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Improving the benchmarking of social media content strategies using clustering and KPI

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Abstract

The organizational impacts of adopting social media have been on the top key concerns of organizations entering these environments. Organizations are, in fact, allocating time, effort, skills, human resources and technology and this raises the constant need to measure the ROI and legitimize the use of social media in the context of organizational development. However, how can organizations attempt to measure the efficiency and return on investments on a social media content approach that has not been strategically designed? In this paper, we report on previous research which we have further developed into a more comprehensive and solid analysis of types of social media content strategies that are being implemented in the Higher Education Sector, using clustering to group analogue content strategies and social media KPI to measure the efficiency of each of the main i. This work is based on a previously proposed editorial model for the design of social media content strategies for Higher Education Institutions, and results show which are the most relevant strategic areas of communication and corresponding return, in terms of publics' engagement, that organizations can obtain.

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1. Introduction

The profound alterations in society and in the communication management landscape caused by the irreversible growth of social media platforms has impacted organizations, thus concerns related to its usage and management have been on the agenda of organizations entering these environments.

In fact, organizations have been rushing to adhere to social media networks following the worldwide trend to create a social presence in multiple channels, reaching for and aiming essentially at mediatization [1], without previously defining a clear strategic approach, which should, for instance, be built upon clear insights on their target audience and an editorial plan/calendar, that can foster the achievement of the overall business objectives. Nevertheless, when adopting social media, organizations are, in fact, allocating time, effort, skills, human resources and technology [2] and this raises the constant need to measure the return on these investments (ROI) and legitimize them in the context of organizational development.

However, how can organizations attempt to measure the efficiency and return on investments on a social content media approach that has not been strategically designed/aligned and is a set of unarticulated processes and situational messages? The lack of a clear social media content strategy is posing real challenges for companies trying to measure their social media communication intervention/efforts and the ROI allocated to these environments, so two other questions need to be answered: what is it that the organization wants to accomplish on social networks (setting goals) and will those goals be able to foster the organizations overall performance and mission (determining efficiency)?

Considering the Higher Education sector, it is also necessary to bear in mind an increasing global competitive environment, where the decreasing number of student enrolments and reduced budgets, due to, for instance, a decreasing government support has pushed organizations to act in self-promotion and engagement with broader audiences. In this context, these organizations have been pushed to seek for additional financial funding and to devote a large amount of efforts to ensure brand awareness and distinctiveness, to assure survival.

Higher Education Institutions (HEI) deal with broad range and diversity of organizational publics which raise distinct communication and management needs. Social media content strategies aimed at organizations with such a diversity of stakeholders' expectations, service distinctiveness, societal expected intervention and corresponding external pressure are lacking research. Thus, it is important to research, reveal, systematize and bring forward modes of intervention that can provide the balance between their institutional and transactional needs, to ensure their survival and competitive potential. In fact, the lack of research on this field is also stated by Qi and Mackie[3], who report on a wider spectrum of social media research on educational purposes, which we further detail in the following sections.

In order to address the above mentioned questions and identified lack of research, in this paper, we report on previously conducted work (sections two and three) which we have further developed into a more comprehensive and solid analysis of social media content strategies in the Higher Education Sector (HES), using clustering for categorizing strategies and social media key performance indicators (KPI), which allowed us to bring forward the efficiency of each category of social media content strategies (sections four and five).

2. Previous work

To provide answers to the research questions, we analyzed the population of Higher Polytechnic Portuguese Education Institutions websites and compiled a list of the social media tools that these organizations were using. For, this initial analysis we concluded that Facebook was the most prominent social media network being used by these organizations, whose representativeness was above 60%. For this reason, we decided to conduct research on these organizations' Facebook pages (43 organizations) during one entire schoolyear (twelve months).

A total of 14.958 messages were obtained and (after data cleaning) were classified, using five text mining classifiers, according an editorial model [4, 5] that we have designed specifically for this type of organizations, and which includes seven editorial areas: 'Education', 'Research', 'Society', 'Identity', 'Administration', 'Relationship' and 'Information' [4, 5].

