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How to Engage Consumers through Effective Social Media Use—Guidelines for Consumer Goods Companies from an Emerging Market

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Abstract: This study aims to establish actionable guidelines and provide strategic insights as a means of increasing the social media effectiveness of consumer brands. Post-related factors in addition to the contextual and temporal factors influencing consumer engagement (i.e., reposting, commenting on or liking posts), as an indicator of social media effectiveness, are considered in detail in the research model. Moreover, the model considers differences between industries as well as social media platforms. A total of 1130 posts made by four brands, two each from the durable goods and fast-moving consumer goods sectors, were collected from Facebook and Twitter in Turkey. Through predictive analysis, four different machine learning algorithms were utilized to develop easy-to-apply plans of action and strategies. The findings highlight the significant impact of videos, images, post frequency and interactivity on engagement. Furthermore, social media platforms and the brands themselves were found to be instrumental in influencing engagement levels, indicating that more than one formula is needed for effective social media management. The range and depth of the post-related factors (e.g., image type, video length, kind of interactivity) considered go far beyond those found in the significant majority of similar studies. Moreover, the unique setting and the novel data analysis algorithms applied set this study apart from similar ones.

Keywords: social media; customer engagement; brand fan pages; post popularity; machine learning; Facebook; Twitter

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1. Introduction

In the last decade, consumers have been increasingly communicating with both marketers and other consumers through dynamic networks known as social media. Currently, the number of social media users worldwide exceeds four billion, a figure that includes an almost 9% increase in 2019 alone [1]. In parallel with that considerable increase in users, year-by-year marketers have adopted social media marketing for a variety of objectives including advertising, research, customer relationship management, after-sales services and sales promotions. As the February 2018 Forbes Chief Marketing Officer (CMO) Survey points out, companies spend almost 12% of their marketing budgets on social media [2]. The majority of managers are in agreement that social media is primarily used for "brand building and brand awareness" activities. Evidence from academic studies also supports the proposition that the effective use of social media helps in improving brand awareness and brand image [3] and even contributes to the financial performance of brands [4,5]. Thus, companies have become invested in brand fan pages (BFPs) with the aim of building relationships as well as encouraging users to share information about their experiences with brands, thereby creating brand attachment [3,6,7].

However, the crowding of popular social media platforms has resulted in a rapid expansion of content available to members. Consequently, information overload has made it increasingly difficult to attract users' attention and motivate them to interact with brand content [8]. Given these circumstances, marketers need clear strategic and applicable insights so they can design and direct effective messages to consumers through social media platforms. Not surprisingly, studies on the factors influencing interaction or engagement as indicators of marketing communication effectiveness on BFPs have gained more attention in recent years [9–13]. The extant literature on advertising effectiveness and word-of-mouth communication indicates that certain message attributes such as message content, creative message format, level of interactivity offered and temporal factors such as the timing and frequency of posts should be considered in the planning and designing of posts. Followers' responses—including reposting, commenting on and liking posts—and the total interaction created by those responses per follower (also referred to as engagement) represent the overall effectiveness of social media posts. Studies have indicated that several post characteristics such as interactivity (e.g., links, hashtags) and creative post formats (e.g., text, images, videos), in addition to message content, influence customer interaction and engagement [10–12,14]. However, in the majority of these studies, the relevant variables are considered as aggregates and in-depth analyses of the subcategories are lacking. For instance, the vividness of post content is simply treated within the scope of images, text or videos, while detailed categorizations such as short video vs. long video or types of images posted are not taken into consideration. Undoubtedly, examining the detailed subcategories of those factors as well as their impacts on consumer engagement would enable companies to extrapolate strategic and tactical insights for effective social media management. The research model utilized in the present study incorporates common factors that have been deemed significant in the literature and extends them by adopting a more comprehensive perspective that considers each factor within the framework of multiple subcategories.

In general, major studies in the literature dealing with such topics have worked with relatively small sample sizes. For instance, Sabate et al. [15] examined 164 posts, Pletikosa Cvijikj and Michahelles [16] took into account 100 posts and de Vries et al. [10] looked at 355 posts. Extending the datasets may improve the validity of the findings and enable more detailed analyses of each factor, which may lead to deeper insights and as such those points are among the primary aims of this study. Moreover, influential studies are commonly carried out in the US and a European perspective as well as evidence from emerging markets are lacking in the literature.

Another issue that is commonly overlooked despite the evidence from the literature is the effect of the context, industry or brand, as well as the social media platform itself, on communication effectiveness [17–19]. The majority of previous studies took into account only one industry and focused on a single platform for example, [15,20] and brands themselves were often not considered as influential factors in studies that incorporated multiple brands for example, [10].

In terms of the analysis methods applied, studies in the literature have utilized regression, ANOVA and univariate analysis to highlight the significance of various factors affecting follower engagement. Despite their valuable contributions to the field, however, these studies have to a large extent failed to provide applicable managerial insights. Even when highlighting the significant predominance of a given variable over the others, it is not always possible to shape social media strategies and tactics through the utilization of factors with the largest regression coefficients in attempting to develop winning social media posts. For instance, posts on weekdays may perform better than those on weekends and posts with images might work better than those with videos, which could lead to the recommendation that images should be posted on weekdays but not on weekends and videos should never be used. To overcome these problems, relevant machine learning algorithms such as decision trees were chosen, to come up with easily applicable tactics and insights. One of the few studies that applied machine learning algorithms in studying online brand fan pages and information on user behavior is Chiu's [21]. Although the objective of that study is to propose a recommendation system, thus differs from the present study, the use of the decision trees provides practical and valuable classifications to those seeking to develop recommendation systems on social media.

This study thus aims to not only address the aforementioned research gaps but also investigate in detail post-related factors including the different dimensions of post creative format and post content, as well as contextual and temporal issues affecting brand social media post effectiveness, while also taking into account possible differences between industries, brands and social media platforms. In line with those goals, the basic objectives of the study are to:

1. Analyze the impacts of the creative format of posts in terms of the multiple subcategories of interactivity and vividness on engagement;
2. Examine the various types of post content with regard to whether they are informative, entertaining, promotional or advertising-oriented and analyze the impacts of each type on engagement;
3. Investigate the effects of temporal factors such as the days when posts are made and the number of days between posts, in addition to contextual factors such as industry and platform, on engagement;
4. Determine the most effective factors for increasing engagement by coming up with a strategic and actionable guide (using decision trees and sensitivity analysis) for social media managers.

This study is structured as follows. First, an in-depth review of the relevant literature is carried out and related factors that are considered to be influential on engagement are discussed. Second, the research methodology is discussed, the data collection process was explained and a detailed account of the analysis algorithms that were applied are provided. Third, the study's results are presented and the main findings and managerial implications of the study are discussed along with the limitations of the paper and future research directions. Finally, in a separate section, the paper is concluded.

2. Background and Related Work

2.1. Brand Communication on BFPs and Consumer Engagement

The emergence of several large online social media platforms developed with Web 2.0 technologies has led to a rapid increase in information flow between brands and consumers, as well as among consumers themselves. In parallel with these developments, companies have been making considerable investments to create brand communities (e.g., BFPs) with the aim of interacting with customers. This interaction is frequently realized through brand posts on BFPs and followers (including fans and loyal or potential consumers) engage with the posts by liking or commenting on them. In recent years, brands have striven to yet further build relationships and engage with their customers through social networking sites such as Facebook and Twitter to enhance consumer engagement [14,22].

During a mere decade, social networking sites have become extremely popular. Facebook, for example, claims that it has 2.7 billion active members as of 2020 [1]. Social media users not only become friends with other members but also become followers of brands on dedicated BFPs. As with the case of online brand fan groups, brand fans can share their enthusiasm about brands and engage with them on social media by commenting, liking posts on BFPs or resharing themselves [7,13,23]. In general, BFPs are indicative of customers' relationships with brands and they provide members with sources of information and social benefits [13,24,25]. By becoming a member of virtual communities such as social media BFPs, consumers may obtain access to a wide variety of relationship benefits, including those that are practical, social, economic or entertainment-based [25].

