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Winning post strategies that generate engagement: A QCA approach

Jasmina Berbegal-Mirabent[1], Xènia Caballero[2]

[1]*Universitat Politècnica de Catalunya (Spain)*

[2]*Universitat Internacional de Catalunya (Spain)*

jasmina.berbegal@upc.edu, *xeniacaballeroe@gmail.com*

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Abstract

Purpose: Fashion companies are using an increasing amount of resources to generate social media content to provoke an impact and engage customers. A wrong message or image – but also an inaccurate combination of the different elements that characterise a post – can jeopardise brand reputation. The way brands communicate with potential customers is of utmost importance as it creates its online identity and presence, and this is ultimately linked to customer loyalty. Given that a post contains different elements (e.g., image, people, background) this study seeks to explore which combination(s) of elements should brands consider to generate superior user engagement with their posts.

Design/methodology: After conducting a comprehensive literature review on social media marketing a set of critical factors that relate to content engagement are envisioned. Next, drawing on complexity and configuration theories, we perform fuzzy-set qualitative comparative analysis (fsQCA) to identify different strategies (i.e., combinations of critical factors) companies might follow to engage with customers successfully. The empirical application focuses on the Instagram activity of a retail clothing company.

Findings: The findings reveal that posts conducive to superior engagement should: (i) be simple, product-related or experience-related, (ii) use few but meaningful hashtags that are representative of the brand, (iii) show people's faces, and (iv) send an inclusive message.

Practical implications: This study sheds new light on how brands should communicate on social media networks to generate improved impact for their posts.

Originality/value: This study goes beyond traditional approaches that overlook the joint effect of the different strategic design choices (i.e., combination of critical factors) for posts on the outcomes of interest (in our case, number of likes, comments and views).

Keywords: Instagram, Qualitative comparative analysis, Content engagement, Post, Impact strategy

Jel Codes: L81, M31

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1. Introduction

Keeping in touch with friends and family was the early use for social media, but, over time, its usage has evolved, and companies now use social media to communicate directly with customers to promote their products, offer discounts and promotions and inform them about any kind of news regarding the company (Ismail, 2017). Brands create content to share with their followers, and this content is the instrument that stimulates interaction (Algharabat, Rana, Alalwan, Baabdullah & Gupta, 2020; Plumeyer, Kottemann, Böger & Decker, 2019; Sabate, Berbegal-Mirabent, Cañabate & Lebherz, 2014). Content affects the brand reputation, so the objective is to define a strategy that strengthens that reputation. Word of mouth marketing (WOMM) – also called social media marketing – is the branch of marketing devoted to social networking and it is responsible for the creation of content. WOMM differs from traditional word of mouth in that organisations are the ones encouraging its dissemination with professional marketing techniques (Kozinets, De Valck, Wojnicki & Wilner, 2010). WOMM takes advantage of the shift in trust which makes the recommendations and experiences of other consumers seem more reliable than traditional marketing tools (Sabate et al., 2014).

Social media marketing contributes to the creation and enhancement of a brand community (Escobar-Rodríguez & Bonsón-Fernández, 2016). The operation of brand communities on social media can increase the amount of brand trust and brand loyalty as a result of improved customer relationships with the brand, the company, other consumers and the products (Laroche, Habibi & Richard, 2013). Brand communities also have a positive influence on brand attitude (Wang, Cao & Park., 2019).

Followers of brand profiles on social media tend to be committed and loyal to the brand, converting WOMM activities in a tool that effectively intensifies the relationship with customers and builds brand loyalty (Park, Hyun & Thavisay, 2021). According to Nadeem, Andreini, Salo and Laukkanen (2015), continuous updating of social networks with new products is critical to build trust that might be later transformed into loyalty. Social media currently represents a more trustworthy source of information to the vast majority of its users compared with traditional marketing promotion tools; therefore, social media activities can be considered part of the strategy to gain brand consciousness and act as an informative source for customers to get updated details about the products offered by the brand (Ismail, 2017). Additionally, the effort consumers need to undertake to find the desired information can be substantially reduced thanks to social media.

Although brands might control the conversations on their online social media sites, the crowd (or the followers) can also step in and redirect the discussions. This is a high-risk scenario (in case of receiving criticism or negative messages), but at the same time, it is also a way to democratise engagement between firms and consumers. Vivid content has a greater ability to create experiences that resemble the real world more closely, which in turn, generate greater user engagement (Estrella-Ramón, García-de-Frutos, Ortega-Egea & Segovia-López, 2019) and allow user to co-create the content (Hsu, Nguyen & Huang, 2021). One strategy brands can use to regain control over what users are talking about is the use of influencers. Posts in which influencers participate tend to achieve a high share rate, so the brand influences the conversations users might have as a response. Influencers are individuals who can shape users' behaviours and attitudes in terms of consumption decisions through online channels. Having influencers promoting a certain product can result in a strategic and very powerful asset (Sokolova & Kefi, 2020; Uzunoglu & Kip, 2014), and besides increasing engagement, it also increases the expected value of the brand (Jiménez-Castillo & Sánchez-Fernández, 2019).

In short, social media generates a double effect in which users are interacting and engaging with brands and, simultaneously, are disseminating the content generated by the brands they follow by sharing it with their family and friends (Klassen, Borleis, Brennan, Reid, McCaffrey & Lim, 2018). Therefore, social media users become brand advocates for the brand, increasing its reach (Sabate et al., 2014). This is why it is so important to analyse the underlying basis of the impact generated – that is, the content shared.

This study sheds new light on how brands can generate improved impact for their posts on social media networks. Given that a post contains different elements (e.g., image, people, background) the research question driving this investigation can be formulated as follows: *Which combination(s) of elements should brands consider to generate superior user engagement with their posts?* To answer this question, we build on the principle of conjunctural causation, which allows us to test the joint effect of the different strategic design choices for posts on the outcomes of interest (in our case, number of likes, comments and views). Specifically, the methodology used is qualitative comparative analysis (QCA), as it does not focus on the net effect of the factors on the outcomes, but instead, on how factors (or antecedent conditions) should be combined.

