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The siren’s song: visual and textual elements impact on location-based marketing campaigns

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Introduction

The digital ad spending reached USD 455bi, with mobile accounting for USD 288bi (Statista, 2024). Although mobile ad spending accounted for 63% of all digital ad spending, knowledge of how brands can use mobile technology to reach their customers effectively is still evolving. The appeal about mobile is that is offers great targeting and personalization opportunities, factors that deserve further investigation. The use of mobile promotions to drive customers to stores is growing, with more than 3/4 shoppers using mobile devices along with in-store shopping (Statista, 2024). Some mobile campaigns present more expressive store visit performance numbers than others, which leads to wonder what increases the effectiveness of the mobile ad messages.

The objective of this study is to analyze which visual and textual features are predictors of higher store visit rates in mobile campaigns. Based on previous theoretical and research work (Pantano & Priporas, 2016; Bakapoulos et al., 2017; Beeck & Toporowski, 2017; Gutierrez et al., 2019; Tseng et al., 2019), the study hypothesizes that the mobile promotion message content plays an important role as a performance driver in store visits. However, there is not a clear picture of which elements of the message content can be associated with performance results, which shall be analyzed.

Location Based Marketing (LBM) increases relevance of mobile advertisements (Banerjee, Xu & Johnson, 2021). According to Azemi et al (2022) both message content and visuals affect the success of mobile marketing. Yet, studies regarding which specific visual and textual elements have a positive impact on such relevance are still underdeveloped.

Statistics on mobile promotions usually reflect the stage of payments made by the online channel, known as last-click metrics. Mobile advertising effect on campaign performance regarding store visits has not yet received much systematic attention, despite its influence on purchase decisions. There is a wide range of formats and possibilities that are unique to the mobile medium such as location-based advertising, display advertising inside different mobile applications and mobile coupons (Persaud & Azharl, 2012). Hence the importance of further research on their impact on consumers response. Gutierrez et al. (2019, p.303) mention that further research is needed to achieve a more universal and comprehensive understanding of the main determinants for mobile location-based advertising. Therefore, this study intends to identify visual and textual elements of mobile ads using computer vision, providing further comprehension on mobile promotional messages content, and its effect on performance results.

Theoretical background

The definition of "mobile" has rapidly evolved from describing the mobile phone device to more broadly encompassing a range of mobile computing devices (i.e., Tablets, wearables, and smart speakers) and mobile services (i.e., apps and virtual assistants) (Tong et al., 2020). Mobile products include both smart portable devices that can interactively respond to customers' requests and virtual services that satisfy customers' demand on-the-go (Tong et al., 2020, p.66). That is, it includes both hardware mobile devices and virtual mobile applications. Therefore,

this research's definition of "mobile" includes both hardware and software altogether, and it includes cell phones, Tablets and wearables, devices that can be used on-the-go, with a ubiquitous character.

Mobile commerce already accounts for 70% of worldwide retail e-commerce sales, although that still represents a small part of total retail purchases, around 30% (Statista, 2024). Either way, the mobile impact on purchases is very expressive. It is not just about converting through the mobile app, it is about mobile driving research and consideration, and facilitating fulfillment . That is why Mobile has been analyzed under the online-to-offline (O2O) model (Chiang et al., 2018). Among other things, the O2O model looks at online as a discovery mechanism for consumers, that works as foot traffic generator for merchants that enables physical purchasing. A key concept for the online-to-offline perspective is geolocation.

Mobile geolocation is a relatively novel technology, and studies on its effects on customers' responses are still scarce. Location-Based Marketing is based on the smartphone model, that started with the launch of iPhone in 2008. In 2011, the Mobile Marketing Association defined Location-Based Marketing as: "any application, service, or campaign that incorporates the use of geographic location to deliver or enhance marketing message/service". Mobile geolocation allows retailers to design much more assertive communication strategies to attract customers to their stores, addressing the consumers when they are most receptive to it.

As of today, with the advances in technology, there are many options to more accurate geofencing and geobehavior data. Geolocation uses a variety of different information sources to identify a user's location. Geofencing is a virtual perimeter for a real geographic area used for the activation or delivery of advertising focused on users who are present within a certain radius of a point previously defined as a geographic coordinate, an address, a commercial establishment, etc. Geobehavior is the behavioral profile of users based on the places frequented. For example: a Geobehavior Parents group is formed by users who attend primary schools, theaters, and cinemas in schedules of children's plays and films, pediatricians, and playgrounds (Hands, 2020).

In this context of better understanding the role of mobile technologies in a cross-channel shopping journey, regarding the influence, multiples touch points and convergence of online to offline, the following research question is proposed: which visual and textual features of push online mobile messages generate more visits to brick-and-mortar stores? Despite the growing impact of mobile in marketing tactics, little is known about the location dependence and mobile message content on customer behavior (Beeck & Toporowski, 2017). Extending the works of Luo et al. (2014), Danaher et al. (2015), Molitor et al. (2016), Beeck and Toporowski (2017) and Cliquet (2021), the objective of this study is to analyze which visual and textual features of push online mobile messages generate more visits to brick-and-mortar stores, connecting online efforts to offline behavior, in a cross-channel perspective.

In academic terms, the research expects to contribute to advancing the knowledge on the effects of mobile promotions in a cross-channel perspective, looking at online communication (mobile push) and offline behavior (store visits).

Table 1 refers to prior geolocation studies. Hui et al. (2013) and later, Grewal et al. (2018) analyzed mobile usage in offline shopping. Luo et al. (2014) and Fong et al. (2015) worked with temporal and locational information with SMS messages. The focus lied on competitive pricing strategies. Dubé et al. (2017) extended their work with a geo-targeting pricing analysis. Molitor et al. (2016) also

focused on geolocation pricing strategies. The authors demonstrated the tradeoff between distance and discount levels when it comes to mobile messages. Danaher et al. (2015) looked into mobile coupon redemption and noted that time of delivery significantly influence redemption. Beeck and Toporowski (2017) raised the flag of the importance of looking into other mobile promotion content strategies. Li et al. (2017) then looked at another mobile promotion contextual element: the weather. Ghose et al. (2019) looked at trajectory-based targeting and Högberg et al.(2020), at customer labeling on mobile messages. Lastly, Cliquet (2021) with new methods for enlarging geomarketing.