Depending on the types of interactivity offered by a given platform, the followers of brand fan pages may engage with brand posts by liking, commenting on, and/or sharing/reposting them [7]. In the literature, the interactions between brands and users are formulated as consumer engagement, which has been defined as "behavioral manifestations that have a brand or firm focus, beyond purchase, resulting from motivational drivers" [16,26]. The concepts of engagement and interaction are interrelated and engagement can be triggered by interacting with post content on social media [27]. Thus, online engagement is reflected in social media through the liking of posts, expressing viewpoints by commenting or reaching out to others, that is, friends, via reposts/shares [28]. Thus, a lack of or low level of user interaction indicates low engagement, which in turn is indicative of weak performance in social media marketing. Each type of interaction promotes the post content to a brand follower's friends on social media [15]. In that way, popular post content is embraced by consumers who share it and such content increases the reach of the message (original content) through peer-to-peer interaction [11,29].

In addition, Kim and Ko [30] found that 70% of the active users of social networks visit social media sites as a means of obtaining information prior to buying a particular product. As such, social media platforms provide marketers with viable platforms for communicating about and promoting their products and brands through organic posts and forms of viral marketing that can potentially be viewed by millions of connected social media users [31].

The importance of effective social media use has been demonstrated in recent research on social media marketing. The evidence suggested that engagement with social media BFPs leads to brand awareness, word of mouth [32] and positive tangible outcomes such as purchase expenditure [33] and purchase intention [32]. Furthermore, Brettel et al. [34] demonstrated that Facebook page visits are a short-term indicator of sales and that Facebook likes are a strong long-term sales driver because of their high carryover effect.

2.2. Factors Affecting Communication Effectiveness on BFPs

Relevant studies on social media and similar digital marketing communications have offered insights into social media effectiveness by highlighting the significant antecedents of consumer engagement and interaction with various brand communications. For instance, in several studies, the vividness of advertisements has been found to affect user interactions with posts on web advertising [35] and that finding is also applicable to social media posts [12,15,36]. Another variable category, content type (as well as the value offered through it), has been identified as a significant driver of engagement and social media effectiveness in a number of studies [10–12,16]. Moreover, those studies have considered the interactivity offered by posts, the timing of posts (e.g., weekdays/weekends) and post frequency as other significant antecedents of consumer engagement. The research model presented in Figure 1 was developed after assessing numerous influential studies about online advertising, social media marketing and BFPs [10–14,16,37–39]. All those relevant factors are discussed in the following subsections.

2.2.1. The Creative Format of Posts (Vividness & Interactivity)

Getting the attention of consumers is one of the major goals of marketing communications and the creative format of marketing messages can be taken up as a significant factor in that regard. According to the Elaboration Likelihood Model, which is widely used in the literature on advertising and electronic word-of-mouth (e-WOM), in low involvement situations, consumers tend to employ a peripheral route for processing information and they engage in more subconscious processing of stimuli [40]. In situations where focusing on a specific message element is not a viable option, affective components and peripheral cues (e.g., animation, music, and/or color) become more instrumental in attitude changes and behavior patterns [41]. Considering that past research on banner ads indicates that the majority of consumers exhibit low levels of involvement when browsing the Internet [42], creative formatting's role in online brand communication becomes evident. As with other types of digital marketing communication, BFP posts can be created in several formats: text only, images/photos (static visuals) or animated photos/videos (dynamic visuals). In the literature, the "vividness" factor has been put forward as a way to evaluate the stimulation level of a message for viewers [43] and help us understand the effects of creative format. When a message caters to more than one sense, it becomes more vivid, so one would expect that using sounds or visuals in a message would be a good means of getting more attention [44]. Studies on the issue have found that animations and videos are more vivid than pictures and text-only posts and the use of photos and videos garners more attention than text-only posts [41,42,45]. Similarly, the literature on web advertising also indicates that banner ads with highly vivid content (e.g., animations) are more effective in attaining higher click-through rates and greater advertising involvement [41,45,46]. Several studies on social media have also observed a similar positive relationship between vivid content and interactions [10,11,15,16,47]. For instance, a study in Singapore on multiple consumer industries [38], others in the fashion industry [13], the travel industry in Spain [15] and the hospitality industry in Turkey [48], found that vivid brand posts (e.g., images and videos) lead to more interactions per follower than their less vivid counterparts (text-only posts). The question of whether images or videos are more influential in attaining higher levels of interaction is open to debate, as several studies have produced contradictory findings. According to Brookes [49], images prompt more engagement than video and text posts and videos outperform text-only posts. It has been argued that there is an optimum level of vividness on social media in terms of generating a positive influence on engagement, after which the positive effect diminishes [14]. Moreover, studies on banner advertisements in which no significant effects for animated content were observed [50,51] or heterogeneity was detected, for example, [39] would suggest that there is a need for further research to investigate one of the most critical dimensions of the creative format of posts—the vividness factor—in more detail. Thus, investigating the use of short and long videos and differing types of images may help us gain deeper insights into this matter.

In contrast to the use of static or dynamic elements, inherently interactive content (e.g., questions and sweepstakes) that is posted on BFPs may also provide an avenue for improving follower engagement. That proposition has been confirmed by several studies on social media consumer behavior in which interactivity was found to affect customer interaction, engagement and involvement [10,11,13,21,36,38,48,52]. Within that context, interactivity can be defined as "the degree to which two or more communication parties can act on each other, on the communication medium and on the messages and the degree to which such influences are synchronized" [53]. Interactive posts can take several forms, such as questionnaires, short polls, contests, links to websites, gamification elements or hashtags and the level of interactivity offered may vary. They can be presented in a textual format or supported with rich visuals, depending on the type of interaction offered. However, while the majority of studies have supported the use of interactive elements, others have highlighted the adverse effects of interactive elements such as links or pointed to a lack of significant impact on interactions, for example, Reference [15].

2.2.2. Post Content (Informative, Entertaining, Promotional)

Brand post content offers value in distinct ways with regard to attracting followers' attention and subsequently triggering interaction and engagement [54,55]. In light of the fact that consumers are motivated by distinct factors in using online services such as social media, post content may be selected with the aim of offering various kinds of content to provide value. Similar to internet use motivations, accessing information on social media is driven by a utilitarian motive [56,57]. A study in Europe by Hudson et al. [58] indicated that the content shared by marketers on BFPs can influence the customer sentiment, which has an impact on customer lifetime value. Informational marketer-generated content was observed to enhance customer sentiment which is an indicator for customer lifetime value. Consumers follow official BFPs and virtual communities so they can receive exclusive and timely information about brands, new products and announcements [59]. Thus, providing value to followers with informative content has been found to be an effective means of increasing user interactions and engagement [11,16,48,60].

Aside from informative content, another way to offer value and entice consumers is by providing entertaining content in posts [56]. The effect of entertainment on generating interest and improving attitudes has been observed in a variety of settings including websites and general internet use [61,62]. Predictably, entertaining posts have been found to lead to improved impressions, interactions and attitudes towards brands on social media [13,16,59,63] and the likeability of the content was found to influence social media engagement [64]. Similar to the issue of vividness, contradictory findings regarding the effect of entertaining posts on engagement have been reached [10,12,48]. Further studies that consider entertainment as a predecessor of interaction and engagement on social media will be useful for clarifying these conflicting findings.

Lastly, promotional remuneration posts that offer tangible benefits, information about special discounts and exclusive campaigns represent yet another promising type of post content that is of value to fan-page followers [65]. Brand posts that offer tangible rewards in this manner were predominantly found to have a positive influence on consumer interactions in mobile advertising [66] and social media brand posts [11]. However, promotional incentives were also shown to have a negative effect on internet banner ad effectiveness [50] and social media post engagement [16,55,67], indicating that the research context (e.g., the industry) and culture may be influential in that regard and as such further studies are needed before generalizable conclusions can be reached.

