Pontifícia Universidade Católica
do Rio de Janeiro

Diana Sinclair Pereira Branisso

From Clicks to Bricks: Effects of Mobile Location-Based Marketing on Retail Stores Visits

Tese de Doutorado

Thesis presented to the Programa de Pós-graduação em Administração de Empresas of PUC-Rio in partial fulfillment of the requirements for the degree of Doutor em Ciências – Administração de Empesas.

Advisor: Prof. Luis Fernando Hor-Meyll Alvares

Co-advisor: Thomas George Brashear Alejandro

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Abstract

Branisso, Diana Sinclair Pereira; Alvares, Luis Fernando Hor-Meyll (Advisor); Alejandro, Thomas George Brashear (Co-advisor). **From clicks to bricks: effects of mobile location-based marketing on retail stores visits.** Rio de Janeiro, 2021. 200p. Tese de Doutorado – Departamento de Administração, Pontifícia Universidade Católica do Rio de Janeiro.

The retail context faces an increasing omnipresence of mobile technologies. Yet, most purchases are still concluded in brick-and-mortar stores. Many issues arise regarding connecting digital with physical, online and offline, with the consumer proximity to physical locations as an important aspect of the mobile marketing strategic context. Little is known about the effects of mobile location-based marketing on store visits. The objective of this dissertation 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. The method consists of a qualitative study, a secondary data study (study 1), field experiments (studies 2 and 3) and an online experiment (study 4), in a mixed-method approach. The qualitative study involved in-depth interviews with C-level managers and mobile experts from major companies in the digital industry. Study 1 analyzed which visual and textual features are predictors of higher visit through rates (VTR) in mobile campaigns, using computer vision and machine learning in a sample of 640 location-based mobile campaigns. The findings show that mobile adds with branding appeal tend to drive more visits to the offline point of sale than those with purchase appeal. A mobile add displaying a person / people tends to drive more visits to the offline point of sale than one with no person. Words “black”, “discount” and “participate” displayed a positive effect. Study 2 tested the effect of the proximity of the consumer to the location in response to mobile push notifications. Study 3 tested the effects of mobile message content (promotional, branded or personalized prompts) combined with geolocation data on store visits. Both studies were conducted in a field experiment in a large shopping mall, with the mall app users. Given the limitations of the data from studies 2 and 3, due to Covid-19 pandemic, a fourth online experimental study was conducted, with 1.534 participants. As theoretical contribution, it provided new perspectives on mobile marketing, location-based communication and push-notification effects on customers’ attitudes and behavior, bringing further insights into the “brand in the hand” marketing era. The results help directing mobile marketing strategic decisions, driving actions of smaller reach but greater precision, with expected higher conversion rates.

Keywords

Mobile Marketing; Location-Based Marketing; Geolocation; Message Content; Mobile Promotion.

Resumo

Branisso, Diana Sinclair Pereira; Alvares, Luis Fernando Hor-Meyll (Advisor); Alejandro, Thomas George Brashear (Co-advisor). **De cliques a tijolos: efeitos do marketing mobile geolocalizado na visita a lojas.** Rio de Janeiro, 2021. 200 p. Tese de Doutorado – Departamento de Administração, Pontifícia Universidade Católica do Rio de Janeiro

O varejo se depara hoje com a crescente onipresença de tecnologias móveis digitais. No entanto, a maioria das compras ainda é concluída em lojas físicas. Muitas questões surgem então com relação à conexão do digital com o físico, do online e do offline, sendo a proximidade do consumidor com relação ao ponto de venda um aspecto instigante do contexto estratégico do mobile marketing. Pouco se sabe ainda sobre os efeitos do marketing baseado em localização nas visitas à loja. O objetivo desta tese é então examinar os efeitos do conteúdo de mensagens mobile e dos dados de geolocalização nas visitas às lojas, conectando os esforços online ao comportamento offline, em uma perspectiva *cross-channel*. O método consiste em um estudo qualitativo, um estudo de dados secundários (estudo 1), experimentos de campo (estudos 2 e 3) e um experimento online (estudo 4), em uma abordagem de método misto. O estudo qualitativo envolveu entrevistas em profundidade com gerentes de nível C e especialistas em mobile de importantes empresas da indústria digital. O estudo 1 analisou quais elementos visuais e textuais são preditores de taxas mais altas de visitação (VTR) em campanhas mobile, usando visão computacional e aprendizado de máquina em uma amostra de 640 campanhas de celular baseadas em localização. Os resultados mostram que anúncios mobile com apelo de marca tendem a gerar mais visitas ao ponto de venda do que aqueles com apelo de compra. Um anúncio mobile exibindo uma pessoa / pessoas tende a gerar mais visitas ao ponto de venda do que um sem pessoa. As palavras “black”, “desconto” e “participar” tiveram um efeito positivo nas visitas. O Estudo 2 testou o efeito da proximidade do consumidor ao local em resposta a notificações *push* mobile. O Estudo 3 testou os efeitos do conteúdo de mensagens mobile (prompts promocionais, de marca ou personalizados) combinados com dados de geolocalização em visitas a lojas. Ambos os estudos foram realizados em um

experimento de campo em um grande shopping center, com os usuários do aplicativo do shopping. Dadas as limitações dos dados dos estudos 2 e 3, devido à pandemia de Covid-19, foi realizado um quarto estudo experimental online, com 1.534 participantes. Como contribuição teórica, os estudos forneceram novas perspectivas sobre mobile marketing, comunicação baseada em localização e efeitos de notificação *push* sobre as atitudes e comportamento dos clientes, trazendo mais insights sobre a era do marketing de "marca na mão". Os resultados ajudam a direcionar decisões estratégicas de mobile marketing, impulsionando ações de menor alcance, mas maior precisão, com expectativa de taxas de conversão mais altas.

Palavras-chave

Mobile Marketing; Marketing baseado em localização; Geolocalização; Conteúdo de mensagem; Promoção Mobile.

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1.
INTRODUCTION

> "*We can take comfort in the emerging consensus that any hope for the scientific study of consumption hinges on our abilities, however fragile and however variegated, to construct meaningful interpretations of consumer behavior.*"
>
> (HOLBROOK; O'SHAUGHNESSY, 1988, p.402)

From the 1990s onwards, digital technology has advanced at a very intense pace (PARASURAMAN & COLBY, 2015), involving online shopping, social media, automation, digital payments, and the emergence of mobile commerce, dramatically changing how the customer journey is experienced (OSTROM et al., 2015). The COVID-19 pandemic has accelerated this digitalization process, bringing major changes in digital trends (STATISTA, 2020; COMSCORE, 2020).

The digital consumer is constantly on the move, short of time, searching for convenience, entertainment, and fun. The digital consumer motivations and believes are essentially settled in a tripod of socialness, hedonism and functionality. The Web 2.0 technology enabled customers to engage in product recommendations, to provide financial resources for product development and to take part in strategic decision-making (PEE, 2016), that is, the technology has enabled customers to engage in the shopping process. The Web 3.0 focused on using a machine-based understanding of data to provide a data-driven and semantic web. And, as of these days, the Web 4.0, also known as symbiotic web, led to the interaction between humans and machines in symbiosis, with mobile devices as the hub of such process.

During the reshaped shopping journey, the consumer deals with many screens - television, Tablets, notebooks, video games… - being the smartphone screen the most coveted one. Consumers have embraced mobile technology, using such devices for various purposes: research, purchases, payments and engaging with other customers. No recent technological innovation has had a more transformative effect on consumers' lives than the virtually indispensable smartphone (MELUMAD & PHAM, 2020). Hence the growth of Mobile Marketing as a field study.

Mobile Marketing

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.

In 2019, adults spent an average of 3,7 hours per day connected on mobile devices, excluding voice activities (APP ANNIE, 2020). Also, over 50% of the web traffic came from mobile devices (STATISTA, 2020), leading businesses to extend their reach to customers throughout this channel. For the first time in 2015, Chinese consumers made more purchases through mobile phones than through computers. Since then, the mobile app usage has soared (APP ANNIE, 2020). At the same time, consumers are overwhelmed with advertising while companies are pressured to improve their performance numbers. In some countries, such as China, US, Norway and Russia, digital has already become the dominant ad medium in expenditure (EMARKETER, 2019).

According to the Mobile Marketing Association (2016), mobile marketing is a set of practices that enable organizations to communicate and engage with their audience in an interactive and relevant manner through and with any mobile device or network. Mobile ad expenditure is expected to reach US$240 billion by 2020 as brands harness mobile potential (APP ANNIE, 2020). Besides, mobile banners do a better job of breaking through when it comes to ad recognition and message recall compared to desktop banners, due to the immediacy and intimacy of mobile (METRIXLAB, 2018). Mobile is fast becoming what Fulgoni and Lipsivian predicted back in 2016 (p.346): “the channel that will shape the future of retail”. Yet, there are many questions and challenges that arise from this transformation.

With the huge offer in the app market with the most varied functions and services, consumers lack time in the agenda and space in the smartphone memory (storage space) to take advantage of all the services available in the app stores. It is a tough task to engage consumers in an app. They make dozens of downloads, but soon find no relevance and uninstall. Apps drain battery, caches data and many have high CPU power usage and, worst case scenario, are irrelevant. The global number of app downloads reached 204 billion in 2019, thanks to growth in emerging markets including China, India, Brazil and Russia (APP ANNIE, 2020). Despite the enormous number of downloads, the uninstallment rates are also high: 31% in US after 30 days in average (APP ANNIE, 2020).

The top markets by consumer app expenditure have all seen double-digit percentage growth during this time, with China in the lead (+270%), followed by Brazil (+80%), the U.S. (+75%), India (+60%), and Russia (+35%) (APP ANNIE, 2020). The so call bricks-and-clicks apps saw strong gains in total user sessions over the 2018-2020 period often out-pacing digital-first apps, which reflects how central is mobile to growing retail business.

In populous countries like India, China and Brazil, a growing demand for online shopping represents a huge growth potential for mobile applications. The portion of digital retail spending done on mobile has been increasing in US: from 16% in 2015 to 31% in 2020 (COMSCORE, 2020; STATISTA, 2020). And total e-commerce sales in the third quarter of 2020 accounted for 14.3 percent of total sales in US (Digital Commerce 360, 2020). Worldwide, e-retail sales accounted for 14.1 percent of all retail sales in 2019. That is, even with significant growth, mobile commerce still represents a small fraction of total sales. However, although a small part of the retail purchases is made by mobile, its 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 (APP ANNIE, 2020). That is why Mobile has also 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.

In that sense, according to Forrester Research Inc., smartphones impacted 34% of total retail sales in the US in 2018, which represents more than $1 trillion. In 2022, the research firm estimates that smartphones will affect 42% of total retail sales. The company defines impact as a measure of the effect of online search on physical retail sales. “Shoppers have integrated smartphones into their product research at every phase of the customer life cycle, from discovery to price checking in-store" (FORRESTER, 2018). The relationship between digital technologies and the retail environment is more complex than what current accounts depict (PANTANO & GANDINI, 2018). During consumer journey, mobile is mostly used for education, information and engagement, not necessarily for the last click. Searching for online information before visiting a store creates an anticipation itch, boosting desire. "Mobile is the hub of omnichannel marketing and retailing with connected customer experience (…) playing an integral role in the physical world, both with respect to consumer's shopping behaviors and firms' targeting strategies" (VERHOEF et al., 2017, p.5). Yet, firms still struggle to measure mobile attribution. Marketers are unclear about the degree to which mobile drives revenue and profitability, in the challenge of accurate attribution (BAKOPOULOS et al., 2017). Hence, rather than focusing on driving more sales via mobile channel, research can also address the mobile opportunities that arise to increase overall sales. That is, understanding how mobile can use, for instance, push notifications to drive sales in physical stores. The path is analytics-driven, clustered data approach. According to Pantano and Gandini (2018), the shopping experience is "no longer limited to the physical point of sale. This means that retailers should be able to provide a shopping experience that is natively networked" (p.690). For example, Kim, Wang and Malthouse (2015) research demonstrated that app adoption and continued use of the branded app increase future spending. However, they also observe "the recency effect" – when customers discontinue using the app, their spending levels decrease. Therefore, the authors point to a need to understand what influences the use of mobile in a cross-channel environment, since its use tends to have a positive impact in customer's overall expenditure. Specifically, regarding how location based-mobile promotions impact foot traffic acquisition and offline purchasing behavior.

Location-based Marketing

Mobile geolocation is a novel technology, and studies on its effects on customers' responses are still scarce. 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. 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”.

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, playgrounds… (HANDS, 2020).

Retail dynamics today go beyond the dichotomy of physical or digital environment. It is commonsense that channels are not exclusive anymore: consumers can relate to physical and digital channels at different times throughout the shopping experience. Due to this growing intertwining between online and offline in the customer journey, some studies (PANTANO & PRIPORAS, 2016; BEECK & TOPOROWSKI, 2017, VERHOEF et al., 2017; GREWAL et al., 2018) recommend further research regarding how to attribute online and mobile activities to physical store purchases. These studies indicate the need to systematically investigate the impact of mobile promotions in offline purchase behavior.

1.1. Research problem and objective

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 and 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), Fong et al. (2015), Molitor et al. (2016) and Beeck and Toporowski (2017), the objective of this dissertation 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.

To better address the problem, the research uses a mixed-method approach, combining a qualitative study, a secondary data study, field experiments and an online experiment. The purpose of the qualitative study was to identify managerial perceptions and experiences about mobile promotions in detail, as well as important variables regarding the mobile marketing relationship to offline store visits. The secondary data study analyzed which visual and textual features are predictors of higher store visit rates in mobile campaigns, supporting the message content definitions of the field and online experiment. At last, the field and online experiments analyzed the effects of location and mobile message content on store visits.

1.2. Relevance

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). Mobile literature (SHANKAR et al., 2016; PANTANO & PRIPORAS, 2016; GUTIERREZ et al., 2019; HÖGBERG et al., 2020) points out to a lack of a more comprehensive approach regarding mobile role in the cross-channel customer journey**.** Particularly, little is known about the effects of mobile location-based marketing on store visits. Mobile advertising and use grow at double digit rates year after year (STATISTA, 2020), yet most purchases are still concluded at physical establishments (Digital Commerce 360, 2020). There are still few studies regarding the effects of mobile efforts in offline behavior, under the online-to-offline (O2O) perspective (CHIANG et al., 2018).

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.

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. There is a research gap in regard to visual and textual elements of mobile message and their effects on offline performance. So far, research on the use of mobile in the purchase funnel has been limited and has mainly been done in practice (LEMON & VERHOEF, 2016). There is yet much to understand in regard to 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 a O2O model.

As Lamberton and Stephen (2016, p.164) mention, the crossover between the online and physical worlds warrants deeper exploration, trying to answer questions such as how do online and offline marketing activities affect one another? What frameworks can we construct to help us understand mobile opportunities as technology advances? For those authors, mobile use represents a domain of online–offline convergence and, "importantly, will require the development of a data-driven theory" (p.165). They advocate that researchers focus on understanding the marketing value of mobile technology aspects that allow marketers and/or consumers to do things that cannot be done with nonmobile technology, such as geo-located ad targeting. This research intends to contribute to theories of mobile marketing, cross-channel consumer behavior as well as to the understanding of geolocation promotions.

The mobile marketing research is still most prominent amongst IT journals, according to Hew's (2016) analysis of the 10 most productive journals in mobile research from 2000-2015. Leading the rank in number of publications counts, comes the *International Journal of Mobile Communications*. In the impact factor criteria, there is the *Computers in Human Behavior.* Whereas in total cites, we have the *Information & Management* journal, followed by *Computers in Human Behavior*. The work published in *Information & Management* has been able to deliver enormous impact, considering the ratio between number of citations and number of publications. There is room for more marketing oriented mobile studies.

Despite substantial efforts to explore the mobile research agenda, mainly by IT journals as mentioned, important topics remain untouched by current research (TONG et al., 2020). As per Beeck and Toporowski's research (2017), only a few studies analyze the impact of the mobile on customer's purchase behavior in a cross-channel perspective. This cross-channel perspective can be either online to offline or offline to online. According to Coelho (2017), when choosing a shopping channel, the consumer can present two types of behavior: showrooming (product search in physical stores and intention to transact in the digital environment) and webrooming (product search in virtual stores and intention of trading in physical stores). Besides, Molitor et al.(2016) recommend the use of offline purchase data for geolocation studies.

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 in order to 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. The research may also provide the basis for a mobile model for companies to attract consumers to physical locations.

The present research is organized in eight chapters. The first is the introduction, and refers to the background, purpose and usefulness of the research. The second focuses on a literature review of prior research that develops the theory and support for hypothesis related to the effects of location-based mobile messages effects on store visits. The third chapter presents the overall methodology used along the research. Chapter four refers to the qualitative study. Following, chapters five, six and seven present the quantitative studies that test the hypotheses. Finally, a discussion of the implications of the findings for the consumer behavior field, particularly regarding mobile marketing. The work concludes with a discussion of the limitations of the study and directions for future research.

Table 1 - Prior Geolocation Mobile Studies

Authors		Method	Indepen	Variables		Goal	Main Conclusions
Hui et al, 2013	Paper coupon	Field Experiment	In-store path length, impulsivity, shopping budget and demographics.	Unplanned expenditure	Mobile promotion coupons. Participants agreed to use a PathTracker belt, embedded with an RFID tag.	Analyze the effect of In-Store travel distance on unplanned spending	Targeted mobile promotions aimed at increasing in-store path length can increase unplanned spending.
Luo et al, 2014	Push (SMS)	Field Experiment	Temporal and geographical distance	Response to discounted movie tickets	Promoted in cooperation with IMAX Theaters. The wireless provider sent SMS messages promoting discounted tickets. Recipients purchased movie tickets by downloading the accompanying movie ticket application.	Analyze how well geographical and temporal targeting strategies work when considered in combination.	In terms of short distances to cinemas, redemption likelihood is highest if the coupons are sent on the same day. For longer distances, a promotional lead time of one day leads to the highest redemption likelihood
Danaher et al, 2015	Push (SMS)	Panel /Observational data	Coupon characteristics and location-based covariates	consumer response to coupon	Mobile coupons sent out to mall visitors by a third party.	Exam the influence of both traditional and new coupon characteristics on the redemption of m-coupons.	Location and time of delivery significantly influence redemption
Fong, Fang and Luo, 2015	Push (SMS)	Randomized field experiment	Competitive locational targeting and discount sizes (20, 40, 60%) - geo-conquesting	Purchase rate	Promotional offers were sent to mobile users located near a focal retailer's own location, a competitor's location, and a benchmark location	Anlyze the causal effects of locational targeting	Large discounts were optimal for the competitive location, whereas medium discounts were optimal for the focal location. Overall redemption rate of 2.5% for all of the treatment combinations
Molitor et al, 2016	Pull	Large-scale randomized field experiment	Providing distance information and a distance-based ranking mechanism (display rank)	Clicks on coupons (click as a positive response)	Mobile coupon aggregator, consisting of 3,152 different stores in 2,589 cities in Germany, for 13 product categories.	Study and quantify the impact of distance on the effectiveness of location-based coupons.	The most effective coupon interface design is based on offers that are sorted by distance; increased distance decreases the likelihood of coupons being chosen. The trade-off between discount and geographical distance is therefore 148 meters per percentage point of discount.
Dubé, J. P., Fang, Z., Fong, N., & Luo, X., 2017	Push (SMS)	Field Experiment	Random prices of competing movie theaters, consumer locations	Ticket purchase	A mobile SMS promotion consisted of an offer to buy one voucher for any 2D movie showing at a given movie theater on the day the SMS message was sent.	To test mobile targeting based on consumers' real-time and historic locations.	Geoconquesting study. Findings demonstrate the importance of considering competitor responses when piloting novel price-targeting
Beeck and Toporowski, 2017	Pull	Online based experiment	Location (home, city, shop) and content (coupon, promotional message)	Intention to redeem	Discount Shopping App	Examine the effect of mobile messages on intention to redeem a coupon or promotional offer, depending on location and content.	Low usage rate for discount mobile applications.
Ghose, A.; Li, B.; Liu, S., 2019	SMS coupons	Large-scale randomized field experiment	No ads; ads from randomly selected stores; ads based on current location information; ads based on trajectory information.	Coupon redemption	June 2014. Shopping mall with more than 300 stores.	Analyze the effectiveness of a novel "trajectory-based" targeting strategy for mobile recommendation that leverages physical movement trajectories and behavioral information.	Trajectory-based mobile targeting can lead to higher redemption probability, faster redemption behavior, and larger transaction amounts.
Högberg, J., Wästlund, E., Aas, T. H., Hjemdahl, K., & Nordgård, D.. ,	Push notification	Field Experiment	Labelling participants with an appropriate trait vs a neutral ad	Geographical data iBeacon (visit to the location)	Mobile messages sent to visitors living in a limited area near Dyreparken Park (Norway).	Investigates modes (pay or nudge) of moving visitors in a tourist location using a location-based service.	The label had a positive and significant effect on moving visitors to the targeted location.

2.
LITERATURE REVIEW

The literature review covered three streams of research, which goes from more broadly investigating Mobile Marketing to a narrower focus on location-based communication: 1) Mobile Marketing: from online to offline, focusing on how mobile technologies affect consumer offline behavior in brick-and-mortar stores (online to offline relationship); 2) Mobile Promotions and the main mobile pull and push promotions in retail settings; and finally, 3) the specific domain of this research, mobile marketing location-based promotions, which comprises the current state of the art in the research on push notification and geolocation, taking an O2O (online-to-offline) perspective and highlighting moderating contextual effects (see Figure 1). The major authors in each stream of research are highlighted in Table 2.

This literature review explores the contributions of mobile marketing theory, as well as the understanding of geolocation promotions, in a cross-channel customer behavior perspective. By identifying strategies that marketers may employ for more effective geolocation promotions, the review provides an overarching framework to synthesize current findings in mobile location-based marketing and identifies gaps in the current knowledge, that lead the research field work.

Figure 1 - Literature overview

Table 2 - Mobile Marketing research themes

	Investigation	Authors
Offline purchase behavior	How mobile technologies affect purchase behavior in retail brick-and-mortar stores.	Andrews et al. (2016) Groß (2015) Bakopoulos et al. (2017) Shankar et al. (2016)
Promotion Strategies	Mobile pull and push promotions in retail settings.	Beeck and Toporowski (2017) Fong et al. (2015) Tang et al. (2016)
Geolocation Promotions	Mobile targeting (location-based) promotions.	Verhoef et al. (2017) Grewal et al. (2018) Ieva et al. (2018) Pantano and Gandini (2018) Fulgoni and Lipsman (2016) Grewal et al. (2016) Hui et al. (2013)

The theoretical framework adopted derives from a reflection on the literature review, covering factors that shaped the conceptual model of the research. It is related to previous literature on the interaction between online and offline channels (HUI et al., 2013, PANTANO & PRIPORAS, 2016, BAKOPOULOS et al., 2017, LESSCHER et al., 2019). It also relies on the theories of Location-based Mobile Targeting (HUI et al., 2013, LUO et al., 2014, MOLITOR et al., 2016, GHOSE et al, 2019, PATSIOTIS, 2020), as well as device-specific promotions and behavioral targeting to develop the study hypotheses. .

1.3. Mobile Marketing - Online to offline

The use of mobile marketing has increased in recent years as consumer mobile usage and receptivity have grown (FONG et al., 2015), but the replacement of the traditional point of sale is still unrealistic (PANTANO & PRIPORAS, 2016). The shopping process has moved towards a reality that integrates, to say the least, the offline and the online opportunities and functionalities. Mobile device channels interact and may interfere with existing channels (LEMON & VERHOEF, 2016). Hence, there is an increasing need for retailers to integrate physical retail settings with mobile opportunities and functionalities (PANTANO & PRIPORAS, 2016; BEECK & TOPOROWSKI, 2017, VERHOEF et al., 2017; GREWAL et al., 2018). As Lemon and Verhoef (2016, p.69) put it, “customers now interact with firms through myriad touch points in multiple channels and media, resulting in more complex customer journeys”. Regarding the online to offline relationship, it urges to better understand how mobile promotions affect consumer offline behavior.

According to Pantano and Gandini (2018), the intensive use of digital communication technologies and social media emerge as an integral part of the shopping experience inside and outside the store. It does not mean, however, that online and offline retailers are following separate paths. The limits are fluid, with many possibilities of convergence. For example, responsive retail sites or applications can expedite the buyer's search by buying or delivering from the store (SHANKAR et al., 2016). Therefore, the offline operational capacity of the company is equally important to meet the online purchase (TANG et al., 2016).

The retail presence today presents a dynamic that goes beyond the dichotomy of physical or digital environment. It is understood today that channels are not exclusive: consumers can relate to the physical and digital channels at different times throughout the shopping experience (DHOLAKIA et al., 2010; LESSCHER et al., 2019). In addition, mobility and ubiquity allowed the consumer to engage in multitasking behavior, comparing product prices or making buying recommendations while waiting for coffee, for example (BRYNJOLFSSON et al., 2013).

