which is that causal combinations of antecedent conditions lead to the expected outcome. Antecedent conditions' coverage of the outcome is 15.1%.

Regarding the third sub-sample analyzed (Italy), the consistency score is 0.986, and the coverage score is estimated at 0.165. These scores highlight as well that the distribution of fuzzy sets in this sub-sample is largely consistent with the previous assertion here made, which that causal combinations of antecedent conditions lead to the expected outcome (Fig. 7). Antecedent conditions' coverage of the outcome is 16.5%.

Regarding the Romanian sub-sample, the complex solution provided by the Quine-McCluskey algorithm shows that four configurations of antecedent conditions affect the outcome. Their combination represents a successful recipe for potential capabilities of the upcoming AI software to achieve a higher interest to test it. Image analysis related capabilities are perceived by Romanian respondents as more influential than audience and sentiment analyses related capabilities.

Moreover, the equifinality principle (multiple paths to a desired outcome may coexist, according to Fiss, (2007)) is proved, as multiple paths of antecedent conditions lead indeed to the outcome (Table 7).

We have codified the impact of antecedent conditions as follows: black circles (●) show the presence of a condition and crossed-out circles (⊗) show its absence (or low impact) (Fiss, 2007; Pappas et al., 2016) while blank spaces represent indifference. All conditions here presented are core conditions. Moreover, consistency and coverage are shown on Table 7, not only with regards to the overall solution but also to each configuration, separately. All values related to consistency scores exceed from the recommended threshold of 0.75. In terms of the negated outcome, we observe that consistency scores fall behind the

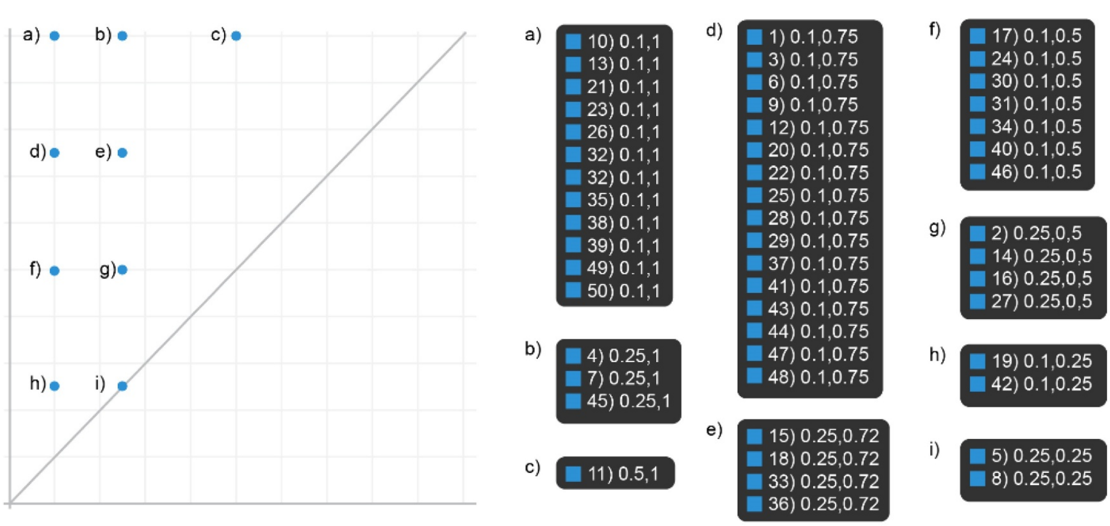

Fig. 5. Distribution of fuzzy-sets for Romanian sub-sample.

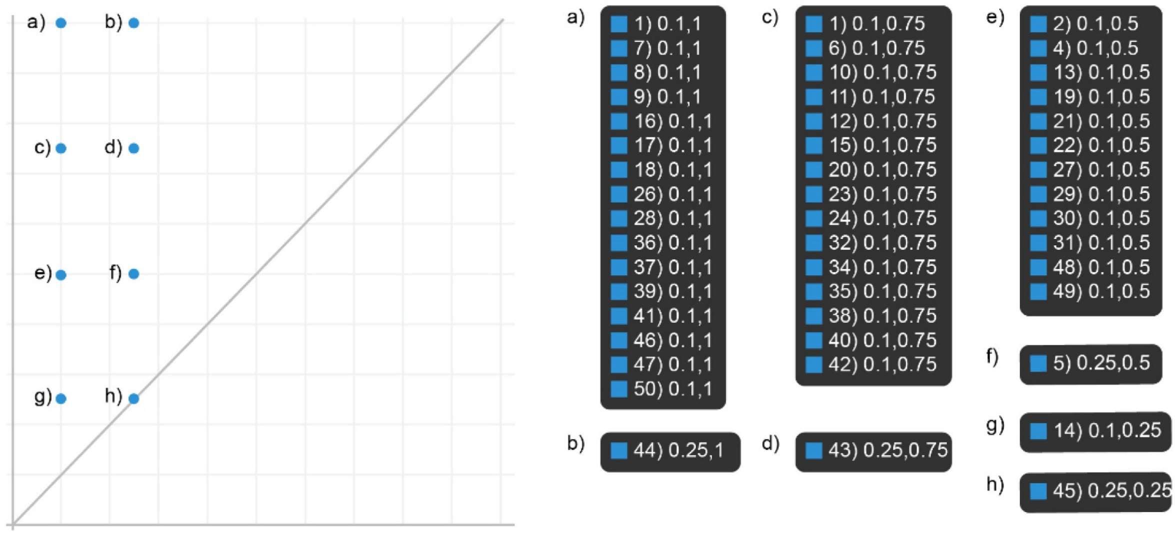

Fig. 6. Distribution of fuzzy-sets for French sub-sample.