2.2.3. Temporal Factors

Studies on advertising and evidence from the industry have indicated the frequency and duration of exposure to marketing communications are critical to the success of marketing campaigns [68]. Similarly, several researchers have identified posting frequency and the timing of posts (e.g., hour, day, month) as significant criteria for the success of BFPs [10,16,37,69–71]. Posting too frequently may result in a situation in which there is not enough time for adequate engagement, as the post will only remain for a short time in the most visible space, the top of a BFP. Frequent posts can also create irritation among followers [72] and lead to fewer interactions per post [10]. Conversely, posting too infrequently may decrease interest in a BFP and result in fewer visitors. Consequently, post frequency should be optimized and in this study, it is taken up within the time frame of "days after the last post." In addition, the month in which a post is made, which may also influence engagement depending on the seasonality of demand, should be taken into consideration in the design of relevant studies, as highlighted by Dolan et al. [60]. However, it should be noted that the existing studies have not arrived at a definitive conclusion regarding the effect of temporal factors on engagement yet. For instance, posting time was found to be an insignificant factor for Facebook follower engagement in studies by Antoniadis et al. [14], Villamediana et al. [70] and Schultz [12].

2.2.4. Contextual Factors

Studies that aim to arrive at generalizable insights have been carried out [10,11], yet the industry in which a brand operates is rarely taken into consideration for its impact on engagement and social media effectiveness [10,12]. Nonetheless, the companies that promote posts and the industries in which brands do business have been found to be influential in social media activities and in increasing engagement [19,73]. Furthermore, Corstjens and Umblijs [74] have demonstrated that the competitiveness of the industry in which a given company operates has a moderating effect on the effectiveness of its social media marketing efforts. Consequently, that factor was incorporated into the research model.

Another significant factor that influences social media effectiveness concerns media characteristics, which denote the social media platform itself. Voorveld et al. [18] have shown that engagement is context-specific and each social media platform generates a different set of experiences that affect the evaluations of followers concerning brand posts. In a similar vein, Li et al. [75] have illustrated that the subjective characteristics of social network sites affect consumers' word-of-mouth sharing. Moreover, the effects of media on advertising effectiveness have been demonstrated in the advertising literature as well [17]. On the other hand, oft-cited studies in the literature mostly focus on a single platform such as Facebook [10–12,38]. Considering multiple platforms in a single study may offer insights into possible differences related to the communication medium. Moreover, such studies could pave the way for establishing generalizable social media strategies and tactics that can improve customer engagement. As such, in the present study, social media platforms themselves are taken up as a variable that influences total engagement levels.

2.3. Research Model

While earlier research has shown several common factors which impact follower interactions and social media effectiveness, few studies have taken into consideration all the common criteria. Moreover, even when all are considered, they are analyzed at an aggregate level with a limited number of subcategories. To date, no studies have considered the relevant factors in as much detail as the model provided in Figure 1, which presents the research model.

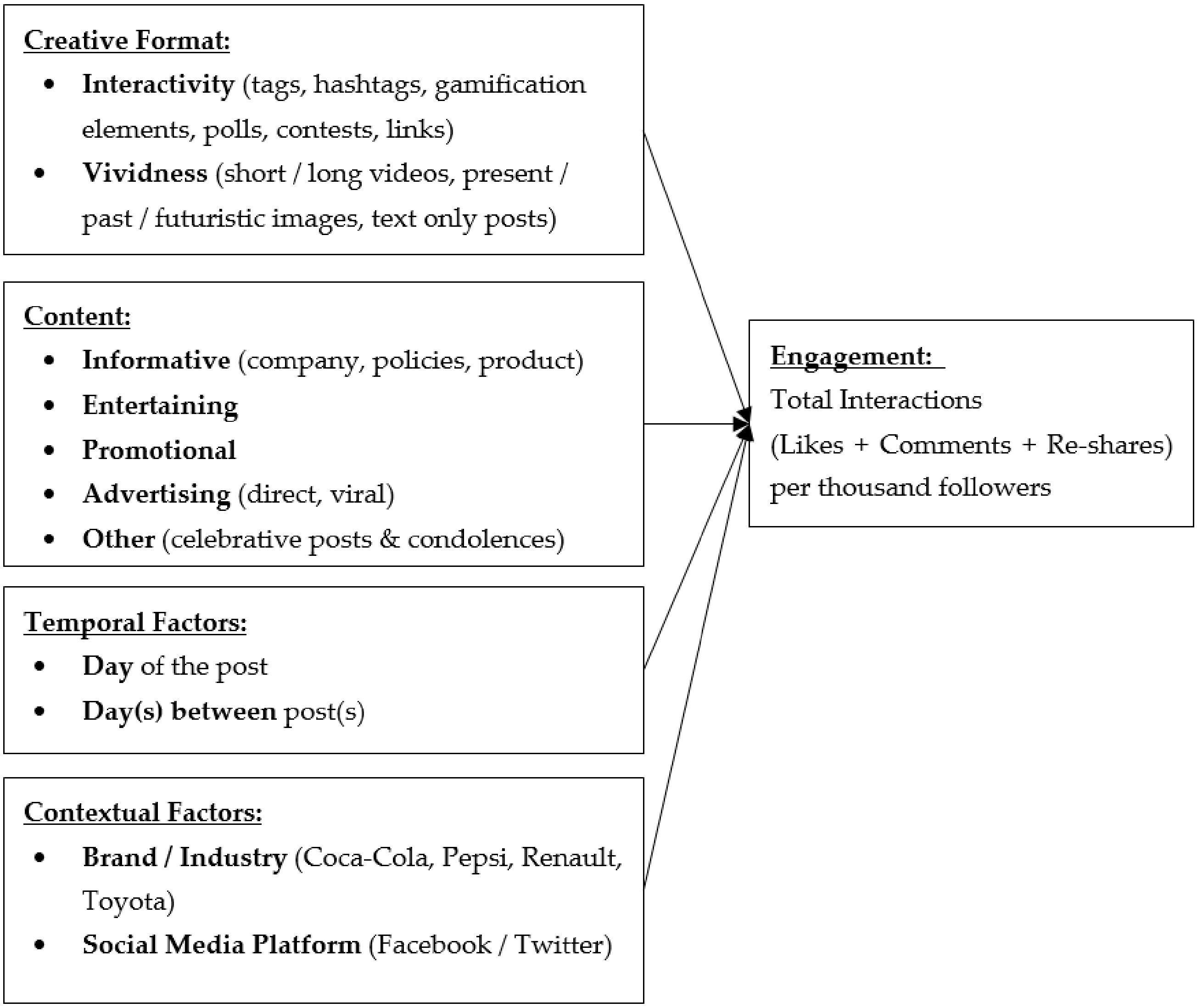

Figure 1. Research model.

3. Methodology

In contrast to the majority of earlier research on social media effectiveness, which has tended to examine a single brand and one social media platform, a more comprehensive approach was taken and included posts that were made on four consumer brands' official fan pages on two platforms (Facebook and Twitter) in Turkey. Data were collected by two independent observers through content analysis utilizing a structured observation form.

Following data collection, coding and recoding, the inter-coder reliability was assessed and then the collected data were analyzed. Several machine learning algorithms were applied to establish a high level of prediction accuracy and to ensure that we generated applicable managerial implications.