While the use of QCA is relatively new in the field of marketing and particularly in social media, there are several works that support its use. For instance, Müller, Mattke and Maier (2018) evaluated which configurations of the perceptions about the ad, the influencer and the product generate higher purchase intention on Instagram. Similarly, Alonso-Dos-Santos, Rejón, Pérez, Calabuid-Moreno and Ko (2018) analysed the impact of sports sponsorship in virtual brand communities providing five causal combinations influencing engagement within those communities. Pappas, Papavlasopoulou, Mikalef and Giannakos (2020) used QCA to identify the combinations of motivations and emotions leading to the creation of satisfied users on social networking sites. As can be inferred, these works had a different purpose from that of the present paper but support the use of QCA in the analysis of social media. Therefore, we suggest that our study can bring new insight into the analysis of how social media networks work.

To narrow down the focus, we concentrate on a specific social media network, Instagram, and measure users' engagement using three different metrics: likes, comments and views. We believe Instagram to be an intriguing platform to examine due to its capacity to enhance brand reputation and appeal to younger audiences (Belanche, Cenjor & Pérez-Rueda, 2019). In the recent years, Instagram has experienced a significant growth, with more than 1.21 billion monthly active users in 2021. Projections suggest that by 2025, the platform will have 1.44 billion monthly active users, representing 31.2% of the global internet user population (Dixon, 2023). Last but not least, Instagram is not only among the fastest-growing social media platforms, but it is also a preferred virtual space for individuals to spend their time (Sheldon & Bryant, 2016). For the empirical application, we analyse data from a Spanish clothing retailer, Oysho. First, we propose a model to measure customer engagement on a social media platform (i.e. Instagram), assess it empirically and discuss the elements driving to it. Second, using a configurational approach, we identify and characterise four strategies that lead to post engagement (when measured in terms of likes, comments and views).

The remainder of the article is structured as follows. Section 2 provides an overview of the existing literature about Instagram and the main elements associated with engagement. Next, in Section 3, we describe the methodological details, including data collection and processing. Section 4 presents the results, while Section 5 discusses the findings. Finally, Section 6 summarises the main conclusions and presents ideas for future research avenues alongside with the limitations that constrain this study.

2. Theoretical underpinnings and related works

2.1. Levels of engagement in Instagram

Instagram is a social network that relies on the creation and sharing of image-based content. Since its launch in October 2010, Instagram has grown to 1 billion users. This platform enables social connectivity between users on the basis of photo and video posting. At a superficial level of interaction, the social network provides the option of *following*. The number of followers an account has reflects the interest of social media users in the content published by that account. As a general rule, the higher the number of followers, the more successful an account is.

A medium level of interaction is that of *liking* and *commenting* on posts (that contain either images or videos), and this is the level that is the focus of this research. *Likes* act as a way of demonstrating shared interest in certain content or as a form of acknowledging the user who made the post (Jang, Han & Lee, 2015), whereas comments are a way through which users express their opinions, which can be positive or negative, regarding the publication and its poster. The larger the amount of likes and *comments* a post has, the more popular it is (De Vries, Gensler & Leeflang, 2012). However, according to a study conducted by Jang et al. (2015) in which the 2 billion *like* activities on Instagram of 20 million users were considered, the authors concluded that Instagram users not only check photos from people they follow, but they also navigate to random photos and simply add likes if they like those photos. Additionally, users tend to like posts rather than to comment on them due to the shorter amount of time they have to consume in doing so (Ferrara, Interdonato & Tagarelli, 2014). In the case of *videos*, Instagram shows how many times they have been played. A *view* is counted when a video is watched for three or more seconds. It should be noted that videos shared as part of a multiple post that includes both photos and videos do not show the number of views. We will discuss this metric further in the empirical analysis.

Finally, Instagram *Stories* allow a deeper level of interaction in which users can *reply* to the stories published by an account, resulting in a direct message being sent to that particular account. Direct messages are a useful tool to reinforce the relationship between brands and their customers, allowing direct interaction between both parties (Motta-Filho, 2021).

2.2. Factors explaining content engagement

Previous studies have mainly measured customer engagement with posts using two metrics, the total amount of likes and comments, and have explored different social media networks. For instance, Klassen et al. (2018) and Coelho, Oliveira and Almeida (2016) looked at Instagram and Facebook, Djafarova and Bowes (2021) as well as Balan (2017) only focused on Instagram, and De Vries et al. (2012) investigated customer engagement on Facebook. Surprisingly, videos seem to have been overlooked. One of the pioneer works analysing this type of post is that by Shen (2019) about the American football team the Baltimore Ravens, in which the author included views as a variable to measure engagement on Instagram.

Our study measures engagement using three different metrics: likes, comments and views. Note that the elements driving a high number of likes, comments or views might be different, and what is meaningful is not the individual effect of a single element but how the different elements are combined (i.e. the strategy adopted).

The existing literature has identified different elements being conducive to superior impact and engagement for Instagram posts. Particularly, much attention has been paid to the nature of the post. Bakhshi, Shamm and Gilbert (2014) claimed that photos were becoming a prominent means of online communication; however, the recent study by Socialinsider (2019) in which 7,433,417 posts were analysed, provides new facts: while more than 75% of brands believe images to be the best content type for Instagram, videos usually get more comments. According to the same study, carousel posts (those including more than one element and up to ten) receive a higher engagement rate per post (up to 5.13%), getting the best median number of likes per post. What these numbers tell us is that visual content has unique properties and the stylistic features in which this visual material is displayed may impact customer engagement behaviour after exposure (Rietveld, van Dolen, Mazloom & Worring, 2020).

Instagram hashtags are hyperlinks and can be used as a promotion tool as well, making content diffusion easier. According to Erz, Marder and Osadchaya (2018), hashtags are essential for brands to generate engagement. It is not only their semantic meaning that matters – for which reason they have to be meaningful and add value – but also the number of hashtags used in a post is a message itself.

Diving deeper in the content of the post, some studies confirm that the presence of people in pictures has a positive effect and increases engagement (Jaakonmäki, Müller & Brocke, 2017). More specifically, research conducted by Bakhshi et al. (2014) found that the presence of faces can result in an increase of 38% in likes and 32% in comments. Furthermore, influencers have been found to be strategic in product promotion (Tafesse & Wood, 2021; Uzunoglu & Kip, 2014), resulting in an increase in the rate of engagement when appearing in posts.