2.1. The classification of messages

Surely, classifying 14,958 posts according to the proposed editorial model is a time demanding task and impossible to be undertaken on the fly if done exclusively by humans, thus, clearly, a far too heavy endeavor to be made by hand. Therefore, we proposed and implemented an automatic method to categorize the posts based on the conjunction of several of the most recent algorithms for text classification or categorization.

To perform the classification of posts we decided to use an ensemble of six of the most promising, and prominent, classifiers using semi-supervised learning: Support Vector Machines [6], Random Forests [7], LogiBoost [8], K-Nearest Neighbours [9], MultiLayer Perceptrons [10] and Deep Neural Networks [11, 12].

On a first stage, we ran a set of 350 manually classified posts through the classifiers for training, and then computed the respective accuracy of the automatic classification. The result of using a 10-fold cross-validation proved the techniques achieved results above 68% of accuracy. On a second stage, we fed the classifiers a bigger set of 512 manually classified posts (by the same human specialist) for retraining, and we recomputed the new accuracy. We got an improvement of only 3% on average for the six algorithms, from an increase of 46% of the sample size. Therefore, we didn't continue to increase the training set to avoid over-fitting.

Hence, we then ran the whole set of 14,958 posts on our six trained classifiers to obtain a predicted category for each post, by each classifier. Finally, we used the mode of these six algorithms as the final result, i.e., we used the prevailing category of the six-set as the final predictive category for each post [13].

3. Previous results and discussion

The classification of messages described in the previous section allowed us to obtain insights on the editorial areas in which HEI have been investing, in relation to each organization's total communication effort (i.e., total number of Facebook messages, for all agents in a one-year period).

After the automatic classification of messages, we computed the relative of percentages of posts per editorial areas and per HEI, which allowed us to determine: (1) the sector's tendency in terms of overall content strategy and (2) to identify three main categories of content strategies being implemented by those HEI. This categorization of strategies was based on the use of the highest and lowest standard deviations among each organization's set of seven editorial areas relative percentages of posts, and allowed us to identify the following categories:

- Decentralized strategies: which tended to focus on several editorial areas with approximate amounts of investment in each one, presenting lower standard deviations;
- Centralized strategies: present higher standard deviations, revealing investments in one or two editorial areas, neglecting all the remaining ones, and;
- Hybrid strategies with disproportional investments in more than one editorial area, with very high investments in two or three areas and low investments in the remaining ones.

Even though we could identify three main categories of content strategies, we could not state that decentralized nor hybrid content strategies would result in more efficient social media content strategies, though the need to address a broad range of stakeholder's expectations would lead us to believe that these were the approaches with the most potential. We have also concluded the centralized content strategies could denote that, either these agents have assigned a very narrow and specific objective to their content strategy, or they are still unable to perceive other possible of content areas, stakeholders' expectations and/or social media channels potential. However, for any of these categories we were not able to account for the performance of the category of the content strategies. Therefore, we believe that we have provided helpful understandings on adjusting / improving an organization's social media content strategy by reveling the content strategies being implemented in the sector, but we were not able efficiently benchmark them, because we could not account for their performance.

Also, using the standard deviation for each HEI's content strategy as a methodology to classify each content strategy into one of the three main groups, proved to be a hard to solve challenge. In fact, if there was no difficulty in finding the top four centralized and top four decentralized strategies, determining the limits for each of these groups was an inviable task, because there were no relevant leaps in the computed standard deviations what allowed us to firmly determine the points where a centralize or a decentralized strategy should be considered as a hybrid one.

Therefore, a new methodology for grouping the 43 unique social media content strategies was needed as well as indicators that we could use to account for their performance.

4. Introducing clustering and social media KPI

Within the 43 schools under analysis, 43 different content strategies were detected, because the intensity of communication (number of posts) in each of the seven editorial areas is different for every school, thus leading to 43 distinct sets of combinations. To differentiate content strategies without conceding to a non-productive nor to a non-generalizable analysis, it was necessary to find patterns or groups of schools with similar content strategies among them. To do so, a clustering analysis was conducted using the *k*-means method [14-17].