3.1. Setting: Consumer Goods Industry and Turkey

Considering that consumer goods companies are among the major driving forces behind the advertising industry and they are major revenue generators for social media companies [76,77], this study focused on this important industry. In terms of the setting, we have focused on an emerging market. Taking into account that emerging markets (i.e., India, Turkey, Brazil, Mexico) constitute a significant proportion of the top countries with the greatest potential of Facebook advertising reach, this is a novel and relevant setting. Turkey was chosen as the setting of the current study because of its prominence as a rapidly growing emerging market that is relevant for consumer goods companies, the popularity of social media platforms in the country and the inherently eastern and western aspects of its consumer behavior. In a related social media study on 50 European destinations, Turkey ranked first in terms of total number of likes, followers, subscribers and views further supporting the significance of the country [78]. According to the Interactive Advertising Bureau [79], as of 2019, digital ad expenditures constituted 31% of all advertising expenditures in Turkey. Approximately 75% of the total population has access to the Internet [80]; moreover, 82% of Internet users are on Facebook and 58% of them are active users of Twitter [81], which is indicative of users' familiarity with the Internet and social media. When these figures are compared to European countries, it is evident that social media penetration in Turkey is lower than that of Northern Europe. However it is superior to the Eastern European region and on par with, or superior to, the Western Europe as well [82].

As the following section discusses in detail, by means of content analysis, the social media (i.e., Facebook and Twitter) brand posts of four consumer goods brands. To reach a large sample of posts and relatively high interaction levels that will help in carrying out statistical analysis, only brands that have high awareness in Turkey were considered in study design. To account for the diverse range of consumer goods industries while also considering the available resources, two companies marketing high-involvement products and two marketing low-involvement products were chosen. From a set of candidate industries and brands, four that use social media more frequently than competing brands in Turkey were chosen and investigated with the aim of identifying the post characteristics and approaches that lead to superior follower engagement.

3.2. Designing and Unitizing

The process defined by Krippendorf [83] was utilized to design and carry out our content analysis and consumer BFP posts on Facebook and Twitter were selected as the context in which to measure post effectiveness. Within the scope of this study, the posts of two brands in the durable goods sector (Toyota Turkey & Renault Turkey) and two in the fast-moving consumer goods (FMCG) sector (Coca-Cola Turkey & PepsiCo Turkey) were examined with the goal of providing deeper insights into industry-specific behavior. Consequently, the unit of analysis consists of the individual brand posts of four consumer companies on Facebook and Twitter platforms.

3.3. Sampling, Coding and Validation

The data was collected with a manual content analysis form. Taking into consideration budget and time constraints, segments of time consisting of four months from two recent years (February, May, August and November for 2017 and January, April, July and October for 2018) and December 2016 were selected as the data collection periods so we could overcome potential seasonality issues. Furthermore, a pilot study was carried out as a means of training the coders and improving inter-coder reliability. In the pilot stage, two assistants coded the same one month's data separately, the results were compared and then the differences in coding were examined carefully to clear up misunderstandings about the variable definitions and categorization to have better agreement in coding. Considering the high number of variables in the study (see Table 1), inter-coder reliability was first assessed using the degree of agreement (i.e., percent agreement) between the two coders and an average figure of 83% was obtained. As a second approach we used Cohen's Kappa, a more robust and conservative statistic that overcomes the issue of random agreement to further assess the inter-rater reliability [84]. The calculated figure of 0.76 for Cohen's Kappa along with the high percent agreement led us to the conclusion that no significant inter-coder issues existed.

Table 1. Key variables and data coding.

Variable	Definition	Coding/Recoding	*n*	%
	Contextual & Temporal Factors			
Industry (String)	Industry of the Brand	Automotive	774	68%
		Beverages	336	30%
Brand (String)	Brand Name	Coca-Cola	261	23%
		Pepsi	95	8%
		Toyota	301	27%
		Renault	473	42%
Post Day (String)	Day of the week -> recoded into weekday and weekend	Weekday	999	88%
		Weekend	131	12%
Last Post Day (Number)	Number of days between the last post (0–26 days) -> recoded into four categories	0: Same day	165	15%
		1: One day,	480	42%
		2: 2–3 days;	290	26%
		3: 4+ days	195	17%
Social Media Platform (String)		Facebook	613	54%
		Twitter	517	46%
	Video & Image Use (Vividness)			
Short Video 0–10 sec (Number)	Video 0–10 s	No (0)	1028	91%
		Yes (1)	102	9%
Long Video 10+ sec (Number)	Video 10+ s	No (0)	853	75%
		Yes (1)	277	25%
Historical Image (Number)	Images depicting past, historical things, people or places	No (0)	1082	96%
		Yes (1)	48	4%
Futuristic Image (Number)	Images depicting futuristic, things, people or places	No (0)	1121	99%
		Yes (1)	9	1%
Contemporary Image (Number)	Images from current things, people or places	No (0)	587	52%
		Yes (1)	543	48%
GIF (Number)	Short animations made of pictures	No (0)	1060	94%
		Yes (1)	70	6%
	Interactivity of Content Shared			
Link to web site (Number)	Links to websites	No (0)	808	72%
		Yes (1)	322	28%
Link or post of other social media (Number)	Links to other social media posts	No (0)	1102	98%
		Yes (1)	28	2%
Gamification (Number)	Gamification applications such as point earning, mini-games leader-boards and so forth.	No (0)	1098	97%
		Yes (1)	32	3%
With Hashtag (Number)	Use of hashtags in posts	No (0)	390	35%
		Yes (1)	740	65%
With Tag (Number)	Use of tags in posts	No (0)	1056	93%
		Yes (1)	74	7%
Question (Number)	Asking questions in posts	No (0)	1027	91%
		Yes (1)	103	9%
Contests (Number)	Sweepstakes users participate by commenting or liking	No (0)	1106	98%
		Yes (1)	24	2%
Event (Number)	Event announcements	No (0)	1036	92%
		Yes (1)	94	8%

Table 1. *Cont.*

Variable	Definition	Coding/Recoding	*n*	%
	Informative Content (Information on . . . . . .)			
Background Company (Number)	Informative content on the company	No (0) Yes (1)	1053 77	93% 7%
Company Policy (Number)	Informative content on company policies	No (0) Yes (1)	1085 45	96% 4%
Specific Product(s) (Number)	Informative content on existing or new products	No (0) Yes (1)	407 723	36% 64%
Non-Commercial Information (Number)	Other Informative content (not on company or products)	No (0) Yes (1)	806 324	71% 29%
The celebrative posts & Condolences (Number)	Observance of days of significance (e.g., national & religious holidays)	No (0) Yes (1) Yes (1)	1031 99 187	91% 9% 17%
	Advertising Content			
Direct (Number)	Ads (usually from mass-media) directly posted on social media	No (0) Yes (1)	451 479	40% 42%
Indirect (Number)	Indirect, viral content; not adopted form mass media ad content	No (0) Yes (1)	699 431	62% 38%
Promotional Content (Number)	Posts on promotions, trials, coupons and special offers	No (0) Yes (1)	1107 23	98% 2%
Entertainment (Number)	Posts with entertaining content	No (0) Yes (1)	943 187	83% 17%
Total Interaction (Number)	All post interaction created	Number of Likes + Comments + Reposts	1130	100%
Engagement (Number)	All post interaction per one thousand followers	(Likes + Comments + Reposts)/(Total followers/1000)	1130	100%

Several subcategories of factors that were deemed to have an impact on engagement were considered in detail to achieve more profound insights. For instance, videos were coded as short and long; images were categorized according to whether they depicted the current environment, people and products or past/futuristic counterparts; informative posts were categorized in three ways: information about products, the company or company policies/procedures (e.g., returns, warranties etc.). In addition, to consider the effect of mass-media advertisement posts on social media, an advertising content construct was incorporated into the study. Finally, a new variable to account for commemorations and celebrative content regarding the observance of significant/religious holidays was appended to the content analysis form following the pilot study. The data coding and recoding methodology used for the variables and related subcategories is provided in Table 1.

Brand post effectiveness was measured by calculating total interactions (the total of likes, shares and comments) per thousand followers. Considering the significant differences between both the number of followers and total interaction figures, the use of a normalized engagement figure enabled us to obtain a comparable metric. Consequently, the number of total interactions was divided by a thousand followers to arrive at a figure for "total interaction per thousand followers" a.k.a. "engagement," a performance metric commonly used by social media platforms and digital marketing agencies. As a result of that methodological structure, this study differs from previous research that primarily focused on one social media platform, a limited range of brand post characteristics and only major types of post content [10,11,16]. Moreover, the study differs from other comprehensive research such as that carried out by Schultz [12] by including a wide range of post characteristics, content types and novel data analysis algorithms. In addition, this study also considers the timing of posts as well as the types of industry or brands as key factors that affect engagement figures.