Due to the risks related to the development of the identity and self-esteem of younger followers, Mañas-Viniegra Veloso and Cuesta (2019) investigated how the attention to fashion promoted by curvy influencers is processed compared with the communications of fashion brands via their Instagram accounts in Spain and Portugal. The results showed that posts with a special emphasis on imperfections – for which curvy influencers raise awareness – were more likely to have a greater impact, reflecting affinity from the public. It therefore seems advisable to take into account diversity issues – in this case, different model sizes – in brand communication campaigns.

Jaakonmäki et al. (2017) also confirmed that pictures including scenery have quite a high impact on the number of likes and comments a post may receive, which suggests that the background might have a role in determining the potential impact of a post.

Other studies underline the importance of the typology of the publication. In the work of Coelho et al. (2015), the authors established a categorisation to distinguish among the following: to advertise a product/post, to promote an event, fan-related activities, general information and promotions. The authors concluded that those categories leading to greater follower involvement were posts related to events (defined as those publications directly connected to the brand) and promotions (those posts promoting the participation of users through a method of rewards). In a related work, De Vries et al. (2012) classified content into four types: interactive, informative, entertaining and contrasting. Their findings are aligned with those of Coelho et al. (2015), as interactive brand posts – such as contests or questions – were those contributing the most to the number of likes and comments. Contrarily, entertainment posts displayed a negative impact in the number of likes, supposedly because they do not provide content related to the company itself and are therefore not relevant to the users' interests.

To conclude, the analysis of the characteristics that make Instagram accounts more successful is of particular interest for companies to fine-tune and readjust their social media marketing strategies in the right direction.

3. Data and method

3.1. Data collection

For the purpose of this work we analysed the case of Oysho, a Spanish clothing retailer specialising in women's homewear and undergarments; the company is part of the Inditex group. In 2022, it had 623 M euros in sales and operated 457 stores at the end of January 2023 (INDITEX, 2023). Oysho's social media strategy is noteworthy, particularly on Instagram. Its posts feature images and videos that showcase the brand's products in a visually appealing and aspirational way, which has proven to be effective in establishing a successful loyal community of followers (over 3.4 millionin 2021) who actively engage with its posts (Orús, 2022). The aforementioned statistics reinforce the selection of Oysho as a case study, as it can offer valuable insights into the essential drivers of customer engagement and assist businesses in creating effective social media strategies.

Data were gathered manually from 1 February to 8 February 2020 directly from Oysho's main Instagram account (@oysho), a verified profile with 2 million followers as of February 2020. By that time the account had 3194 posts published. Given the number of posts per day (at least one, but typically no more than three) and to have a database with a significant number of cases, posts considered were those published from 31 October 2019 until 21 April 2020. The final sample consisted of 200 posts. The time frame considered is believed to be sufficient for the purpose of this research.

To collect relevant information from each post, an Excel spreadsheet was designed. The ultimate goal at this stage was to have as much information as possible from each post. Each of the variables was categorised and coded according to Figure 1. This figure emerges from a detailed analysis of the literature, as described in Section 2.2.

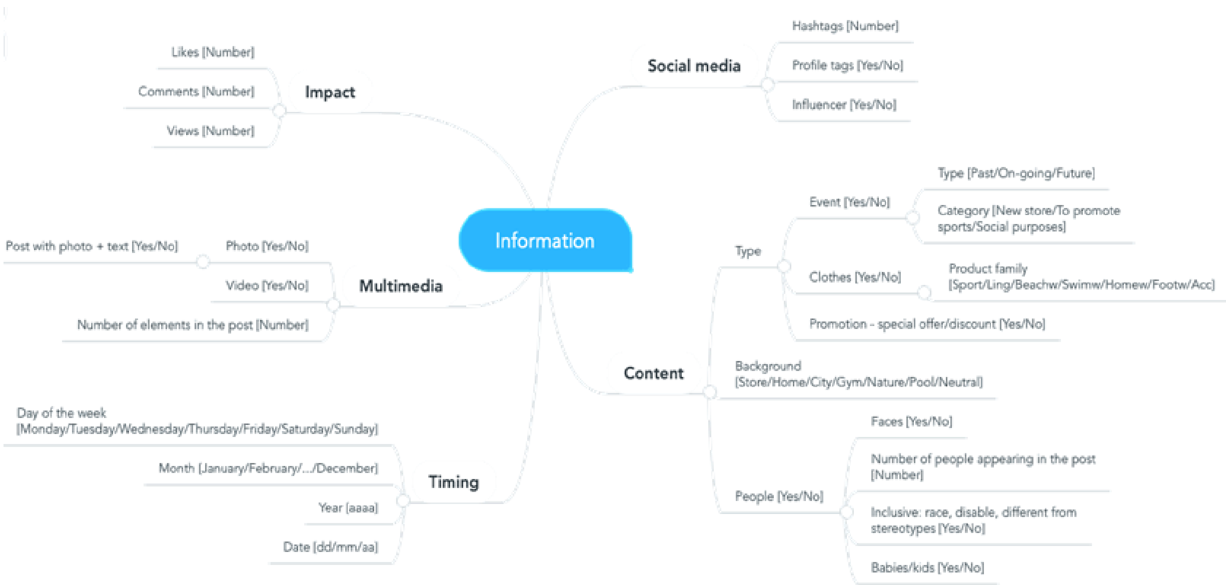

Figure 1. Data per post

3.2. Models

Based on a review of the existing literature on the determinants of likes, comments and views (as summarised in Section 2), for the purpose of this study the critical factors listed in Table 1 were chosen. Three different models were run, one for each type of outcome: *likes*, *comments* and *views*. As discussed above, not all models included the same variables given the different nature of the outcomes (see Section 3.3 for the model specifications). In addition, a fourth model was tested, resulting from the combination of two of the aforementioned outputs: likes and comments. Views were excluded from this model for two main reasons: (i) views have been shown to act differently, and (ii) the sample size would be substantially reduced as only a small proportion (37/200) of the posts in our sample included videos. The purpose of this model was to capture the greatest impact, regardless of its source or origin (either *likes* or *comments*), and this is why the maximum value of the two was taken to construct this new output called *LOC* (Likes OR Comments).