Given a set of 43 observations (x_1, x_2, …, x_{43}), where each observation is a point in a 7-dimensional space (each point's coordinate consist of the seven values for each editorial area in each school), *k*-means clustering aims to partition the *43* observations into k ($\leq$ 43) clusters $C = (C_1, C_2, \ldots, C_k)$ so as to minimize the within-cluster sum of squares (WCSS) (sum of distances of each point in the cluster to the *Ck* center).

To find the optimal *k* number of clusters, fifteen iterations were conducted for *k*=2 to *k*=15, in order to find the stage at which two properties must be found:

1. The within-cluster sum of squares stabilizes (also designated by `tot.withinss`), or in other words, find the stage at which, after encountering a relative minimum for this property, initiating another process with a higher *k* number would result in a similar or just slightly higher / lower value for `tot.withinss`.
2. The between-cluster sum of squares (also designated by `betweenss`) is high enough to cluster points into distinct groups.

The evolution of the `tot.withinss` and `betweenss` values (y-axis) in the *k*=2 to *k*=15 (x-axis) clustering process is presented in Fig. 1. As is it possible to observe we obtain a `tot.withinss` and `betweenss` value for each *k*, and the tendency is for `betweenss` to increase as `tot.withinss` decreases. This indicates that for consecutive higher *k* values of clusters the distance within-cluster points decreases, and clusters are geometrically more distant from each other, because the between-cluster distance increases.

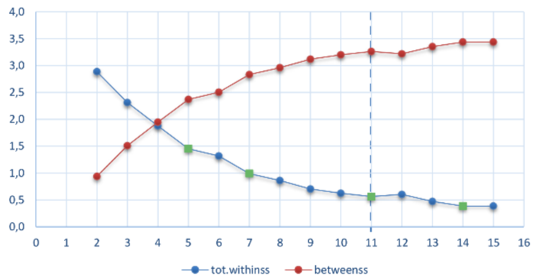

Fig. 1. tot.withinss / betweenss for the *k*=2 to *k*=15 clustering process

Analyzing the possibilities, the optimal *k* number of clusters meeting the above-mentioned properties are (marked in green in Fig. 2): *k*=5, *k*=7 (followed by a smaller decrease), *k*=11 (slight inversion) and *k*=14 (stabilization). For *k*=5 and *k*=7 the between-cluster distance (`betweenss`) is still relatively low, when compared to *k*=11 and *k*=14. The choice then relies between *k*=11 or *k*=14. Considering that the ability to generalize is proportionally inverse to the *k* value, we adopted *k*=11 as the optimal number of clusters. In other words, it would be possible to find higher *k* values meeting the necessary properties, but as this value increases more clusters (groups) are formed, up until the stage where we could get to the 43 observations we began with.

4.1. Classification of social media content strategies

The use of the *k*-means method allowed to obtain 11 clusters of similar social media content strategies, that is, groups of editorial areas with approximate communication intensity values in the same areas. Each cluster is composed by 1 (min.) to 7 schools (max.), as detailed in Table 1.

Table 1. Number and size of the eleven clusters and number of editorial areas per cluster

Cluster no.	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
Cluster size	3	2	5	4	6	6	7	3	1	2	4
No. of editorial areas	6	5	6	6	6	6	6	5	5	5	6

The cluster size indicates the number of schools that have been assigned to that cluster. The smaller cluster is cluster 9, while the biggest cluster is cluster 7. On average, there are 4 schools per cluster, as illustrated in Fig. 2.

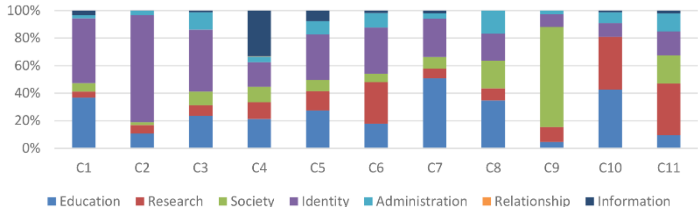

Fig. 2. Means of editorial areas per cluster (classification of content strategies)

The composition of the average communication intensity in each editorial area varies from cluster to cluster, thus each cluster provides an overview of a unique broad content strategy, as illustrated in Fig. 2.