To date no empirical research has been conducted with respect to the impact of geolocation push notifications and store visits, analyzing visual and textual elements of the message content, beyond pricing. This research explores three mobile message dimensions: temporal, spatial and semantic. The research gap lays on visual and textual elements of mobile message and their effects on offline performance. Despite the alert from Lemon and Verhoef in 2016, the research on the use of mobile in the purchase funnel has been limited and mainly done in practice. There is yet much to understand regarding prompting the customer to the store with the mobile messages. The conceptual background of this work starts on contextual marketing theory (Kenny & Marshall, 2000), which states that a marketer's endeavor is always context dependent in an online-to-offline (O2O) model.

In a managerial perspective, the results from the studies provide valuable insights regarding how mobile promotions can be used to guide customers to in-store visits and, therefore, improve retail media budget allocation and increase marketing ROI using mobile. Knowing more about the visual and textual features of online mobile messages that impact store visits, companies can deploy more efficient marketing strategies.

Method

The objective of this study is to analyze which visual and textual features of push online mobile messages generate more visits to brick-and-mortar stores, connecting online efforts to offline behavior, in a cross-channel perspective. For that purpose, the study relied on secondary data of mobile geolocation campaigns data from well-known brands. The study applied the means comparison technique, but the grouping into "treatments" was not under the control of the experimenter. Experiments have some advantages, but quantitative nonexperimental techniques are also useful and can produce important results (Oehlert, 2010).

The unit of analysis was the campaign. It applied computer vision to mobile ads and crossed it over with performance data. The data collection involved 1.753 location-based campaigns from 76 medium and large companies, that ran from November 2019 until March 2020, that is, right before the isolation from the Covid pandemic started. The data treatment involved computer vision (AI & Machine Learning), with observational procedures (Oehlert, 2010).

The use of computer aided software allows the addition of visual elements to the mobile message content analysis. Computer vision, as a research field, is the science that uses a machine to collect and analyze images and videos to extract information from processed visual data (De Andrade et al., 2019, p.1). Indeed, computer vision can yield various marketing insights (Nanne et al., 2020). There are a few computer vision models available, such as Google Cloud Vision, Azure from Microsoft, Amazon Rekognition, Clarifai, IBM Watson Visual Insights,

Clarifai, CloudSight, Sighthound, Face Plus Plus and Kairos. This study decided on Cloud Vision. Google Cloud Vision works on image processing and pattern recognition artificial intelligence techniques. In a test performed by Nanne et al.(2020) with three different computer vision models, Google Cloud Vision performed more accurately in object detection. Google Cloud's Vision API offers powerful pre-trained machine learning models through REST and RPC APIs (Google Cloud, 2020).

Machine learning algorithms have emerged as a robust and cost-efficient method for classifying a large number of images, allowing for automatic detection of visual features without human supervision (Nanne et al., 2020; Argyris et al., 2020; Brei, 2020). It allows for the observation of hidden patterns in the "Big Data" collected from real-world observations, integrating textual and visual realms.

The computer vision algorithm was applied to a set of real data mobile campaigns. A Microsoft recognized ad tech company provided data from mobile ads targeted from November 2019 until March 2020, resulting in a four-month observational period. The tech company collects anonymized location data from over 60 million devices, enabling mobile apps to provide location-aware services while securing the privacy of their users. After users opt-in and consent, the company receives location data associated with the device, not with the user. The tech company then applies encryption techniques and hashes data to increase security and privacy. Data is aggregated and then made available to publishers, ensuring user privacy. Hence, the advertising target is based on physical behavior instead of real identities. Such procedures are important since privacy concerns can ultimately reduce the personalization benefits that companies can deliver to consumers (Andrade et al., 2020).

As per method limitations, the main concern refers to controlling variables. More constructs and variables may affect store visit than the ones considered in the proposed model.

Data Analysis and findings

This study is divided in two phases: 1) identify visual and textual elements of mobile ads using computer vision and machine learning; 2) correlate the identified variables with campaign performance results.

A sample of 4,352 campaign results, including some top global brands, was made available after the signature of a legal non-agreement disclosure by the researcher (technical cooperation agreement). Since the first data set did not include performance data, a second sample was requested. The second sample comprised 1,753 location-based campaigns from 76 different companies, from November 2019 till March 2020. The second data set included performance data. Even though it includes multinational companies, all the data relates to Brazilian consumers responses. The creatives were available in URLs, therefore a phyton code was necessary to automatically access the images.

This study employed a data-driven approach; thus, focused only on the content dimension of the mobile promotions, crossing it over with campaign performance data. The grouping into "treatments" was not under the control of the experimenter: the researcher observed the subjects without interfering (Oehlert, 2010).

Next, the content data was to be extracted from the images. First, the researcher tried to apply Optical Character Recognition (OCR) program to the

images for word frequency count, with no success. Then, machine learning was applied. Based on literature review and previous studies, we compiled a preliminary list of criteria for message content classification (see Table 2). The creative content was also classified based on structures, wording and types of messaging. We added further criteria of which we were aware, based on industry experiences.