Factors		**Description**
Outputs	Likes	Number of likes that a post has received (for posts including either a photo or a video).
	Comments	Number of comments a post has received (for posts including either a photo or a video).
	Views	Number of views a post has received (only for posts with a video).
Antecedents	Elements	Being an element of a photo or a video, number of elements appearing in the post, with a minimum of one and a maximum of ten.
	Hashtags	Number of hashtags appearing in the post.
	Event	For those posts not directly advocating Oysho's products but an event (e.g. promoting a new store, sporting event or dedicated to social purposes).
	Background	Factor identifying the nature of the background, either neutral or not (e.g. posts set in a store, home, city, gym, nature or a pool).
	Faces	Presence of people's faces in a post.
	People	Number of people appearing in a post.
	Inclusive	For those posts with people, if it considers diversity (e.g., includes different body shapes, people from different races, people with disabilities, etc.).

Table 1. Critical factors

3.3. Method and data processing

To determine which combinations of elements (or factors) shape the impact of Instagram posts, this study used QCA, which is a methodology that provides powerful tools for the analysis of causal complexity. Causal factors are assumed to combine to lead to the occurrence of a certain event. Different paths (understood as different combinations) can lead to this occurrence, which is known as equifinality. Another key feature of QCA is that causal factors may have opposite effects depending on the way they combine with each other (Longest & Vaisey, 2008). QCA not only considers the combination of factors being present but also considers their absence (Wu, Yeh & Woodside., 2014). Causal asymmetry is thus assumed.

QCA performs well with any kind of sample, but it is particularly suitable for small-to-intermediate samples, as each case is information rich, and therefore, a limited number of observations is not a constraint (Wagemann & Schneider, 2010). On a related note, QCA bridges the gap between quantitative and qualitative analysis, being sometimes considered a hybrid technique. It therefore requires substantive knowledge from each case, as all factors should be interpreted in terms of sets (Ragin, 2008).

QCA uses Boolean algebra; hence, when quantifying the factors, they should be transformed to a 0–1 scale. The process is called calibration and can be done in two different ways: using crisp sets or fuzzy sets. The former – crisp sets – is similar to dealing with dummy variables. In this case, 1 represents full membership to the set (e.g. a post with a photo) and 0 denotes full non-membership, being completely out of the set (e.g. a post without a photo). Table 2 shows which of the factors of interest were operationalised using crisp sets.

	1 (full membership)	**0 (full non-membership)**
Elements	More than one multimedia element	One multimedia element
Event	Event-related post	Clothes-related post
Background	Specific background (all except those marked as neutral)	Neutral background
Faces	Faces appearing	No faces appearing
People	More than one person appearing	One person appearing

Table 2. Factors of interest calibrated using crisp sets

For the factors for which the level of belongingness to a category matters, the use of fuzzy sets is preferred. Three breakpoints should be defined: full membership (0.95), fullnon-membership (0.05), and a cross-over point (0.50), which is the point with the maximum ambiguity. A common strategy for defining these thresholds is to use percentiles. The 10th and 90th percentile are used to assign the values of full non-membership and full membership, respectively. The median (percentile 50th) denotes the cross-over point. Table 3 shows the specific values used to calibrate the outputs and the number of hashtags, which were transformed using fuzzy sets.

	Full membership	**Cross-over point**	**Full non-membership**
Hashtags	8.00	4.70	1.00
Likes	11408.80	3954.50	1482.30
Comments	50.00*	17.50**	5.00
Views	64255.20	25506.00	15414.00

*The full-membership of the 90th percentile was 54.1, but this was rounded to 50, considering the distribution of the observations.

** Instead of using the median (18), 17.5 was selected. The rationale behind this was to avoid losing the observation.

Table 3. Factors of interest calibrated using fuzzy sets and their corresponding breakpoints

The next step consists in the analysis of necessary conditions. A condition is deemed necessary if all (or nearly all) instances of the outcome show that condition. A condition is necessary if its consistency is high (>0.9) and its coverage is not too low (approximately>0.5). Consistency can be defined as way to quantify the degree to which cases sharing the same conditions present the same outcome, whereas coverage refers to the proportion of the outcome that overlaps with the condition.

Given that we have different models, the analysis of necessary conditions should be conducted as many times as there are outputs. Table 4 shows the results of this step for the four outcomes of interest (*likes*, *comments*, *views* and *LOC*).

Conditions tested *	Likes		Comments		Views		LOC	
	Cons.	Cov.	Cons.	Cov.	Cons.	Cov.	Cons.	Cov.
Elements	0.3583	0.4736	0.3560	0.4884	0.0000	nan **	0.3445	0.5536
~Elements	0.6417	0.4538	0.6440	0.4725	1.0000	0.4657	0.6555	0.5634
Hashtags	0.6367	0.5961	0.6199	0.6022	0.6785	0.4744	0.6091	0.6932
~Hashtags	0.6312	0.5725	0.6373	0.5998	0.5351	0.7460	0.6153	0.6783
Event	0.0611	0.2142	0.0561	0.2042	0.1021	0.2514	0.0658	0.2808
~Event	0.9389	0.4980	0.9439	0.5194	0.8979	0.5157	0.9342	0.6022
Background	0.6856	0.4142	0.7034	0.4409	0.6628	0.5438	0.7040	0.5170
~Background	0.3144	0.6102	0.2966	0.5972	0.3372	0.3631	0.2960	0.6983
Faces	0.7336	0.4262	0.7629	0.4599	0.9350	0.4882	0.7585	0.5357
~Faces	0.2664	0.5927	0.2371	0.5473	0.0650	0.2800	0.2415	0.6532
People	0.5257	0.4748	0.5286	0.4953	0.6634	0.5715	0.5285	0.5802
~People	0.4743	0.4461	0.4714	0.4006	0.3366	0.3412	0.4715	0.5390
Inclusive	0.5326	0.5280	0.5515	0.5674	0.6338	0.6067	0.5419	0.6532
~Inclusive	0.4674	0.4023	0.4485	0.4005	0.3662	0.3321	0.4581	0.4792

Cons. = Consistency / Cov. = Coverage

*The symbol ~ represents the negation of the characteristic (i.e., its absence).