To consider the effects of industry and brands, which are perfectly correlated and cannot be assessed together, the brand variable was chosen to be used in the analysis, as it carries more information (four categories instead of two). Upon calculating the engagement figures, the total follower base of the Pepsi brand was observed to be of a significantly lower magnitude than that of other brands. Pepsi's interaction levels were amplified to a greater extent when converted to engagement. Thus, application of a normalization methodology could not remedy the problem with Pepsi's posts, which all became outliers. Thus, the posts of Pepsi (n = 95) were left out of further analysis. Subsequently, the resulting consumer engagement (normalized total interaction) data (N = 1035) was divided into four quartiles and analyzed using the machine learning algorithms detailed in the following section.

3.4. Analysis Algorithms

Four machine learning algorithms (decision tree, random forest decision tree, logistics regression and artificial neural networks) were used in the analysis instead of regression or structural equation modeling as those approaches display shortcomings in terms of providing a clear roadmap for social media planning and management. Using more specifically defined variables can be beneficial but complex models are harder to manage in regression analysis due to the rapidly increasing number of relations and potential error terms, which can lead to low predictive power. Moreover, although the relationships in heterogeneous datasets may be obscured because of the aggregation of data in such analysis, that may be overcome through the utilization of machine learning algorithms and the detailed operationalization of variables. Seen from this perspective, the most promising algorithms available were found to be decision trees and random forest decision trees which arrive at step-by-step rules that can be utilized as specific digital marketing strategies and tactics managers. Nevertheless, there is no generally accepted single way to choose the right machine-learning algorithm and using more than one algorithm is a common approach in data science [85], thus, multiple algorithms were used to establish high predictive accuracy. The use of several machine learning algorithms is a noteworthy contribution to the literature on social media consumer behavior, in which single multivariate or univariate methods of analysis are commonly used.

In applying Logistic Regression, which works well when the target variable is Boolean, stochastic average gradient and iteratively reweighted least squares solvers were used. Since the optimal learning degree is usually dependent on the data, each one was tried separately and better results were achieved with iteratively reweighted least squares.

The next algorithm, Artificial Neural Networks (ANN), is commonly used for supervised learning or prediction of a class variable. An ANN model consists of three main layers: input, hidden and output layers. Output layers are the labeled class attribute that defines each record in the dataset. There are hidden layers between the input and output layers, each consisting of one or more neurons. Inputs are connected to these neurons with vertexes that carry weighing values. Each node recalculates the inputs and related weights via an activation function [86]. Through the use of a multitude of layers and nodes, the automatic selection of activation functions and network coding/encoding methods makes ANNs strong deep learners [87]. Following ANN learning, the sensitivity of each input variable can be calculated. This may help to partly overcome a major weakness of ANN, the low level of human interpretability. In this study, the sensitivity of the key variables (i.e., inputs) were calculated by using the weights between the inputs and the first layer of the neural network. The multiple values (inputs) of each key variable were summed and normalized to obtain a single weight for each variable (e.g., for long video usage there are two inputs, one for using long videos and another for not using long videos).

The third algorithm, decision trees, are flowchart-like tree structures in which each internal (non-leaf) node signifies a test on an attribute, each branch represents an outcome of the test and each leaf node (or terminal node) holds a class label. In this tree structure, the topmost node is called the root node. The popularity of decision trees in data science is attributable to their appropriateness for exploratory knowledge discovery, an ability to handle multidimensional data and the ease of human assimilation of the intuitive representation of knowledge in tree form [86]. However, they can be affected by the outliers and in order to overcome such overlearning or overfitting problems, ensemble and random forest decision tree (RFDT) models have been developed.

The last algorithm, random forest decision tree learning, hosts multiple decision trees. The number of the trees in the forest is determined by the analyst/researcher. Each of these decision tree algorithms is trained on a different set of records and variables that are randomly chosen with the random forest method [86]. The root of the decision tree is essential for interpreting a decision tree model and is considered to be the most important parameter to explain the target class variable. Thus, in a RFDT model it is critical to know how many times each variable has been the winner to be in the root of the trees. RFDT run on sampled data parts and loop to provide unbiased results and go around of overlearning issue. While decision trees are considered to be weak learners because they may also learn noise, the random forest decision tree model eliminates that shortcoming [88].

All the analyses were carried out on Konstanz Information Miner (KNIME) Analytics Platform v.3.7.1 via the workflows summarized in Figure 2 and as detailed in Figure A2 in Appendix B. The parameters of each algorithm are presented to provide clarity and offer replicability for future studies. For all the algorithms applied, 30% of the data was used for prediction whereas 70% was used for training (machine learning) via the stratified sampling method. As a stratum, the class variable was used so that there would be a balanced dataset in terms of classification. The target column (i.e., class variable) was set as the binned engagement (normalized total interaction). The following tuning hyper-parameters were employed:

5. Logistic regression algorithm: the stochastic average gradient was used as the solver.
6. Decision tree algorithm: the quality measure was selected as the Gini index and reduced error pruning was preferred while selecting the minimum number of records per node as three.
7. Random forest decision tree algorithm: the number of levels was set as 10 and the minimum node size was set as 9. The static random seed was used to come up with 100 models, five-fold sampling (without replacement) was done along with stratified sampling.
8. ANN: the sigmoid activation function was preferred and z-score normalization was applied to the dataset. The stochastic depth and early stopping were used to prevent possible overfitting. The best performing model was obtained via 3 layers and 25 nodes.
9. The synthetic minority over-sampling technique (SMOTE) algorithm was used to overcome class imbalance problems and biases towards certain categories with relatively large observations. The data was oversampled two times for regression and four times for the decision tree, ANN and random forest algorithms.

Accuracy, recall, specificity, error rate and $F1$ score were used for the evaluation of the models. The following formulae, where TP denotes true positives, TN true negatives, FP false positives and FN false negatives, were utilized. Cohen's Kappa measure was also used to assess the degree of agreement between the real data and predictions made by the four algorithms. High $F1$ score, kappa values, accuracy and low error rates indicate higher performance in machine learning analysis.

$$Accuracy = \frac{TP \times TN}{TP + TN + FP + FN} \tag{1}$$

$$Error\ Rate = \frac{FP + FN}{TP + TN + FP + FN} \tag{2}$$

$$Cohen's\ Kappa\ k = \frac{P_0 - P_e}{1 - P_e} \tag{3}$$

$$Specificity = \frac{TN}{TN + FP} \tag{4}$$

$$Recall = \frac{TP}{TP + FN} \tag{5}$$

$$Precision = \frac{TP}{TP + FP} \tag{6}$$

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{7}$$

As depicted in Table 2, a company's total social media engagement can be predicted using post-related parameters, yet the performance of each algorithm varies. The best accuracy and predictive ability were obtained using the decision tree algorithm, which also produces results that can be understood easily by humans. And while the classical logistic regression model calculates variable coefficients, its accuracy was found to be well below that of the competing algorithms.