Table 2 - Text and Image Analysis Criteria (image feature vectors)

Variables	Source
Purchase orientation - hedonic or utilitarian	Bart et al., 2014; Groß,2015; Pantano & Priporas, 2016; Kim & Song, 2020
Attitudinal Driver (branding) or Behavioral Driver (purchase)	Bakapoulos et al., 2017
(Binary indication of) Price	Bakapoulos et al., 2017
(Binary indication of) % off or discount	Bakapoulos et al., 2017
Movement (gif / jpg) and Media Richness	Daft et al., 1987; Tseng et al., 2019; Tseng et al., 2020
Incentive & Rewards / Tangible incentives	Komulainen et al., 2013; Gutierrez et al., 2019
(Binary indication of) People/ animal presence	Mazloom et al., 2016

According to Mazloom et al. (2016) study with fast food brands, posts showing one person or people with products are more attractive and will likely get a higher number of likes. Komulainen et al. (2013) research showed that the general attitude towards mobile ads in games is negative. However, incentives in the form of tangible, flexible and location-based rewards have positive and significant impact on users' attitude. Promotional offers, such as discount coupons, free samples or lucky draws, have been used to enhance the effectiveness and acceptance of mobile marketing (Komulainen et al., 2013).

Google Cloud Vision API and Python programming language were used. According to the API Vision website definition, it offers pre-trained advanced machine learning models, quickly allowing the classification of an image into millions of predefined categories, as well as offering detection of objects, faces and printed or handwritten texts. As an API (Application Programming Interface) was used, it was also necessary to use a programming language to access the API, because the API is a set of routines and standards established by a software for the use of its functionality by applications that do not intend to involve details on the implementation of the software, but only use its services.

First, the images were uploaded to the Google Cloud Storage service for use in Vision Cloud. Then, using the Python language, and using the API Vision documentation, the images were processed in the service using the text detection (TEXT_DETECTION) and object detection (localized_object_annotations) features. As a result, the API service provides structured text output in JSON (JavaScript Object Notation) format with the extracted texts and all the objects identified in the images. Using the images outputs, through the Python language, some sentences were built with conditional IF-ELSE commands to identify the true or false conditions for each variable in each of the images. According to Alantari et al (2021), the choice of the algorithm should be context dependent, for its predictive ability.

Thus, for the PRICE variable, the sentence considered that if there was a character "R$" in the image, "1" would be returned for the variable. If there was a character "R$" along with the words "purchases" and "in ", "0" would be returned,

as it was previously identified that some images brought values in Reais that were not prices, but values related to promotions such as “for every R$200 in purchases, win ... ". If there was no character 'R$' it should be returned "0" for the variable PRICE. A dummy variable indicated whether the mobile ad had (or did not have) a pricing element in the message content.

The sentence of the DISCOUNT variable established that if there were the character "%" or the words "bonus", "promotion", "promotions", "discount", "discounts", "clearance", " sell out", "sale", " off ", “offer” and “offers" in the image, "1" would be returned, if there were neither "% "or the words quoted, "0" would be returned.

In the case of the variable "PURCHASE", if the variables PRICE or DISCOUNT were equal to "1", then the sentence of the variable would return "1", if none of them were equal to "1", then "0" would be returned. For the variable ADDRESS, the sentence established that if there were "R.", "Av.", "Al." or "Rod." in the images, "1" would be returned for the variable, if there were no abbreviations mentioned, "0" would be returned.

The sentence of the variable BRANDING determined that if the variable PURCHASE was equal to "0", it would return "1" for the variable BRANDING. Likewise, if PURCHASE was equal to "1", then it would return "0" for BRANDING. A judge re-evaluated this classification, with a sample of 10% of the ads, with a 96% congruence. The branding label does not refer to the logo presence, it refers to the message focus. It differentiates between a shopping appeal or a distinctiveness appeal. The message is classified as branding when the focus of the message is on the elements of the product or on the distinctive elements of the brand. As Jones and Bonevac (2013) pose, there are many definitions around branding, but essentially it refers to differentiation.

Regarding the sentences of the PERSON and ANIMAL variables, they were established as follows: if there were the words "person" and "animal" in the output of the objects (object recognition), the sentences would return "1" for each variable, if there were no words cited, "0" would be returned for each variable.

Using programming, it was determined that the responses of each sentence for each image would fill a Table in the DataFrame structure, where the columns would be Filename, Price, Discount, Purchase, Address, Branding, Person and Animal, so each line would correspond to an image, and it would be filled with the name of the image in the Filename column and "0" or "1" for each of the other columns. Subsequently, the Creative column was created, corresponding to the first four characters of the Filename column.

At last, a join operation (JOIN) was performed on the Table created with another performance Table provided that contained the columns Creative_interface_id, Total_views, Total_clicks and Visits, relating the columns Creative and Creative_interface_id of the Tables. As a result, a new conjoint Table was generated with the columns Creative, Filename, Price, Discount, Purchase, Address, Branding, Person, Animal, Total_views, Total_clicks and Visits. After creating the final Table, a .CSV file was generated in Python with the data of the Table columns separated by semicolons. Then, the .CSV file was imported into Excel, using the semicolon as a column divider. In order to make fair comparison of content variables, the researcher decide to drop the movement criteria, because it required to transform each gif animation into a set of set of frames. The brand recognition elements were deleted from the examples below.