Besides, the location-sensitive nature of smartphones opens the way for communication that is sensitive to the location of the customers (HÖGBERG et al., 2020). Compared to desktops, mobile devices, such as smartphones and Tablets, offer additional benefits such as ubiquitous connectivity, automatic customization, point of sale without contact and greater agility for customers. According to Naegelein et al.(2019), devices can be distinguished along the dimensions of usability and ubiquity. Ubiquity, thanks to portability, is related to the possibility of accessing information anytime, anywhere – the perpetual contact (PHANG et al., 2019). Usability refers to device specific characteristics, including display size, portability and mode of interaction (touch vs non touch). Mobile devices are portable, with small display sizes and touch interfaces, and possess a ubiquitous character.

Convergence is one of the important issues related to the digital world, for instance, in the sense of mobile incorporating more and more functions, such as fulfillment, search and discovery, data provision, payment and customer service shopping (SHANKAR et al., 2016). For example, Amazon has become the digital arm of many small businesses offline. Thus, other convergences between the online and offline worlds are about to emerge. In fact, Pantano and Priporas (2016) highlight the importance of integrating retail physical configurations with online opportunities. For instance, searching for purchases at collection points is a perceived benefit, avoiding delivery problems and allowing consumers to check merchandise, thus reducing risks (PANTANO & PRIPORAS, 2016). The offline channel weighs positively on the possibility of product inspection and on the social aspects of the shopping experience. On the other hand, the online channels offer the benefit of convenience, with the removal of temporal and spatial barriers. The purchase orientation - hedonic or utilitarian - is another important factor that influences the choice of the channel. In addition, the gender, degree of consumer involvement and habit have a significant influence on the choice of physical or digital channel (COELHO, 2017).

A first glance at Mobile Marketing

As per the mobile analysis, the seminal theories continue to influence current researchers. Seminal theories examining acceptance of new technologies such as Diffusion of Innovation Theory (ROGERS, 1983), Technology Acceptance Model - TAM (DAVIS, 1989) and Unified Theory of Acceptance and Use of Technology - UTAUT (VENKATESH et al., 2003) are the core to most of the research regarding mobile (SAN-MARTÍN et al., 2016; HUBERT et al., 2017; GUPTA & ARORA, 2017). Such studies extended those models with new constructs for evaluating and measuring the willingness of acceptance of mobile for shopping.

The first influential theory dates back to the 1970s, with a focus on a broader view of technology (the first mobile call happened in 1973). The Reasoned Action Model has been successful in predicting and explaining behavioral intention by the influence of subjective norms and customer's attitude. According to Fishbein and Ajzen's (1975) theory of reasoned action (TRA), intention represents the tendency to perform certain behavior and is preceded by social influences, personal beliefs and motivations. Over a decade later, Davis (1989) introduced an adaptation of TRA, the technology acceptance model (TAM), to explain computer usage behavior, and then proposed it to explain and predict the acceptance and use of information technology. Davis' model (1989) has been the most cited amongst mobile marketing researchers. Davis, Bagozzi, and Warshaw (1989) proposed a seminal study to understand why people accept or reject computers, by measuring intention-usage correlation within a 14-week window. There was a strong influence of perceived usefulness and a smaller yet significant effect of ease of use. Such historical evolution can be clearly seen in the bibliometric coupling in Figure 2.

Later on, Venkatesh and Davis (2000) presented a theoretical extension of the Technology Acceptance Model (TAM), using longitudinal data, referred as TAM2. According to the model, two types of processes influence user acceptance of technology: social influence processes and cognitive instrumental processes. In 2003, Venkatesh et al.performed an extensive comparison of eight technology acceptance models and their extensions. They merged TAM to develop the Unified Theory of Acceptance and Use of Technology (UTAUT), a model to address new technology introductions.

It was not till the turn of the century that the research focus explicitly embraced mobile. Wu and Wang's (2005) work was one of the firsts to extend Davis's (1989) Technology Acceptance Model for mobile commerce. Surprisingly, perceived ease of use did not affect behavioral intent, but compatibility did. Later, Chong, Chan and Ooi (2012) also studied consumer intention to adopt mobile service extending TAM and the Diffusion of Innovation Model (ROGERS, 2003), including constructs such as trust, cost, and social influence. Lin and Wang (2006) were pioneers in addressing customer loyalty in mobile commerce.

From acceptance to connection: the digital does not stand alone

Figure 2 presents the citation cluster of mobile marketing authors. The study chose the Web of Science's Social Sciences Citation Index (SSCI) as a database and defined the criteria for searching the articles. The search was restricted to the topic (title, keywords, or abstract) using the keywords 'Location-Based Marketing' or 'Mobile Marketing' and its derivatives, from 1979 to 2020. But only from 2004 on, the Mobile Marketing research field showed citations. Next, a cluster analysis was performed with the support of VOSviewer 1.6.13 software, which allows the quantitative analysis of a research area through historical data (authors, citations, co-citations, among others), as well as identifying the main trends. VOSviewer helps the understanding of bibliometric networks through map visualization.

As shown in Figure 2, the red cluster concentrates the research on acceptance of mobile (BAUER et al., 2005; SCHARL et al., 2005; TSANG et al., 2004), but with the focus on mobile campaigns, mainly on acceptance of SMS messages. There is a stronger link of citations from the red to the green cluster with the work of Barwise and Strong (2002), exploring the effectiveness of SMS text messaging as an advertising medium for reaching young adults. Unlike prior work, which has mostly investigated mobile marketing focusing on the acceptance of new technologies context (blue cluster) (DAVIS, 1989; ROGERS, 1983; VENKATESH et al., 2003), a recent distinct research stream (green cluster), has mainly focused on important insights on connecting online efforts to offline behavior. These studies assess how targeted mobile promotions can attract additional customers to physical stores and also increase unplanned spending (HUI et al., 2013).

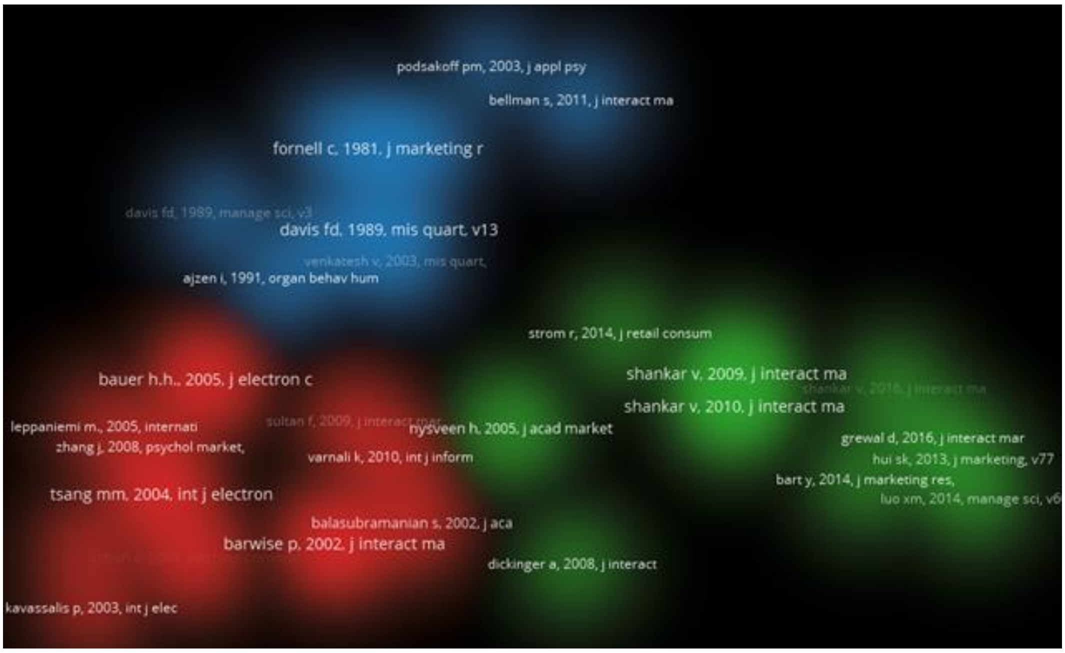


Figure 2 - Mobile Marketing Research – VosViewer Citation cluster

Table 3 - Mobile Marketing research – most cited studies

Authors	Main findings	Citations 2016 435	2017 551	2018 591	2019 908	2020 468	Total 4090
Shankar, Venkatesh, Hofacker, and Naik (2010)	Mobile consumer activities, mobile consumer segments, mobile adoption enablers and inhibitors, key mobile properties, key retailer mobile marketing activities and competition	35	30	27	35	17	229
Shankar and Balasubramanian (2009)	Drivers of mobile device/service adoption, the influence of mobile marketing on customer decision-making, formulation of a mobile marketing strategy, and mobile marketing in the global context	22	26	21	28	5	178
Lamberton and Stephen (2016)	Digital Social Media as a facilitator of individual expression, a decision support tool, and a market intelligence source.	2	20	42	77	33	174
Scharl, Dickinger, and Murphy (2005)	Message and media characteristics influence in three dependent success measures: consumer attention, consumer intention and consumer behavior.	15	13	12	14	7	164
Bellman, Potter, Treleaven-Hassard, Robinson, and Varan (2011)	Apps positive persuasive impact in increasing interest in the brand and brand's product category. Apps with an informational/user-centered style are more effective at shifting purchase intention	22	19	24	29	16	137
Kaplan (2012)	What mobile social media is, what it is not, and how it differs from other types of mobile marketing applications. How firms can make use of mobile social media for marketing research, communication, sales promotions/discounts, and relationship development/loyalty programs.	24	27	22	12	12	135
Zhang and Mao (2008)	Two key determinants of TAM, the perceived usefulness and perceived ease of use of SMS advertising messages, predicted the intention to use them. Trust in SMS advertising and subjective norms also contributed to the intention to use.	7	10	5	10	6	127
Varnali and Toker (2010)	To classify the literature on mobile marketing and assess the-state-of-the-art in order to facilitate future research.	10	12	11	11	5	109
Winer (2009)	The kinds of new media that companies are using to engage customers and the challenges that these media present from the perspective of the marketing manager.	12	15	8	9	8	103
Fong, Fang, and Luo (2015)	Competitive locational targeting produced increasing returns to promotional discount depth, whereas targeting the focal location produced decreasing returns to	10	22	21	31	8	93

The most cited mobile studies are presented in Table 3. Some of these studies suggest factors that enhance mobile shopping adoption (SHANKAR et al., 2010; ZHANG & MAO, 2008), either having a positive effect or working as key mediating mechanisms, whereas others are focused on factors that curtail such technology adoption, such as perceived risks and, most importantly, they present the mobile marketing effect on the customer decision-making process (BELLMAN et al., 2011; FONG et al., 2015). It should also be noted that customers' intrinsic characteristics might affect the mobile adoption intention (PATSIOTIS et al., 2020). In a quest for a more comprehensive framework in mobile shopping, recent studies added different factors to the seminal technology acceptance theories. For instance, Parasuraman and Colby (2015, p.59) updated their Technology Readiness Index, a "scale to measure people's propensity to embrace and use cutting-edge technologies". Such theories, however, mostly analyze mobile through a last click perspective, focusing on whether the purchase happened on the mobile device. But, as Bakopoulos et al. (2017, p.458) point out, the challenge now is to target mobile moments of relevance across the customer journey.

Mobile Marketing and its evolving role in the customer journey

Lemon & Verhoef (2016) refer to the customer purchase journey as the process a customer goes through, across all stages and touch points, that makes up the customer experience. This path-to-purchase is also referred to as the marketing funnel. Back in 1973, Engel, Kollat, and Blackwell proposed a five-step framework to better understand customers' buying behavior. These five stages include 1) problem recognition, 2) information seeking, 3) alternative assessment, 4) purchasing decision, and 5) subsequent buying behavior. Nowadays, these phases of the customer journey are each time more iterative and dynamic (LEMON & VERHOEF, 2016). According to Bakopoulos et al. (2017, p.450), marketers have two goals: strengthen consideration for the brand by reinforcing image perceptions (top of the purchase funnel) and drive sales (lower funnel). Therefore, we can aim at measuring attitudinal consideration (upper funnel) or actual behavioral (lower funnel) to identify consumers at the right moment and use media to trigger immediate response and drive acquisition. That is, there is a choice of attitudinal survey-based metrics (consideration) and/or actual behavioral metrics.

Despite the fact that digital media redesigned the customer journey, research into the cross-channel effects, i.e., offline-to-online, is still scant (LESSCHER et al., 2019). The existing ones focus on the effects of digital banners and website visits on offline purchase likelihood (SRINIVASAN et al., 2016, LOBSCHAT et al., 2017). Verhoef et al. (2017) refers to this notion of consumers moving through different preliminary stages before eventually conducting a purchase as the search-purchase funnel. There is yet much to understand regarding the role mobile plays in cross-channel, search-purchases funnels.

For instance, consumers' intrinsic characteristics also affect the mobile adoption intention. There are differences in consumers according to the stages of adoption in a technology's life cycle (ROGERS, 2003; PARASURAMAN & COLBY, 2015). Young and social media savvy participants with a generally high interest in shopping are usually networked shoppers (PANTANO & GANDINI, 2018). Consumers that feel overwhelmed by technology and that are skeptical about its correct functioning are inhibited to adopt new technologies (PARASURAMAN & COLBY, 2015). Whereas consumers that have a positive view of technology (GUPTA & ARORA, 2017; PARASURAMAN & COLBY, 2015), such as tech pioneers and influential leaders, are usually motivated to adopt technology innovations (PARASURAMAN & COLBY, 2015). Mobile marketing is supported by consumer innovativeness and personal attachment towards mobile technologies (PANTANO & PRIPORAS, 2016).

The consumer's perception of a lack of physical contact in digital channels – the "dehumanizing effect" (PARASURAMAN & COLBY, 2015, p.62) is still ambiguous, working as a driver for some and as an inhibitor to others (PARASURAMAN & COLBY, 2015; CHAPARRO-PELAEZ et al., 2016). New technologies require that not only companies master new skills, but also that customers do (PARASURAMAN & COLBY, 2015), taking the perceived ease of use to a new level. Customers still experience anxiety and lack of confidence in using mobile shopping (GUPTA & ARORA, 2017).

Indeed, literature has struggled to explain why consumers that evaluated a technology-based service positively yet may choose not to adopt it (HEIDENREICH & HANDRICH, 2015). As to this question, Heidenreich and Handrich (2015) replay that convenience in use may be the key to positive evaluation followed by adoption of mobile services.

Mobile adoption intention is strongly affected by perceptions of usefulness (utilitarian performance expectancy) and ease of use (effort expectancy) (GROß, 2015; PANTANO & PRIPORAS, 2016), especially regarding the apps (TANG et al., 2016). Greater instant connectivity and greater hedonic motivation are associated with greater perceived usefulness and greater perceived ease of use of mobile shopping applications (HUBERT et al., 2017). However, due to with the technical limitations of mobile shopping technologies compared to desktop-based e-commerce technologies, such as smaller screens, contextual marketing may negatively affect the perceived ease of use (HUBERT et al., 2017).

Hubert et al. (2017) research investigates whether there are mobile shopping acceptance drivers that are context sensitive and others that matter independent of the context, by analyzing three mobile shopping application types: location sensitivity, time criticality, and extent of control. When mobile shopping makes use of location information, customers consider it to be better designed (HUBERT et al., 2017). Hence, geolocation marketing can be correlated with increasing perceived usefulness and usability.

San-Martín, Prodanova & Catalán (2016) reinforce that satisfaction with the mobile shopping experience has a positive impact in mobile shopping adoption, but Pantano & Priporas (2016) go one step further, searching for the benefits that create such satisfaction. In common, most studies show that convenience is key to mobile.

Gupta and Arora (2017) brought new lenses to mobile shopping using behavioral reasoning theory, analyzing “reasons for” and “reasons against”. Consumers undertake cost-benefit tradeoffs in purchasing decisions. Before that, Maity and Dass (2014) had also applied behavioral reasoning theory, conjoint with media richness theory, in order to investigate the impact of media richness on consumers’ channel choice of in-store, e-commerce or m-commerce. Consumers would rather adopt the mobile channel for shopping in simpler decision-making tasks, due to low media richness (MAITY & DASS, 2014). Mobile shopping is prevalent in low-consideration contexts. It is not suitable for higher involvement categories, at least not as a primary touch point (WANG et al., 2015). Mobile is a digital paradigm shift in retail. Retailers should be on their way to adopt a mobile mind-set if they wish to perform a successful cross-channel strategy. Hopefully, the new research avenues that are widely open in mobile will benefit the millions of customers who are yet to experience mobile benefits.

1.4.
Mobile Promotion Strategies: push notifications

The advances in mobile technologies are affecting the customer purchase behavior, particularly in an array of pull and push promotion strategies. In functional terms, location-based coupons can be either pushed to users (i.e., mobile push) or provided on demand via specific applications in which users can intentionally browse through available coupons (i.e., mobile pull) (XU et al., 2009). Basically, mobile pull and push offers vary on the delivery mechanism. That is, in the pull mode, the user generates the request (i.e, for a coupon) and in the push mode, the company generates the request (KIM & SONG, 2020). In a pull scenario, users are explicitly searching and asking for these offers (MOLITOR et al., 2016). Whether in a push scenario, users here are not explicitly asking for these offers; these offers are automatically pushed out to them (based on a variety of targeting criteria). Mobile push notifications can be transmitted via SMS or app-based notifications. The push-based coupon is more appealing to managers because it gives them better control over the coupon inventory and the decision about which coupons to target to people at particular times and locations (DANAHER et al., 2015, p.711).

Unlike pull-based information, push-based information requires strategies to attract individuals who may not have much interest in the brand. In that way, the customers can get highly personalized promotion messages about the right product (what) at the right time (when) at the right place (where) (KIM & SONG, 2020). Besides, according to Molitor et al. (2016), mobile pull differs from mobile push in three distinct categories: i) user’s perception, ii) interaction with coupons/ads, and iii) interface design. Mobile pull tends to be less often considered as spam and less privacy intrusive, giving users more control over their interactions with the provider, since it refers to users actively searching for a product or a service. Location-based Services (LBS) include both push (when the consumer’s location will trigger an event) and pull (search related to a location and tracking service) apps (PATSIOTIS et al., 2020, p.1040).

Tang et al. (2016) applied an innovative approach to the adoption of mobile purchases when analyzing this phenomenon from the perspective of channel migration using the push-pull-mooring (PPM) theory. Based on human migration studies, this theory suggests that there are negative factors at the origin that push people, while positive factors at destination act to attract people to them, as well as mooring factors that facilitate or inhibit their decisions to migrate. The Tang et al. model (2016) tested the inconvenience of traditional internet channels and the perception of high prices as factors of pressure; perceived utility and perceived ease of use of mobile shopping as attraction factors and high costs of change and low security / privacy as mooring factors in the background analysis that influence the decisions of consumers on the migration of online shopping (based on PC) for mobile purchases. The cost of change was not significant in the results, but safety was in line with what other studies of acceptance of mobile technology have already shown (SAN MARTÍN et al., 2016; HUBERT et al., 2017).

Push notifications can also be related to habit formation for mobile. The seminal Unified Theory of Acceptance and Use of Technology (UTAUT) has introduced habit as a predictor of usage of mobile by consumers (VENKATESH et al., 2012). Habit relates to more automatic cognitive processes (LIN & WANG, 2006) and therefore is associated with greater perceived usefulness and greater perceived ease of use of mobile shopping applications**.** Habit has a positive effect on customer loyalty. However, Hubert et al's (2017) research has shown that consumers still need to develop the habit of mobile as a shopping tool. The repeated mobile purchase is product of prior habitual usage (LIN & WANG, 2006). Indeed, Bart et al. (2014) research showed that mobile advertising work effectively by triggering consumers to recall and process previously stored product information. Therefore, companies should provide temporary rebates and other incentives to stimulate repeated behavior. In fact, Shankar et al. (2016) stress that unexpected promotions increase the sense of serendipity in the mobile process, which helps to increase consumer engagement. Also, how push notifications offer a convenient way to stimulate unplanned purchases by reaching customers when they are close to a store, point-of-purchase, or purchase consideration (ANDREWS et al., 2016, p.16).

Beeck and Toporowski's study (2017) provided evidence of the potential risks and benefits of sending mobile messages to customers, as part of digitalization strategy for brick-and-mortars using new technologies. For the authors, mobile targeting is influenced by the content of the mobile message and the customer's location upon receiving the message. That leads us to linking mobile pull push promotions with geolocation strategies.

Simply put, mobile geolocation targeting works like this: 1) GPS is used to detect and delimit the location area in which the audience is located, such as within a radius of 100 meters from a certain store at that address. 2) Through the wi-fi signal, the indoor environment where the user and his smartphone are is understood. If the user does not connect to the establishment's wifi, the technology works anyway, only detecting the signal strength. 3) The inertial sensors - accelerometer and magnetic field - of the cell, which are constantly on, assist in the interpretation of movements and displacement in the environment.

1.5.
Location-based mobile promotions

"Allow Instagram to access your location?" Installing new mobile applications (apps) usually comes along with this well-known notification. Many apps (e.g.: Ifood, Uber, AccuWeather, Trip Advisor, Facebook) continuously track user location in exchange for providing underlying services, such as determining distance ran, local weather forecast, directions to nearby destinations or to check into a location to share with friends. Other apps, however, do not directly provide underlying services, instead, they analyze the data retrieved from users tracking through mobile geolocation in order to design much more assertive communication strategies, as push notifications.

Location based marketing (LBM), or actions based on geolocation or geofencing, is one of the most fertile fields for Mobile Marketing. Location-based marketing is defined as the use of mobile marketing to target consumers within a particular geographic area. In other words, the location of a consumer is determined by attaining the longitude and latitude of his/her mobile device through GPS or cell tower triangulation (BeaconStac, 2019). In location-based mobile (LBM), the location of a person or an object is used to determine the application or service. Location-based mobile services include mobile marketing based on consumer's location (UNNI & HARMON, 2007). LBM is a means for advertisers to reach out through personalized messages sent directly to mobile phones using their geographic location. The mobile phone users' willingness to disclose their location and other personal information is "an essential piece of such strategy" (GUTIERREZ et al., 2019, p.295). The locational targeting of customers within certain designated areas (typically near a firm's own location) is referred to as geofencing (activation perimeter). The ability to support location-based applications is a unique feature of mobile devices (GREWAL et al., 2016). According to the Mobile Marketing Association (2016), geobehavioral marketing refers to the ability to target unique audiences and/or users based on the context of a given location, past or present location behaviors. Mobile technologies empower researchers and managers to draw insights on marketing phenomena in a way that were impractical to study in the past, since mobile technologies provide access to customers' real-time presence (FONG et al., 2015), altogether with a number of data provided by this most intimate device.

Locational targeting has been widely adopted by mobile marketers, with Ad Networks already providing media inventory based on geofencing. Geolocation actions are mainly aimed at boosting unscheduled buying behavior, since they usually occur close to the point of sale. There is also competitive locational targeting, the practice of promoting to consumers near a competitor's location, using mobile geolocation promotions as competitive weapons (FONG et al., 2015).

The differential of mobile lies precisely in the uniqueness that the functionalities of mobile devices offer, particularly geolocation. This location-sensitive nature of smartphones opens the way for communication that is sensitive to the location of the customers (HÖGBERG et al., 2020). Using the consumer's location for purchases allows you to enter the context in the process: the right product, for the right person, at the right time, just what the mobile allows due to its ubiquitous character. Mobile allows the company to approach the customer in different situations and points of contact, linking the offer to the consumption context. Besides, a mobile promotion is less obtrusive because mobile notifications are easy to check with a glance or ignore if so desired (FONG et al., 2015, p.728).

There are two major types of mobile ads, display ads and push notifications. If delivery is made via display, it is necessary to wait for the user to be with the cell phone “open”, browsing an app or a website where your ad is competing in a fight against the last BID (advertising bids on a programmatic purchase platform) to gain the visible impression. And there is the push technology, which allows you to deliver geolocated media without having to go through the web mobile or in app environment. But to do this, there must be direct agreements with publishers so that they can send via the application's own SDK.

The studies that adopted a field experiment methodology for mobile marketing (HUI et al., 2013; LUO et al., 2014; DUBÉ et al., 2017) were mainly focused on individuals’ responses to push notifications that offered coupons discount. Nevertheless, it is worthwhile to point out that product type, consumer characteristics, time, and location of the message received also might influence mobile coupon redemption rates (BEECK & TOPOROWSKI, 2017). There is a range of technologies that can be used for location tracking, such as Wi-Fi, RFID, GPS, or beacons. Individuals’ resistance and resource availability are some of the barriers that need to be surpassed. Beacons, for instance, relies on enabling the smartphone Bluetooth. Since it drains smartphones’ battery, only a small percentage of users keep it on. As per the GPS, the data accuracy depends on signal reception and such search also drains batteries. Additionally, it is essentially important do not breach privacy policies within the General Data Protection Regulation. For instance, the research cannot deal with categories such as hospitals or churches.

Push notifications are an important tool for the increase in offline retail sales due to mobile promotions, since they are a way to speak directly to a user, promoting products or offers and converting unknown app users to known customers. According to the 2018 Push Crew Notification Report, 39.8% subscribers wanted more relevant and personalized notifications. More than 74% of the audience think that receiving more than 5 notifications in a day is too many. Most people believed that Push Notification users should send less notifications and send personalized and relevant notifications. Besides, unsubscription Rate and Frequency of notifications have a direct relationship. Unsubscribes increase when frequency increases. That means, push notifications should be more targeted and accurate, and geolocation may help with that.