recommended threshold of 0.75.

Regarding the French sub-sample, the complex solution provided by the Quine-McCluskey algorithm shows that sentiment analysis related capabilities are perceived by respondents as more influential than audience and image analyses related capabilities (Table 8). The equifinality principle is also proved, as four combinations lead to the outcome, even if the configurations reflecting a negated outcome have shown consistency scores under the recommended threshold of 0.75.

Regarding the Italian sub-sample, the complex solution provided by the Quine-McCluskey algorithm shows that audience analysis related capabilities are perceived by respondents as more influential than sentiment and image analyses related capabilities (Table 9).

The equifinality principle is not proved in this case, as only one combination of antecedent conditions leads to the outcome, with a consistency score higher than the recommended threshold of 0.75, while the two other combinations of conditions that yield a negated outcome showed consistency scores under the recommended threshold.

First proposition is partially supported, as the configurations of antecedent conditions (capabilities of the future AI software, divided into three categories: audience, image and sentiment analysis) show equifinality with regards to the interest to test the upcoming software features for Romanian and French sub-samples, but this principle is not supported in the Italian sub-sample.

These findings reveal that the second proposition is supported, since the causal recipes that lead to the highest interest to test the AI software features are different for Romanian, French and Italian sub-samples. More precisely, image analysis related capabilities proved to be the most influential for Romanian sub-sample, while sentiment analysis related capabilities were shown to be the most influential in French sub-sample, and audience analysis proved to be the most influential in Italian sub-sample.

Table 7
Causal recipes for intention to test the future AI-based software within the Romanian fuzzy-set sub-sample.

Configuration	High intention to test the future AI-based software 1	2	Low/no intention to test the future AI-based software 1	2
Image analysis related capabilities	●	●	⊗	⊗
Audience analysis related capabilities		⊗		⊗
Sentiment analysis related capabilities	⊗		⊗	
Consistency	0.87	0.85	0.35	0.36
Raw coverage	0.85	0.83	0.94	0.96
Unique coverage	0.03	0.02	0.01	0.03
Overall solution consistency	0.84		0.34	
Overall solution coverage	0.87		0.98	

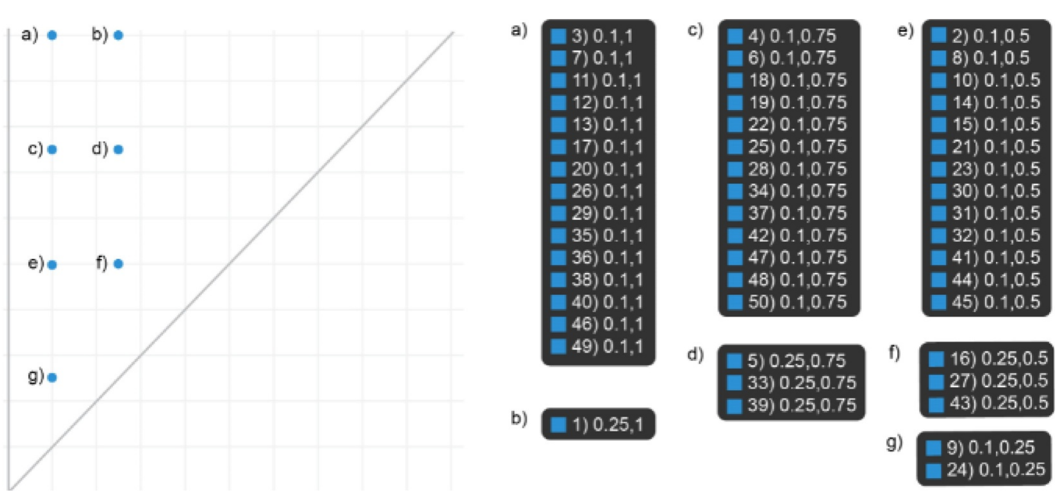

Fig. 7. Distribution of fuzzy-sets for Italian sub-sample.

Table 8
Causal recipes for intention to test the future AI-based software within the French fuzzy-set sub-sample.