Variable Branding appeal Conceptual definition: institutional communication which focus is the brand, with no direct reference to pricing. Counterpoint: purchase appeal	
1(Positive Samples) = branding appeal	0(Negative Samples) = purchase appeal

Figure 1 – Variable branding appeal

Variable Person Conceptual definition: binary presence of a person	
1(Positive Samples) = with person	0(Negative Samples) = without person

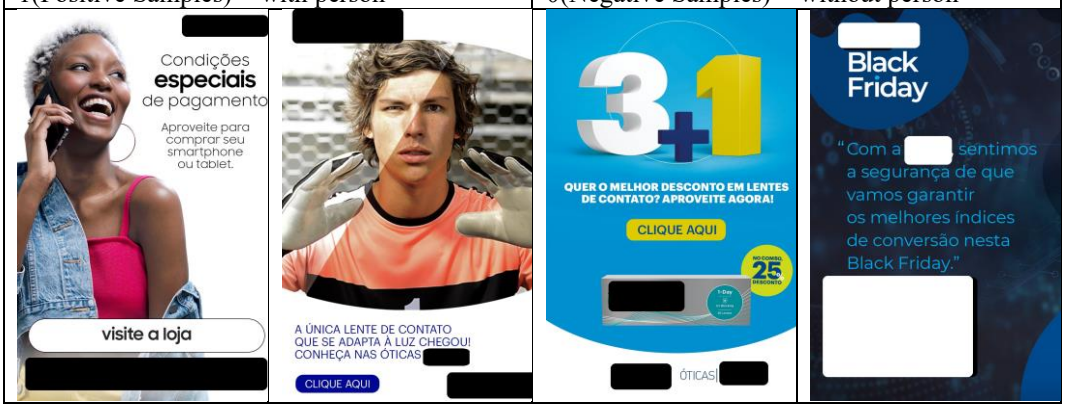

Figure 2 – Variable person presence

The function text_detection from the AI and machine learning software from Google Cloud used OCR to detect text within images. We then used the NVivo Software to codify the output. We performed a frequency count and selected the most frequent words (>99) that could alter the message content: black, discount, no, store, promotion, valid until, new, purchase, check and participate. From such wording analysis, derived new binary variables. The industry was inferred by the company's name.

Table 3 - Word Count from NVivo with Cloud Vision output

Word	Extension	Count	Weighted percentage (%)
black	5	279	001,42
desconto	8	246	001,25
oboticário	10	233	001,19
até	3	212	001,08
com	3	173	000,88
2019	4	161	000,82
não	3	151	000,77
loja	4	135	000,69
promoção	8	127	000,65
400	3	124	000,63
weekweekweek	12	124	000,63
válida	6	123	000,63
ack	3	116	000,59
novo	4	116	000,59
compre	6	108	000,55
cumulativa	10	108	000,55
itens	5	108	000,55
mais	4	106	000,54
consulte	8	105	000,54
brasil	6	101	000,51
participe	9	99	000,50

The selected words were grouped into three cognitive categories:

- Sense of action: buy, consult, shop
- Sense of reward: black, discount, participate, promotion
- Sense of ephemerality: valid, new, no

A common assumption in mobile studies is that by sending mobile coupons that require consumers to make timely purchase decision, a sense of urgency may be created that increases their impulsive purchase likelihood (Phang et al., 2019).

Wording	
Black	Store (lojas)