** Stands for "Not of a Number" and means there is no proportion of the outcome that overlaps with the condition

Table 4. Analysis of necessary conditions for likes, comments, views and LOC

As can be inferred from the table, there is only one necessary condition, which is common for the models of *likes*, *comments* and *LOC*: the absence of an event-related post. However, this condition is not necessary to explain views. In the views model, the presence of faces appears to be a necessary condition. Moreover, it is important to highlight that it makes no sense to consider the factor elements in the views model, as Instagram only shows views when there is one *element* that coincides with being a video. Following this logic, the resulting four models are shown in Equations [1]–[4]:

$$Likes = f(Elements, Hashtags, Event, Background, People, Inclusive) \quad [1]$$

$$Comments = f(Elements, Hashtags, Event, Background, People, Inclusive) \quad [2]$$

$$Views = f(Hashtags, Event, Background, Faces, People, Inclusive) \quad [3]$$

$$LOC = f(Elements, Hashtags, Event, Background, People, Inclusive) \quad [4]$$

The following stage in QCA deals with the construction of the truth table, a matrix that sorts cases by the combinations of causal conditions that are sufficient to the outcome, considering all logically possible combinations.

The truth table has 2^k rows, with k being the number of causal conditions included in the model. To conduct this analysis, both the frequency cut-off and the consistency cut-off have to be determined. The former determines how many cases a row has to populate to be included in the analysis, and the latter is the threshold at which a combination of conditions is coded as contributing to the outcome – that is, setting the outcome to 1 for rows with consistency higher than or equal to the value of consistency cut-off. The default values 1 and 0.8, respectively, are the ones used in this study.

Next, simplification assumptions are made in the minimisation process, expressing how logical remainders should be treated – that is, how they do or do not contribute to the outcome (present, absent or present/absent). Simplifying assumptions are driven by theory regarding how a given condition might be causally related to the outcome. At this stage, some prime implicants could emerge and should be discussed. This occurs when the minimisation process cannot be further reduced. Again, the theoretical background and the researchers' knowledge of the field (and sample) are applied to break any ties and obtain a simplified expression.

4. Results

Tables 5 to 8 contain the results of the four models tested. The software fsQCA version 3.0 was used. The results reported here refer to the intermediate solution (i.e. include selected simplifying assumptions to reduce complexity), with an overall solution coverage ranging from 0.25 to 0.6. Although low in some cases, it can be considered acceptable. Its low value may be explained by the fact that some posts are used as advertisements. The overall solution consistency is high (at least 80% of cases leading to the outcome explained by the pathways shown in each model).

4.1. Likes

Seven different causal paths are envisioned for likes. Raw coverage moves from 0.02 to 0.07, meaning that there is no dominant path. Turning to the specificity of the results, from a vertical reading of Table 5 it can be concluded that the absence of an event leads to higher engagement in all of the seven solutions except in L7. The results also seem to support the argument that users are less engaged when posts are set against a neutral background (again L7 shows a different pattern), which implies that a specific background is counterproductive. The inclusivity factor is relevant to the outcome in all paths except in one. Nevertheless, the six causal configurations that consider the factor influential show different behaviours: while L2, L3, L4 and L7 defend its presence, L5 and L6 require its absence. Finally, for the remaining factors – elements, hashtags and people – there is no clear trend about the effect, with each being present in half of the pathways and absent in the other half. This diversity in the direction and the effect of the antecedent conditions on the outcome (i.e. asymmetry) supports the use of QCA.

Model: ***Likes***	**Causal configurations**						
Antecedent conditions	**L1**	**L2**	**L3**	**L4**	**L5**	**L6**	**L7**
Elements	o		o	o	•	•	•
Hashtags	o	o		o	•		•
Event	o	o	o	o	o	o	
Background	o	o	o	o	o	o	•
People	o	o	o			•	•
Inclusive		•	•	•	o	o	•
Raw coverage	0.0395	0.0226	0.039	0.0697	0.0523	0.0301	0.0641
Unique coverage	0.0247	0.0078	0.0242	0.0549	0.0295	0.0073	0.0641
Consistency	0.9677	0.9581	0.89	0.9073	0.8398	0.6875	0.8628
Overall solution coverage							0.2502
Overall solution consistency							0.8480

*The black circle (•) denotes de presence of a factor in a given configuration. Its absence is represented with a white circle (o). Empty cells represent ambiguous conditions.

Table 5. Results for the likes (L) model

Looking at the sufficient configurations, from a horizontal reading of Table 5, the two paths with the highest raw coverage values deserve further attention (L4 and L7). Two opposite strategies are suggested. While the former (L4) advocates for simpler posts with one multimedia element, few hashtags and a neutral background, the latter (L7) proposes posts with multiple elements, a high number of hashtags and a specific background. Additionally, L7 does not consider the factor event whereas L4 suggests its absence to be relevant. However, both find agreement in the relevance of inclusivity.

4.2. Comments

Six different causal paths are observed (Table 6). Raw coverage indices are quite low, ranging from 0.01 to 0.14, which may again indicate no predominance of any given path.

Model: ***Comments***	**Causal configurations**					
Antecedent conditions	**C1**	**C2**	**C3**	**C4**	**C5**	**C6**
Elements		•	o	o	•	o
Hashtags	o			o	•	o
Event	o	o	o	o	o	•
Background	o	o	o		•	o

Model: *Comments*	Causal configurations					
Antecedent conditions	**C1**	**C2**	**C3**	**C4**	**C5**	**C6**
People	o	o	o	•		•
Inclusive		o	•	•	•	o
Raw coverage	0.0879	0.0632	0.0347	0.1423	0.0797	0.0104
Unique coverage	0.0303	0.0199	0.0204	0.1423	0.0797	0.0104
Consistency	0.9024	0.7475	0.82	0.8164	0.8222	1.0000
Overall solution coverage						0.3605
Overall solution consistency						0.8159

*The black circle (•) denotes de presence of a factor in a given configuration. Its absence is represented with a white circle (o). Empty cells represent ambiguous conditions.

Table 6. Results for the comments (C) model

As advanced in the analysis of necessary conditions, the absence of the factor event is determinant in all the configurations except one (C6). The role played by the background is worth examination. In four cases, neutral backgrounds are preferred (C1, C2, C3 and C6), while C5 is the only configuration that requires its presence. Elements, people and inclusive are relevant in five out of six solutions presented, excluding C1, C5 and C1, respectively. Posts with one multimedia element showing one person and being inclusive are recommended in one path (C3). Finally, the factor hashtag is the one that seems to be less relevant, as it is only considered in four configurations, suggesting a low number of them in three cases and a high number in only one case.