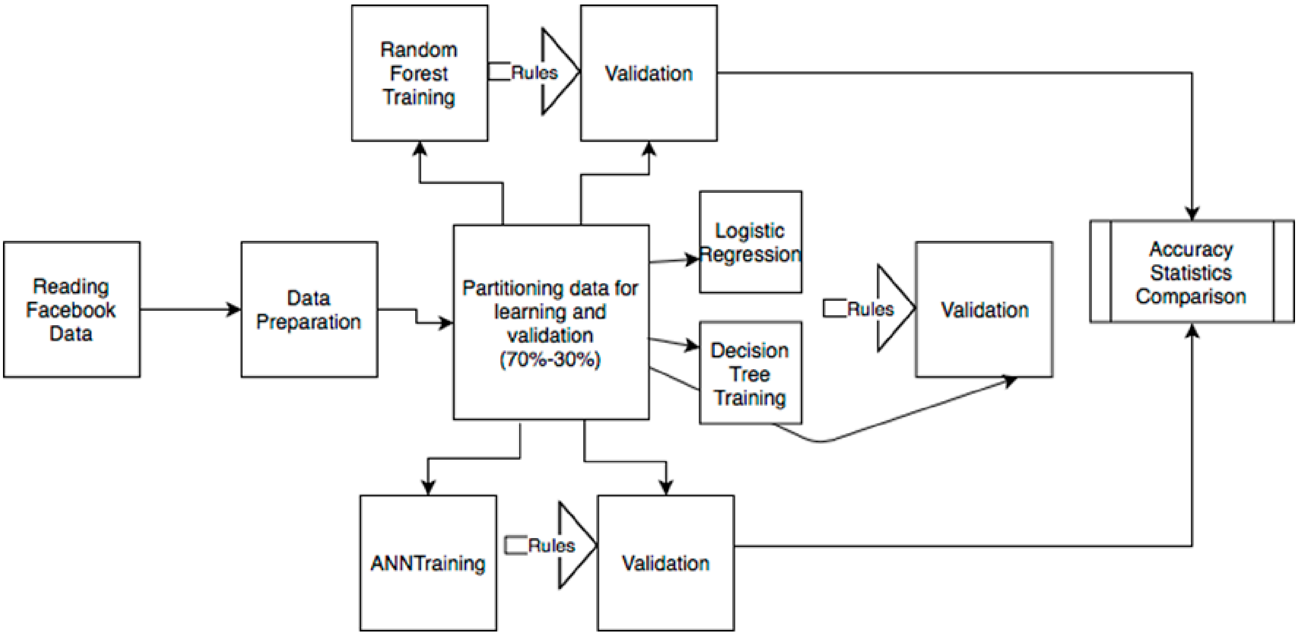

Figure 2. Analysis framework.

Table 2. Algorithm performance.

Algorithm	Accuracy	Error Rate	Cohen's Kappa	Recall	Specificity	*F1* Score
Decision Tree	0.8094	0.1906	0.7459	0.8094	0.9365	0.8094
Artificial Neural Networks	0.7791	0.2209	0.6750	0.7797	0.9264	0.7785
Random Forest Decision Tree	0.6613	0.3387	0.5230	0.6612	0.8871	0.6607
Logistic Regression	0.4403	0.5597	0.2539	0.4403	0.8135	0.4385

4. Results

The following sections provide a discussion of the results of the best performing algorithm, decision tree learning, along with insights obtained from the random forest decision trees and the second-best performing algorithm, ANN.

In order to obtain insights that are easy to apply, the ruleset output of the decision tree analysis (i.e. 328 rules) were assessed along with the trees themselves. The criteria (rules) that lead to higher interactions (labeled Bin-3 and Bin-4) and lower interactions (Bin-1 and Bin-2) were compared. Moreover, the output of the random forest decision tree model was also provided in Table 3, which depicts the number of times a certain variable is used for splits in the first three (higher) levels of the 100 decision trees created. The variables with higher counts are considered as significant factors that can predict engagement.

Table 3. Random forest decision tree attribute selection results.

Variable *	#Splits Level 0	Splits Level 1	Splits Level 2	Candidates Level 0	Candidates Level 1	Candidates Level 2
Brand	14	27	46	14	33	74
Weekday/Weekend Post	0	5	14	23	37	68
Post Frequency	18	23	40	20	43	81
Social Media Platform	21	22	27	22	38	72
Short Video 0–10 s	1	5	8	12	41	75
Long Video 10+ s	0	13	14	11	39	71
Historical Image	8	11	13	19	34	60
Futuristic Image	1	1	2	16	38	71
Present Image	1	8	22	18	38	76
GIF	2	7	4	21	41	79
Link to web site	6	4	18	18	33	62
Link to or post of other social media	5	3	5	21	42	66
Gamification elements	0	4	8	20	36	75
Hashtag Use	7	9	16	19	36	65
Tag Use	3	2	8	17	28	77
Questions	0	1	4	13	32	67
Contests	0	1	2	25	40	67
Events	2	6	18	19	46	85
Entertainment	0	4	13	14	42	73
Info on Company	6	6	10	14	32	73
Info on Company Policies & Procedures	1	11	9	21	49	76
Info on Product(s)	1	4	21	16	31	82
Non-Commercial Info	0	5	21	20	34	80
Celebrative content & condolences	3	8	14	15	39	76
Direct ad content	0	5	8	24	35	81
Indirect (viral) ad content	0	4	15	27	38	83
Promotional Content	0	1	2	21	25	85

* splits: the number of times that an attribute is selected for split at the top three levels of the 100 trees.

Social media platform, brand and days between posts emerged as notable primary factors that consistently ranked in the top tiers of the decision trees. Those factors were followed by video content, interactive content and informative content. The decision trees obtained through the analysis were too large, so they are provided in a summarized format (the first three levels) in Figure A1 in Appendix A.

The results of the random forest tree algorithm highlight the significant role of the social media platform, brand and days between posts as criteria affecting total engagement. Similarly, the ANN sensitivity analysis results provided in Table 4 also emphasize the significant impacts of using interactive elements such as gamification features, tags, links and hashtags on total engagement. Moreover, contextual and temporal factors such as last post day, brand and social media platform variables were found to be influential in improving total engagement.

Table 4. Artificial Neural Networks (ANN) sensitivity (ordered).

Category	Sensitivity	Sub-Category	Sensitivity
Interactivity	27.08%	Last Post Day	13.58%
Last Post Day	13.58%	Brand	9.08%
Information	12.11%	Social Media Platform	4.43%
Image	11.46%	Gamification	4.05%
Brand	9.08%	With Tag	3.73%
Video	6.61%	Event	3.59%
Social Media Platform	4.43%	Link or post of other social media	3.52%
Advertising Posts	3.74%	GIF	3.51%
Weekday/Weekend post	3.17%	Long Video	3.48%
Entertainment	3.13%	Info on Specific Product(s)	3.46%
Celebrative content & condolences	2.93%	Question	3.36%
Promotional Content	2.67%	Contests	3.29%
		Info on Background Company	3.26%
		Post Weekday/Weekend	3.17%
		Short Video	3.13%
		Entertainment	3.13%
		Present Image	3.06%
		Celebrative content & condolences	2.93%
		Link to web site	2.88%
		Non-Commercial Information	2.75%
		Promotional Content	2.67%
		With Hashtag	2.66%
		Info on Company Policy	2.64%
		Historical Image	2.61%
		Futuristic Image	2.29%
		Indirect ad content (viral)	1.88%
		Direct ad content	1.86%

5. Discussion

In light of the findings of both the decision tree and random forest decision tree analyses (i.e., assessment of the trees and rulesets), several practical takeaways can be identified. It is evident that there are several best practices, not just one golden rule that works for all brands on each social media platform. First, the social media platform utilized and the brand itself are among the primary factors that are influential in engagement (i.e., total interactions per follower). In the random forest analysis, the first three levels of the decision trees frequently consisted of the brand name and social media platform. This indicates that each platform (Twitter and Facebook) has a unique structure and demands a distinct ruleset to attain increased interaction. Similarly, the different rulesets regarding brands may be attributed to the industry at hand and the distinct follower profile(s) of each brand. Nevertheless, the findings reveal several best practices that can serve as guidelines for achieving higher follower engagement. The rules found to be applicable and meaningful are highlighted in Table 5 as the significant actionable guidelines and practical implications of this study. To emphasize the more noteworthy findings, tree branches with low number of observations (<5) and branches that did not provide actionable rules were omitted from the assessment. The decision trees generated through the random forest algorithm were also considered, in addition to the tree resulting from the "decision tree" algorithm analysis.