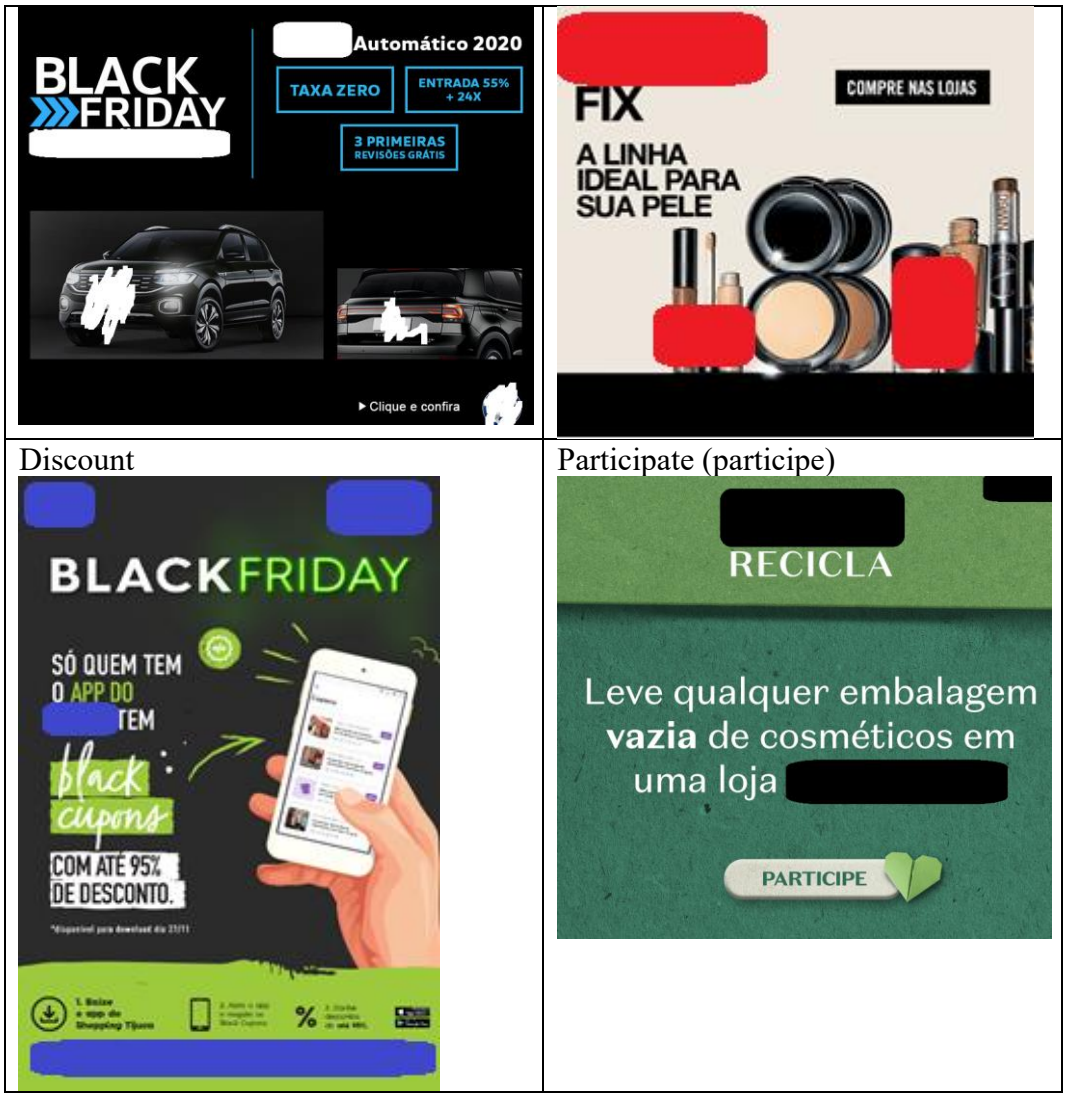

Figure 3 – Wording variables

Results and Discussion

In order to analyze the results, t-tests were performed, to access if there is a statistically significant difference between the means of two groups (i.e, ads with or without a person). Besides the t-tests, Analysis of Variance (ANOVA), Analysis of Covariance (ANCOVA) and Linear Regression were also performed on the dataset. The goal was to compare the effects of content variables, looking for the ones that provide drivers for offline visits. The linear regression looks into which variables better explain the number of visits made to the physical store based on the evaluation of information from the images of the advertising campaigns, the number of views and the number of clicks, whether the ANOVA verifies if there are any statistically significant differences between the means of two or more groups.

This secondary data study analyzed which units were in which treatment groups; the study did not have control over the assignment (Oehlert, 2010). Thus, it realizes that observed differences in responses between treatment groups could

very well be due to other hidden mechanisms.

The study begins the analysis by performing sampling adequacy testes on the items. There were no missing values, so we looked for potential outliers. Cases above 4.5 in the standardized score were removed, checking along with a box-plot analysis. For instance, cases with a VTR above 100% were removed, despite having a logical explanation for such (the consumer may visit a store more than once). Fifteen outlier elements were removed from the sample[1], resulting in a sample of 625 valid campaigns. There is a wide difference of clicks and visits in the campaigns. Campaigns from well-known brands received as much as 1.470.638 mobile add views, whist others received just 241 views (Figure 4).

Figure 4 – Descriptive Statistics of the secondary data study

Apart from the performance data, all variables are dummy. The mean decimals indicate the relative frequency (respectively rate) per category of each dummy variables.

Table 4 – Descriptive Statistics variables for the secondary data study

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation	Variance
Views	625	241	1470638	63451,45	128945,626	16626974338
Clicks	625	1	8094	251,41	590,786	349027,758
Visits	625	1	30071	2264,42	3709,086	13757321,01
CTR	625	0,13%	1,48%	0,4588%	0,20964%	,044
Valid N (listwise)	625					

Descriptive Statistics

	N	Mean	Std. Deviation	Variance
ShowPrice	625	,091	,287	,083
ShowDiscount	625	,353	,478	,229
PurchaseAppeal	625	,395	,489	,239
ShowAddress	625	,009	,096	,009
BrandingAppeal	625	,605	,489	,239
Person	625	,170	,376	,142
Animal	625	,008	,088	,008
Black	625	,290	,454	,206
Desconto_s	625	,234	,423	,179
Não	625	,184	,387	,150
Participe	625	,150	,357	,128
Loja_s	625	,232	,422	,178

From the Descriptive Statistics (Table 4), we notice that there were very few adds displaying Animal imagens or Addresses (<0,01). Therefore, we discarded such variables for the analysis. Interesting to notice that even adds from the Pet Industry did not use animals in the creatives.

The following campaign data was granted by the company:

organization_name	Total_views	Total_clicks	Visits	Creative_interface_id

Therefore, the study calculated the visit-through rate (VTR) and click-through rate (CTR) of each campaign. Next, it checked for the assumptions

[1] Cases that were removed: 25, 36, 43 86, 87, 91, 92, 115, 521, 522, 603, 604, 622, 630, 631

regarding t-tests, the significance test of the difference between the means. Since the data showed high asymmetry coefficient, the study transformed the data into logarithms in order to comply with such premise, approximating the data from a normal distribution. To deal with the large variation in the number of visits and clicks, we applied the Napierian logarithm to make it resemble a Gaussian distribution (see the Figure 5)

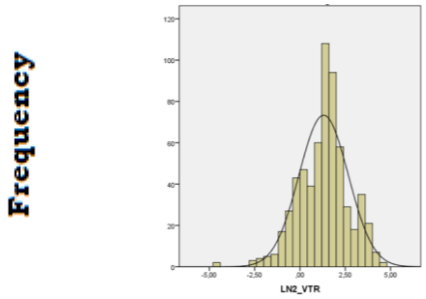

Figure 5 – Frequency distribution

A non-parametric test for the difference between the means - the Mann-Whitney test - was also conducted, also indicating a significant difference between the groups. The mean rank for adds with branding appeal was 362,8 versus 237,29 for adds with a purchase appeal. From this data, it can be concluded that the VTR for adds with branding appeal was statistically significantly higher than the purchase appeal group (U = 27973, p < .000) (see appendix a).

Table 5 – t-tests for equality of means (VTR log)

Variable	Yes	No	Mean difference between groups	t	Sig (2-tailed)
Branding appeal* (vs purchase appeal)	10,83%	4,59%	6,24%	-7,838	,000
Person*	13,89%	7,22%	6,67%	-2,516	,013
Wording (Black)*	4,46%	10,11%	-5,65¨%	7,390	,000
Wording (discount)*	3,31%	9,90%	-6,59%	6,178	,000
Wording (participate)*	9,36%	8,18%	1,18%	-6,168	,000
Wording (no)*	4,78%	9,23%	-4,45%	2,952	,003
Wording (store)*	6,82%	8,82%	-2,00%	2,014	,044
Wording (valid)	**	**	**	0,848	,397
Wording (consult)	**	**	**	0,783	,435
Wording (promotion)	**	**	**	1,1638	,102
Wording (new)	**	**	**	0,792	,428

*Statistically significant differences between groups.