As it is possible to observe, typically each content strategy is composed of two to three predominant editorial areas and not all strategies integrate all the seven editorial areas. For a clearer view of how many editorial areas are represented in each broad strategy (cluster), this information is also depicted in Table 1.

There is not one single content strategy integrating the seven editorial areas, although most the of the strategies are composed by six areas. Only four of the strategies are composed by five editorial areas. Overall, the most prominent editorial area in the sector is 'Identity' in cluster two (C2), with an average expression of 78% in 2 schools (size of C2, cf. Table 2), combined with small portions of other editorial areas, namely: 'Education' (11%), Research (6%), 'Administration' (3%) and 'Society' (2%). The prominence of the editorial area 'Identity' had already been detected in previous work [4, 5], as illustrated in Fig. 6 a) where the overall sector content strategy is illustrated. This editorial area has a visible expression in several other clusters, namely C1 (47%), C3 (45%), C6 and C7 (33%) and C7 (28%) and is integrated in all the 11 clusters.

Similarly, the editorial area 'Education' has also a representative portion in almost all the clusters with higher values in C7 (52%), C10 (42%), C1 (37%) and C8 (35%). As identified in the sector tendency analysis, 'Identity' and 'Education' are where the major communication investments rely on, revealing two accentuated needs of higher education institutions: managing organizational image and reputation and advertising higher education courses.

Another evident aspect of Fig. 2 is the expression of the editorial area 'Society' in C9. However, it wouldn't be accurate to generalize based on this cluster since it integrates only one school. It consists of a content strategy that is clearly composed by a very distinct distribution of editorial areas with no similarities to other content strategies identified in the sector, and the only one to incorporate such an intensity in communication in that editorial. Also, note that C4 is the only cluster where the editorial area 'Information' is prominent.

Clusters C2 and C9 are, therefore, the two most centralized clusters, since communication effort tends to focus on one main editorial area. They are also the smallest clusters, together with C10. It is not, however, possible, at this point, to state that the centralization of content strategies is intrinsically linked to the size of the cluster. In fact, it wouldn't be accurate to claim that the bigger the cluster the more decentralized the content strategy is. Take, for instance, C7, which is bigger in size than C5 and C6, and is comparatively more centralized in the editorial area 'Administration'.

The editorial area 'Relationship' is non-existent in all the clusters, and for the clusters incorporating less editorial areas, 'Information' and 'Society' are the areas not included in the content strategies of clusters C2, C8 and C9 and C10, respectively. This is a clear indicator of a high deficit of investment in two-way symmetrical communication and dialogue with organizational publics, failing the largely announced essence of social media environments, which leads us to believe that these organizations are mainly aiming at mediatization but failing at mediation.

4.2. Clustering content strategies and computing their performance

Measuring the performance on social media is intrinsically linked to the type and amount of the interaction of the audiences with the content published on pages. For this reason, Facebook's 'likes', 'shares' and 'comments' are used as manifest variables for the publics' engagement according to a weighted scale, since these interactions are not all worth the same: 'shares' and 'comments' require, at least, more time and commitment from the users interacting with content. Therefore, in the next section, we explain how we created a score function, based on a weighted scale, to improve de quality of the measurement of interactions with audiences.

4.2.1. Using a score function to determine the weighted engagement per editorial area

The value of Facebook's interactions is a widely-discussed topic, because the Facebook's EdgeRank has never been completely disclosed by the company. It consists of the formula utilized to decide which content should be displayed to who and when on the Facebook's wall feed. The formula is composed of several factors such as the affinity between the content creator and the content viewer, how recent the content is, and the weight assigned to each of the interactions, among other indicators. Since there is no consensus on the weight associated to these interactions, a survey was conducted to decide on the weighted scale to be used in our research.