2.3.1. Location-based push notifications and visits to the store

Location and other data signals allow companies to target key segments of customers who much more likely would respond positively to the promotional offer (BAKOPOULOS et al., 2017). Behavioral notifications refer to personalized messages sent based on past activity someone has done in the app or real-time information like location. Contextual targeting refers to identifying customers who were browsing relevant content about the category on their mobile devices (BAKOPOULOS et al., 2017). Mobile device channels offer new location-based, time sensitive opportunities to create firm-initiated touch points (LEMON & VERHOEF, 2016). Behavioral targeting and contextual targeting justify their incremental cost and improve the performance of campaign results: more consideration, more sales, further dollar expenditure (BAKOPOULOS et al., 2017). Geolocation actions are mainly aimed at boosting unscheduled buying behavior (HUI et al., 2013), since they usually occur close to the point of sale. According to Patsiotis et al. (2020) research, LBS are most useful for last-minute decisions, informing about a good offer or for reminding consumers of a company they know.

When you know where customers are and how they behave, you can not only customize offers but also give them rewards and personalized experience. The results of Grewal et al. (2018, p.102) studies indicate that mobile phone use in-store can increase purchases overall because customers "divert from their conventional shopping loop". In a previous Walmart study, activation by location had a higher impact on store visitation than activation of past shoppers (BAKOPOULOS et al., 2017).

Thus, location-based reveals an opportunity to enhance the customer experience in the physical store and the online-offline integration of the brand. “Proximity location targeting, when matched with expandable mobile display units, also improves the impact of advertising in terms of driving foot traffic” (BAKOPOULOS et al., 2017, p.450). Planning the timing and location of marketing messages can lead to a more efficient outcome (LUO et al., 2014). Fang et al. (2017) analyze whether mobile promotions that are triggered by geofences (i.e., sent when a customer enters a pre-defined area around the promoting store) are more effective compared with those received without geo-fences. Depending on how a geofence is set up, it may request mobile push notifications, trigger text messages or alerts, or send targeted advertisements on social media. They find six to twelve times more purchases compared with store promotions without geo-fences. That is, consumers receiving a notification close to the offline site will chose to move to the location to a greater extent than those receiving it further away. This leads to the first hypothesis:

H1: For customers at a proximal distance, those who receive a push notification are more likely to visit the store than those who do not receive it.

2.3.2. Location-based push notifications and message content

Based on previous research (HUI et al., 2013; LUO et al., 2014; FONG et al., 2015; BEECK & TOPOROWSKI, 2017; GUTIERREZ et al., 2019), it has been established the use of location as a competitive weapon in mobile promotion strategies. The effectiveness of mobile promotions is guided by the principle of context - taking the right action at the right place and time (VERHOEF et al., 2017). However, location seems to be just part of the equation. What is the right action to be taken? That drives us to wonder about message content. In Patsiotis et al.(2020, p.1044) qualitative research, ‘content’ appears to have a moderating effect regarding mobile advertising, as it affects the ways consumers perceive the message (informative, irritating, entertaining).

Previous studies have demonstrated that the distance to the point of sale impacts the likelihood of a purchase (MOLITOR et al., 2016), especially if it is some type of coupon. And research shows greater redemption of coupons sent to mobile devices (HUI, et al.2013; KLABJAN & PEI, 2011). The reason that distance might matter more on mobile devices (compared with PCs) is that mobile coupon applications are used as a ubiquitous information medium with the intention to bring consumers (back) to physical retail stores (MOLITOR et al., 2016, p.10). As Fong, Fang & Luo (2015, p.726) put it, mobile promotions can now reach consumers when and where they are most receptive. The difference between an ad being perceived as interruption or as a welcome hello is often timing, referring to the consumer's moment and mindset. One of the great challenges for marketers is to be able to talk to people when they are more receptive to the brand message. In these cases, both the location and timing of the message are crucial.

If the purpose of the campaign is branding, the fact that the user is exposed to the brand via branded communication is relevant. Achieving viewability and, perhaps, engagement shall be sufficient. "Mobile particularly is effective for established brands, which customers have less need to research or validate" (BAKOPOULOS et al., 2017, p.449). However, if the goal is conversion, a message that promotes customer action shall be pursued. In fact, Shankar et al. (2016) stress that unexpected promotions increase the sense of serendipity in the mobile process, which helps to increase customer engagement.

However, the perceived value of a location-based coupon may depend on the actual geographic location where users open and access their mobile coupon application (MOLITOR et al., 2016). According to Fong et al. (2015), it is shortsighted to conclude that locational responsiveness to mobile promotions is merely a function of proximity to a retailer's own stores. Product type, customer characteristics, time, and location of the received message influence mobile coupons redemption rates (BEECK & TOPOROWSKI, 2017). For instance, Fong et al. (2015) analyzed the effects of discount depths on competitive locations, with the cooperation of a mobile service provider. They reached the conclusion that high discounts were optimal for the competitive location, whereas medium discounts were optimal for the focal location. The results of Beeck and Toporowski (2017) research indicate that mobile messages can be highly effective for users of discount apps when the customer is near to the shop. Therefore, they recommend measuring the effects of mobile shopping messages in real shopping settings with various promotional messages. Based on the aforementioned research, this study reasons that if the offer is sent to the consumer at the time he approaches the store, it increases the chances of using the promotion, especially if the content is promotional, rather than branded.

H2a: For customers at a proximal distance, those who receive a promotional content are more likely to visit the store than those who receive a branded content.

H2b: For customers at a proximal distance, those who receive a personal content are more likely to visit the store than those who receive an impersonal content.

A key word in mobile promotion is permission. “Real-time location information is potentially quite sensitive, and consumers may not always understand the lengthy terms and conditions they agreed to” (VERHOEF et al., 2017, p.7). Technologies such as beacons, with the customers’ permission, enable retailers to go beyond targeting. Retailers have the opportunity to collect data, measure real-time shopping behavior and customize promotions (BEECK & TOPOROWSKI, 2017). Mobile beacons are an entirely different marketing communication tool than mobile messaging, in that it requires a consumer to install the app. But, once installed, customers' use of mobile technology generates information that can be captured by firms for targeting purposes (VERHOEF et al., 2017). The process of mobile activation is extremely delicate and therefore must be very well planned. In fact, smartphones are the most personal device consumers have today, and as such, one of the richest sources of data for retail conversion (FULGONI & LIPSIVIAN, 2016).

Because of the geolocation effect on boosting unscheduled buying behavior, these impulse purchases may generate regret and a negative feeling in customers. To minimize these negative effects, push notifications should in fact contain a benefit that adds value to the customer, preferably a customized one. There is a common perception that better-targeted ads necessarily require access to customers’ personal data, with improved targeting techniques being advantageous for firms (KIM et al., 2019). Well-targeted ads are objectively more personalized; thus, they should by definition be more relevant and interesting to customers (KIM et al., 2019, p.908). Targeting an ad based on customer behavior can increase the person-product fit, and consequently, the ad effectiveness.

Theories of self-disclosure suggest that consumers' willingness to disclose personal information is based on their assessments of the costs and benefits (ANDRADE et al., 2002, p.350). We can draw a parallel with push notifications opt-ins: for customers to disclose their location to companies, they make an assessment of the costs and benefits offered. Another benefit of mobile is its unique services, mainly related to the possibility of offers based on location in real time (FAQIH & JARADAT, 2015; GUPTA & ARORA, 2017). This offer comes in the form of personalized messages based on user-selected preferences, requiring less effort in finding information (EASTIN et al., 2016). Systems can adapt their behavior to individual use, automatically recognizing some information about customers (PANTANO & PRIPORAS, 2016). Therefore, we raise the hypothesis that:

H3: The degree of content personalization is positively related to store visits.

Behavior-based recommendations can include both online and offline behaviors. Apart from Ghoose et al. (2015), little previous work base on offline behavior to provide online recommendation. If the purpose of the campaign is branding, the fact that the user is exposed to the brand via institutional communication is relevant. Achieving viewability and, perhaps, engagement, shall be sufficient. Mobile particularly is effective for established brands, which consumers have less need to research or validate (…). However, if the goal is conversion, a message that promotes consumer action shall be pursued. (BAKOPOULOS et al., 2017, p.449).

2.3.3
Location-based push notifications and high engagement content

The online shopping experience has matured from push strategies to an entertaining social experience (KHANSA et al., 2012), where consumers are empowered and have an active role in co-creation of value. Mobile communications have evolved from one-sided company to customers notifications to actually engaging customers in the process.

Digital Marketing encompasses Mobile Marketing, and although these concepts have many similarities, they are not exactly the same (MAITY & DASS, 2014). The mobile construct can cover the device, the technology, the channel, or other aspects. Regarding the device, mobile is any centrally connected portable device that can be used on the move, such as a smartphone or a Tablet (SHANKAR et al., 2016). Despite the similarities, online and mobile bring different experiences to the customer . Both have in common the separation of the moment of purchase from the moment of collection/consumption, eliminating the traditional time and space barriers of physical retail (PANTANO & PRIPORAS, 2016). It is anytime, anywhere shopping. However, smartphone shopping allows customers to shop when they are on the go, with no time or space constraints (TANG et al., 2016), while e-commerce requires an area for the PC or notebook, which may impose certain times and locations.

While the time and space restrictions were removed, other barriers were added. There are now technological frontiers, including the ability to use technology and customer knowledge to deal with it (PANTANO & PRIPORAS, 2016; TANG et al., 2016). New technologies require not only firms to master new skills, but also customers to master them (PARASURAMAN & COLBY, 2015), bringing ease of use to a new level. Customers still experience anxiety and lack of trust in the use of m-commerce (GUPTA & ARORA, 2017). Thus, mobile shopping tasks should be easy (user-friendly and simple transaction process) and cost-effective to attract customers (TANG et al., 2016). “Because of mobile phone’s highly interactive nature, more engaging promotion activities are possible, which is significantly different from traditional one-way communication from marketers” (KIM & SONG, 2020, p.1). With location-based services, mobile promotions can be more effective in that consumers can receive relevant, targeted, and interactive information specific to their location or consumption context (KIM & SONG, 2020, p.1).

Moreover, mobile promotions should be fun and enjoyable, since hedonic motivations such as perceived entertainment are so important in m-commerce that they can even provide a better explanation for technology adoption than utilitarian motivations, such as perceived utility (VAN DER HEIJDEN, 2004). Since screens are smaller, media richness is affected in mobile communication (PANTANO & PRIPORAS, 2016). Media richness is related to the ability to communicate information to the customer through text, audio, video, and face-to-face messages (MAITY & DASS, 2014). Otherwise, the lack of user-friendly interfaces on smaller screens can turn into discomfort and inconvenience. This limitation of information space (small keyboards and small screens) may make interaction via mobile mentally and physically exhausting, and therefore cognitively onerous (SOHN et al., 2017).

Media richness is defined as the degree to which a medium can facilitate shared meaning (DAFT et al., 1987). Other studies extended media richness theory to explain the media capability in expressing rich information by using the four aspects of media richness (TSENG et al., 2017): immediate feedback; multiple cues; personal focus; and language variety. Immediate feedback refers to the capability that allows rapid bidirectional communication and rapid response messages. Multiples cues refers to text and icons, whether personal focus makes reference to emotions. At last, language variety involves a large pool of symbols (TSENG et al., 2019).

The use of game design elements is one of the strategies useful to enhance non-game goods and services by increasing customer value and encouraging value-creating behaviors such as engagement (HOFACKER et al., 2016). In fact, entertainment in mobile is important to achieve satisfaction and positive word-of-mouth (SAN-MARTÍN et al., 2016). To be fun and enjoyable, the m-site's design "should facilitate the opportunity for interactivity between the client and the company, or between several clients" and give the option of viewing and interact better with images (SAN-MARTÍN et al., 2016, p.609).

Thus, entertainment in mobile is important to achieve satisfaction and positive word-of-mouth (SAN-MARTÍN et al., 2016). To be fun and enjoyable, the mobile site design "should facilitate the opportunity for interactivity between the client and the company, or between several clients" and give the option of viewing images (SAN-MARTÍN et al., 2016, p.609). Smartphone displays are several inches smaller than a laptop or PC display. Thus, customizing or targeting advertisements becomes more critical on a smartphone (MOLITOR et al., 2016). Due to the increasing importance of entertainment as means to achieve customer engagement in mobile, the use of instant connectivity is significantly related to perceived ease of use (HUBERT et al., 2017; MAITY & DASS, 2014). Kim and Song's findings (2020) showed that individuals who played a game showed a higher level of perceived value in mobile promotions compared to those who did nothing. The concept of effort justification, derived from the theory of cognitive dissonance (Festinger, 1957), is that one gives greater value to outcomes that require greater effort to obtain in order to justify the greater effort. That is, individuals tend to value highly those goals or items which have required considerable effort to achieve. The study also suggest that game-based coupons work especially well for utilitarian products, while survey-based coupons justify the hedonic products better.

Unlike prior work, which has mostly considered online-to-online responses, but in light of the earlier arguments, this review summarizes the findings that may stimulate additional work in this nascent field. The effort is on discussing how to deliver more effective mobile message content, based on geolocation data in order to drive store visits and to connect online efforts to offline behavior. Ergo, we build on the literature of contextual marketing and behavioral advertising to posit that the geolocation mobile promotion directed to the customer once he approaches the store increases the chances of a positive response to the communication. We also posit that the effect is moderated by the type of message, promotional or branded, personalized or engaging.

Table 4 – Research Hypotheses

Hypotheses	
H1	For customers at a proximal distance, those who receive a push notification are more likely to visit the store than those who do not receive it.
H2a	For customers at a proximal distance, those who receive a promotional content are more likely to visit the store than those who receive a branded content.
H2b	For customers at a proximal distance, those who receive a personal content are more likely to visit the store than those who receive an impersonal content.
H3	The degree of content personalization is positively related to store visits.

The literature review allows an investigation of what is known so far about location-based push notifications and how planned strategies related to visits to store, coupons offer, personalized content and high engagement content would affect customer offline behavior in brick-and-mortar stores (online to the offline relationship). However, to better understand the effectiveness of each one of these strategies, empirical tests are needed. By testing them, the demonstration of the expected effects may help in directing mobile marketing strategy, driving actions of smaller reach but greater precision, thus with higher conversion rates.

The main premise behind the research model is that location-based mobile message content is positively related to store visits, in a cross-channel perspective. Context and convenience as the primary drivers of the effect (visits to the offline point of sales generated by mobile notifications), considering that context and convenience are represented by geolocation and message content. That provides the base for a mobile model for companies to attract consumers to physical locations. The Mobile App Attribution Model (MAAM) considers cross-channel environments, in a quest to better understand the role of mobile communication in consumer offline behavior.

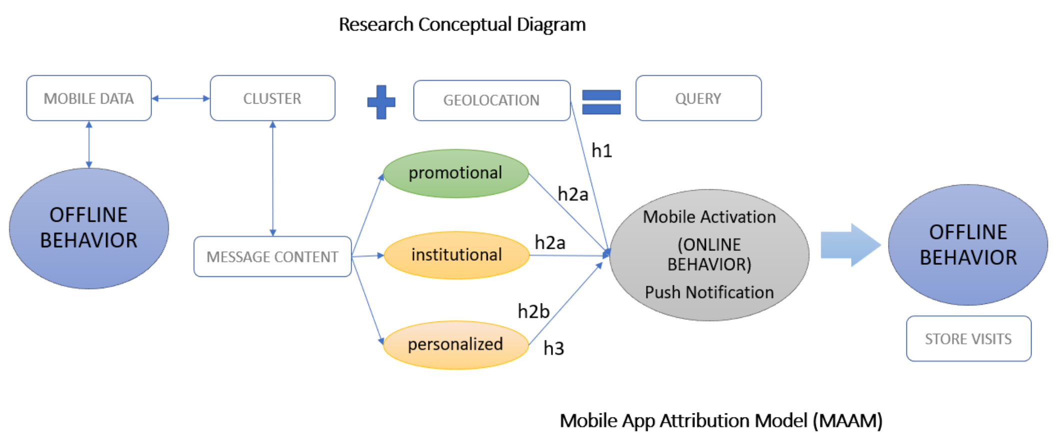


Figure 3 - Conceptual Diagram

3.
METHOD

This chapter describes the type of research and the procedures adopted in the study, particularly concerning data collection, data treatment processes and data analysis.

3.1.
Type of research

The objective of this dissertation 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. The research uses a mixed-method approach to assess knowledge on mobile promotions and offline behavior, in a cross-channel perspective. The research consists of a qualitative study, a secondary data study, field experiments and an online experiment. Each method is suitable for eliciting a different perspective on the topic, seeking to uncover a different type of knowledge that, once combined, should provide a broader understanding of the phenomena (KOLL et al., 2010).

Creswell and Plano Clark (2011) define mixed-methods research as those studies that include at least one quantitative strand and one qualitative strand. These authors highlight one important characteristic, which is mixing – or integrating, or linking – the two forms of data. This can be done either concurrently, by combining or merging them, sequentially, by having one build on the other, or embedding one within the other. The rationale behind the choice for a multi-method approach was that one type of data alone might not provide the broader picture or adequately answer the proposed research question (MERTLER, 2018).

3.2.
Research Steps

The research includes six parts: literature review, conceptual model and hypotheses development, qualitative in-depth interviews, secondary data study, experimental design and field and online experiments. The goal of the first one, literature review, was to identify the main paradigms, theories and variables of mobile marketing geolocation promotions, in order to build the research framework. The next allowed to examine the operationalization of the variables in the extant literature and to develop the research hypotheses. Following, the third part, the qualitative study, aimed at identifying managerial perceptions and experiences about mobile promotions in detail, as well as important variables regarding the mobile marketing relationship to offline store visits.

The fourth part consisted of a study using secondary data of mobile geolocation campaign data from major brands. Despite the means comparison technique, in this study, the grouping into "treatments" is not under the control of the experimenter. While experiments have some advantages, quantitative nonexperimental techniques are also useful and can produce important results (OEHLERT, 2010).

Finally, the fifth and sixth parts, the experimental design and field plus online experiments, to test and evaluate the effects of the selected variables. The experimental design is the definition of the general structure of the experiment. Whist the in-depth interviews explore subjective aspects of decision making, experiments help access the quantitative perspective of such decisions, by comparing treatments and the outcomes. That is, experiments help compare the effects (OEHLERT, 2010) and identify causal relationships (HERNANDEZ et al.2014).

STEP	RESEARCH TYPE	GOAL	DATA COLLECTION	DATA TREATMENT
1	Literature Review	Identify the main paradigms, theories and variables of mobile marketing geolocation promotion.	Extensive review of the literature, in order to build the framework that will support the research. Database Web of Science.	Bibliographic and bibliometric research. Analysis with VosViewer software.
2	Develop a conceptual model and hypotheses.	Hypotheses development. Check for research operationalization consistent with the literature.	****	****
3	In-depth exploratory interviews.	Exploratory approach. Examine managerial perceptions about mobile and visits to offline stores.	In-depth interviews with key players. Recording and transcription of the interviews.	Content Analysis .Criteria: pre-defined based on the literature review + emerging from the field (Bardin, 1977).
4	Secondary Data Study	Analyze which visual and textual features are predictors of higher visit through rates (VTR) in mobile campaigns	1.753 location-based campaigns from 76 medium and large companies, Nov 19 – Mar 20	Computer vision (AI & machine learning) and observational study (Oehlert, 2010)
5	Experimental Design	Improve the precision of the results in order to examine the research hypotheses.	****	****
6	Field and online experiments.	Test and evaluate the effects of the selected variables.	Behavioral observation and data extracted from the geolocation software (field) and an online questionnaire.	Group means comparison (experimental and control group)

Figure 4 - Synopsis of Research Structure

3.3. Research Design and Limitations

3.3.1 Qualitative Study

The first stage of the field studies is qualitative (DENZIN & LINCOLN, 2000) with in-depth individual interviews, in order to gain a broader perspective of the phenomena, to assist in the analysis of the quantitative studies and to provide further comprehension of the research problem. In a discipline as applied as marketing, qualitative methods enable a deeper understanding of behavior (GRANOT et al., 2012, p.2). Qualitative studies are inherently designed to provide explanations. Qualitative research for theory building is gaining prominence in management research. The growing complexity of the managerial context asks for approaches to create action-oriented knowledge (SINGH, 2015, p.132). The limited research on mobile-specific marketing tools (PATSIOTIS et al., 2020) suggest the use of qualitative methods of data collection, which is a suitable methodological approach to relatively new or less researched contexts.

Qualitative methods, such as in-depth interviews, are indicated to explain how people act in certain arrangements (MILES & HUBERMAN, 1994) and to allow to the depth of the problem (REMENYI et al., 1998). Besides, qualitative research with executives is a path to identify researchable topics (JAWORSKI, 2018). Therefore, the purpose of the qualitative study was to identify managerial perceptions and experiences about mobile promotions in detail, as well as important variables regarding the mobile marketing relationship to offline store visits. The qualitative perspective helped understanding other aspects of mobile geolocation promotion effects. This is aligned with three criteria proposed by Jaworski (2018) to dominate the selection of the focal topic: the problem is significant for marketing practice, it can precipitate a body of research on the topic and it is relatively new to the marketing discipline.

The qualitative study followed the steps proposed by Singh (2015), based on the works of Glaser and Strauss (1967), Dyers & Wilkins (1991) and Miles and Huberman (1994). The steps were: a) research question, framework and design; b) data collection and transcription; c) line by line or chunk by chunk coding; d) code classification; e) interpreting the data and identifying salient themes; f) memo writing as the analytical handle; g) description, analysis and explanation; h) comparative analysis and refinement; i) outputs and discussion. Burton-Jones and Lee (2017), based on the Grounded Theory method, suggest the same aforementioned steps for qualitative research. They also list a few principles that were followed by this qualitative study: theoretical sensitivity and management of preconceptions; constant comparison and different slices of data; theoretical sampling; and iterative, emergent, theoretical coding.

3.3.1.1. Limitations, validity and reliability issues

In order to ensure validity and reliability in qualitative research (HEALY & PERRY, 2000; MCGREGOR & MURNANE, 2010; GRANOT et al., 2012, BERKOVICH, 2018), interviewers should place participants' comments in context, reduce opportunities for idiosyncrasies and checks for internal consistency. Also, "by interviewing a number of participants, experiences can be compared and connected" (GRANOT et al., 2012, p.5). For Healy and Perry (2000, p.123), the validity should be a contingent one, meaning that the goal is to develop a ``family of answers" that cover several contingent contexts and different reflective participants, albeit imperfectly. In that context, validity is about generative mechanisms and the contexts that make them contingent.

The main limitation of a qualitative study is related to the impossibility of statistical generalization. However, the qualitative study can arrive to analytical generalizations (FLICK, 2004; HEALY & PERRY, 2000). Another limitation is that the quality of the results depends largely on the researcher's ability to conduct the interview. Besides, one should also bear in mind potential limitations resulting from interviewee's bias, a risk in the coding process: a researcher familiar with the study tends to seek out and record content aligned with the literature (SCHMIERBACH, 2009). One of the difficulties was to grant access to C'level managers, who are people, in general, with little time available. Thus, the process of obtaining access to respondents was long and winding.

3.3.2. Quantitative Studies

The quantitative studies involve the fourth, fifth and sixth steps. The quantitative studies were designed to investigate how the content and the geolocation data of the mobile messages impact store visits, in a cross-channel perspective.

The secondary data study, study 1, is a text and image analysis of real mobile message contents from mobile campaigns. Studies 2, 3 and 4 are experiments. In studies 2 and 3, subjects were prompted to visit the point of sale, according to variations in the context (distance and message). It was conducted in a large shopping mall in the Northeast of Brazil in February, 2021, with the mall app users. The mobile message content and the distance to the offline site were experimentally manipulated. Study 2 tested the effect of the proximity of the consumer to the location in responses to mobile notifications. Study 3 tested whether the content of the message indeed predict a different response on the dependent variable. Regarding product category for studies 2 and 3, there was a choice between high-involvement, infrequent purchase items or lower-involvement, frequent impulse purchase ones. According to Voorveld et al. (2016), consumers more often rely on offline channels for low-involvement products or when buying a product for the first time. Analyzing category-specific differences, users usually prefer coupons from the following categories: cafes, clubs and bars, errands, fashion and accessories, multimedia and restaurant. Therefore, the category choice was for movies and restaurants (the food court). Given the limitations of the data from studies 2 and 3, due to Covid-19 pandemic, a fourth online experimental study was conducted, with 1.534 participants.

In the first set of analysis, represented by Study 1, the unit of analysis is the campaign. In the following studies, the unit of analysis is the user. According to Hunt (2010), four conditions are necessary and sufficient to be able to infer a causal relation: temporal sequence, concomitant variation, non-spurious association and theoretical support, all of were pursued during the studies.