t-test: VTR and Branding Appeal

Regarding the Visit though rates (VTR), the results suggest a statistically significant difference of means between the groups of adds with branding appeal compared to the group of ads with no branding appeal (with purchase appeal) (M branding appeal = 10,83% vs Mpurchase appeal = 4,59%; p-value < .001). The tests revealed significant differences between the branding and purchase appeal conditions. There is a mean difference of 6,24% between groups. That means that an add with branding appeal tends to drive (6,24%) more visits to the offline point of sale than an add with purchase appeal. Unlike adds with a purchase appeal, that focus on prices and rebates, adds focusing on branding appeal focus on consumer values. That is in congruence with Hornik et al.(2017) conclusions that consumers

respond to emotional appeals more favorably than to rational appeals.

t-test VTR and person

Regarding the visit through rate (VTR), the t-test result suggests a significant difference of means between the groups of adds with the presence of a person compared to the group of ads without any person (t = -2,516; p-value <0,013). There is a mean difference of 6,67% between groups. That means that an add displaying a person tends to drive (6,67%) more visits to the offline point of sale than one with no person. That reinforces Mazloom et al.(2016) study conclusions, that posts showing one person or people with products are more attractive and will likely get a higher number of likes.

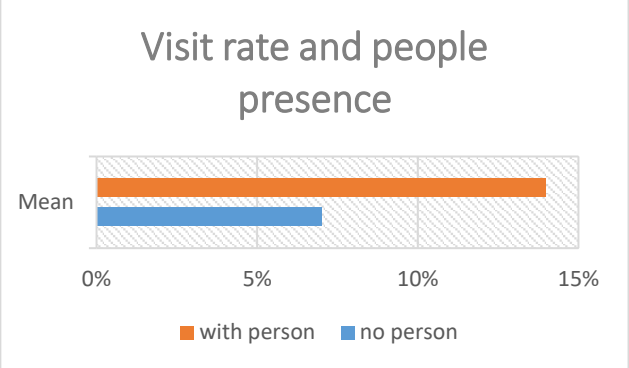

Figure 6 – Mean plots VTR and person

t-test VTR and wording

Regarding the visit through rate (VTR), the results suggest a significant difference of means between the groups of adds that display the following words: black, discount and participate, straightening the importance of a sense of reward in mobile adds, as Komulainen et al. (2013) and Gutierrez et al.(2019) posited.

Univariate analysis involves statistical techniques that focus and highlight the structure of simultaneous relationships between 3 or more phenomena (Cooper & Schindler, 2003). The following model helps to explain which variables of a mobile add have an effect on the number of visits to stores. In this case, the independent variables are categorical (branding appeal, purchase appeal, presence or not of price, discount and people, and wordings) and the dependent variable is metric (visits to the offline site). We performed a Univariate Analysis of Variance (ANOVA), in order to spot the combination of content variables that provides the best driver for offline visits.

Table *6* – Between subjects factors ANOVA

Between-Subjects Factors		
		N
BrandingAppeal	0 no	248
	1 yes	377
Person	0 no	519
	1 yes	106
Black	0 no	444
	1 yes	181
Discount	0 no	479

	1 yes	146
“Participe”	0 no	531
	1 yes	94
No	0 no	510
	1 yes	115

Regarding the Analysis of Covariance, the statistically significant covariates are the interactions between the expressions “no” and “discount” and “no” and “participate” ($p < .01$).

Tests of Between-Subjects Effects

Dependent Variable: LN_VTR

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	362,561[a]	9	40,285	31,311	,000
Intercept	334,894	1	334,894	260,291	,000
BrandingAppeal	29,155	1	29,155	22,661	,000
Person	3,129	1	3,129	2,432	,119
Participe	16,463	1	16,463	12,795	,000
Black	,269	1	,269	,209	,648
Desconto_s	6,782	1	6,782	5,271	,022
Não	32,791	1	32,791	25,487	,000
Participe * Black	13,916	1	13,916	10,816	,001
BrandingAppeal * Person	6,332	1	6,332	4,921	,027
LN_CLICKS	163,938	1	163,938	127,418	,000
Error	791,266	615	1,287		
Total	2218,637	625			
Corrected Total	1153,827	624			

a. R Squared = ,314 (Adjusted R Squared = ,304)

Table 7 – Parameter Estimates

Dependent Variable: LN_VTR

Parameter	B	Std. Error	t	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
Intercept	5,651	,632	8,935	,000	4,409	6,893
[BrandingAppeal=0]	-1,096	,266	-4,116	,000	-1,619	-,573
[BrandingAppeal=1]	0[a]	.	.	.	.	.
[Person=0]	-,558	,146	-3,826	,000	-,844	-,272
[Person=1]	0[a]	.	.	.	.	.
[Participe=,00]	-2,051	,581	-3,532	,000	-3,191	-,911
[Participe=1,00]	0[a]	.	.	.	.	.
[Black=,00]	-1,120	,585	-1,915	,056	-2,268	,029
[Black=1,00]	0[a]	.	.	.	.	.
[Desconto_s=,00]	,463	,202	2,296	,022	,067	,860
[Desconto_s=1,00]	0[a]	.	.	.	.	.
[Não=,00]	-1,010	,200	-5,048	,000	-1,402	-,617
[Não=1,00]	0[a]	.	.	.	.	.

[Participe=,00] * [Black=,00]	1,963	,597	3,289	,001	,791	3,135
[Participe=,00] * [Black=1,00]	0[a]	.	.	.	.	.
[Participe=1,00] * [Black=,00]	0[a]	.	.	.	.	.
[Participe=1,00] * [Black=1,00]	0[a]	.	.	.	.	.
[BrandingAppeal=0] * [Person=0]	,653	,294	2,218	,027	,075	1,231
[BrandingAppeal=0] * [Person=1]	0[a]	.	.	.	.	.
[BrandingAppeal=1] * [Person=0]	0[a]	.	.	.	.	.
[BrandingAppeal=1] * [Person=1]	0[a]	.	.	.	.	.
LN_CLICKS	-,390	,035	-11,288	,000	-,458	-,322

a. This parameter is set to zero because it is redundant.