The survey was conducted on a total population of 190 individuals, which included HEI students, teachers and communication professionals. Individuals were given a scale of 1 to 10 to classify 'likes', 'comments' and 'shares' according to the following question: "*When an organization evaluates the quality of interactions with his Facebook fans, which do you believe that should be the value (weight) assigned to each of the following interactions?*". The mode of classifications obtained resulted in: one 'like' equals 5 points, one 'comment' equals 8 points and a 'share' equals 10 points. The number of weighted points obtained in each editorial area was than computed and is depicted in Fig. 3 a), and it consists on the total number of interactions ('like', 'share' and 'comment') multiplied by its corresponding weight. The score function used to calculate the "weighted engagement" per editorial area allowed us to obtain which are the editorial areas more prone to receive interactions from the audiences.

As it is possible to obverse, the editorial area 'Identity' is the one with the highest score, followed by the editorial area 'Education'. In fact, if we consider the total amount of effort (number of messages) and response (scored engagement) for each editorial area in the sector, these two editorial areas consist of the ones where response is higher or approximate to the devoted efforts by organizations, as illustrated in Fig. 3 b).

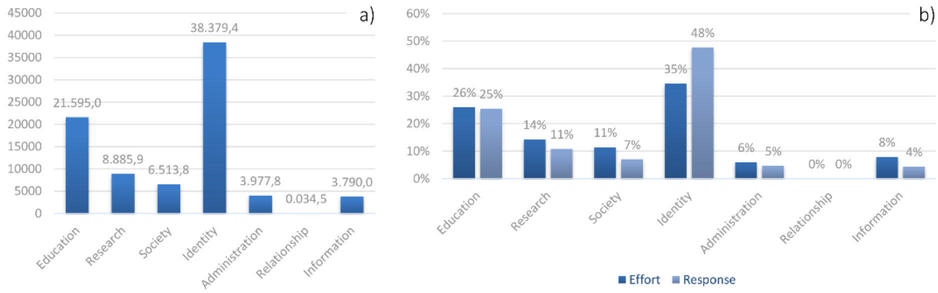

Fig. 3. (a) Total engagement score per editorial area; (b) Relation between effort and response by editorial area

In all the remaining editorial areas, the weighted response is lower that the effort devoted to that same editorial area.

4.2.2. Computing performance by cluster

Computing the performance for each of the clusters presented in Fig. 1 allowed us to perceive the effectiveness of each cluster in terms of generating audience response, which we are considering as the key variable to determine the effectiveness of a group of content strategies. As we have previously explained, each cluster is composed by a percentage of messages in a certain editorial area. Therefore, to compute each cluster's efficiency, we multiplied the percentages of editorial areas that compose it by the score function we have previously identified.

Applying this formula allowed us to obtain the total score per cluster and, therefore, to compute the average engagement per cluster and for the strategies integrating that same cluster. The average engagement per cluster we have computed is depicted in Fig. 4, where the number of score points is shown by cluster. As is its possible to verify the two most well performing cluster, in terms of scored engagement are cluster C2, C1, C7, C6 C5 and C8.

A benchmarking methodology was used to measure the performance of each school on Facebook. According to Porter[18] "a successful firm is one with an attractive relative positioning", which should translate as an outcome and not as a cause. The author also states that, "competitive advantage is attained within some scope, and the choice of scope is a central one in strategy". The main goal of benchmarking the organization's performance is to seek to improve their practices on a regular basis by continuously developing inter-organizational learning processes. In this case, the scope comprises the set of messages and interactions generated on Facebook, during one schoolyear.

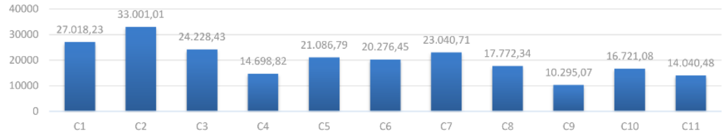

Fig. 4. Engagement per cluster (in points)

When comparing Fig. 2 and Fig. 4 it is possible to conclude that the first categorization of social media content strategies into centralized, decentralized and hybrid strategies, that we had proposed in previous work, has no relevance for benchmarking purposes. In fact, if we compare the two most centralized clusters – C2 and C9 – in cluster C2 we obtained the highest engagement among clusters and on C9 one of the lowest engagement scores.