From a theoretical perspective, the results of the three algorithms are largely in harmony with the extant literature, yet there are points that contradict the findings of certain studies. Regarding the creative format, different types of interactivity used in brand posts (i.e., gamification, tags, links and hashtags) emerged as noteworthy variables that are instrumental in shaping engagement (interactions per follower) positively. This finding parallels that of social media consumer behavior research, in which the interactive content provided in posts was found to be influential on the total number of likes and/or comments [10–13].

In this study, however, through the use of decision trees, which interactive element works better is indicated and that leads to superior insights.

Table 5. Context specific actionable guidelines.

<table>
<tr><th>Brand</th><th>Facebook</th><th>Twitter</th></tr>
<tr><td rowspan="5">Toyota</td><td>Avoid posting more than once daily</td><td>Post daily or once every 2–3 days; avoid posting more than once daily or posting less frequently than once every four or more days</td></tr>
<tr><td>Use short videos</td><td>Use long videos</td></tr>
<tr><td>If not using videos, use hashtags</td><td>Use hashtags if you are posting more than once daily</td></tr>
<tr><td>If not using videos or hashtags, post once every 1–3 days and ask questions and avoid giving direct links to other pages or posts</td><td>Use viral videos if posting daily</td></tr>
<tr><td>If posting long videos, post on weekdays not on weekends</td><td>If not posting long videos, use tags with GIFs</td></tr>
<tr><td rowspan="6">Renault</td><td>Better engagement if posting once every 1–3 days</td><td>If you are not posting specific product information on Twitter, use hashtags (preferably on weekdays)</td></tr>
<tr><td>Don’t post more than once daily; If posting more than once daily, use short videos</td><td>If you are posting specific product information on Twitter, use entertaining posts or questions</td></tr>
<tr><td>Use links to websites or other posts if you are posting every 2 + days</td><td>Using indirect advertising content is better than using advertising content if using images.</td></tr>
<tr><td>Avoid posting informative posts that have non-commercial information content</td><td>If not using hashtags, use long videos.</td></tr>
<tr><td>If you are rarely posting (4+ days between posts) informative posts regarding company perform better</td><td></td></tr>
<tr><td>If you are rarely posting (4+ days between posts), providing links in post content performs better on Facebook than Twitter</td><td></td></tr>
<tr><td rowspan="7">Coca-Cola</td><td>On weekends, use links</td><td>Gamification performs better</td></tr>
<tr><td></td><td>Long videos perform better</td></tr>
<tr><td colspan="2">On both platforms, use tags</td></tr>
<tr><td colspan="2">On both platforms, if not using tags, use gamification</td></tr>
<tr><td colspan="2">On both platforms, if not using tags or gamification and posting rarely (once every 4+ days), use entertaining posts</td></tr>
<tr><td colspan="2">On both platforms, use images instead of short videos if posting daily</td></tr>
<tr><td colspan="2">On both platforms, if posting more than once each day, post short videos on weekends.</td></tr>
</table>

Notably, some studies have found that entertaining content does not have a significant influence on engagement and certain interactive content (i.e., links) have a weak influence in terms of improving engagement [10,12]. As demonstrated by Dolan et al. [60], entertaining content may lead to passive engagement with social media post content (e.g., its consumption), not active engagement (interaction). Thus, it can safely be said that there are contradictory findings in the literature, as other studies claim that entertaining posts increase engagement [13,16,59,63]. However, these conflicting results may be related to the context, industries and brands that the studies focused on.

In this study, product-related informative posts were observed to lead to superior engagement in the automotive industry but not in the beverage industry. For that reason, marketing managers should only opt for informative communication strategies on online platforms for high involvement products such as cars. The findings of similar studies which indicate a lack of significance for informative content for example, [10] may be attributed to the heterogeneity of the data, possibly caused by the inclusion of different industries in the dataset or the aggregation of the informative post content (e.g., information about products, companies and procedures considered together).

In terms of content vividness, it was found that the use of videos led to higher engagement levels. These findings offer important strategic insights and budget allocation cues for managers who are responsible for social marketing decisions. It was observed that long videos are more influential than short videos, according to the ANN sensitivity results. Moreover, the use of futuristic or historical images did not emerge as a significant factor for increasing engagement. However, it should be noted that the number of observations for those categories was limited in the dataset. The use of contemporary images emerged in decision trees as a significant factor and in certain cases, it was observed that image use led to superior engagement (e.g., for Coca-Cola when posting daily). The ANN sensitivity results also indicate that images are more influential than videos on engagement and that contemporary images represent the most significant subcategory. This is in agreement with the findings of Pletikosa Cvijikj and Michahelles [16], Sabate et al. [15] and Trefzger et al. [20], who posited that posts with images are superior to other formats and/or have the strongest effect on total interactions.

Among the algorithms applied, it was observed that the number of days between posts had a significant influence on engagement, a finding that was also noted in an influential study by de Vries et al. [10]. This relationship is complicated, as Table IV illustrates, yet it is evident that posting frequency is instrumental in attaining superior post performance, as the ANN sensitivity results indicate. Moreover, posts on weekdays and weekends also create differing engagement levels, so the postdate emerges as a noteworthy factor, as was demonstrated by Moro et al. [37]. However, the overall effect is low, as the ANN sensitivity analysis demonstrates, which may explain why posting time emerged as an insignificant factor impacting follower engagement in studies such as those by Antoniadis et al. [14] and Schultz [12].

Another finding of significance concerns how promotional posts with tangible benefits (i.e., remuneration posts) constitute an insignificant factor in improving follower engagement. The literature in this regard is contradictory. While this finding coincides with that of Pletikosa Cvijikj and Michahelles [16] and Aydin [48] that was carried out in Turkey, it contradicts that of Luarn et al. [11]. This may partly be attributed to the difficulty of enforcing regulations concerning misleading promotional content in social media adverts (e.g., iPhones for one-third the original price, mismatches between real products and photos) or the intrusiveness that consumers may feel when they encounter promotional posts on their feed [89]. Moreover, there is evidence on interaction effects (use of brand personality content together with promotional content) to increase engagement levels in the literature [67].

Limitations

Despite the broad scope of this study, it has a number of limitations. While the ways that each variable was defined and operationalized in the literature were carefully considered during this research, it became evident that there are still yet different approaches to operationalizing those factors. Consequently, the variables/factors included in the research model are not exhaustive and the content of posts can be assessed from a variety of perspectives. Moreover, each factor could be assessed in even more detail (e.g., images could be categorized according to dominant colors and components, etc.) than the scope of the present study permitted.

As another limitation, the number of brands and fan-page posts analyzed, although higher than that of average studies on social media engagement, could have been increased more. Thus, one possible avenue for future research could involve carrying out a similar analysis with a greater number of observations and brands.

6. Conclusions

The present study contributes to our current knowledge about social media use and brand engagement in several ways. First, the findings demonstrate the complexity of social media page management. It is apparent that there is no overarching single rule but rather several rules should be considered for each social media platform. This study also shows that best practices differ between brands. Using a comprehensive research model that takes into detailed account several post-related factors, numerous venues for improving engagement have thus come to light in this research.

Second, this study differs from the extant literature by employing machine-learning algorithms, which have increased in popularity in recent years due to their high predictive power and low resource requirements. Among the algorithms used, decision trees were found to provide more practical insights compared to regression and structural equations in which different factors are provided as coefficients but not as applicable tactics. The use of these algorithms offers strategic direction and detailed actionable guidelines that can be followed in the design of effective social media communications. In this study, regular decision trees outperformed RFDT model, a derivative of regular decision trees. Although this may be due to the dataset that have been used in the study, we report that the use of RFDT may not be a necessity in all cases.

Third, the setting differs from the norm in the literature and centers on Turkey, an emerging economy. In terms of social media use, Turkey ranks among the Top-8 markets and it is situated at the crossroads of Europe and Asia, which offers a unique locale for gaining insights into developing markets and mixed cultures. Furthermore, the relatively large sample size and the comprehensive design of the study, which adopts a more detailed approach in classifying the relevant factors affecting engagement, led to deeper insights.