3.3.2.1.
Limitations, validity and reliability issues

As per field experiments method limitations, the first concern refers to controlling variables. Controlling concomitant variables in the field is a challenge and the extent to which the researcher fails to control then should be reported. Besides, a researcher can build in skewed views of the treatment effects by erroneously selecting treatment levels to be studied (BLACK, 2011, p.453) and confounding interaction may be misleading. In theory, any phenomenon that affects the dependent variable in an experiment should be either entered into the experimental design or controlled in the experiment (BLACK, 2011, p.453). So, a limitation of the study is that more constructs and variables may affect store visit than the ones considered in the proposed model. Another limitation of the experiment method is the trade-off between internal validity and external validity, that is, an increase in internal validity causes the study to lose realism and generalization capacity (lower external validity), while a closer approximation of reality and the search for generalization (greater external validity) may lead to a lack of control and, consequently, to the emergence of alternative explanations for the results found (less internal validity) (SCHRAM, 2005; MALHORTA, 2011).

4. QUALITATIVE STUDY: MOBILE EXPERTS

This section details the qualitative study exploring the domains of mobile promotion and offline consumer behavior. The method used for this qualitative study was in-depth interviews followed by content analysis. The purpose of the qualitative study was to identify managerial perceptions and experiences about mobile promotions in detail, as well as important variables regarding the mobile marketing relationship to offline store visits. Interviews were conducted with C'level managers from the digital industry responsible for conducting mobile promotions.

4.1. Research Design and Data Collection

According to McGregor and Murnane (2010) classification, this study seeks relations and regularities via empirical-positivistic qualitative research, with semi-structured in-depth interviews and content analysis. The interviews were conducted with key players and experts from the digital industry, regarding the online-to-offline relationship, having mobile as a hub. In total, 13 in-depth interviews were performed with leading digital experts in the industry, including martechs specialized in mobile and geolocation. The first interviews, in July and August 2019, were set in person. The later ones, in September and October, 2020, were made using Zoom conferencing tool or WhatsApp video calls, due to Covid-19 pandemic restrictions. The choice of Zoom or WhatsApp was up to the interviewee, according to the type of consent given, agreeing or not to video recording. The interviewees were previously introduced to the topic of research. The consent was asked prior and at the beginning of the interview. The interviews began with mobile promotion questions adjusted to the interviewee's context. Interviews continued until no new information emerged, indicating theoretical saturation.

The interviews were performed in Portuguese and later translated to English. The interviews lasted between thirty minutes and two hours, according to the interviewee's availability. All the responses were recorded and later transcribed. The interviews were semi-structured (see annex III). Therefore, in some cases other questions were raised to further improve the understanding of the issues discussed. Open questions during in-depth interview stimulate a direct conversation, allowing patterns to be observed, from which categories are generated (DENZIN & LINCOLN, 2000). Open-ended questions can be very revealing, enriching the knowledge of the researched subject, which clearly occurred throughout the study. The interview script included questions regarding location-based promotions; how mobile promotions affect consumer offline behavior; message content; personalization; best practices regarding message content in mobile context; major challenges regarding geolocation and mobile marketing.

Table 5 - Summary of respondents.

POSITION	COMPANY TYPE
VP of Global Strategy and Operation	Leading Social Media with 270 million users
Head of Marketing (Brazil)	Worldwide leading ecommerce with reported a net income of 11.59 billion U.S. dollars
General Manager	Private location awareness tech company
Business Intelligence Manager	Geolocation behavioral biometrics company
Head of Mobile Solutions	Technology services
Chief Growth Latam	Backbone data & mobile media
Connection Diretor	Marketing & Advertising
Marketing Manager	Behavioral Data
Marketing Director	Design & Branding
Head of Sales	Geolocation behavioral biometrics company
Partner	Shopping Malls
Key & Strategic Sales App Business	Nasdaq listed global technology company for impactful advertising.
CEO	Technology company that brings together data intelligence and contextualized activation.

4.1.1. Data Analysis

Data analysis was performed based on the content of the interview transcripts and complementary materials sent by the interviewees (cases, reports, videos and ebooks). The collected data was analyzed with content analysis techniques, following the steps suggested by Bardin (2006): pre-analysis, codification, categorization, and analysis. The content analysis is commonly used as an analytical method for qualitative content (KOHLBACHER, 2006). It is applied to identify any comparable and contrasting themes from which new knowledge is identified (MILES et al., 2014; KOHLBACHER, 2006). The interviews produced qualitative data on which content analysis was undertaken to assess and explore multiple perspectives on the phenomenon. The technique is intended to go beyond the common sense of subjectivism and achieve scientific rigor, but not the rigidity (MOZZATO & GRZYBOVSKI, 2011).

Thus, the analysis explored differences and similarities, identifying common themes, based on the extant literature. All interpretations were supported by the interview transcripts. First, the researcher immersed in the data, with careful reading to increase the productivity and relevance of the data analysis (BARDIN, 2006, p.29). The exercise of comparing the content collected in the field work led to the recognition of patterns, in order to "tag" the identified phenomena.

Following, it was necessary to encode the material in order to treat it (BARDIN, 2006, p.103). Some of the codes had been suggested by the literature; others were created in the process of reading and rereading the interviews, in a process of analyzing the content for common themes (SINGH, 2015). The relevant chunks of the transcriptions were placed under broad categories. The salient themes identified were further developed by referring to the extant literature on the topics. Here, the subjective sense-making by the researcher plays an important element in theory building (WEICK, 1989). First, the initial framework, and second, the exercise of arriving at the description and explanation based on marrying inductive and deductive approach served the purpose of axial coding (MILES & HUBERMAN, 1994), searching for linkages between data. Data bias was handled by exploring consistency and inconsistency across data points. Consistency refers to similar perspective from multiple respondents and across different data points (SINGH, 2015). The researcher coded data in order to probe for meaning, while at the same time relating emerging concepts back to the revised literature.

The next step was the categorization of the elements, that is, creation of categories to support the analysis. Safeguarding the quality and systematization requirements is necessary to guarantee the possibility of analytical generalization of the data interpreted using content analysis (FRANCO, 2008). Part of the categories were defined a priori based on the literature, but mostly they emerged from the field. Once the categories were defined, each interview was analyzed again, following the "cross-case analysis" logic (KOHLBACHER, 2006). This comparative and systematic analysis allowed to identify patterns related to the investigated phenomena.

4.2.
Results treatment and analysis

The following themes emerged from the narratives: a) mobile promotion and offline consumer behavior; b) mobile message content; c) mobile ubiquity and consumer context; d) conquests and challenges in the field. Each theme was divided into categories (sub-themes) that were generated from the literature and the field. Each category was further analyzed. Tables 6, 7, 8 and 9 were developed for each theme with the assistance of lexical research by MaxQDA 2020, in the light of mobile marketing theoretical approaches.

I) Online to Offline: mobile promotion and offline consumer behavior
   a. Mobile promotion as a discovery mechanism
   b. Mobile promotion as foot traffic generator
   c. For convenience and instant gratification
   d. Fulfillment facilitation
   e. Habit formation

II) Mobile Message Content
   a. Personalization
   b. Engagement
   c. UX and usability

III) Mobile Ubiquity and Consumer Context
   a. Targeting moments of relevance
   b. Geolocation
   c. Location-based mobile promotions
   d. Customer Service and Logistics

IV) Conquests and Challenges

a. Cluster, Cohort Analysis and Privacy
b. Attribution and performance
c. Reality beyond promises.

4.2.1. Category Analysis and Discussion

Most interviews started with a general discussion about the growing importance of Mobile. Mobile importance ranges across countries and industries. For some, it is already vital, as one interviewee mentioned:

> But the Brazilian consumer, as well as that of India, are the two countries where this (mobile) is stronger, more and more people are surfing, accessing and actually buying on mobile. It is not an equal movement worldwide. Not necessarily in the app, but in the mobile browser (...) I would say that at least 50, 60% of everything sold today (digitally) is mobile. I see numbers in the 70% range too (the Head of Marketing).

The 2019 Coronavirus Pandemic crisis was a milestone regarding the Digital transformation and an impulse for mobile. It was a game changer for mobile, but yet, not enough to dethrone the physical, as mentioned by one of the interviewees:

> The ecommerce sales still represent a small percentage of the total retail sales. (...) You have a huge population that still does not make digital purchases. With the coronavirus, this number accelerated, we gained about two years of digital growth, but still… (the VP of Global Strategy).

Then the interviews proceed to more specific themes, as follows.

I) Online to Offline: mobile promotions and offline behavior

Whilst mobile continues to be a key driver of digital ad spending growth worldwide (EMARKETER, 2018), offline sales still stand for most retail results.

Yet, this dichotomy between digital advertising and offline sales is only apparent. As Tong et al. (2020, p.65) put it, mobile devices integrate digital experience with offline behavior, changing the consumer journey and exposing new business opportunities. This growing interdependence is evidenced by the interviewees:

> The digital and the offline are integrated into the consumer's life. (...) the smartphone makes it possible for companies to have access to new data on people's behavior. (...) the devices (applications) that we have installed, in addition to connecting us, are devices that collect information from us (the Connections Director).

> We separate our geolocalization part here as an insight tool. That's why we even have a series of tools, and our activation tool. (…) It has happened several times that we have verified through my insight tool that not necessarily my (mobile) media tool was the most effective. So, I think it’s super important even this detachment, first because I think mobile, it is indispensable as a strategy, but you can’t push the bar and think that that’s the right channel, so sometimes you’ll find out that another medium is converting better (the CEO).

> Throughout this time that I have been with mobile marketing, the on and off integration via mobile took place via beacon, this in 2014, 2015. Beacon were those stones that were placed in the store and then via Bluetooth it kind of characterized which place in the store the user went to, etc. In other words, the path that user took, how long he spent in each gondola ... Since then, a lot has changed. Beacon technology is almost gone, few companies actually use it, but other technology profiles have emerged (the Key & Strategic Sales App Business).

Mobile devices incorporate both a virtual information search and physical travel trajectory, providing a seamless online to offline experience (TONG et al., 2020, p.67). However, the fact that the content is today delivered on smartphones does not necessarily means it is mobile by design:

> I think there are challenges in n aspects. The first challenge is: making a mobile strategy is one thing, having your media delivered on your cell phone is another, social has become mobile as a result, but it is not mobile, you are doing social. Sometimes you do media on portals and the media is delivered on mobile as a result, but the strategy was not mobile. Today, in some websites, seventy, eighty percent of the audience is mobile, so even if you don't want to, you're going to do a mobile campaign, but you didn't think, you're not targeting as mobile (...) I think the first point is for brands to understand whether they are doing mobile or not (the CEO).

Mobile channel is increasingly working as a hub across digital channels and physical locations. Regarding the new roles mobile plays in the O2O customer journey, that is, how this integration across channels via mobile occurs, the following topics emerged: mobile as a discovery mechanism and a foot traffic generator; mobile as a source of convenience and fulfillment; and how yet such roles are attached to the new habits to be incorporated by the digital consumers.

> The person begins to be tracked even before being converted. Through what the person seeks you can monitor people who have a greater tendency to make a certain type of acquisition or purchase, whether online or in a physical store. (...) Zero moments of truth (with reference to Google search moments) directly influence consumer decisions to go to a physical store. You can be in a city you have never been to, type in the mobile browser “cafeteria” and according to those results you decide which cafeteria you will enter. These moments directly influence the fact that a person uses the digital medium to make the decision to go to the physical store! This is for the good and for the bad of it (the Connections Director).

Mobile seems to play an important role in leading the customer throughout the purchase funnel, working first as a discovery mechanism and then, as a foot traffic generator. “I have no doubt that the smartphone can influence the choice of where to consume” (the Chief Growth Officer LatAm). When we consider the dictionary definition of timing – the ability to choose to do something at the right moment – one could say that adjusting the message to the customer journey is a valid attempt to adjust its timing.

> The results depend a lot on the moment of the journey the user is on. For example, if he is in the awareness phase, I see that video campaigns have performed well. And it's difficult to talk about performance when we talk about awareness, these are two antagonistic words. And also, video click-through rates vs. in-app display click rates. When we are talking about consideration, the guy already knows my brand and then I want to make him buy with his smartphone, some things have brought cool results. First, campaigns between partners (i.e, Magalu and Netshoes) and app install campaigns via players. It also gives a lot of results to take the user who was on the web and bring it to the application. Regarding conversion, the main point is how you align the communication with that user. Conversion campaign has to be very much in line with what the user expects (the Key & Strategic Sales App Business).
>
> Second point, is to find a combination of media, okay? (...) the push, it is not a support medium, for example, it is not a retargeting medium, because it is a medium that generates an impact, it's the beginning of the funnel. Imagine a brand that you don’t know, that you’ve never seen, arriving at Push with an image, ok, it enriches the context. Now imagine a retargeting, which you see on the display media, you receive the push, sometimes five times, because retargeting is a machine gun, so imagine you receive five pushes a day, five days in a row, from the same product? You’d throw the phone on the wall. (the CEO).
>
> I would say that the most important thing today is to understand the flow that goes from platforms to ecommerces, or to app downloads. We live more in the digital environment. But I'm sure that digital will influence the offline. The most important thing is to understand which are the tools of this consumer who browses digitally and will make their purchase offline. Who will search online and will make the purchase offline (the VP of Global Strategy).

Mobile push notifications work as first party media, but also as media inventory for third parties. That is, a company does not need to develop an app in order to use mobile promotion, as one interviewee explains:

> (...) There are two ways: we license software so a company can hire our software and put it on their application, and they send the pushes. For instance, McDonalds puts this technology in its app, from that moment on they get all the intelligence that we already have, and it sends messages through its app. Otherwise, I have mobile apps that work as media such as Climatempo, Cittamobi, manufacturers, such as LG, Positivo, Claro operator, or there are applications that we have a business partnership. They also use the push for their necessity, but it becomes a media inventory that is marketed so then a company that doesn’t have

> an application can use it, or even if a company has an application. As a company, it has an application it's restricted only to those who have it. And sometimes you want to extrapolate, getting an additional audience, that is more or less how it works (the CEO).

This cross-channel customer experience driven by mobile requires companies to adjust both online and offline store experiences, as the VP of Global Strategy narrated with this example:

> And then you have examples of companies such as Best Buy that had to make a big change in the business model, because they understood that they could no longer compete with Amazon, Home Depot and so on, they had to change the consumer experience in the physical store, in order to continue selling through the physical store. Quite often the person arrives at the store with the price, look here, can you make that price? The person arrives at the physical store with the expectation of being able to negotiate based on the research data that took place online. It is necessary to have a motivation for this consumer to go inside the physical store (the VP of Global Strategy).

As Danaher et al. (2015, p.711) put it, "the challenge is to connect mobile promotions to actual redemption behavior". And this redemption behavior, that is, actual offline sales, is now attached to expectations created in the online world. "The marketing decision had to do with experiencing something from the online world of the brand but experiencing it in the real world" (the Marketing Director). The digital stimulus reflects on the expectation that is created for the offline.

Quite often the physical channel is not ready to respond to the demand generated by the digital channel. Companies are preparing for mobile push promotions, but they are not ready for consumer pull moves.

The digital consumer is short of time and eager for convenience. People search mobile for instant gratification. The ubiquity of mobile, removing barriers of time and space, is key to convenience. According to the narratives, this convenience can be translated both as a means to approach the offline world (i.e, expediting deliveries with the buy online, pick-up in store mode) or a means of value creation (i.e., as a time saver or for the right context – being there when the customer needs it). "The shopping experience is no longer limited to the physical point of sale. This means that retailers should be able to provide a shopping experience that is natively networked" (PANTANO & GANDINI, 2018, p.690). As a couple of narratives exemplify:

> Free shipping is something that makes it a huge convenience, I can talk about my experience as a customer. You have the app downloaded, so the app also helps for convenience right, because you get in there. I think that the thing about free shipping, talking about the date, fast delivery, having the product at a price, at a price that you know will be competitive, all of this for me, this is the maximum convenience. I don't have that anymore, the need to put together a set of items to make a list to go to the pharmacy ... Convenience involves creating value, and it's not just price (it's also price). For example, making the experience easy, fluid, with a lightweight app. It is the one-click process. But to be one-click, the customer needs to trust the company. For cheap things, imagine paying for parking, the time it takes, the effort of going to the mall (...) for these little everyday things, it really ends up changing your life. Even for basic clothing. The one that has no mistake, that you know the brand, know the size. Adding it all up should reduce hours of your life, doing that kind of thing, which, for me, is not a priority. So I think the consumer behavior did change (the Head of Marketing).

> It depends. What does convenience mean to you? For me, saving time is worth much more (than a discount). Time, the economic value of time is, the value that grows the most. It's not the euro, it's not bitcoin, it's time. Time is the currency that has the highest growth rate (the Chief Growth Officer LatAm).

Familiar with new channels, the consumer demonstrates his intention to switch between online and offline frequently in the future, increasingly joining e-commerce, opting for alternative purchasing channels and a hybrid experience.

> Six years ago…, there was already a lot of people who would check prices before buying, check the smartphone to see if the price was right, to see whether the reviews were positive, to see if suddenly this store or the other was more convenient, and then at that moment it was starting to have a hybridization - between online and offline. We are starting to mix things up, it grew because the mobile, the smartphone ended up concentrating more and more functions in our daily lives (the Chief Growth Officer LatAm).

> The number of people who wants to buy online and pick up at the physical store increased, so we didn't see this movement so much before, but now people see the value in it, because they can go to the website, search in as many stores as they want, decide where to buy and ask to deliver it to the store because she can get it out faster than if the person were to wait it arrive to her house. So, there are a lot of people talking about this and also this movement that the pandemic generated from selling via WhatsApp, selling via Instagram, things that were not so strong before, for example talking to the seller of the physical store via

> WhatsApp. People want to continue buying like this even when isolation is completely gone (the Head of Branding).

The fast pace of digitalization increased customers' expectations regarding fulfillment. Mobile can be involved in the fulfillment promise in several ways including presentation of latest inventory availability information, delivery date estimates, and options for expedited delivery, as well as delivery shipment notifications and update facilities.

> I think now, very accelerated by isolation, there is an even greater tendency for this interaction (digital / physical) to happen, so we even have a study that is about omni-channel journey, in which we asked people how they intend to purchase from now on, attributes related to the multichannel journey they intend to use, and we noticed an increase in the number of people that, for them, it doesn't matter if they buy online or offline, they just want to have a good experience. What appears are comments like: Do you prefer to buy clothes online or offline? Whatever, I just want to be able to buy what I want, find what I want and that it be easy (the Head of Branding).

The issues related to freight are still relevant to the public, which can lead to disengagement. Proof of this is that 63% gave up on an online purchase because of the amount charged for shipping (research document brought by one of the interviewees). When it comes to app, mobile strategy focuses on the long run, it involves habit formation (see figure 6). As one interviewee explained, when the person downloads the app, it is a sign that the person trusts your company. It is a loyalty sign. Either she downloaded it because she wants to monitor promotions and receive notifications or because she is buying and wants to track the order. Or because she trusts so much and knows that she will always look for things there. "There is trust behind an app" (the Head of Marketing). And a clear marketing goal is to win lovers, people loyal to the brand, to the service you provide or to the product.

> "Using the app, downloading the app, is an explicit sign of loyalty. At least of intent on loyalty, that I somehow trust you. This is very good because it means that I am investing now and it will bring me results in the long run. Because trust, loyalty is about long-term value" (the Head of Marketing).

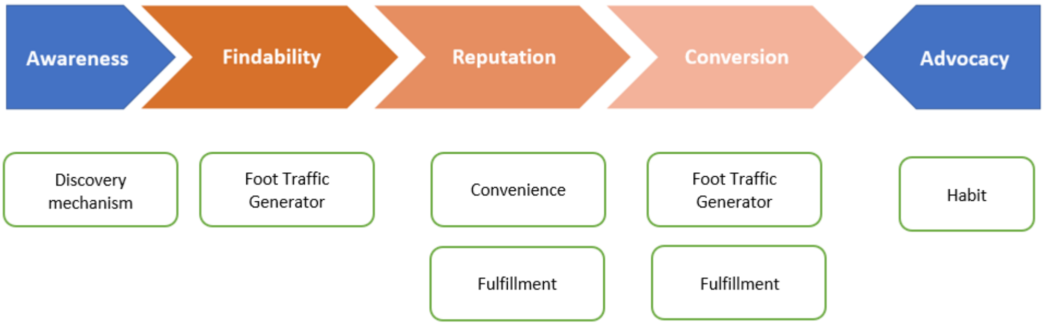


Figure 5 – Mobile promotion and the customer journey.

Table 6 – Theme 1 mobile promotion and offline consumer behavior

Theme 1: Online to Offline: mobile promotion and offline consumer behavior			
	Description	**Main Associated Terms and Expressions**	**Illustrative statements**
Mobile promotion as a discovery mechanism	Mobile as a mechanism of search and discovery on the shoppers' path to purchase (SHANKAR et al., 2016)	Serendipitously discover of a potential purchase – "find store location/directions", access promotional offers, find product information, find product reviews.	The pandemic ... what it caused is very strong. Before the pandemic, what was growing was online as a discovery mechanism (for offline shopping). (...) There was a lot of online inviting to the event, for the experience, dinner, restaurant, everything that was outside the computer environment and was valued as an experience (…) Then there was a major shift in digital transformation. (...) but now you have the cost but you don't have the ambience. There was a shock (the Marketing Director). As a digital platform, we optimize our tools to provide experience, obviously, for the website or in the app. The (online) industry has few tools for generating offline sales. And the ones that have, I would say, have not enough critical mass. Few do. (the VP of Global Strategy).
Mobile promotion as foot traffic generator	Foot traffic is a term used in business to describe the number of customers that enter a store, mall, or location.	Customer acquisition, find product availability in-store; drive people to store.	More incentives to pick up in store rather than drive to the store. The visit to the shopping center should be pleasant and stimulating, it is not a hard sell moment (the Retail Specialist).

For convenience and instant gratification	Convenience is among the primary motivations for using mobile in a shopping context (SHANKAR et al., 2016).	Find where specific products are sold; make a purchase; “free shipping”; “the app helps for convenience”. Convenience involves creating value, it is not just price (the Head of Marketing).	Consumer purchase by cell phone and physically withdraw the product, reducing logistical costs. It is a trend towards products for immediate consumption (the Head of Mobile Solutions). It is necessary to unify the discourse between convenience and privacy (the General Manager). The mobile and physical store have complementary characteristics (the Marketing Director).
Fulfillment facilitation	Execution of what is proposed and defined.	Needs satisfaction and service fulfillment; fulfillment associated with service levels (customer service). Achievement, satisfaction, execution, performance.	Even in the company, we argue that from now on the journey will be O2O, right, so whether it starts online ending offline or the other way around, we have to take care of the consumer experience as a whole (the Head of Branding). And finally, there is the issue of infrastructure, when you leave from a percentage of sales of 10, 12% of the online for maybe, in 5 years from now, to 30%, major revolutions happen. Companies stop looking at it as their side business and start seeing it as their core business, which is eating up their core business. It is a feeling of cannibalization. (...) It is a huge moment that we are just beginning to see (the VP of Global Strategy).
Habit formation	Habit as a predictor of mobile usage by consumers (VENKATESH et al., 2012)	To lead the customer; habit and customer profile.	Much of what we invest in the digital world you do not invest only for that day's transaction. This investment of the day's transaction, it does not pay off. You invest for the transaction of the day and everything you know can come later. And the app tells you that it will come much later. The return tends to be greater, with more frequent purchases (the Head of Marketing). The physical store and the online store have different decision times. They are people who decide differently on how to buy. (...) The best of all worlds is always a strategy that combines the two. Online gives me access to purchases that I might not otherwise have, but the physical store helps you build brand truth. There is a building of trust in the world. (...) The online store helps with the issue of distribution capacity. And the physical store, in building trust (the Marketing Director).

II) Mobile Message Content

The messaging strategy plays an important part in mobile marketing plans. If, on one hand, mobile message has the potential to reach the customers at the right place and at the right time, on the other, it offers the challenge of talking to a distracted consumer on small screens. As posed by one of the interviewed companies' slogan: "we are mobile artisans creating big ideas that fit small screens". When it comes to mobile message content, the following topics emerged: personalization, engagement, and usability.

The mobile technology allows for "anywhere, anytime" messages. But since the smartphone is the most intimate device consumers own, such message communications are particularly prone to be perceived as highly intrusive and are likely to cause annoyance when they are deemed irrelevant. Thus, a critical issue to unleash mobile capabilities is to communicate mobile messages in ways that are consistent with people's needs and preferences (PHANG et al., 2019). "The more I segment, the less opt-out I will have, as the message will interest you more" (the Head of Marketing).

> The message strategy has to be related to the conversion funnel. The content of the message must be adjusted to the moment of the person's journey. People have different moments with brands. Each step of the funnel will offer you a more suitable CTA (call-to-action). We know that in retail the price issue is very relevant. But we already have cases of retail groups like Zona Sul, Pão de Açúcar, which are focusing on experience, brand building, and are benchmarks for the market (the Connections Director).