Configuration	High intention to test the future AI-based software 1	2	Low/no intention to test the future AI-based software 1	2
Image analysis related capabilities	⊗	⊗	●	
Audience analysis related capabilities		⊗		●
Sentiment analysis related capabilities	●			●
Consistency	0.84	0.84	0.62	0.66
Raw coverage	0.87	0.85	0.44	0.32
Unique coverage	0.04	0.02	0.15	0.03
Overall solution consistency	0.83		0.62	
Overall solution coverage	0.89		0.48	

5. Conclusions, implications, limitations and further research

The main outcome of a successful AI-based software for social media marketing relies on its ability to deliver performances, based on promised capabilities. Accepting the findings from this cross-cultural research conducted in three countries, could lead to the development of AI-based software for Social Media Marketing that will be dominated by incentives to challenge the best practices in this field. Moreover, according to Guo-Fitoussi et al. (2019), innovation requires more than one IPR to protect AI Media software's intangible assets.

The in-depth analysis of the cases here explored reveals that in Romania the combination between the deep-learning algorithms' ability to identify places and moments of product consumption and the ability to correlate sales by forecasting the frequency with which a brand appears in social media photos represents the causal recipe that gets to a high interest in image analysis module of the future AI Media software. On the other hand, in France the combination between the ability to classify each user-generated content based on variables such as tone, sentiment, or topic, while reviewing a product/service and the ability to track the reaction to new products in the market or promoted on social networks represents the causal recipe that drives to a high interest in sentiment analysis module of the AI Media software. Finally, in Italy, the combination between the ability to categorize social media posts by their stage in the customer buying cycle and the ability to make recurrent decisions on which content to publish at when to do it in order to get the maximum reach represents the causal recipe that leads to a high interest in audience analysis module of the AI Media software.

Following our statistical study of the data, we can deduce that differences between gender, intergenerational aspect, and work position do not constitute significant factors when we study the awareness level of the applicability of the Machine Learning in the professional field of respondents. On the contrary, this level can be explained through the country of residence in the case of the participants of the survey, their professional experience and their frequency of use of software based on Machine Learning algorithms in their professional field. Hence, we can conclude that the cross-cultural issues play an important role in the evaluation of the awareness level. Furthermore, the reluctance to Machine Learning technologies depends on the professional portrait of the participants.

The professionals studied in this paper can be considered as potential clients for the future AI-based software. This study allows to developers of the upcoming AI software to target and adapt their business models on cross-cultural and professional profiles of respondents from digital agencies.

As the design of AI software belongs only to the planning phase, we hope that valuable feedback from potential users, regarding their expectations on the proposed capabilities and features, could help developers to avoid pitfalls that could threaten the software development process.

When being in the pre-design phase of the AI Media software, the research team should use the experts' feedback to identify the main issues to be solved before the implementation of core capabilities focused on image, audience and sentiment analyses, as other authors suggest (Trkman and Trkman, 2018). Innovative capabilities of AI Media software are required to deliver constant novel solutions for users, but this brings as well enormous benefits for strategic positioning, in line with the ideas shared by researchers like Phillips and Linstone (2016) and Paul (2018), Soriano (2010).

The limitations of this study are highlighted as follows: first, the data were gathered for 150 digital agencies from Romania, France and Italy, which has a limited impact on the generalizability of our findings. Second, this study only examines three antecedent conditions regarding the interest to test this innovative AI-based software for Social Media Marketing. A further research will involve the application of a trained model to track real-time data on social media contents; in such way, we will be able to analyze and visualize the pathways to achieve the best audience in real-time. Because we approached truly random sub-samples in each target country, we have tested the model to only ensure fit validity, although predictive validity cannot be provided (Woodside, 2014). Future research aims at testing the impact of the AI Media software capabilities on improving the work of digital agencies' social media marketers, as soon as this technological platform is fully available for users.

Acknowledgments

This research was conducted within the framework of the project FutureWeb, launched by Romanian Ministry of Research and Innovation, CCCDI – UEFISCDI, project number PN-III-P1-1.2-PCCDI-2017-0800/86PCCDI/2018, within PNCDI III. This work was supported by the project "Excellence, performance and competitiveness in the Research, Development and Innovation activities at "Dunarea de Jos" University of Galati", acronym "EXPERT", financed by the Romanian Ministry of Research and Innovation in the framework of Programme 1 – Development of the national research and development system, Subprogramme 1.2 – Institutional Performance – Projects for financing excellence in Research, Development and Innovation, Contract no.

Table 9
Causal recipes for intention to test the future AI-based software within the Italian fuzzy-set sub-sample.

Configuration	High intention to test the future AI-based software 1	Low/no intention to test the future AI-based software 1	2
Image analysis related capabilities	⊗	●	
Audience analysis related capabilities	●		●
Sentiment analysis related capabilities		⊗	⊗
Consistency	0.83	0.60	0.62
Raw coverage	0.83	0.45	0.48
Unique coverage	0.83	0.07	0.01
Overall solution consistency	0.83	0.55	
Overall solution coverage	0.83	0.55	

14PFE/17.10.2018. Romanian authors are grateful for the collaboration with the colleagues from France and Italy, which led to a cross-country approach of the results.

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