The results revealed a slight two-way interaction between branding appeal and the wording "participate". With parallel lines, it shows no inter-correlation between the presence of a person and a branding appeal in the add. Same happens with the purchase appeal. That means, the presence of a person in the add has a positive effect on visits, regardless of the add's appeal. The interactions were calculated with a 95% confidence interval.

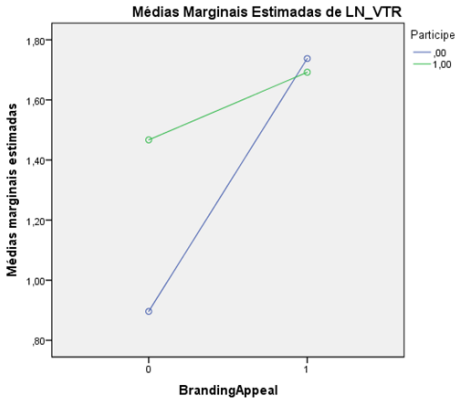

Figure 7 - Interaction between branding appeal and wording for log VTR.

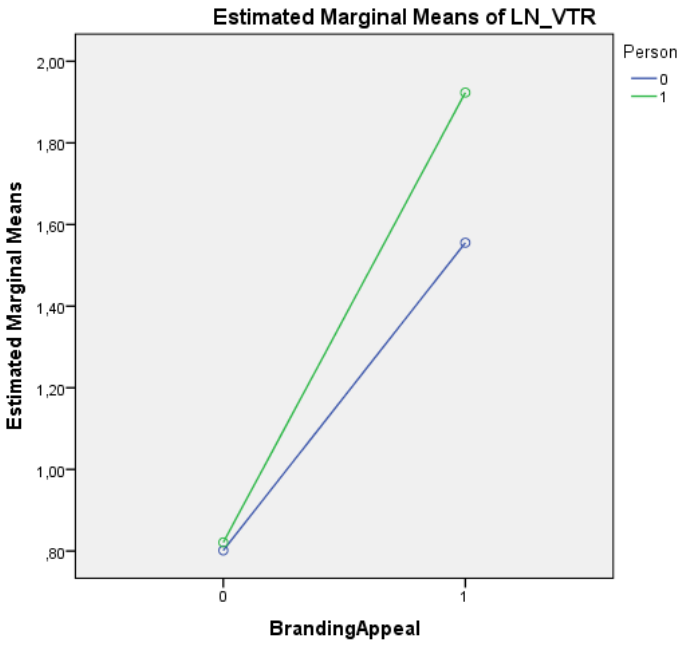

Figure 8 - Interaction between branding appeal and person for log VTR

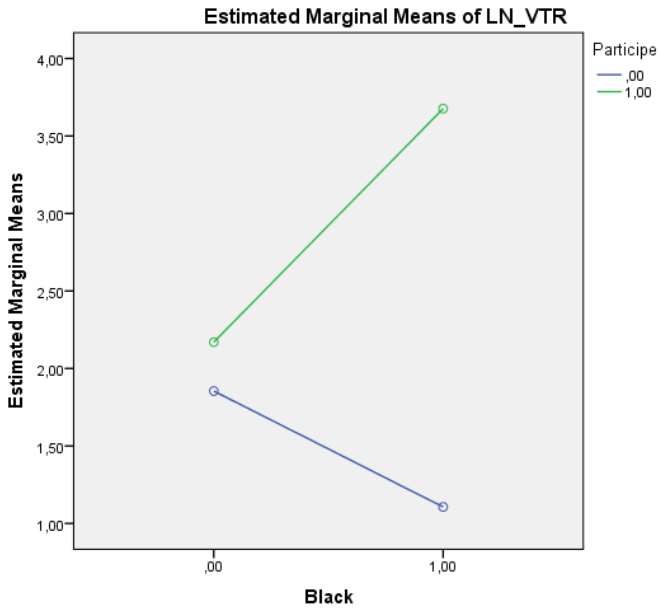

Figure 9 - Interaction between wording ("Black" and "participe") for log VTR

8. Black * Participe

Dependent Variable: LN_VTR

Black	Participe	Mean	Std. Error	95% Confidence Interval	
				Lower Bound	Upper Bound
,00	,00	1,720[a]	,105	1,514	1,925
	1,00	1,808[a]	,151	1,511	2,104
1,00	,00	,876[a]	,122	,636	1,117
	1,00	2,928[a]	,582	1,785	4,071

a. Covariates appearing in the model are evaluated at the following values: LN_CLICKS = 4,5823.

9. BrandingAppeal * Person

Dependent Variable: LN_VTR

BrandingAppeal	Person	Mean	Std. Error	95% Confidence Interval	
				Lower Bound	Upper Bound
0	0	1,496[a]	,167	1,167	1,824
	1	1,400[a]	,282	,846	1,955
1	0	1,939[a]	,182	1,582	2,295
	1	2,497[a]	,216	2,073	2,920

a. Covariates appearing in the model are evaluated at the following values: LN_CLICKS = 4,5823.

Discussion and conclusions

This study analyzed which visual and textual features are predictors of higher offline store visit rates from mobile campaigns, with the aid of computer vision, machine learning and image detection applications. It analyzed 640 creatives from mobile campaigns that ran from November 2019 until March, 2020. It brought some insights into the use of language and images that can help create mobile campaigns that have greater potential for engagement and conversion.