At the configuration level, the ones presenting higher raw coverage values deserve more attention (C1 and C4). These two configurations seem to be significantly different, as they only converge in the factors hashtags (proposing a lower number of them) and event (suggesting the presence of posts related to the products offered by the company). Regarding people, while both paths consider it a relevant factor, they present opposed views; C1 supports the presence of only one person, whereas C4 is in favour of more than one person appearing in the post. Posts with one multimedia element and those that are inclusive contribute to the impact of C4, while they are irrelevant for C1. Conversely, a neutral background complements C1 even though this factor does not affect the outcome in C4.

4.3. Views

Four causal paths emerge (Table 7). At the factor level, the presence of people showing their faces is required to achieve a higher impact (which is consistent with the finding in the analysis of necessary conditions), with the exception of V1. Moreover, the factors hashtags, event and people are considered influential in all of the configurations presented. Posts with few hashtags, related to clothing and in which more than one person appears are suggested in three out of the four paths, while the contrary is recommended in the remaining one. Finally, background and inclusive factors are required in all solutions proposed except in V2 and V4, respectively, but with different effects on the outcome.

Model: *Views*	Causal configurations			
Antecedent conditions	**V1**	**V2**	**V3**	**V4**
Hashtags	o	o	•	o
Event	•	o	o	o
Background	•		o	•
Faces		•	•	•
People	•	•	o	•
Inclusive	o	•	•	
Raw coverage	0.0551	0.2879	0.1416	0.2995
Unique coverage	0.0552	0.0656	0.1416	0.0772
Consistency	0.9694	0.9745	0.9139	0.9754
Overall solution coverage				0.5618
Overall solution consistency				0.9613

*The black circle (•) denotes de presence of a factor in a given configuration. Its absence is represented with a white circle (o). Empty cells represent ambiguous conditions.

Table 7. Results for the views (V) model

Raw coverages range from 0.06 to 0.30, with V2 and V4 being the ones that represent a higher number of cases in our sample. These two configurations converge in describing posts leading to higher engagement – measured in views – with few hashtags, dedicated to products the company is selling, not to events, and in which there are people appearing and showing their faces. However, the background is not relevant to the outcome in V2, which is contrary to V4, in which a specific background is found to increase the number of views. Unlike V2, V4 does consider inclusivity as relevant.

4.4. LOC (Likes OR Comments)

Seven different causal paths emerge at this point. In this case, the results displayed in Table 8 suggest that none of the factors considered is required in all of the solutions proposed. First, event and inclusive are present in six out of seven configurations, excluding LOC6 and LOC1, respectively. The majority of configurations (LOC1, LOC2, LOC3, LOC4 and LOC5) propose the absence of an event-related post, as found in the analysis of necessary conditions. Regarding inclusivity, four configurations (LOC3, LOC4, LOC5 and LOC6) suggest its appearance, while two of them are built upon its absence (LOC2 and LOC7). Elements, background and people are included in five configurations and are irrelevant in two of them (LOC1 and LOC5, LOC3 and LOC4, LOC2 and LOC4, respectively). Three configurations recommend posts with only one multimedia element, one person appearing and a neutral background, suggesting the opposite for the two remaining configurations. Finally, hashtags only influence four paths, a low number in three (LOC1, LOC4 and LOC7) and a high number in only one (LOC6).

Diving deeper into the resulting configurations, three of them deserve further attention, as they have the highest raw coverage values (LOC3, LOC4 and LOC5). They converge in suggesting the presence of clothes-related post and posts that consider inclusivity. LOC3 and LOC4 are equal in proposing posts with only one multimedia element – unlike LOC5, which finds elements insignificant – and does not care about their background, again contrary to LOC5, which calls for a specific background. LOC3 and LOC5 recommend posts in which only one person appears but do not find the hashtag factor relevant. This is opposite to LOC4, which implies the factor people is not influential and suggests the presence of few hashtags.

Model: *LOC*	**Causal configurations**						
Antecedent conditions	**LOC1**	**LOC2**	**LOC3**	**LOC4**	**LOC5**	**LOC6**	**LOC7**
Elements		•	o	o		•	o
Hashtags	o			o		•	o
Event	o	o	o	o	o		•
Background	o	o			•	•	o
People	o		o		o	•	•
Inclusive		o	•	•	•	•	o
Raw coverage	0.0781	0.0805	0.1958	0.2418	0.205	0.0543	0.0088
Unique coverage	0.0275	0.0421	0.0203	0.1344	0.0417	0.0543	0.0088
Consistency	0.9393	0.7442	0.7237	0.8828	0.7103	0.8879	1.000
Overall solution coverage							0.5430
Overall solution consistency							0.7982

*The black circle (•) denotes de presence of a factor in a given configuration. Its absence is represented with a white circle (o). Empty cells represent ambiguous conditions.

Table 8. Results for the likes OR comments (LOC) models

5. Implications of the results: Winning strategies behind posts

This section discusses the results of the models tested, for each of which a subsection is created. Note that here we do not elaborate on the findings for the LOC model. Although the results obtained are informative, the resulting patterns observed do not seem to lead to a clear strategy, but instead, take insights from those identified in the *like* and *comment* models.

5.1. Likes

Diving deeper into the cases explained by the different causal configurations, two main strategies seem to be envisioned, which we call the *simplistic* and *enriched* strategies. In the *simplistic* strategy, posts tend to be simple, asking for the presence of only one element, have few hashtags and a neutral background. Such posts send a clear and specific message of what the brand wants to communicate and, consequently, they easily attract the attention of the user without the distraction of too much information. In such cases, the presence of only one element and a neutral background is helpful in not dispersing users' attention but rather absorbing all of their interest, which in turn translates into their impulse for reacting to the post (with a like). Figure 2 contains two examples of posts that follow this strategy.