"Customization pays off, and it's not in my opinion, it's in the opinion of the numbers. (...) it is a fact that if the segmentation is well done, it works" (the Chief Growth Officer LatAm). Another interviewee explains how geolocation information can be used for competitive targeting or behavioral targeting:

> Let's say that I work for Arcos Dourados and I want to know who are the people who pass in front of McDonalds. From the moment the company can understand who the people who pass by that particular place are, it obviously manages to campaign for that specific audience, focusing on increasing sales for that particular McDonalds. In other words, the interest of companies is to understand who the users are and from that try to bring a conversion. Obviously, it is also very important to know how

> many people pass by, especially if you want to open a new point of sale. But to me it seems more useful if I can get this data for conversions, regardless of what type of conversion it is (Key & Strategic Sales App Business).
>
> The client has to assign different weights (for store visits), so, for example, I take a guy who goes to McDonald's every week and impact him and he goes to McDonald's. I think McDonald's continues to do the brand building to guarantee that the person will keep going. But he’s willing to invest in that a smaller value than taking a guy who hadn’t been in McDonald’s for six months. And even worse, he went to Burger King, so this is the type of analysis that I think is interesting. So, we take that too, from the competitors. So, store visits metric, it has been overly simplified in the past (the CEO).

Short-message-service mobile coupons are inexpensive, quick to disseminate, and can be customized on the basis of location, personal information, and prior purchase behavior. Mobile coupons expiration length should be shortened to help signal time urgency (DANAHER et al., 2015), as one of the interviewees illustrate:

> Thinking about how to get the consumer's attention, a word is context. A company that works well is Ifood, with fun messages at the right times. (...) Besides the emotional triggers, there are several psychological triggers that can be worked on. For example, people prefer 50% discount to a $ 10 discount, and sometimes 50% represents only $ 7. The issue of "only until today", is another emotional trigger. If I don't buy today, I won't buy more at this discount. These emotional triggers work, but it will depend on consumer to consumer. We have to contextualize it at the end of the day, hence the wealth of data. Companies use very little from the data they can get from customers. (...) Few companies have this accuracy in curating a message (the Connections Director).

Privacy calculus theory (PCT) states that consumers make privacy-based decisions by evaluating the benefits any information may bring against the risk of its disclosure (XU et al., 2011), and that perceived benefits have more significant influence than the perceived risks/costs (WANG et al., 2015). On one hand, there is an increasing criticism on how algorithms encourage people’s addictions and break their privacy. On the other, the algorithms offer the ability to make lives easier through personalized offers of what we need:

> I train all my browsers, I teach them to give me the things I want to see, I found my apartment training the Instagram algorithm (...) just like the matrix film, you can also become aware of what it is (the algorithm), and use it to your advantage (the Chief Growth Officer LatAm).

> We started to analyze how people behave based on linguistic elements. So, what is the best way to talk to this person who is more towards the end of the conversion or another person who is yet at the beginning of the purchase journey and then this methodology that we did, this behavior analysis, this linguistic analysis gave a guideline for us. This is the best way to communicate in each step of the customer journey (the Head of Branding).

Mobile devices provide "interactive features to engage customers" (TONG et al., 2020, p.64), such as cameras, speakers and text communication features. And engaged customers provide higher revenues in the long run, hence the struggle for achieving customer engagement via mobile. As the Head of Marketing and the Head of Branding explain:

> There's a cool thing that happens in the app, that a lot of people who use it consent to receiving push notifications. So, it is easier to communicate with that person. Because it is very simple to send a push, we segment. It is rare for us to send a push to the entire base. We control opt-out a lot (the Head of Marketing).

> ~~So,~~ we even created a communication methodology called People Marketing, which is about what is the best way to communicate with people and make them engage with brands without being that dull thing and always the moment that person is on the customer purchase journey (the Head of Branding).

Another tale told by the Head of Branding also illustrates this point. One of the hits of the pandemic was the musical lives. In tune with this movement, some of the big companies in the market adjusted their communication strategy, seeking greater engagement, as in this case told by the Head of Branding about the live of a famous country singer and a large department store:

> We wanted the person who had (watched the live) to have this experience of continuity of communication, so we took some actions: the first was when the person entered the site, a message would appear: come here, take a look at something, with a discount coupon from the blogger and then there was this continuity in the communication of the two channels. Then we made a third communication saying Live is over, but the

> promotions are not, come take a look. So, we managed to take advantage of this deal and had a nice result.

Another example of a campaign integrating the online and offline world was the following:

> Because we already did it, already tested it. He saw that if we segment a person only by online or only by offline behaviors, the result was not the same as when we crossed this information, so we crossed this information, the average provided results eight times greater than using only one vertical. (...) That's why in the case of Telecom X we used what we call O + O {online plus online} segmentation (the Chief Growth Officer LatAm).

The role of mobile is intrinsically attached to easiness of use, hence the naturality that the UX and usability themes came up. "Many companies are realizing the importance of investing in user experience, so that the design be as intuitive as possible" (the Head of Mobile Solutions). As another interviewee mentioned: "and then we used creativity in a very simple way because you have eight seconds of average attention time that you can dedicate to a mobile banner, up to eight seconds, so you cannot make conversions or engagements that take longer than that" (the Chief Growth Officer LatAm).

> Mobile marketing's first challenge is market evangelization. Few companies have people who really understand mobile marketing. Then, the attribution part is a pain point (...) and there are companies trying to solve this, at least between the web and the app. Few companies today invest in the application so that the user feels comfortable using the application and does not open the computer to do the conversion (Key & Strategic Sales App Business).

> Especially because you have different generations using the smartphones, what is easy for one, it is not easy for the other. You have consumers who are looking for different things, different categories, so one thing is the person who will buy in the app a cleaning product, something else is the person who is going to buy a computer in the app, which is less usual (...) So you need to have a good shopping experience, fast, trustworthy, which is not easy to get to , because people are very different (the Head of Marketing).

Table 7 – Theme 2 mobile message content

Theme 2: Mobile Message Content			
	Description	**Main Associated Terms and Expressions**	**Illustrative statements**
Personalization	Mobile message personalization (KIM & SONG, 2020), that is, tailoring to customer profile, past behavior and needs (BAKOPOULOS et al., 2017).	Custom product alerts; high and low personalization via CRM data; “personally identifiable information (PII)”; “safe-harbor identity matching”; not use sensitive data; respect personality, avoid dull things.	The company already works with some standard segmentations. We have proximity (impacting people within a certain radius), retargeting (impacting people who have been in the PoS of the advertiser or competitor in the last 15, 30 or 60 days), indoor (impacting people within the PoS) and clusters (a set of users defined based on common behavior). We can study better according to the advertisers which targeting would be more appropriate (the BI Manager). Honestly, it is not common to analyze message content effects. One of the rare occasions in which we looked was a Carrefour campaign that reached a 10x lift. In this case, the discount offered was huge. (the Head of Sales and the General Manager). We understand what the stages of the buying journey are, from then on our team started to perform linguistic analysis, so what did we do? Took a universe of all communications and started to identify the communication nuances that worked the most and we understood, such as, when we talk in a more loving way it works more at the beginning of the journey… if we use any financial attribute it works more for people who are at such a stage of the journey… because it also serves as a guide for our customers not to end up burning money because they might offer a financial benefit at a time that they didn't even need to offer, so we can differentiate it (the Head of Branding).

Engagement	Refers to the involvement of the shopper in the shopping experience through mobile (SHANKAR et al., 2016).	Engagement levels; gamification; short attention window; adjusting communication strategy; enhance and measure engagement. Cross-channel campaigns have the potential to help customer engagement (the Head of Branding).	If I told you that I have three great things to do today, one of them is taking care of mobile, it is engaging people with the app, not just the mobile browser (the Head of Marketing). Cross-channel campaigns have the potential to help customer engagement (the Head of Branding). (comparing push with RCS) The push helps a lot, because people who are used to push, you do not open the app, you hit your eye and see. Sometimes you get WhatsApp, you keep an eye on the message, you don't even look, I saw the push , I decided. (...) there is the push with image, you can have a much more impactful job, the person solves right there, visually (the CEO).
UX and usability	The extent to which a product can be used by specified users to achieve specified goals with effectiveness, efficiency, and satisfaction in a specified context of use (INTERNATIONAL ORGANIZATION FOR STANDARDIZATION, 1998).	Stickiness, positive attitude. Mobile requires good UX design.	And then there is the challenge of the experience as a whole. For example, we have a lot of people who download the app and then you realize that they don't buy. So there's the challenge of getting the best experience, a more fluid experience, because in the app, people don't want to spend hours doing that, it has to be very fluid and we haven't gotten there yet. A light app, easy to use, and that solves a good part of the person's problem. It is not a simple equation (the Head of Marketing). There is so much in the equation, the generational question, how each one learned, the type of purchase being made, whether it is a functional purchase or if you have a greater emotional relationship, there is no single formula. It is important to look at how the tools can help within what you want for your business (the Marketing Director).

III) Mobile Ubiquity and Consumer Context

One of the highlights of mobile is its omnipresence in the mobile journey due to its ubiquitous character. Therefore, mobile can be used for targeting moments of relevance. Hence, other topics related to the contextual trait of mobile are geolocation, location-based promotions and customer service and logistics.

One of the great challenges for marketers is to be able to talk to people at times when they are most receptive to the brand message. Companies seem to be putting a great effort into identifying the step of the journey the customer is, as some authors have mentioned before (OSTROM et al., 2015; BAKAPOULOS et al., 2017; PANTANO & GANDINI, 2018). That seems to be the current interpretation of targeting moments of relevance. However, mobile marketing is set apart from other marketing strategies by its hyper-context personalized targeting, that is, location, time, environment, companion, and dynamic competition (TONG et al., 2020). Such data is provided by the ubiquity of mobile devices, hyper-context information provided by GPS, accelerometer, sensor and gyroscope, among other things (i.e., social media listening and customer search intent). For instance, in this mobile campaign exemplified by one of the interviewees:

> The user landed on a dynamic landing page, in an add, activated by geolocation. The landing page was different according to the user location, no user landed on the same landing page (the page showed the cell phone recharge points next to the user). That is an example of personalization, of mobile customization. (...) then we monitored the visits at twenty-two thousand sale points to see how many visits happened. (…) So the landing page was never the same. In fact, it wasn't even a landing page, it was an add (the Chief Growth Officer LatAm).

Indeed, distance has been shown to influence consumer response (DANAHER et al. 2015). The fact that the campaign created a personalized, interactive map, refers to what Hubert et al. (2017) posited, that when mobile shopping makes use of location information, customers consider it to be better designed. In addition to the number of impressions and clicks, the company delivered the number of calculated routes, as the interviewee explains: “All these data were analyzed by point of sale, so the customer at the end of the campaign was able to cross-check with the data of each supplier. In addition, the campaign and the report were externally audited with visit and geolift metrics. “Geolift is the effect of the campaign on visitation of those impacted” (the Chief Growth Officer Latam). One of the interviewees explained that geolift is different from attribution:

> We have this online media project, we have an OOH {out-of-home} project, with practically all the big OOH companies and we are launching one now with Kantor Ibope that the same thing, to measure, to see the effectiveness of television advertising, according to visit flows (…) for me, this is not attribution. Attribution is something else, it's another analysis (the CEO).

> We were also able to have a view of the geolift, that is, the effect of the campaign on the visitation of those impacted. This effect is isolated by comparison with the variation of the control group, which was not affected. The result of this difference is attributed to the campaign. Considering all segments, we had an average geolift of 4.54%, that is, analyzing the visits before and during the campaign period, we can conclude that there was an increase of visits to the point-of-sale (the Chief Growth Officer Latam).

> (...) in online digital media you attribute the last click, as we call. You do the media, the person clicks, you know she clicked, then she goes to a certain site, then she buys or doesn't buy, she can even go back to the site later, but you can have a sort of attribution, in X days window of time. (on mobile) what we do now is not attribution, it's an inference metric. From a controlled base of users, we had the universe of X percent of the people who went to the store. For example, from a thousand people, out of these thousand people, how many were in the supermarket chain store? So many. From those people that went to the store, how many had I impacted, how many I did not impact (…). In the second derivative, I also show the people that I impacted, who they are, which ones had never been there, which ones have been but have not been there for more than 30 days and which ones were there in the last 30 days. In fact, you can't tell if the person was there because of my media. Because when it's digital, the guy clicked, he liked it. When the media is 100% digital, this journey is more obvious. When you have an inference about going to a physical store, you can't guarantee it, because I may have seen the push, I may have seen them on television, I may have heard them on the radio, I may have seen such a billboard, (…) In my opinion, there are many different types of visit cost (…) It doesn't have to be individual, it can be per group, the clusters (the CEO).

This citation is illustrated with Figure 6 below.

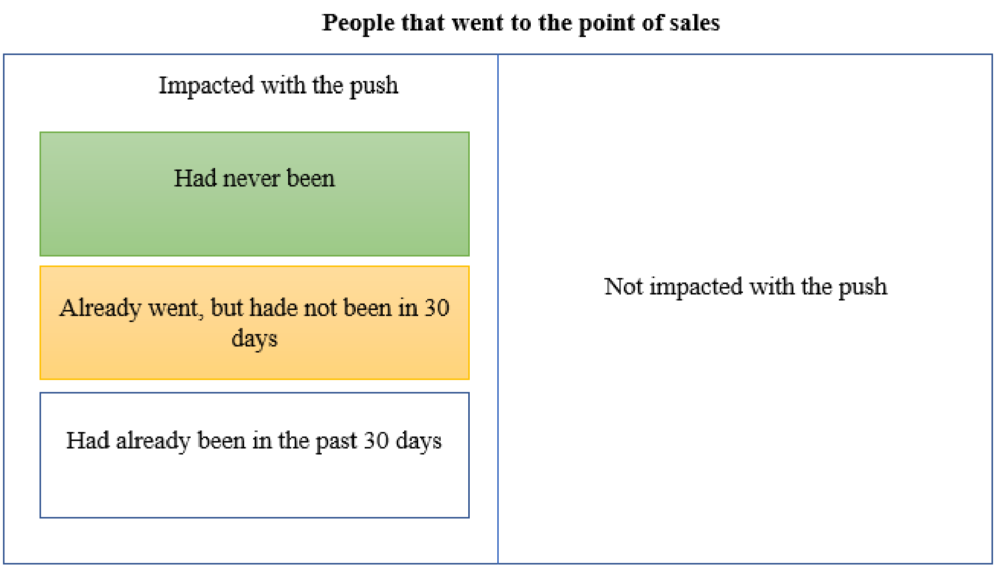


Figure 6 - Example of mobile push inference report

> Mobile media, it has to be contextual media, and there are several examples, but there is one that I really like. We did a campaign once for a non-alcoholic beer. Okay, it's beer, it's alcohol-free and consequently it was lighter too and the motto of the campaign was sportsmen. We wanted to catch the guys who practice sports during the week, who often don't want to have a beer during the week because they don't want to disturb the next day's sports routine, especially those who practice sports early in the morning. (…) Thinking about geolocation, the client wanted to impact people when they arrive at the gyms and parks. But it makes no sense to talk about beer early morning. It is one thing for you to geolocate the segmentation, another thing is the context. Instead, we proposed to talk to people that have the habit of running, who have the habit of going to the gym but ... because the push is in time real, it had to be sent latter (the CEO).

That campaign is about content relevance, it refers to the degree to which mobile location-based advertising is uniquely tailored to the target consumers' preferences and needs (XU et al., 2009). Mobile technologies are always referred to as the anywhere, anytime tools, as they alleviate both spatial and temporal constraints. Hence, managers often wonder how the time and space dimensions could be used to increase mobile promotion effectiveness. Context is not just about when you can get many clicks, but also when people are open to purchasing. As one interviewee explains, people click a lot in Social Media during late nighttime, but it does not mean that I am willing to fill out a form to purchase it. The contextual factors are important to perform mobile targeting (PHANG et al., 2019). The places a person goes to reveal a lot about them: routine and habits, tastes and possible needs, their behavior profile. And nowadays, the smartphone usually accompanies us in practically all daily activities. One of the interviewees used the metaphor of geolocation as the real-life cookie: "Actions that take into account which was the person's online consumption profile and which was this person offline profile, that is (...) the geolocation technology is like a real-life cookie" (the Chief Growth Officer LatAm). Providers of MLBA (mobile location-based advertising) need to ensure their personalization efforts include sending the most relevant message to mobile users at the most relevant time and when the user is in the most relevant location (GUTIERREZ et al., 2019, p.302).

> Besides social media, there are some platforms that give you greater accuracy in delivering the message. Message delivery is contextualized by geolocation. And from there you can create other levels of message customization (...), by product usage history, by digital behavior. I can really contextualize the message not only by its location. The location is just the filter. I still have the user's behavior that, through the mobile data, I can speak to him in a more assertive way. This is a very well-adjusted, very sophisticated process. And that only happens thanks to the tripod (IoT, Big Data, IA), I have cell phones capturing data from people, I throw that data into the cloud and I have algorithms and (artificial) intelligence and companies focused on identifying and clustering these people in order to deliver the message to them (the Connections Director).
>
> The way in which each company uses this (geolocation) information is different. But the way I understand it is most used is to set up a cluster to try to bring conversions, to have a higher click or conversion rate (Key & Strategic Sales App Business).

By sending the consumer messages that are tailored to their interests, identity, location and time, mobile location-based advertising offers the benefits of contextualization (GUTIERREZ et al., 2019, p.297). Mobile coupons might enable stores to offer smaller discounts if the proximity and time is convenient to consumers (DANAHER et al., 2015, p.711). Some narratives exemplify that:

> I'm using one channel to take me to the other, for example I'm on the bus and I see the ad (...) suppose you want to know which X department store is the closest to you? take a look here and through the QR Code opens the map that shows all the locations of the brand. Then I can choose the closest to me. (…) To be able to take the person to use online to take the person offline (the Head of Branding).

> My sister picks up the phone and decides where she is going to have dinner, picks up the phone and decides where to buy clothes (based on the discount coupons she receives on her cell phone). And my father is the same, he was always very technologically developed, so he goes on the basis of geolocation to see which services are closest to him so that he can optimize his schedule (the Chief Growth Officer LatAm).

Another use of geolocation information is for geofencing: “For example, Ifood, which segment the restaurants that are close to customer X to make an announcement from there” (Key & Strategic Sales App Business). As the interviews showed, mobile coupons are all about time and place (DANAHER et al., 2015, p.711).

> As we are much more digital, our goal is to generate digital experimentation. Hence, geolocation is important, we hear about it, but it is not a top 10 item. Now we see the phenomenon of betting sites growth. Some American states are beginning to release betting sites. It is a new industry, with lots of money involved. So now I started to hear a little more about geolocation, because as the advertiser cannot advertise nationally, he needs geolocation tools (the VP of Global Strategy).

> We had done a study and seen that the great Achilles heel of geolocation was the lack of transparency. Everyone sold the visit at the store but no real effort was made to attribute it to the vehicle and also had no effort to measure it by third parties (the Chief Growth Officer LatAm).

Geolocation strategies seems to work best with a multiple combination of points. As the Chief Growth Officer LatAm explained: “It is on a large scale that you will be able to optimize large flows of people. To take people to a single point, do leafleting. Just as in digital, you need to have space for optimization so you can have better results”.

> This flows very well due to the evolution of the platforms. When we are talking about geolocation strategies, there is a very high level of assertiveness of the main social platforms in Brazil. Facebook, for example, is the largest network in terms of active users and you have a very high level of accuracy. If I want to talk to women of a certain profile who are within 1 km of a point, I can do it. (...) So the level of geolocation is fully accurate, especially on social platforms. With the advent of the programmatic platform, you have some platforms with an even greater accuracy (the Connections Director).

> (I ask my clients) Have you ever wondered if the visits you were buying were new ones? He (the client): "but what is the difference?" the difference is that I am a geolocation company. I know who goes to McDonald's every week, I can easily only deliver media to those who already go every week, so, do you want anything easier than that? Which is the reverse of digital media, that in the digital media, although the assignment is simpler, you don't know that. If a Retailer does not give you his cookie pool, which is his customer base, you cannot segment those who already access the retailer's site. So, when a retailer hires a retargeting company, he knows that he is hiring retargeting, he pays for the retargeting price and he puts the tag in there. When you do geolocation, I do not need the Retailer to know who has been there, I have it by myself, so if the relationship is not transparent, the retailer will never know if he is paying for the new customer, for recurring customers, for customer that went from the competitor or for a client that hasn't been there for a while, there are very few clients that are aware of that difference. I think the market really needed to mature a lot about this, because otherwise you buy a pig in a poke (the CEO).

However, the use of geolocation feature goes beyond advertising targeting. Such precious information has also been used to logistics decisions. For instance, geolocation platforms (Logan, Inloco and others) were also used to address the widespread effects of the COVID-19 pandemic in Latin America, a behavior changing initiative.

> Geolocation is the Achilles heel of companies. Everyone is learning. (...) Before, the person had to leave to go to the place of consumption, now the place of consumption comes to the person. The logistics part, which delivers the sale (...) we were used to selling and the person took it. Now the product goes to the person. So where the person is becomes an issue. Even from a global perspective. (...) Geolocation begins to show real challenges, which is ... logistics (the Marketing Director).

Marketeers tend to associate performance to visits and sales, but there is a new possibility: the awareness lift, that measures the variation in behavior (i.e., stay home) in the group of people who were exposed to the campaign. Mobile promotion emphasizing urgency has been shown to influence mobile promotion responsiveness (DANAHER et al. 2015). With accurate geolocation information, that sense of urgency can be translated into delivery promises, for instance.

Geolocation: great but overrated? While the potentialities of geolocation were reaffirmed and praised by some interviewees, other questioned its feasibility:

> During my lectures I had to say: geolocation is cool, but mobile is not just that. Mobile is the top of the funnel, mobile is conversion, mobile is social commerce, it's the possibility for you to segment in a different way (...) we even used to joke: mobile geocannibalization. People were associating too much mobile with geolocation. It is an important vertical, just as mobile online behavior is. There are two verticals (online and offline), it is a waste not to use them in an integrated way (the Chief Growth Officer LatAm).

> In my particular situation, geolocation does not yet enter the equation, but it would be possible. But it is because I use very little, if anything, of personal data. It's quite complicated~~.~~ Because you may have the person's address, but they may have purchased a gift. So, for now, we use little of geolocation. We focus on the shopping behavior on the website, such as categories, frequency, mainly this (the Head of Marketing).

> (...) the message profile they (a fintech) place for each of these stages of the funnel is very clear. For example: downloaded the app, message to finish the registration. Then, the first contribution remains to be made. And after other services that you don't use yet (...) The major point is to be totally aligned with my goal and with something that I'm interested in clicking. As soon as you send me a lot of push notifications, I start giving up on you. (...) the customer journey is first party information, the company owns it. The geolocation information usually needs a third player to pay for the information of the user's location. Does it make sense for me to create this cluster? It makes super sense to create this cluster. How much more I will spend is a crucial point. It's analogous to DMP (programmatic media), it's great, but how much more do I need to spend to use DMP? Sometimes this extra X is what makes the campaign lose its margin and stop being profitable (the Key & Strategic Sales App Business).

One of the most interesting possibilities of geolocation is to promote campaigns focused on offline conversion: the user's visit to the physical establishment. The geolocation technology is perfect exactly for this type of action, as it is possible to measure the physical visits of users impacted by digital ads. This is an innovative way of measuring the real impacts of a digital campaign. Location-based data allows retailers to target consumers with tailored content, including ads and discount offers, at a time when they are most receptive to taking a trip to the store. Yet, costs and the dependence on third-party seem to be barrier for the adoption of such marketing strategy.

> There are two issues: it's not just the quantity (of views and clicks) but also the perceived value. Because when you segment a lot and you're going to do a very specific campaign, sometimes

> you have the same work or even more, of planning and creation work to deliver a campaign that will impact a smaller target. And then you have, any company has fixed costs too, they are not only variable costs, so its unit cost increases. Then you say, but this campaign is giving a CPM of $70, but I'm used to paying $5 for the CPM. But you talk to the whole of São Paulo in an attempt to sell. Here, you're reaching the target. So, I think that touches on the issue of the attribution challenge. Because as an assignment, it is a little difficult to measure how much this campaign literally generates in results. So who can't do the math, when you see a step in the funnel that it is a little more expensive than you're used to, it scares. So I have a lot of questions about the unit cost. Now those who can do the math, can understand that at the end of the day you will have a better ROI, because you will have a much more segmented customer (the CEO).

Figure 7 illustrates the pillars of mobile context. It includes not only location, but also customer data and the appropriate approach.