The goal was to compare the effects of message content variables in mobile promotions, looking for the ones that provide drivers for store visits, based on the evaluation of information from the images of the mobile advertising campaigns and its overall performance data. That is: which variables better explain the store visit rates based on the evaluation of information from the images of the advertising campaigns, the number of views and the number of clicks? Prior to this study, no empirical research had investigated non-monetary mobile message content effects, via push notifications, on store visits, connecting online efforts to offline behavior.

As academic contribution, the research enhanced the theories of mobile marketing, geolocation and behavioral targeting, from a cross-channel perspective. This research explored three mobile dimensions: temporal, spatial and semantic. The main scientific contribution was to analyze the causal effects of the message content (visual and textual features) that generate more visits to brick-and-mortar stores. It demonstrated the importance of a branding appeal in mobile message content.

An add with branding appeal tends to drive (6,24%) more visits to the offline

point of sale than an add with purchase appeal. Unlike adds with a purchase appeal, that focus on prices and rebates, adds focusing on branding appeal focus on consumer values. That is in congruence with Hornik et al. (2017) conclusions that consumers respond to emotional appeals more favorably than to rational appeals. Also, an add displaying people tends to drive (6,67%) more visits to the offline point of sale than one with no person. That reinforces Mazloom et al. (2016) study conclusions, that posts showing one person or people with products are more attractive and will likely get a higher number of likes. Interesting to notice, 60% of the mobile adds from the sample display a branding appeal. However, only 17% of the adds from the sample display a person, a managerial opportunity for advertisers in charge of mobile campaigns. From the Descriptive Statistics Table, it stands out that there were few adds displaying animal images. Even adds from the Pet Industry did not use animals in the creatives.

As Ghoose et al. (2015, p.2) pointed out, the digital trace of consumers' offline behavior has become increasingly critical for businesses today, to understand consumers' inherent preferences and improve marketing strategies. Of course, this should be done anonymously, not at the individual level, but with clusters of predictive behavior. Geolocation comes as a unique touch in such process. Mobile marketing has the power to help brands build personal relationships with the customers. However, there is a thin line between making the customer feel special and making them feel stalked, due to the intimacy character of mobile devices. In the Mother's Day, for instance, messages like "Your mother deserves the best" generate more engagement than others like "Have you bought a gift for mom yet?". According to the results, mobile favors messages with an emotional branded appeal.

The research question referred to the visual and textual features that may work as predictors of higher visit through rates (VTR) in mobile campaigns. Variables that displayed a positive effect: branding appeal, person/people presence, use of words black (Friday), discount and participate. The results revealed a slight two-way interaction between the following words: "black" and "participate" / "discount" and "no".

Regarding the visit through rate (VTR), the results suggest a significant difference of means between the groups of adds that display the following words: black, discount and participate, straightening the importance of a sense of reward in mobile adds, as Komulainen et al. (2013) and Gutierrez et al. (2019) posited. The results displayed no two-way interaction effect between branding appeal and the presence of a person / people. That means, the presence of a person in the add has a positive effect on visits, regardless of the add's appeal.

As per managerial implications, this research contributes by enlightening the factors that are likely to affect mobile advertising campaign performance. Understanding how mobile technology can be used to guide customers to in-store purchases helps improve retail media budget allocation to increase marketing ROI for mobile campaigns. Knowing more about the motivations for adopting mobile throughout the shopping journey in cross-channel environments, companies can deploy more efficient marketing strategies. Such as that branded mobile content has a significant and positive relationship with store visits.

The first limitation of this study is that the causal inference was limited by the lack of random assignment of the intervention. Another limitation is that it observed which units were in which treatment groups; we didn't get to control that assignment (Oehlert, 2010). Thus, we realize that observed differences in responses

between treatment groups could very well be due to other hidden mechanisms. For the cloud vision study, the limitation was data it required specific know how for the codification and the setup. Therefore, the study used just part of the available data. Due to technical limitations, the study could not analyze the media richness variable. Future studies can include more variables that may also affect store visit than the ones considered in the proposed model. Last, the model is not a prediction one, but rather targeted at effects explanation.

A suggestion for further research is to include product category involvement in the analysis. According to Bernritter et al (2021), out-store location-based mobile marketing work better for price promotions when the involvement is low and non-price promotions when the involvement is high. Hence, that is a variable to be considered in further analysis.

Another suggestion for future research is the matter of possible cannibalization between channels. What if the effort to attract customers to one channel detracts them from the others, for instance, due to different pricing strategies? Channels from a same company should not be turned against each other. Apparently, contradictory channel strategies may end up turning against the company itself, but that deserves further investigation. Another is regarding conversion for high involvement items in mobile, considering confidence in the seller versus screen size. Other is to analyze the linguistic elements of the mobile message across the customer journey. The effects might be different along the steps of the journey.

This study did not consider questions regarding the relative effectiveness of advertising between mobile and other channels, neither did it consider mobile message content impact on mobile purchase behavior. Further studies could look at online communication (mobile push) and online behavior (clicks and site or app visits). Also, it would be interesting to analyze the interaction effects of mobile marketing with other media. These worthwhile questions were beyond the scope of the current research but could be promising avenues for future studies. This study was a first step in the challenging quest for comprehending the variables in mobile promotion messages that affect the consumer response in the offline world. Following studies shall pursue further enlightenment for the improvement of mobile campaign performance.

Mobile is a critical avenue for cross-channel growth, not only regarding conversion, but also by facilitating fulfillment and driving research and consideration, the ideal context for push notifications. Hopefully, future research will bring insights to the next phase of this exciting mobile phenomena. For now, the challenge remains on how to transform mobile data into contextual marketing strategies. The beautiful power of digital technologies, mainly data provided by mobile, is to allow the tailoring of communication. Tailoring to the consumer needs, tailoring to where the consumer is, both in body and mind. It goes beyond advertising: it is about building a message to you. The “brand in the hand” marketing era came, but we are still scratching the surface of the challenges it brought along, like knitting together siloed parts of the customer experience. For that, think mobile.

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