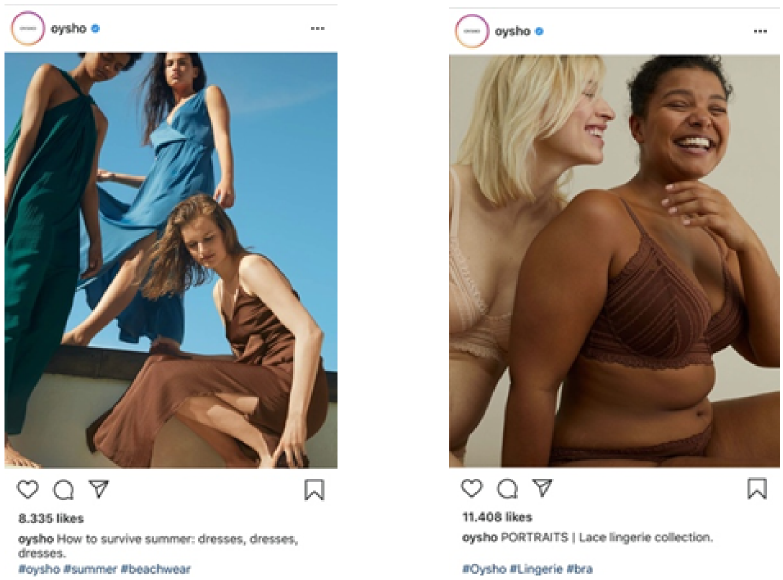

Figure 2. Examples of the simplistic strategy (Source: Instagram, @oysho)

The second strategy (*enriched*) adopts the opposite approach and consists in intensified and more elaborate publications, which include a higher number of elements and hashtags, and showing an explicit setting (e.g. a store, home, city, gym, pool or nature). In this case the motto is to enrich the content as much as possible. The rationale behind this strategy is to catch the attention of users by providing them with lots of details that evoke a specific activity, experience or context in which anyone would like to find themselves involved. Figure 3 shows two examples illustrating this strategy.

Figure 3. Examples of the enriched strategy (Source: Instagram, @oysho)

5.2. Comments

If the aim is to achieve a high number of comments, the different configurations for the comments model suggest two potential strategies that differ in their focus, namely *product oriented* and *experience oriented*. The former, as its name indicates, cares about creating content that enhances and focuses its attention on the product being shown. It thus requires the presence of only one person and a neutral background, putting all of the emphasis of the post on the product itself. Inclusivity is neither important nor relevant for posts following this strategy, as the only message to be transmitted to the user is that of the product. It is, however, important to point out that despite the product being important, all of the cases aligned with this strategy are posts in which the people appearing in them show their faces. Figure 4 presents a selection of two posts that follow this strategy.

Figure 4. Examples of the product-oriented strategy (Source: Instagram, @oysho)

The second strategy, *experience-oriented* posts, embraces those posts that emphasise moments and/or lifestyle. The message is not only to show the products offered but to describe visually what sort of experiences are associated with them, and therefore, show situations the user may experience when consuming the products. For these posts, the presence of more than one person matters, because these moments/experiences are expected to be shared with others, rather than being experienced alone. Inclusivity is also a factor that triggers the number of comments a post will have. Sending a message of opening up to diversity without excluding or marginalising anyone is crucial when selling the associated experiences in the globalised world in which we live. The fact that experience-oriented posts also require the presence of only one multimedia element per post, together with the need to share few hashtags, signals that it is necessary for consumers not to be overexposed to distractions. Finally, it is important to note that, similar to the previous strategy, showing the faces of the people appearing in them is relevant (see Figure 5 for some examples), in line with experience-oriented posts.

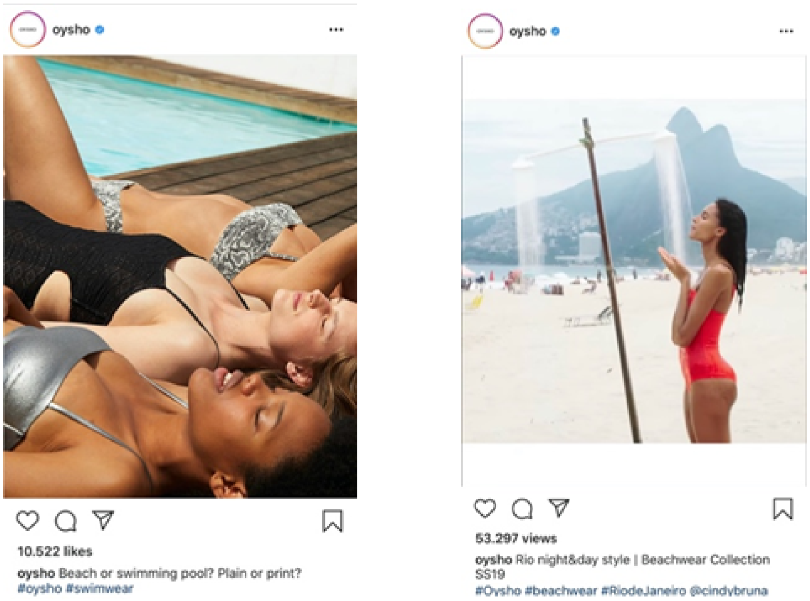

Figure 5. Examples of the experience-oriented strategy (Source: Instagram, @oysho)

5.3. Views

Videos tend to have more views than likes, but the higher the number of views, the higher the probability of receiving likes. Figure 6 graphically illustrates this relationship for those posts in the sample that contained videos (37 observations). For each post, we computed the ratio of likes over views (i.e. the number of likes a post received compared to the number of views). This indicator gives a rough estimate of the proportion of users that watched the video and liked it. The values (expressed in percentages) range from 3.72% (minimum) to 8.20% (maximum), with 6.06% being the median (represented in purple).

Figure 6. Likes over views

If we zoom in and only focus on those cases that are well explained by the configurations listed in Table 7 (13 cases, around 35% of the sample), we can plot a scatterplot confronting the number of likes and views received by each post (see Figure 7). The observations seem to follow a linear regression, with a positive slope coefficient (β=16.743). The Pearson correlation between these two variables (number of likes and views) is also positive (0.8511) and significant (p-value<0.000), signalling that both the simplistic and enriched approach might be valid and conducive to user engagement.