This study points out that the prominence of contextual factors such as social media platforms and the effects of industry/brands in designing social media strategies, thus this is can be counted among the major theoretical implications that have commonly been overlooked in the literature. For instance, according to the results, informative post performance differs with regard to the type of consumer industry that the brand operates in. Informative communication on social media may lead to superior engagement when the brand is offering high involvement products such as cars.

Moreover, the use of videos and images, post frequency and interactive post elements were found to play a critical role in the success of social media posts, which confirms the findings in the extant literature. Those interactive elements such as gamification, tags and hashtags are significant means of attaining better performance in the realm of social media. Nevertheless, how those elements should be structured and used may differ between cultures and that is an issue that may be of particular significance for European consumer companies and global brands. Elaborating on the potential effects of culture on tag and hashtag use and questioning the presence of global customer segments (vs. local ones) in that context could emerge as a viable avenue for future research.

Thus, this study does shed light not only on the role of contextual factors cited above but also implies that cultural characteristics have a potential impact on social media strategies and their results as highlighted by Hudson et al. [90] and Lin et.al. [91]. To conclude, this study conducted in an emerging country confirms the importance of new and diverse factors on social media success and at the same time underline the need for examining the impact of cultural characteristics on the issue.

Author Contributions: Conceptualization, N.U. and G.A.; methodology, G.S., G.A. and N.U.; software, G.S.; validation, G.S. and G.A.; formal analysis, G.S.; resources, N.U. and G.S.; data curation, G.S. and G.A.; writing—original draft preparation, G.A.; writing—review and editing, G.A., G.S. and N.U.; visualization, G.S. and G.A.; project administration, G.A and N.U. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

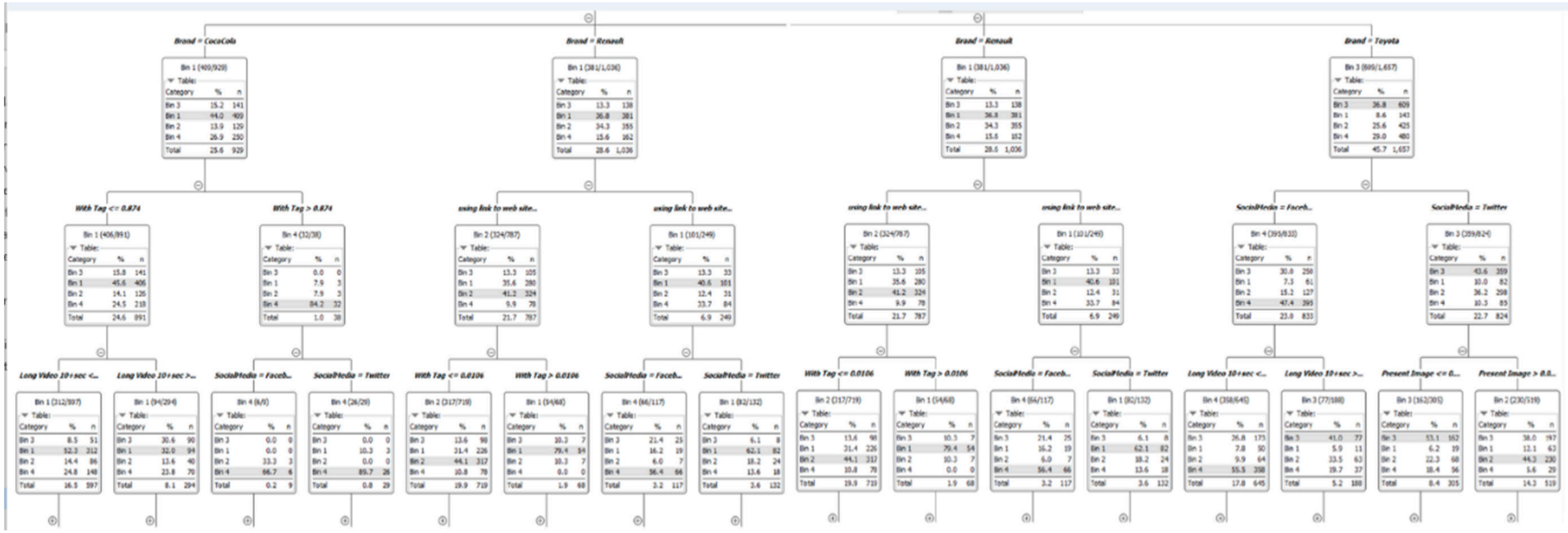

Figure A1. Decision Trees.

Appendix B

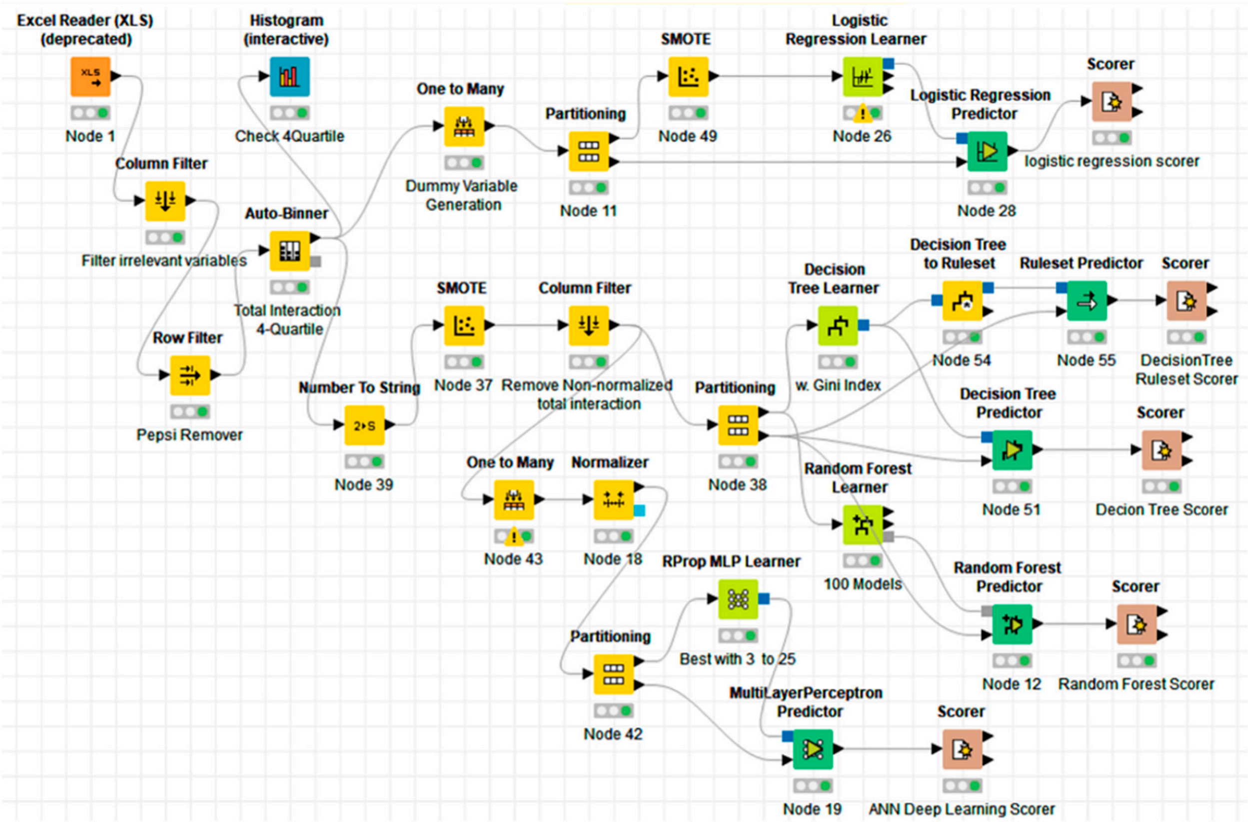

Figure A2. Knime Analysis framework.

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