These new findings have lead us to believe that the centrality of the de content strategy is not a strong indicator for its ability to succeed among the audiences. In fact, in Figure 2, C2 and C9 could both be classified as 'centralized' content strategies, however, considering the weighted score given by Figure 5, the ability to generate engagement in C2 is as twice as the ability to generate engagement in C9. This leads us to conclude that the (de)centralization of strategies is not the prime indicator for pointing out benchmarking agents in the sector. What we believe to be the key aspect determining the best performing agents in the sector is the relative proportion of inclusion of the editorial area 'Identity'.

Again, comparing Figs. 2 and 4, it is clear to perceive that the higher the percentage of messages devoted to the editorial area 'Identity', the higher the engagement generated among the audiences and, therefore, the higher the success accomplished within that same strategy. This applies, primarily, for clusters of strategies C1, C2 and C3, which include the content strategies of HEI B4, F5 and G4 (C1), F1, H1 and H1 (C2) and E5, J1, J4, L2 and P6 (C3), as illustrated in Fig. 6 b). An overall analysis of these content strategies lead us to conclude that centralized strategies, with higher focus on the 'Identify' editorial area, are the most prone to generate higher engagement among the public of the Facebook's page.

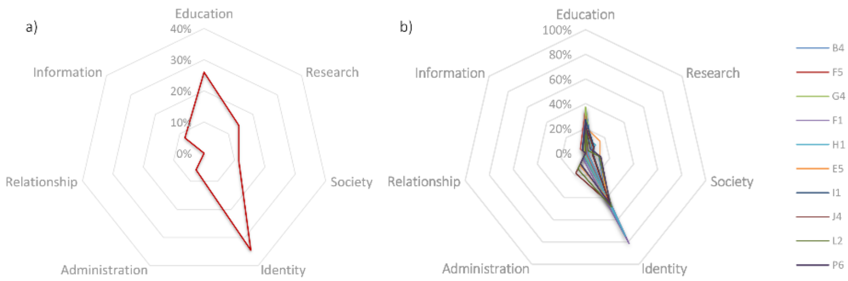

Fig. 5. (a) Sector tendency [4, 5]; (b) Visual representation of the top performing content strategies in the sector

As lustrated in Fig. 6 b), these strategies incorporate medium to high levels of messages regarding: institutional events (celebrations, awards and tributes, graduation ceremonies, etc.); students, faculty and staff honorable mentions; institutional promotion, advertising (identity, image, reputation); Corporate Social Responsibility initiatives; institutional clipping and, among others, the participation / representation in fairs and exhibitions. In fact, this is a particularly relevant communication domain in the HES. The projection of the organizational identity is key to maintain and protect a strong reputation since it determines its distinctiveness. HEIs' reputation is one of the main factors impacting students' and parents' choice of the educational service provider, being able to provide HEI with a "first-choice" status [4]. The organizational reputation also serves as an indicator for the underlying quality of the services provided and of its performance, thus being extremely relevant for the development of (commercial and institutional) partnerships' and to the extension of its societal intervention.

5. Conclusions and discussion

In this paper, we have brought forward the main editorial areas which, according to the widely known social media KPI, are worth pursuing. These conclusions are built upon the classification of social media messages according to editorial model proposed by Oliveira and Figueira[4], the clustering of social media types of content strategies and the input of the KPI that major social media monitoring tools are providing. Research results provide clear insights on what type of messages are most prone to gather audience's interaction, which can aid organizations to better design their content strategies to obtain the best return possible in terms of efforts invested on social media. Undoubtedly, audiences demonstrate a higher propensity to interact with messages related to the organization's identity and image, which we consider to be the key element to include in the design of a social media content strategy for HEI, when considering the wide variety of other social media proposed editorial areas.

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