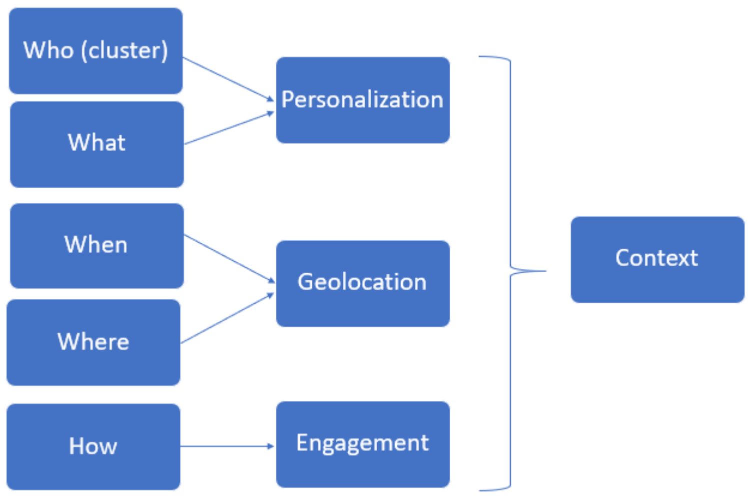


Figure 7 - Mobile Context Elements

Table 8 – Theme 3 mobile ubiquity and consumer context

Theme 3: Mobile ubiquity and consumer context			
	Description	**Main Associated Terms and Expressions**	**Illustrative statements**
Target moments of relevance	Due to mobile portability, ubiquity is related to the possibility of accessing information anytime, anywhere – the perpetual contact (NAEGELEIN et al., 2019; PHANG et al., 2019), allowing marketers to target moments of relevance across the customer journey (BAKOPOULOS et al., 2017) via mobile.	Assertive communication; consumers' receptiveness; target size; "targeted notifications"; "data for targeting". Message delivery is contextualized by geolocation (Connection Director). Targeting without infringing privacy (the BI Manager).	The algorithm tries to help you with your shopping experience. This happens on the push, it happens on the homepage, it happens on the email (the Head of Marketing). Distance can be measured by proximity or by place. Measure by proximity: impact people within a certain radius to the store. Ideal for street locations. Measure by place: latitude and longitude, using places mapping. Allows for more precise indoor measurements, such as differentiating among floors. (the BI Manager). That today we have an algorithm that serves to identify whether the person has a greater or lesser propensity to buy and from then on, we know if they have a greater intention of buying, then they are already at the end of the customer journey, or if the person is not demonstrating so much intention to buy, than she is more at the beginning of the journey (the Head of Branding).
Geolocation	Functionality present on mobile devices used to identify the user's location (HANDS, 2020).	Content related to the location, relevant services in the location. Three types: competitional, proximity and behavioral: Geolocation information can be used for geofencing, competitional targeting or behavioral targeting (the Chief Growth Latam). "Not cheap"; "increases costs"; "needs a third player"; "cool"; "lack of transparency"; "Achilles heel"; "not a priority"; "important but not so important";	Each country has some idiosyncrasies of digital advertising, of mobile advertising, for example, Mexico is more advanced in terms of programmatic purchasing, and Brazil is the most advanced country in terms of geolocation (the Chief Growth Officer LatAm). Another trend is geolocation, which allows you to be impacted on a product or service where you pass. It did not have the advance that we imagined, because people got tired of receiving so many notifications (the Head of Mobile Solutions). Geolocation is an important feature, but it is not the core of what we have to do. It depends on the business and the business model. If the focus is national online sales, geolocation is important but not so important (the VP of Global Strategy). As well as you can know what you like on the basis of the websites you go, the ones you visit (online), it is the same, you can find out what

		"challenging"; "accurate on social platforms". "The way each company uses geolocation is different".	kind of consumer you are if I see real places where you go (offline), it's the same, it's identical (the Chief Growth Officer LatAm).
Location-based mobile promotion	Promotion that uses geolocation data. Can be divided into geofencing or geobehavior.	App downloads to monitor promotions. Location-based data allows retailers to target consumers with tailored content (the Key & Strategic Sales App Business).	The brand does not need to know who the person is, the focus is the result. What the data has to say is whether that person has a chance to buy. Thus, the customer is referred to as an ID. This ID is not associated with any civil identification, but with a pattern of behavior (the Head of Sales). The filtering of the ads is done by the offline behavior of the consumer. Online behavior is very aspirational (the Head of Sales). It is possible to distinguish between a new visit and a recurring visit (generated from mobile to the pos), which also has its value (the Head of Sales).
Customer Service Logistics	Location-based services beyond promotion, such as loss prevention, store planning, tracking and customer service (LMBA, 2020).	Delivery time; fast delivery; expedite delivery; service provision; logistics requirements; efficiency.	Often people turn on the push notifications because they want to receive information about their delivery. They have one more reason to give me consent to text them (the Head of Marketing). Geolocation is being frequently used to monitor product delivery, it is a way to give satisfaction to the customer and make him more confident (the Head of Mobile Solutions).

IV. Conquests and Challenges

The proliferation of mobile technologies makes it possible to go beyond the real-time snapshot of consumers' static location and contextual information (GHOSE et al., 2019). Yet, this is a new game that just a few companies have learned well how to play, due to the many tasks, rules and challenges it involves. It involves clustering, cohort analysis, privacy issues; plus, attribution and performance measures. At the end, reality is still beyond promises.

> This possibility is not utopian as there are already companies that do, but it is a minority. Most Brazilian companies are not even structured to make the CRM work. LGPD {General Data Protection Law} will help companies look better at their data (the

> Connections Director).
>
> Personalized and geolocated actions are still a little incipient, even because the costs are high. This part of geolocation is not a cheap thing, few companies do it and therefore it also increases the costs. I see a lot more of big companies, big players doing it, and testing, putting their feet in the water to see what works and what doesn't. Is it worth the higher cost? Is it not worth it? Few companies are doing it and whoever is doing it is still testing it (the Key & Strategic Sales App Business).

Mobile is able to offer precision metrics that were not available on other channels, providing a much wider range of information to understand the consumer and understand how marketing actions are assimilated. Along with the increase in consumer data, discussions about privacy and the conscious use of technology are also growing: “today, the biggest question mark is the data and the use of the data” (the VP of Global Strategy).

> The challenge now is data management. If I have a user that has on average eighty-two applications installed, and that at least half of them accepts to share data, that is, I have a lot of different data sources, I need to stop to think if I really want to produce an app, how relevant this really is to my consumer (the Connections Director).
>
> Vehicles were selling visitors and people were buying, without auditing. We at (company X) never sold the visit, we always used the visit as a performance goal, like a key performance indicator. We will use it and see how much this result is, but I will not charge you for it. I will charge you for what you can measure such as clicks, impressions, views (the company has been working with an external visit audit for three years) (the Chief Growth Officer LatAm).

The pay per visit cost can be an illusion of safeness for media. As the CEO explains: “If a customer says: I’ll pay X reais per visit, I have an idea of the conversion rate, of the average ticket, so a rule of three here, I almost have no more risk of doing media and not generating results. I say: think twice”. The firs app download campaigns were expensive. Then the value considerably dropped – low price, but no quality. Then the market reconsidered, and prices rose to a reasonable amount for targeted downloads. As the interviewee explains:

> What is happening today with geolocation is what happened some time ago with the app downloads. (…) Whenever there is a new technology, expectations go high up and normally expectations go up, not only for the buyer side for the seller side, as a miracle solver that latter falls into the valley of disillusionment.
> (the CEO).

Dealing with data involves dealing with personalization, clustering and privacy issues. Because of data privacy laws, business models based on personalized advertising, for example, mobile data, such as geolocation or personal data from apps, will require building a relationship of trust with consumers. Data may not be passed on to third parties without the express consent of the data subject. And the data cannot be used for a purpose other than the pre-defined one. That is, data can only be used with consent within the specified purpose.

> Today, speaking of 2021, with the new user information laws, it will even be interesting to see what this part of on-off integration will be like, of monitoring where the user goes. Because companies will no longer be able to hold this information in order to characterize who that user is (LGPD). That is, as much as they know that a certain user is passing in front of a bank branch, they will not be able to know that the person is Mary or John. So I think that will change the profile of how companies will be able to use this type of (geolocation) information (the Key & Strategic Sales App Business).
>
> That's why I say that you need a data ecosystem (...) if you stay only in your data, you may have bias that can lead you to make mistakes, because you have no parameter for comparison (...) you have to gather the pieces of data that come from aggregators, first party, second party, third party (...) all anonymously, to know as faithfully as possible how many people are passing around here, through that point of sale (...) all this to make a look alike of people (the Chief Growth Officer LatAm).

In this process, respect to privacy policies is essential:

> In regard to behavioral targeting, it is important that the criteria do not breach privacy policies within the General Data Protection Regulation. For instance, the research cannot deal with categories such as hospital or churches. Possible behavioral criteria (considering offline data) are: visits to category of places, such as restaurants (in general) or gyms; offline location behavior; installed apps (consider that children may install apps in parent's devices); and type of mobile device and mobile operator (the BI Manager).

Marketers should be aware that consumers are more sensitive to feelings of irritation/annoyance from the interruptions of mobile location-based advertising than by the fact that their personal data has been used (GUTIERREZ et al., 2019). Therefore, efforts need to be made to reduce mobile users' perceptions of intrusiveness.

> Data Strategy is essential (...) I don't know if you are following this discussion of IoS 14, Apple announced that it would restrict the use of data for platforms to target and measure, they backed off for now, postponing to 2021 (...) but metrics, data for targeting and measurement is a differential. As you have better data, the advertiser can target better and measure better who is buying. Today our measurement is already based on what the user does, the RoaS (return on ad spend). It optimizes over what the user does, and this generates more value. So the advertiser knows how much he can pay for that user, he knows the fair price for that ad (the VP of Global Strategy).

> The trilogy of the digital revolution involves: IoT, Big Data (we are talking about data zetabites) and algorithms with artificial intelligences. From that moment the revolution begins, as I begin to better understand people's behavior in their intimacy. (...) This construction makes it possible for us to have a very precise level of accuracy to the point of creating the proper arguments to make the person leave their home and enter a physical store. Or enter a physical store, research on the price of that product and decide whether to buy at that store or at another online (the Connections Director).

> The world of Big Techs today is trying to consolidate this just for them, so I think that there are privacy issues of LGPD, which is favorable to users, but when you take platforms like Google and Apple and start to restrict, because the mobile exists or in Google or in Apple, there is no other way (…) Both Apple and Google are media companies, but the point is not whether they will or will not collect user data. The point is that they will or will not make user data available to other companies. But for them everything is valid… So, I think one of the great challenges of the market is this. That you have Apple not sharing IDFa anymore but having a proprietary solution. When you have Google complicating the collection of geolocation data… but Google Maps always collects whenever and however it sees fit… (…) Any time you have a market concentration, the impact reaches the consumer (the CEO).

> Updates to operating systems have been limiting access to user data through the apps' SDKs, this creates a need to complement data sources, to maintain relevance, coverage and, consequently, visibility of what happens in the real world. Much has been said about O2O as if there were a passage between two separate worlds, online and offline, but the reality of things shows us that reality is O + O, that is, already fully hybrid with syncretic gates

> and in most cases, implemented through the almost omnipresence of mobile devices (the Chief Growth Officer LatAm).

Location-based advertising is a means for advertisers to reach out through personalized messages sent directly to mobile phones using their geographic location. The mobile phone users' willingness to disclose their location and other personal information is essential piece of such strategy (GUTIERREZ et al., 2019, p.295). Despite the existence of more sophisticated mechanisms such as attribution platforms, the good old email seems to be still commonly used as an on-off attribution tool, as the Head of Branding posited: “What people normally use now as a key identifier is the email. So, if I go to a store (…) through this email it makes the match with the base and it is understood that it is the same person”. Yet, everything could also be captured by the smartphone ID, to monitor consumer behavior.

> Omnichannel attribution in general is a challenge. Even the main attribution players also suffer from this omnichannel thing. I will give you an example of a large (bank Y) that had a volume X of organic installation. But there is no such thing as organic installation. This guy took some path that led him to download the application from the bank. Either he saw a billboard, or a campaign on the desktop and ended up downloading it on the phone. My honest view is that there is no such thing as organic attribution. Somewhere in the conversion line there was something that pulled the trigger. But it is very difficult to know at what time or channel this happened (the Key & Strategic Sales App Business).

> The biggest challenge of the market is to know how to handle and use this (mobile) data for a more qualified, individualized communication, in a hyper segmented way. Which is what happens when Netflix tells you that that series is 97% relevant to the guy. For your wife, it will be 84% relevant, for your friend, it will be 57%. This is a hyper segmented curation, based on data (the Connections Director).

> There was a client, a Retailer, who was working on the campaign to sell smartphones. He said I have a USD 0,40 visit cost. I said people go to your store because they go, they go to buy many things... there is a supermarket inside, there is a locksmith, it doesn't make sense for you to consider all the visits. Working with geolocation to generate results, which is this metric in the offline world, is very challenging (the CEO).

Mobile expands data possibilities, going from static to dynamic mobile communication. That enhances the importance of clusterization and cohort analysis, as well as privacy concerns, with the need to obtain consent within specified purposes. From the interviewers' statements, data management and performance challenges emerge. Regarding data management, it requires data pool, IoT and algorithms. That is a pre-requisite for better targeting and better measurement. Despite the struggle, increasing the quality and relevance of mobile promotion can be a path to reduce user's perception of intrusiveness in such an intimate device. The possibilities are vast, but…at what cost for the companies? Will the results make up for the investment requirements? That is one of the many challenges in the foreseeable mobile future.

> The smartphone, the way we know it, must have another 10, 15 years of life. The concept of mobile is actually intrinsically related to the concept of mobility, because you are ubiquitously reached by technology (the Chief Growth Officer LatAm).

Table 9 – Theme 4: Conquests and challenges

Theme 4: Conquests and challenges			
	Description	**Main Associated Terms and Expressions**	**Illustrative statements**
Cluster, cohort analysis and privacy	Cohort: a group of people treated as a group. Cluster is a grouping or categorization of users based on pre-established criteria (HANDS, 2020).	Customer segments: smartphone clusters comprise many attributes; General Data Protection Law; privacy prerogative; privacy policies; cohort segmentation. Throw that data into the cloud and I have algorithms and artificial intelligence and companies focused on identifying and clustering (the Connection Director). The world of Big Techs today is trying to consolidate this just for them (the CEO).	We have data on consumer buying behavior. (...) The app, or those who did not download the app, we follow the same way. I can follow the buying behavior of a consumer engaged on the desktop. Again, I am not able to connect "consumer A" to this behavior. I am looking at groups. Groups that are doing more of this, groups that are doing more of that. We look at what we call COHORT, which are the customer segments (the Head of Marketing). Privacy is not synonymous with consent. Privacy goes beyond transparency and control (the General Manager). The company data does not connect to any external database. We do not use name ID, only encrypted versions of ID (the Head of Sales).

Attribution and performance	Attribution model refers to understanding how each media participates in achieving the result (HANDS, 2020). Performance refers to accomplishment and fulfillment.	"visit as a performance goal"; "no such thing as organic attribution"; "pain point"; differs from inference metrics; differs from awareness. Omnichannel attribution in general is a challenge (the Key & Strategic Sales App Business).	The company's view of the consumer is still very fragmented. There is an initiative to try to understand more the consumer in different channels, but only when he complains (…) (the Head of Mobile Solutions). The more engaged, the more I see their buying behavior. It is the same type of data, only with more intensity. The importance of mobile is not about data type (the Head of Marketing). Growing importance of RoaS (revenue generated on the apps) (the VP of Global Strategy).
Reality beyond promises	Promises that still remain on the horizon; reality check.	Much has been said about O2O as if there were a passage between two separate worlds, online and offline, but the reality of things shows us that reality is O+O (the Chief of Growth Officer LatAm).	No, companies have not yet learned to use the data. They are learning. (...) people do not know how to drill, do not know the question of changing the questions of order. Who knows very well is Amazon (...) what you have of most powerful is to look at the data, to understand your consumer, and companies are outsourcing this, thinking that it is just an algorithm and a lot of numbers. (....) people are not understanding what data can deliver because it is necessary to polish, and you must like polishing data. People want quick and easy answers, and this is not data culture (the Marketing Director). (in malls) The retailer has no interest in reporting sales as this makes the rent more expensive (the Retail Specialist). I think one of the main challenges is to be able to deliver an easy experience, you know, that is not too heavy, I say on the cell phone itself. (…) people don't have a super smartphone, so you have to be able to deliver a good experience in an app that's light, that doesn't take up a lot of cell space, so that the person does not need to delete the app. This is a pragmatic challenge (the Head of Marketing).

Final Considerations

The analysis of in-depth interviews revealed the following themes: how mobile promotions affect consumer offline behavior; the importance of mobile message content; mobile ubiquity and its relation to consumer context; conquest and challenges brought by the mobile era. The analysis privileged respondents' words to ensure validity of the findings. The key take aways per theme are presented in table 10.

Table 10 – Key take aways

Online to offline: mobile promotion and offline consumer behavior	• Mobile plays an import role between the zero moment of truth and offline visits. • The one-to-one mentality seems to prevail on the digital environment. For the offline consumer, digital tools are still used as a one-to-many weapon, as in large scale broadcast campaigns. • Part of the expectations created online are expected to be fulfilled offline, that includes price and service level. • If the company is going to do a digital activation of a certain product, it must question whether it is ready to respond to this activation through cross-channel.
Mobile message content	• Context (how) englobes personalization (who and what) and localization (when and where). • Segmentation and personalization can be fueled by location data. Geolocation information can be used for geofencing, competitional targeting or behavioral targeting. • Push is one of the main engagement tools, being used both for upsell and cross-sell. • Possible criteria for personalization: actual location and time of the day, prior geolocation behavior, prior purchase behavior, customer profile (i.e., demographics or apps installed), the mix of online and offline behavior. • Geobehavior targeting: understand who the users are and from that try to bring a conversion. • The importance of demonstrating continuance of communication identifying and respecting the customer journey and adjusting linguistic elements.
Mobile ubiquity and consumer context	• The ability versus the viability of the hyper-context personalized targeting provided by mobile. High costs. Technology and data needs. • Geolocation is the real-life cookie. • Geodata can be used to segment, to impact or for attribution.

	• Personalization works best at scale, including in the mobile context. • Optimal geolocation campaigns require big data for lookalike strategy making. And that requires strong first party data and partnerships.
Conquests and challenges	• One path to privacy is dealing with clusters and cohort analysis. • Privacy respect requires, among other things, consumer consent. And consent requires trust. • Efforts to reduce mobile users' perceptions of intrusiveness. • Personal is not the opposite of privacy, it can be used for a greater purpose. • Growing importance of first party data and building a data ecosystem. • Date culture is not about quick and easy answers.

Regarding interviews with senior marketing executives, Jaworski (2018) points out that it results in a field-based perspective on a particular issue and the challenges that the firm (or executive) faced in attempting to make progress. Put in academic terms, the interview focuses on both the dependent variable (i.e., the issue) as well as some of the potential independent variables that impact success (i.e., what factors seem to predict improve on the issue? What factors seem to create barriers to progress?) (JAWORSKI, 2018, p.3). In that sense, the issue is the use of mobile data to increase results, and potential variables that impact can be: the stage of the customer journey, geobehavior, location, usability, personalization and privacy respect.

The content analysis indicate that the O2O model is evolving to an O+O model, where online and offline are integrated in the customer journey, with mobile moving from being a bridge to being an integral part of the path. The findings suggest that companies are expanding their mobile targeting tactics from a location based one to a mobile targeting that includes a mix of locational and behavioral targeting (from geolocation to geobehavior). Besides, the analysis points to the use of data to elaborate the content and to deliver the mobile message in a way that increases the chance that the person receiving the message converts. Regard to the interviews and the literature reviews, the concept of location is not what it used to be. It became even more important after a disruption such as Covid. The concept has broadened from the physical location to the consumer context – what is the location of the consumer mind? Where is the consumer in the decision-making process? How to use geodata along with other consumer data to interject the decision-making points? The work to transform location data in real customer experience is still in progress.

One of the study limitations is that the findings are not generalizable to other contexts without further research. There are some interesting exploratory, descriptive studies taking place (i.e, TONG et al., 2020; CLIQUET, 2021) and sooner further inquiries from the area tend to be made using advanced technologies and under a causal perspective. As one of the interviewees pointed out, it not as of today that we have been living “the year of mobile*”:*

> In the advertising market, there is a long time tale that this “year of the mobile” had to arrive… people kept counting on that year after year. They just did not notice that we have been living the mobile year for a long time… (the Chief Growth Officer Latam).

Geodata can be used for segmentation, impact and attribution. Regarding geo message types, there are competitional, proximity and behavioral messages. However, all these possibilities come at a cost, since it involves partnership data, intensive use of servers and a dedicated BI team. Last but not least, dealing with the wealth and volume of data generated by Mobile Marketing is a challenge that managers are to face in the years to come.

5.
STUDY 1: Computer vision, mobile ads and performance data

The use of mobile promotions to drive customers to stores is growing, with mobile advertising representing over 70% of all U.S. digital ad spending and more than 3/4 shoppers using mobile devices along with physical shopping (STATISTA, 2020; GOOGLE, 2019). By 2023, about 10 billion dollars should be invested in mobile media in Latin America. The amount will then represent 81.3% of the total digital ad spending. Today, this investment is around 7.17 billion dollars and represents 69.9% of the total (EMARKETER, 2019). Yet, some mobile campaigns present more expressive visit performance numbers than others, that leads us 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 offline results. However, there is not a clear picture of which elements of the message content can be associated with performance results, particularly regarding to (offline) store visits. 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.

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.

5.1. Method

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 number of 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 the user. The tech company then applies encryption techniques and hashes to increase data 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).

5.2. Procedures

A sample of 4,352 campaign results, including some top global brands (FORTUNE, 2020), 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 global 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 (appendix b).

This study employed a data-driven approach; thus, focused only the content dimension of the mobile promotions, crossing it over with campaign performance data. In this study, the grouping into “treatments” is 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 11). 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 11 - 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 to increase 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.

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 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 recongnition), 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 8 – Variable branding appeal

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

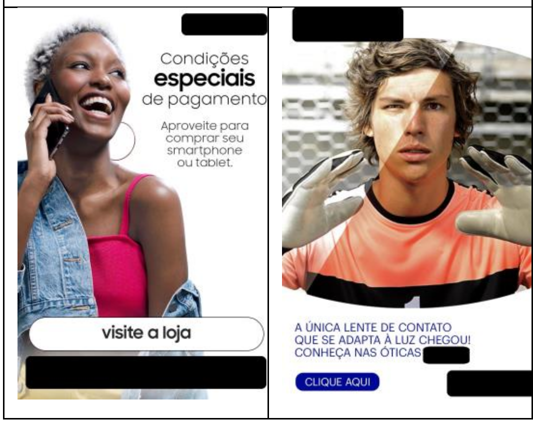


Figure 9 – Variable person presence

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 12 - 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).

<table>
<tr><td colspan="2">Wording</td></tr>
<tr><td>Black</td><td>Store (lojas)</td></tr>
<tr><td>
</td><td>
</td></tr>
<tr><td>Discount

</td><td>Participate (participe)

</td></tr>
</table>

Figure 10 – Wording variables

5.3. Results and Discussion

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. 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.

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 15).

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					

Figure 11 – 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.

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

Table 13 – Descriptive Statistics variables for the secondary data study

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 (Figure 16), 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 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 17)

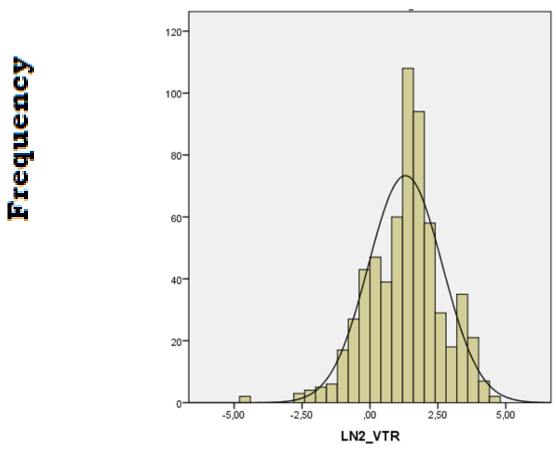


Figure 12 – Frequency distribution

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 14 – 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.

5.3.1.
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) ($M_{\text{branding appeal}}$ = 10,83% vs $M_{\text{purchase appeal}}$ = 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.

5.3.2.
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.

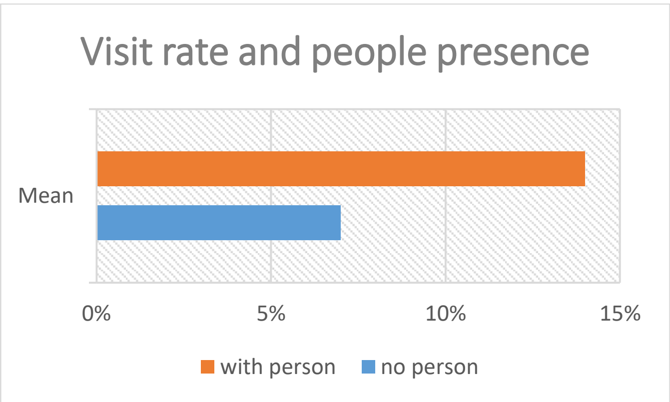


Figure 13 – Mean plots VTR and person

5.3.3.
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 15 – 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 16 – 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]	0ª	.	.	.	.	.
[Participe=1,00] * [Black=,00]	0ª	.	.	.	.	.
[Participe=1,00] * [Black=1,00]	0ª	.	.	.	.	.
[BrandingAppeal=0] * [Person=0]	,653	,294	2,218	,027	,075	1,231
[BrandingAppeal=0] * [Person=1]	0ª	.	.	.	.	.
[BrandingAppeal=1] * [Person=0]	0ª	.	.	.	.	.
[BrandingAppeal=1] * [Person=1]	0ª	.	.	.	.	.
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.