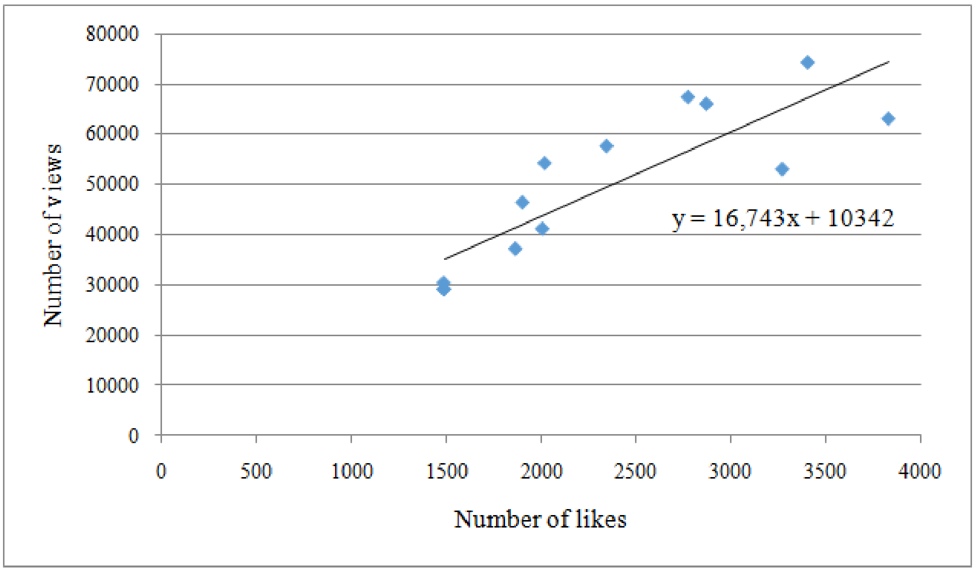

Figure 7. Likes over views for the posts explained by the configurations in Table 7

Finally, it should also be noted that a detailed analysis of these cases suggests that a common approach followed is also in line with that of the experience-oriented strategy. This is not surprising, as videos tell stories which recall experiences, which in turn, attract users' reactions. There is, however, some discrepancy in the number of people that should appear in such videos. The rationale behind this diversity is that the causal configurations in Table 7 evoke two scenarios: experiences to be enjoyed alone (in which only one person appears) and those to be shared with others (including more than one person in the video); therefore, depending on the type of experience to be recalled, single or various individuals should appear in it.

5.4. Characterising the key features and strategies

In this study we found empirical evidence that the posts generating more engagement in terms of the three metrics analysed are product focused and not event related. That is, Instagram is not the place to promote events related to the brand, as users are looking for content related to the core of the brand: the product(s). The social network should therefore be used as a showcase for the clothing the brand is selling, like physical shop windows but in a virtual space. This finding supports the early work of De Vries et al. (2012), who found that posts categorised as entertaining have a negative impact on the number of likes, which can be explained by the non-existent relation of the posts with the brand itself.

This study also revealed that hashtags are a useful tool to generate engagement, although an excessive use of them may cause the opposite effect and discourage the user from reacting. A hashtag is a message per se; accordingly, hashtags need to be selected carefully. According to Erz et al. (2018), choosing a few, relevant (representative of and specific to the brand) hashtags is recommended.

A key and novel finding is that inclusive content seems to play an important role in generating engagement, as it makes all potential customers feel accepted as part of the brand community. Hence, it is highly advisable to include posts that send a message of acceptance, showing that people – whatever their race, gender or disability – can equally enjoy the brand's products. This finding is consistent with the recommendation of Mañas-Viniegra et al. (2019) to include a diversity of model sizes in brand communication campaigns. Moreover, the presence of faces also increases post impact. The logic behind this finding is that faces transmit a message of safety, confidence and proximity to the user, as has been found in the works of Jaakonmäki et al. (2017) and Bakhshi et al. (2014).

In terms of the recommended strategies brands should follow, Table 9 summarises the main features of the ones we were able to characterise (see sections 5.1 to 5.3). After analysing the overall effect of posts on the three outcomes of interest, one of the key conclusions reached is that simpler posts are preferred. Such posts are more direct and better engage with the user, providing fewer stimuli so as not to distract the user from the core message. Another remarkable finding is that the orientation of the posts may vary. We observed that some publications focused on the product and others, although they also show the product, centred on the experiences and the moments associated with it. No clear predominance for either of these two strategies was identified; consequently, they may be equally valid to create impact. Lastly, videos with posts that generate greater impact tend to be experience oriented, as the nature of video makes it easier for them to represent such moments and how one could feel while consuming the product advertised.

Complexity	Focus
Simplistic Sends a specific and concise message	**Product-oriented** Embraces the characteristics of a certain product
Enriched Provides lots of content to engage with	**Experience-oriented** Puts emphasis on the experiences associated with a certain product

Table 9. Post strategies and characteristics

6. Concluding remarks

This paper contributes to the existing marketing literature on how brands can generate improved impact for their posts on social media networks. The Instagram posts from Oysho's profile (@oysho) were used as a case of study, and three metrics were considered to measure impact: number of likes, number of comments and number of views. With the use of QCA, we were able to identify different strategies, as impact can be achieved following diverse pathways. The overarching conclusion is that posts pursuing superior engagement should be simple, product related or experience related, using few but meaningful hashtags that are representative of the brand, showing people's faces and sending an inclusive message.

Although following a rigorous methodology, this study is not free of limitations, which in turn, open up opportunities for future studies. First, posts can be sponsored in an attempt to reach a larger and more targeted audience, a fact that increases the number of likes, comments and views. However, which posts from our dataset were sponsored was not publicly available, so the advertising effect of sponsored posts is beyond the scope of this research. Second, future research should explore Instagram stories, an in-app feature launched in April 2016 that allows users to post photos or videos that automatically disappear within 24 hours. We acknowledge the difficulty in collecting such data given its volatility, yet, we encourage future studies to investigate the engagement effect they have in users and which content is the most suitable one for this type of post. Third, the time frame is a limiting aspect of this study. We acknowledge that the sample size is limited, but it still comprises a significant number of posts. Expanding the sample would have implied collecting posts with different chances of generating impact (due to their exposure time and thus introducing potential biases as a result of different seasonal special offerings). Fourth, as in any empirical analysis, the restricted number of factors that can be considered in the model might not have allowed controlling for other factors which may provide additional insights. We encourage future studies to look at other elements that have been overlooked. Fifth, unfortunately, it was not possible to confront the findings of the empirical analysis with the current communication strategy being used by the company, Oysho, to assess their validity. Further research might consider combining different research methods, mixing qualitative with quantitative data. Another interesting line of research consists in comparing our results with those in other fast fashion retail brands to come up with a more generalised pattern for the behaviour of the different factors triggering likes, comments and views. Finally, future studies might consider combining different data mining and sentiment techniques that simultaneously allow characterising posts based on their appearance (as it is done in this work) and the linguistic styles used—see for instance the recent study by Deng, Hine, Ji and Wang (2021).

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