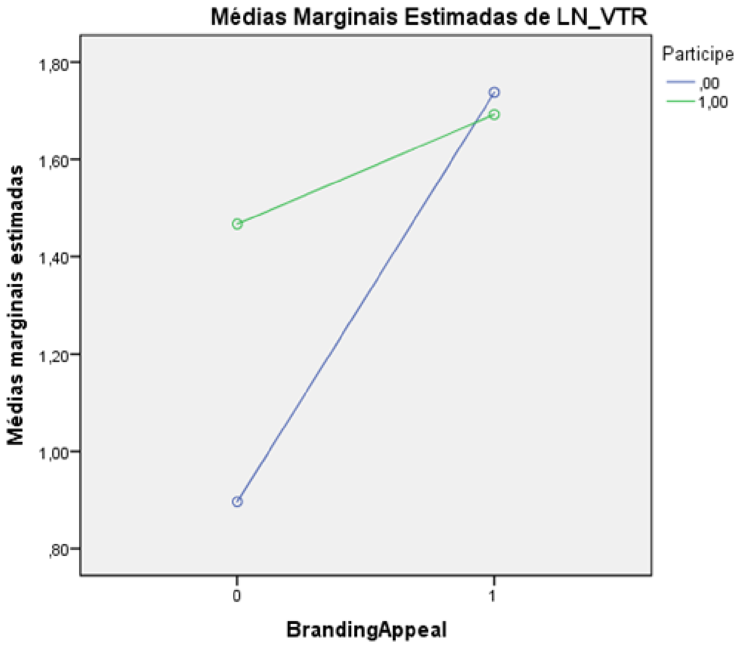


Figure 14 - Interaction between branding appeal and wording for log VTR.

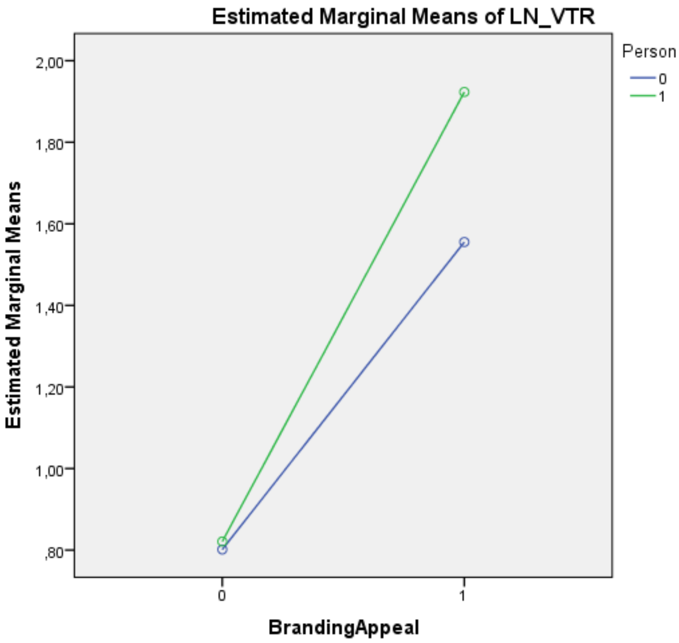


Figure 15 - Interaction between branding appeal and person for log VTR

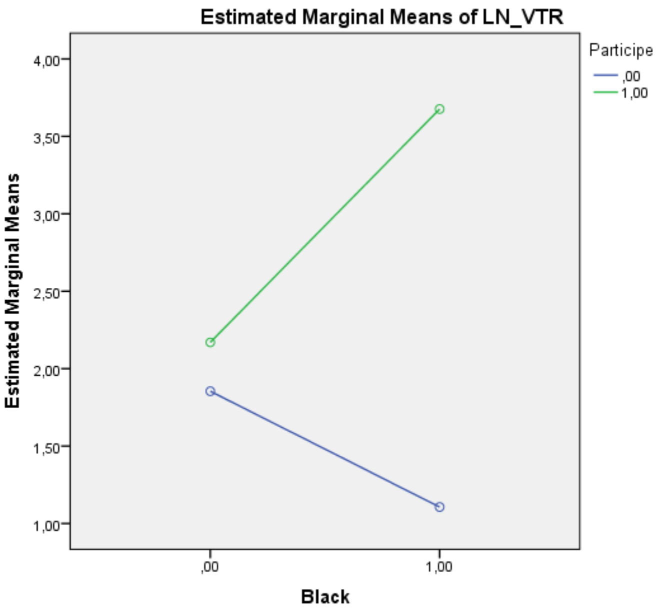


Figure 16 - Interaction between wording (“Black” and “participe”) for log VTR

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.

5.4. 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.

The goal was to compare the effects of message content variables in mobile promotions, looking for the ones that provide drivers for offline 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 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?

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, discount and participate. The results revealed a slight two-way interaction between the following words: “black” and “participate” / “discount” and “no”.

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 a person / 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, we notice that there were few adds displaying Animal imagens. Even adds from the Pet Industry did not use animals in the creatives.

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.

The first limitation is that the causal inference was limited by the lack of random assignment of the intervention. Another limitation is that we 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. Last, the model is not a prediction one, but rather targeted at effects explanation.

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. The intention is to pursue this enlightenment through the following studies.

6.
FIELD EXPERIMENTS

The purpose of this field study is to examine the effects of mobile message content and geolocation data (proximity to physical locations) on store visits, connecting online efforts to offline behavior, in a cross-channel perspective. According to mobile marketing literature, reaching customers at the right place and at the right timing should result in higher response rates. Moreover, properly timed promotions to customers in targeted locations should produce a positive incremental effect over nontargeted or asynchronous promotions (FONG et al., 2015; MOLITOR et al., 2016). Besides, customers navigate between online and offline channels, but most end in a physical environment. More than half of the web browsing takes place via mobile devices and 65% of Google searches are done through these devices (STATISTA, 2019). However, the majority of retail sales is still represented by brick-and-mortar stores (85%, according to a 2019 report from Statista). Mobile advertising literature has provided little guidance on which factors are likely to affect mobile advertising campaign performance (BART & STEPHEN, 2014). Hence, to design the experiment, this study relies on the premise that the content of the message and the consumer's geolocation for the push notification affect store visits. The results from study 1 supported the message content definitions of the following experiments, to aid testing the hypothesis 2a, 2b and 3.

STUDY 2

Study 2 tests the effect of the proximity of the consumer to the location in response to mobile notifications. This study investigates the following:

H1: For customers at a proximal distance, those who receive (do not receive) a push notification are more (less) likely to visit the store.

The rationale for the use of location-based notifications is that geographic proximity increases the relevance for consumers and thus the effectiveness of these campaigns (MOLITOR et al., 2016). If the proximity of the location positively affects the response rates, hence the redemption rates should be higher for customers close to the offline site. Therefore, companies should consider the customer geolocation prior to sending push notifications. The hypothesis was tested using a 2x2 experimental design with distance and mobile push notification factors.

Procedures

In Study 2, participants took part in a between-subjects, four-group experiment (2x2). Subjects are consumers that have the mall app installed, are active users, updated the app version and opted-in to geolocation permission. The study included both iOS - Swift and Android - Java users. The participants were randomly assigned to one of two conditions of a single factor, that is, received the push notification (yes or no).

The control group is the group of individuals that have the app installed and could be tracked regarding offline site approach but do not receive the notification. Random distribution was applied (MALHORTA, 2011). In the control condition, the subject did not receive a push notification offer. The underlying randomization process was solved by a server-sided allocation mechanism (i.e., participants had no ability to select themselves into a particular treatment group). The idea is to measure the impact by comparing the lift between the treatment group and the control group (MALHORTA, 2011). The messages were triggered by a location-based service.

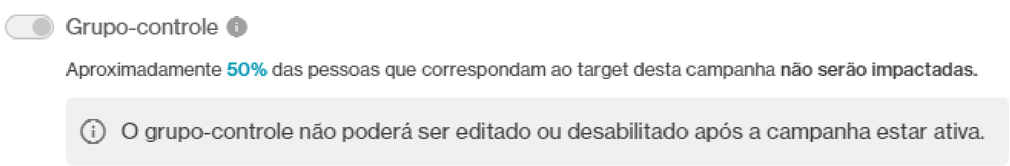


Figure 17 – System set up for the control group

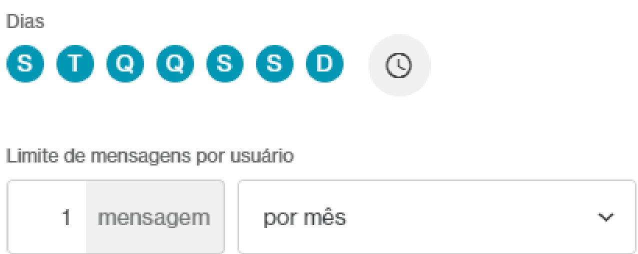


Figure 18 – System set-up one message per user per month

The study was conducted in a field setting. Participants were not informed of the study, since it is a real time campaign that was designed and monitored to work as a marketing experiment. A field setting is critical for external validity because the targeting relies on real-life context (FONG et al., 2015, p.729). The receipt of the notification was manipulated: half of the user base receives the notification (treatment) and half of the base does not receive (control). In the field, internal validity is weaker (SCHRAM, 2005; MALHORTA, 2011).

Push notifications were sent in different dates, arranged with the mall marketing team, delivery date of the message was duly noted. Ghoose et al. (2015) study noticed a difference in response in weekends and weekday messages, suggesting customers are likely to be in an "exploratory" shopping stage during the weekend. Besides, the location-based advertising application seems slightly more effective during nighttime (MOLITOR et al., 2016). Unfortunately, the study could not measure time as predicted. The setup of the message delivery was made through the geolocation platform, but the actual delivery was made through Firebase. The participant received the push notification even if the app was closed. The experiment happened in consecutive days in February, 2021. According to Malhorta (2011), it is important to decrease the time interval between observations to minimize the possibility of history confusing the experiment. In such push notification systems, there are different user engagement levels: message request, message sent, visualization, click and visits. Such levels could be measured, but not manipulated, in the system. Therefore, the study was able to compare people that received the message and went to the offline site vs participants that received the push but did not go to the offline site, as well as the offline behavior of those that did not receive the message.

First, the location company SDK was installed in the mall app. After installation or updating the application, the location company asked the app user for permission to collect data through of the presentation of the privacy policy. It is important that the app be upgraded for location tracking. With active location technology, the company starts detecting the presence of smartphones in offline sites through smartphone sensors (Wi-Fi, GPS, Bluetooth, inertial sensors, among others.). The user must remain for at least five minutes within the offline site for the visit to be computed. The visit data is consolidated in clusters. The visits to the offline site were measured in a fifteen-day window from the app notification trigger.

There is a range of technologies that can be used for location tracking, such as wifi, rfid, gps, beacons, each on presenting pros and cons. Beacons, for instance, relies on enabling the smartphone Bluetooth. Since it drains the battery, only a small percentage of users keep it on. As per the GPS, the data accuracy depends on signal reception and such search also drains batteries. Therefore, the choice for this unique location technology company adds on precision and accuracy of the experiment. Besides, all messages will be sent only with customer permission (opt-in), in a welcome addition face previous aforementioned experiments of such location-based nature. Nevertheless, the engagement with Data Protection General Law, combined with restrictions imposed by Covid-19 pandemic, resulted in much smaller numbers than predicted.

The Coronavirus pandemic had the obvious consequence of a drastic reduction of people leaving their homes. Pandemic probably stopped people from attending most places other than the essentials as often as before. The second impacted the number of active users in the app that opted in for push notifications. The database was reduced to one tenth of the forecasted sample. The app was installed in 38.300 devices. However, only 12.800 are active users. Situation on October 22nd: 1,215 users with the geolocation SDK, and of these, only approx. 20% with opt-in for location. The researchers decided to wait longer to see if such numbers were to increase after the Pandemic ceased. But then, in January 2021, the researchers decided to proceed with the study using another app from the group, whose numbers were slightly higher. The chosen mall has more than 380 stores, with 17 anchors and 15 megastores, including major brands. More than 30 gastronomy options and a complex with 12 movie theaters. A structure of 101,000 m² of store area in a total of 295,000 m² of built area, and a parking lot with 5,600 parking spots. It represents quite a significant location in the city.

The researcher was in contact with other companies with a larger user base that were also interested in the experiment. However, the advertising platform with geolocation feature was sold to a large retailer and would no longer be available from April, 2021 on. The martech market walks fast.

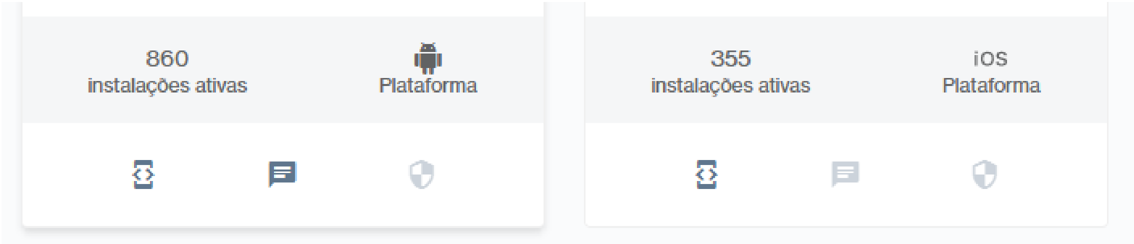


Figure 19 – Active app installments with geolocation opt-in, October 2020.

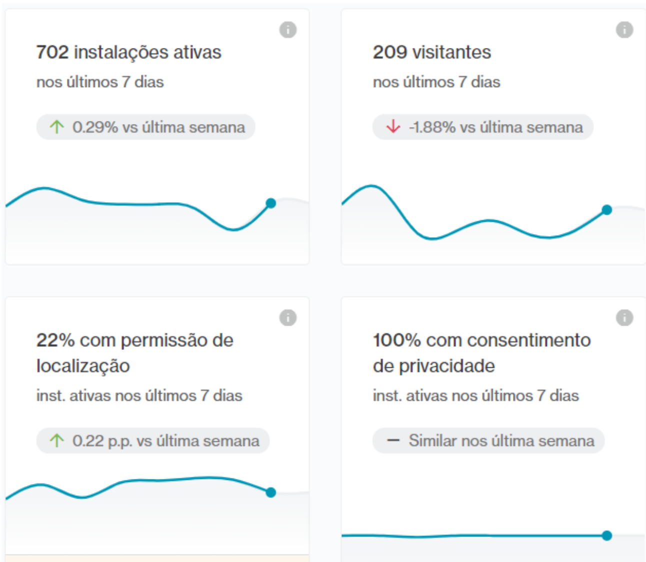


Figure 20 - Salvador Mall opt-in data in 27.01.2021

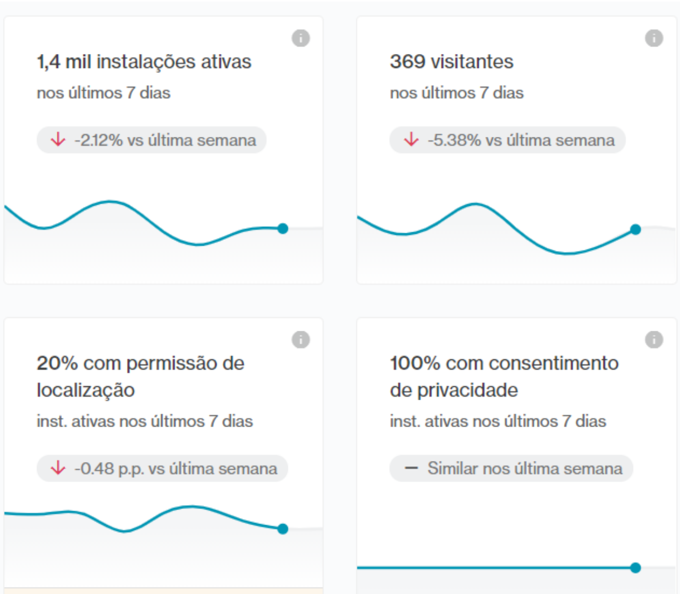


Figure 21 – Fortaleza Mall opt-in data in 27.01.2021

To test hypothesis 1, the study applied Logistic Regression. Logistic Regression is used to analyze the relationship between variables, where the dependent variable is binary (WASSERMAN, 2004). It is a method for studying the relationship between a response variable Y and a covariate X. The covariate is also called a predictor variable or a feature. The logistic regression was used in this study to test the relationship between visits and location and push notifications. Sample size was of 543 app users that the filled the criteria to receive the mall push notification. The variables of the logistic reg in this study are the following:

Dependent variable: visits to the offline location (yes or no) – shopping mall. As mentioned, the dependent variable was captured through a proprietary technology developed by the tech company, combining wifi, GPS and other proprietary technology, Microsoft certified.

Independent variables: push notification and distance to the offline site. Random assignment of the independent variables enables the estimation of causal effects to test the hypothesis.

Table 17 - Variables for studies 2 and 3

	Variables	**Type of variable**		**Categories / Scale**
Dependent	Visit **	Nominal	Dummy	0 = no visit 1 = yes visit
Independent	Push	Nominal	Dummy	0= yes push 1= no push (control)
Independent	Message content	Nominal	2 or more levels	0 = branding online 1 = branding offline 2 = promotional 3 = personalized
Independent	Distance from POS (km)	Scale		
Independent	Number of visits	Scale		
Independent	Interval (days) (from push to first visit)	Scale		

External variables: variables that influence a visit to an offline site and that could be controlled, such as customer profile; special dates for retail; point of sale promotions; local advertisement; weather; time; store size and location, price, product availability and location at the gondolas, brand awareness, among others. It is important to keep the extrinsic variables at the same level for both the control group and the experimental group (MALHORTA, 2011). Regarding external variables control, apart from the manipulated elements, the other elements should be as similar as possible. One important variable pointed by Dubé et al.(2017) is competition movements. Therefore, the study should consider what marketing campaigns are performed by competitors throughout the study. Regarding that, February had no special date for retail. In order to decrease the influence of such external variables, the groups were equally distributed, the so-called random assignment of subjects to experimental conditions. Such procedure is necessary to isolate, as much as possible, the effects of the external variables, in order to ensure internal validity (MALHORTA, 2011; HERNANDEZ et al., 2014).

Results & Discussion

The data treatment choice followed the research type and data collection procedure. For the field experiment, the data treatment involved group means comparison between the experimental and the control group. Since the dependent variable is categorical (visit yes or no), the analyzes proceeded with logistic regression, to investigate if the location and the push notification have an effect on moving the participants to the targeted location. As per the concomitant variation, when there is a correlation between two variables (a statistical measure of the association between these variables), there is evidence in favor of causality; that is, changes in the level or presence of the cause-variable must be systematically associated with changes in the level or presence of the variable-effect (HUNT, 2010).

Despite the fact that the geosystem was setup to target for a 5km radius, the results presented much longer distances. Therefore, for Tables 16 and 17, the study considered near up to 10.000 mts and far, distances above that (driving distances). The results from table 16 and 17 show that the number of app users eligible to the push notification that did not receive it (the control group) was much higher than the ones that received. The explanation provided by the geo company was the following: "The control group always records when the trigger is activated, whether for the target group, it depends on several factors, such as device connection, which end up making it too late to send the push when we receive the information".

Table 18 – 2x2 experimental design

		Distance		
		Near	Far	Total
		Count	Count	Count
Push	yes push	49	54	103
	no push	246	194	440

Table 19 – Total count push vs distance

				Distance		
				Near	Far	Total
				Count	Count	Count
Push	yes push	Visit	no visit	84% (41)	83% (45)	83% (86)
			yes visit	16% (8)	17% (9)	17% (17)
	no push	Visit	no visit	64% (156)	56%(108)	264
			yes visit	36% (90)	44% (86)	176

Since the city has an area of approximately 313 km² (a radius of nearly 18km), first the study considered as outliers those distances above 20 km.

Table 20 – Experimental design (no outliers)

		Visit		
		no visit	yes visit	Total
		Count	Count	Count
Push	yes push	64	8	72
	no push	210	138	348

Table 21 – Variables in the equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	Distance	,000	,000	,231	1	,631	1,000
	Push(1)	-1,664	,391	18,119	1	,000	,189
	Constant	-,485	,175	7,697	1	,006	,616

a. Variable(s) entered on step 1: Distance, Push.

According to the regression, there was no significant effect for distance. And looking at the push notification variable, the probability to visit is smaller when the app user receives the push. Therefore, H1 is not supported. However, the number of people that received the push and visited is very small ($n < 20$), which could be misleading in the analysis. The low sample size does not allow any unquestionable conclusion.

Regarding expected results, the experiment aimed at spotting the existence of real-time geolocation targeting effects. The study did so by comparing the visit rates for targeted and nontargeted groups. The study balanced the challenges presented when trying to study an actual behavior. As Hernandez et al. (2014, p.114) put it, experimental studies involving behavior measurement are more subject to errors and more difficult to perform. Nevertheless, since consumer behavior is one of the most relevant aspects of marketing, and since people do not always do what they say they will, it is a challenge worth facing.

STUDY 3

The purpose of the experiment is to measure the effect of mobile message content and the geolocation data as drivers of store visits, connecting online efforts to offline behavior, in a cross-channel perspective.

Table 22 - Hypotheses

H2a	For customers at a proximal distance, those who receive a promotional content are more likely to visit the store than those who receive a branding content.
H2b	For customers at a proximal distance, those who receive a personal content are more likely to visit the store than those who receive an impersonal content.
H3	The degree of content personalization is positively related to store visits.

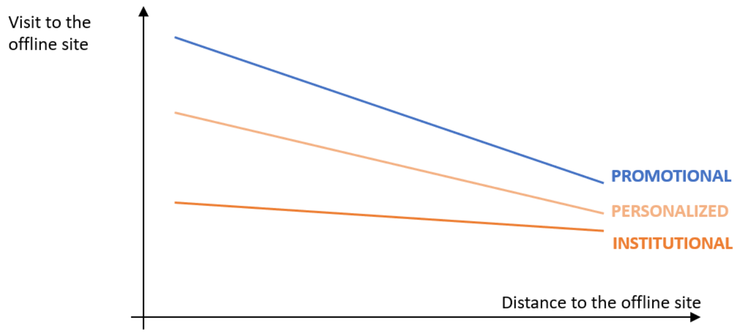


Figure 22 – Hypotheses diagram

Procedures

A full factorial 2x4 design (near; far / online, branding, promotional, personalized) yielded eight experimental groups that enabled the study to disentangle and test the impact of proximity and message content on visit rates (table 22). The previous design had contemplated a 2x3 experiment, but the Marketing Department asked to include one more content variable in the study (online branding appeal, as they had just launched a new website as a reaction to the pandemic situation). As in study 2, the underlying randomization process was solved by a server-sided allocation mechanism (i.e., participants had no ability to select themselves into a particular treatment group). The factorial designs are used in studies that aim to test the effect of two or more independent variables on the dependent variables (HERNANDEZ et al., 2014, p.105). The advantage of this type of study is to allow the analysis of both the main effects of each of the factors and the possible interactions between them.

Test unit: consumer that has the mall app installed and updated the opt-in according to the General Data Protection Law. The participants were randomly assigned to one of the conditions, personalize (n= 28) or not (promotional n = 133, offline branding n = 130, and online branding n= 252). With four different types of message content and two possible geolocation classifications, the manipulations resulted in 8 randomized experimental cells.

Table 23 – Total count push vs message content

		Content			
		Online	Branding	Promotional	Personalized
		Count	Count	Count	Count
Push	yes push	54	26	18	5
	no push	198	104	115	23

Regarding the push notification landing page, it directs to the mall Instagram page, since the home page did not have a security protocol. For the experiment, all individuals must have the same probability of being selected for one or the other experimental condition (HERNANDEZ et al., 2014), that is, the sample should be randomly distributed. There was no association between individual characteristics and the independent variable as required.

Factors: distance to the offline site and message content. Different levels of the factors must produce different responses on the dependent variable (HERNANDEZ et al., 2014). The manipulation of independent variables includes:

- Message content: promotional prompt
- Message content: institutional prompt - online-offline branding appeal
- Message content: personalized prompt

Prompt: promotional and branded messages

Context variables such as price, type of promotion, colors, number of sellers in a store, type of message of an advertisement, can be manipulated directly (HERNANDEZ et al., 2014). This study manipulated the type of message, more specifically, the message content. Molitor et al. (2016) responses suggest that distances to stores are an important driver of mobile coupon response. Also, the coupon discount amount has a positive and significant impact on the choice of discount coupons. There is a trade-off between distance and discount depth. The further or the more random you approach the customer, the higher needs to be your discount. Dube et al. (2017) indicate that the ideal control condition receives a message with a notification without an actual price discount, which is exactly what was performed in this experiment – the branded message. The authors did not include that variable then because their corporate partners did not feel comfortable sending consumers promotional SMS messages without some sort of deal included. Hence, this study compared the effects of promotional and branded messages, complementing previous studies.

Regarding the promotional content, it referred to an special deal offered to mall app users. Regarding the branded content, the message explored the mall appeals. Preliminary message content suggestions were sent to the Marketing Manager, that edited then to suit both the experiment and the mall purposes. Visual examples of the final message prompts are displayed below.

Geolift Campaign (Branding 1)

Geolocation target: people up to 5 km from the target mall

The message read: “Make dinner? Love it! #not. Too lazy to cook? It is dinner out day! Check out the many restaurant options in Mall X!”.

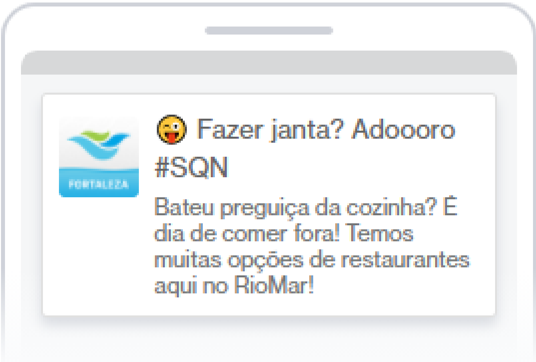


Figure 23 – Branding campaign message

Online Campaign (Branding 2)

Geolocation target: people up to 5 km from any mall in Fortaleza. The message read: “The mall stores now in your house. Now you can shop from the Mall X stores without leaving your house. Access or download the app”.

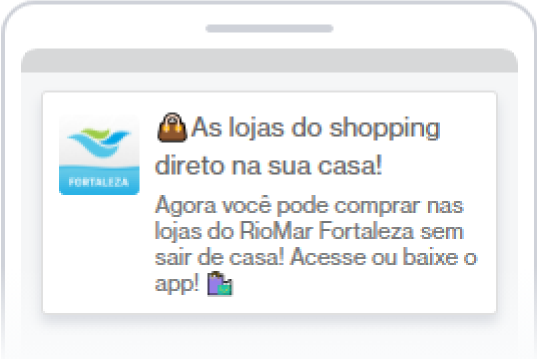


Figure 24 – Online campaign message

Promotional Campaign (free parking for lunch)

Geolocation target: people up to 5 km from the target mall. The message read: "Free parking for lunch. Come have lunch at Mall X from 10am to 02pm, spend over R$15 and the parking lot is free".

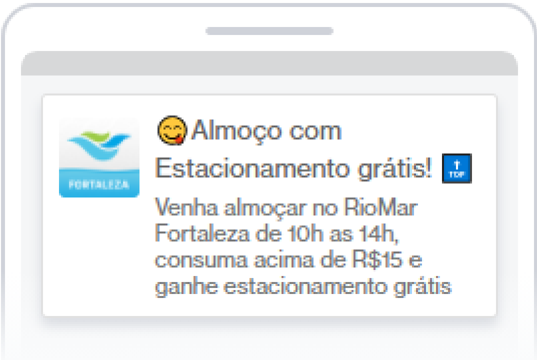


Figure 25 – Promotional campaign message

Prompt: personalized messages via geo behavioral targeting

This study helps understanding how content messages with behavioral targeting enhances versus detracts visits to offline sites. The personalization was applied via behavioral data – geo behavior. The overall offline movement captured by consumers smartphones can provide even richer information about consumer preferences (GHOOSE et al., 2015). The platform offers targeting capabilities that use both real-time location, providing our horizontal dimension, and historical location, used to infer past behavior (DUBÉ et al., 2017). The personalization of the messages applies the same principles of recommendation systems in order to send the push notification. The messages were different according to the geo behavior profile, that is, the type of place the app user goes to. The managerial rationale is that discounts for notifications should be applied in extreme cases only, the first approach being delivering the right message at the right time, adjusting the content to the person. Therefore, the message labelled the participants according to their previous geo behavior (fitness and wellness; home; college). Regarding the behavior targeting, it is important that the criteria do not breach privacy policies within the General Data Protection Regulation. Regarding privacy versus personalization, Kim et al. (2019, p.909) research suggest that consumers assess the attractiveness of an advertised product by looking to its fit with, or personalization to, their needs and wants. They argue that ads with a better fit and personalization to consumer needs and wants may drive higher ad effectiveness, as long as it does not breach privacy boundaries. For instance, the research cannot deal with categories such as hospital or churches. Possible behavioral criteria (considering offline data):

a) Visits to category of places, such as restaurants (in general), gyms, etc. | Offline location behavior
b) Apps installment (consider that children may install apps in parent’s devices)
c) Type of mobile device and mobile operator.

The study worked with a) visits to category of places. It considered the categories with the largest number of visits on the past 30 days from the campaign starting date.

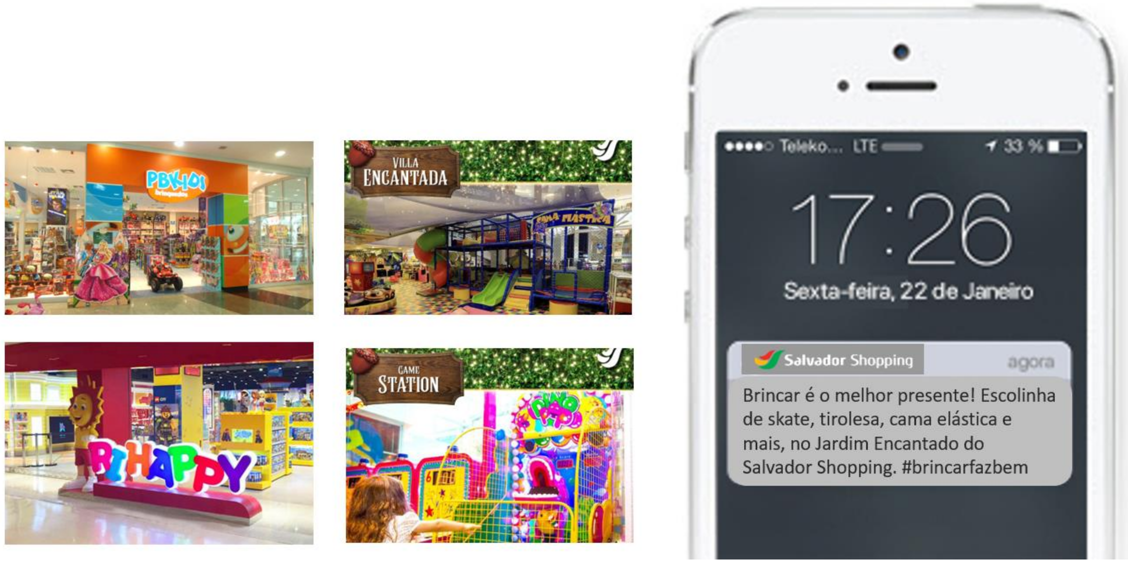


Figure 26 - Conceptual example of personalized message based on geobehavior

The user that goes to playgrounds and toy stores receives a message with play content for kids.

Campaign Personalized 1 (Fitness and Wellness)

Geo behavior target: people who arrive at Fitness and Wellness establishments (i.e, gym, spa). The message read: “There is time for 2021. Gym, beauty shops, fitness clothing and more at Mall X. Run and enjoy”.

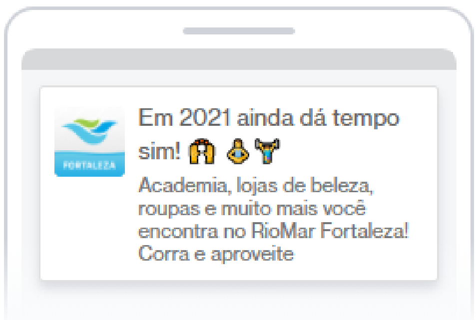


Figure 27- Personalized mobile message (fitness and wellness)

Campaign Personalized 2 (Home)

Geo behavior target: people who arrive at Home Accessories stores (i.e, construction, furniture, electrical appliances). The message read: “Taking care of the house is taking care of you. Mall X has the best stores to make your house even more beautiful and confortable”.

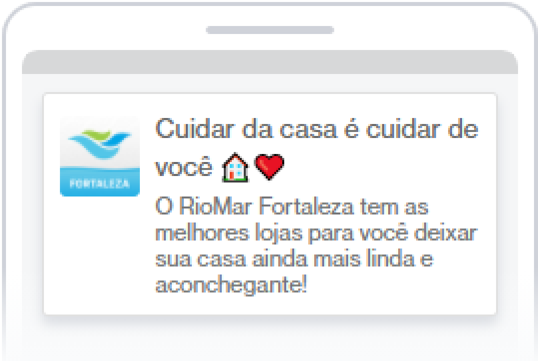


Figure 28 – Personalized mobile message (home)

Campaign Personalized 3 (College Students)

Geo behavior target: people who arrive at Universities. The message read: “Movies? In safety! At Mall X, all the security protocols are available for you to enjoy. Come!”.

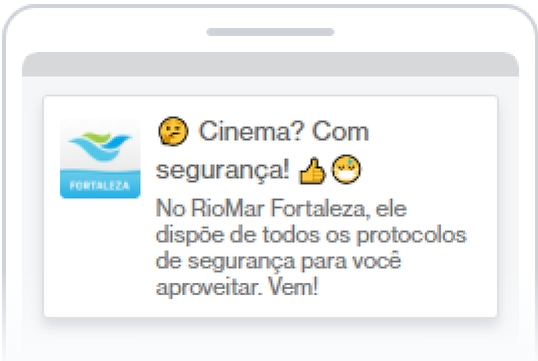


Figure 29 – Personalized mobile message (college)

For the personalized campaigns, the study was very specific regarding location (geobehavior, or influence of location visit), not increasing the campaign reach to close by locations.

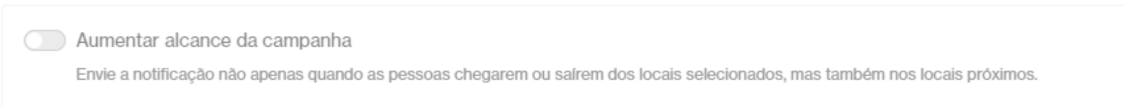


Figure 30 - System set-up geolocation reach

There was the possibility of working with personally identifiable information (PII) safe-harbor identity-matching firms (e.g., LiveRamp or Neustar), that integrate identity data in a PII-protected way (BAKOPOULOS et al., 2017). However, personally identifiable information protects the data, not the privacy, since it directly refers to the individual. Hence, the choice if for a geo technology that analyzes location data without identifying customers, neutralizing privacy concerns. According to Bakopoulos et al. (2017, p.451), due to the nature of mobile, the method needs to rely on something more permanent than cookies, because mobile users often delete cookies and, therefore, the connection between exposure and sales might be lost. To measure mobile in-app advertising (which comprises 90 percent of the mobile advertisements and does not accept cookies), it is important to connect a device ID to a person.

> "The role of individual-level data and the use of PII safe harbors simplifies the ability to merge data from different sources. This approach, moreover, can lead to the creation of detailed datasets that include media-exposure inputs along with behavioral and attitudinal outcomes, including sales data or store visitation" (BAKAPOULOS et al., 2017, p.453).

Indeed, retailers should be aware of the privacy concerns preventing some customers from using mobile stimuli (BEECK & TOPOROWSKI, 2017). There is a managerial challenge regarding person-level data and bringing one-to-one-marketing campaigns to life.

Regarding distance measurements, there are two different types:

- Measure by proximity: impact people within a certain radius to the store.
- Measure by place: latitude and longitude, using places mapping. Allows for more precise indoor measurements, such as differentiating among floors. Then the system calculates the distribution of distances: the challenge is that would be Euclidean distance, distance in a straight line, which does not reflect the real travelled distance, but a radius of influence, such as an offline heat map.Some places location can be obtained through Internet crawling, but then the information is not as reliable. Hence, the use of a specific location technology.

Possible covariables: Other covariates can relate to demographics (inferred residence, inferred place of work), which the study could not access due to the number os participants, and analytics results, such as views and clicks. Such variables can help measure latency response. Testing for the window of time for the response is important because some types of responses are more immediate than others. Therefore, the study checked for moderators that build into that: number of visits and interval of days between the notification and the first visit.

Results & Discussion

The geodata company delivered four complementary sets of data:

- Base 2: impacted devices with geodata
- Base 2: impacted devices with no geodata
- Base 3: visits with geodata
- Base 3: visits with no geodata

Base 2 (impacted and visitors) contains the distance in meters from the impact site or where the impact would have been made to the place visited (shopping mall). Base 3 (impacted and visitors) does not contain the impact x visit (shopping mall) distance but has a larger volume of records. For these two data extractions the hashed_mad_id was used and as it is possible to consider this sensitive data, it was replaced by "device1", "device2" and so on.

The spreadsheets had to be matched via device ID. First, devices were arranged to be with the same number of digits (3) in each spreadsheet. Device1 became device001. Then, they were arranged in ascending order. A unique key was created by concatenating device and campaign in the two spreadsheets and with vlookup the data of the visit, visit and control group date were pulled. The total of visits was added based on device and campaign. Since the merging was manual, it was verified via “if” excel formulas. Calculated data once the spreadsheets were merged: a) number of visits per user b) interval between the notification and the visit (from the first visit).

Study 3a – database with geolocation data and visits

Study 3b – database without geolocation data (only visits)

Since the dependent variable is categorical (visits to offline site yes or no), the analyzes proceeded with logistic regression.

Study 3a – database with geolocation data and visits

For a clearer view of the message content effects, the study performed a logistic regression in SPSS. According to the results, the distance does not have a significant effect on store visits. However, the push notification and its message content have a significant effect (p<.01). Since the number of personalized observations was low, the study also considered the model without this content option. From the different content version, the online one generated more visits.

Table 24 - Study 3a database – mobile message content (n = 543)

		Content									
		Online		Institutional		Promotional		Personalized		Total	
		Visit		Visit		Visit		Visit		Visit	
		no visit	yes visit	no visit	yes visit	no visit	yes visit	no visit	yes visit	no visit	yes visit
		Count	Count	Count	Count	Count	Count	Count	Count	Count	Count
Push	yes push	46	8	21	5	14	4	5	0	86	17
	no push	99	99	71	33	82	33	12	11	264	176

Table 25 - Study 3a database – distance, push notifications and visits

		Content															
		Online				Institutional				Promotional				Personalized			
		Push				Push				Push				Push			
		yes push		no push		yes push		no push		yes push		no push		yes push		no push	
		Visit		Visit		Visit		Visit		Visit		Visit		Visit		Visit	
		no visit	yes visit	no visit	yes visit	no visit	yes visit	no visit	yes visit	no visit	yes visit	no visit	yes visit	no visit	yes visit	no visit	yes visit
		Count	Count	Count	Count	Count	Count	Count	Count	Count	Count	Count	Count	Count	Count	Count	Count
Distance	Near	17	5	53	44	15	2	44	23	8	1	51	19	1	0	8	4
	Far	29	3	46	55	6	3	27	10	6	3	31	14	4	0	4	7
		22	22,7%			17	11,8%			9	11,1%			1	0,0%		
		32	9,4%			9	33,3%			9	33,3%			4	0,0%		

Table 26 – Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	Distance	,000	,000	,009	1	,924	1,000
	Push	1,296	,287	20,379	1	,000	3,653
	Content			13,454	3	,004	
	Content (branded)	-,625	,237	6,969	1	,008	,535
	Content (promotional)	-,763	,237	10,366	1	,001	,466
	Content (personalized)	-,178	,417	,183	1	,669	,837
	Constant	-1,348	,296	20,749	1	,000	,260

a. Variable(s) entered on step 1: Distance, Push, Content. Base category = online content

Table 27 - Content vs distance

Dependent Variable: Visit

Content	Distance	Mean	Std. Error	90% Confidence Interval	
				Lower Bound	Upper Bound
Online	Near	,304	,052	,219	,389
	Far	,341	,046	,266	,417
Branding	Near	,263	,060	,164	,362
	Far	,240	,078	,111	,368
Promotional	Near	,230	,072	,111	,349
	Far	,287	,077	,160	,413
Personalized	Near	,077	,167	-,198	,351
	Far	,334	,132	,116	,552

Table 28 - Content vs push

Dependent Variable: Visit

Content	Push	Mean	Std. Error	90% Confidence Interval	
				Lower Bound	Upper Bound
Online	yes push	,146	,064	,040	,251
	no push	,500	,033	,445	,554
Branding	yes push	,187	,093	,034	,340
	no push	,316	,047	,238	,394
Promotional	yes push	,222	,110	,042	,403
	no push	,294	,044	,221	,367
Personalized	yes push	-,074	,217	-,431	,283
	no push	,484	,097	,324	,644

Table 29 – Duncan test

Visit

Duncan[a,b,c]

Content	N	Subset	
		1	2
Promotional	133	,28	
Branding	130	,29	,29
Personalized	28	,39	,39
Online	252		,42
Sig.		,162	,105

Means for groups in homogeneous subsets are displayed. Based on observed means.

The error term is Mean Square(Error) = ,216. a. Uses Harmonic Mean Sample Size = 72,868.

b. The group sizes are unequal. The harmonic mean of the group sizes is used. Type I error levels are not guaranteed.

c. Alpha = ,1.

Study 3b –visits only database

The second database included a larger number of participants (n=804). Since it did not have the location information, it could include the users with no opt in for sharing location data (distance measurements). One first interesting insight is that the mobile push notification effect is stronger on the first 24hours (Figure 38), which reinforces the perishable character of push notifications.

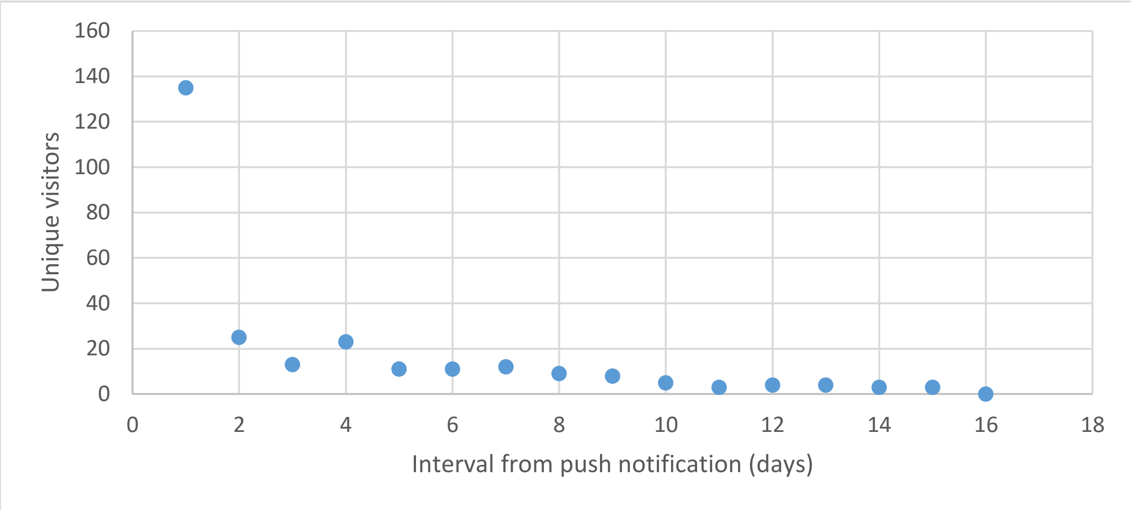


Figure 31 – Push notification and interval from first visit (in days)

Table 30 - Experimental set-up (study 3b)

		Content				
		Online	Branding	Promotional	Personalized	Total
		Count	Count	Count	Count	Count
Push	Yes push	137	76	67	22	302
	No push	229	118	129	26	502

Table 31 - Visits per mobile message content (study 3b)

		Content				
		Online	Branding	Promotional	Personalized	Total
		Count	Count	Count	Count	Count
Visit	No visit	225	138	142	29	534
	Yes visit	141	56	54	18	269

Table 32 - Experimental set-up (study 3b)

		Content							
		Online		Branding		Promotional		Personalized	
		Visit		Visit		Visit		Visit	
		no_visit	yes_visit	no_visit	yes_visit	no_visit	yes_visit	no_visit	yes_visit
		Count	Count	Count	Count	Count	Count	Count	Count
Push	yes_push	107	30	56	20	47	20	15	6
	no_push	118	111	82	36	95	34	14	12

Table 33 – Crosstabulation content vs visit

			Visit		
			No visit	Yes visit	Total
Content	Online	Count	225	141	366
		% within Visit	42,1%	52,4%	45,6%
	Branding	Count	138	56	194
		% within Visit	25,8%	20,8%	24,2%
	Promotional	Count	142	54	196
		% within Visit	26,6%	20,1%	24,4%
	Personalized	Count	29	18	47
		% within Visit	5,4%	6,7%	5,9%
Total		Count	534	269	803

The promotional message group was the only one with a visit rate higher for users that received the push notification. Since the dependent variable is categorical (visit yes or no), the analyzes proceeded with logistic regression. 0 stands for the online content; 1 for the branded; 2 for the promotional and 3, for the personalized.

Table 34 – Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	Content(1)	-,432	,193	5,005	1	,025	,649
	Content(2)	-,529	,195	7,393	1	,007	,589
	Content(3)	,036	,323	,013	1	,911	1,037
	Push	,634	,163	15,177	1	,000	1,884
	Constant	-,876	,153	32,660	1	,000	,417

a.. Dependent variable: visit yes or no.

Table 35 – Crosstabulation content vs push

Dependent Variable: Visit

Content	Push	Mean	Std. Error	95% Confidence Interval	
				Lower Bound	Upper Bound
Online	yes_push	,219	,040	,141	,297
	no_push	,485	,031	,425	,545
Branding	yes_push	,263	,053	,159	,367
	no_push	,305	,043	,221	,389
Promotional	yes_push	,299	,057	,188	,409
	no_push	,264	,041	,184	,344
Personalized	yes_push	,286	,101	,088	,484
	no_push	,462	,091	,283	,640

Table 36 – Visit means per message content

Dependent Variable: Visit

Content	Mean	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
Online	,352	,025	,303	,401
Branding	,284	,034	,217	,351
Promotional	,281	,035	,213	,349
Personalized	,374	,068	,240	,507

Table 37 – Duncan Test

Visit

Duncan[a,b,c]

Content	N	Subset	
		1	2
Promotional	196	,28	
Branding	194	,29	,29
Personalized	47		,38
Online	366		,39
Sig.		,828	,133

Means for groups in homogeneous subsets are displayed. Based on observed means.

The error term is Mean Square(Error) = ,214.

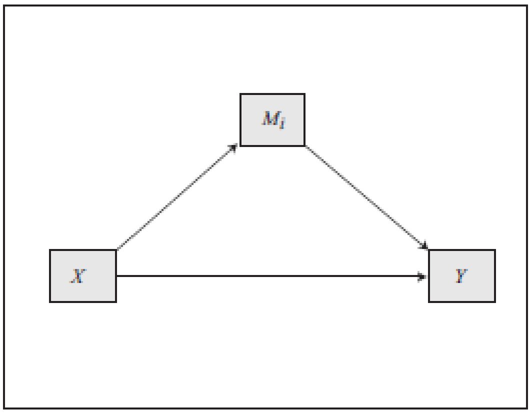
a. Uses Harmonic Mean Sample Size = 116,735.

b. The group sizes are unequal. The harmonic mean of the group sizes is used. Type I error levels are not guaranteed.

c. Alpha = ,1.

The study analyzed the content of the message as a **mediator** of the relationship between notification pushes and store visits at 95% confidence level:

Model 4




```
*************************
Model  : 4
    Y  : Visit
    X  : Push
    M  : Content

Sample
Size:  803

*************************
```

Model

	coeff	se	Z	p	LLCI	ULCI
constant	-,9462	,1487	-6,3618	,0000	-1,2377	-,6547
Push	,6175	,1617	3,8187	,0001	,3006	,9345
Content	-,1601	,0802	-1,9968	,0459	-,3173	-,0030

These results are expressed in a log-odds metric.

****************** DIRECT AND INDIRECT EFFECTS OF X ON Y *****************

Direct effect of X on Y

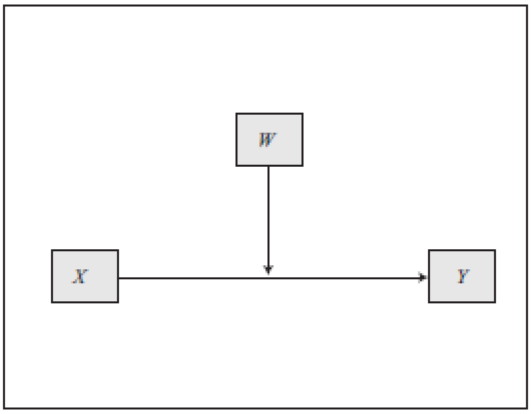
Effect	se	Z	p	LLCI	ULCI
,6175	,1617	3,8187	,0001	,3006	,9345

Indirect effect(s) of X on Y:

	Effect	BootSE	BootLLCI	BootULCI
Content	,0004	,0129	-,0266	,0281

The study analyzed the content of the message as a **moderator** at 95% confidence level:

Model 1




```
**************************************************
Model  : 1
    Y  : Visit
    X  : Push
    W  : Content

Sample
Size:  803

Coding of categorical W variable for analysis:
 Content       W1       W2       W3
    ,000     ,000     ,000     ,000
   1,000    1,000     ,000     ,000
   2,000     ,000    1,000     ,000
   3,000     ,000     ,000    1,000
```

Model

	coeff	se	Z	p	LLCI	ULCI
constant	-1,2716	,2066	-6,1554	,0000	-1,6765	-,8667
Push	1,2105	,2453	4,9351	,0000	,7297	1,6912
W1	,2420	,3325	,7279	,4667	-,4096	,8936
W2	,4172	,3376	1,2359	,2165	-,2444	1,0788
W3	,3553	,5254	,6764	,4988	-,6744	1,3850
Int_1	-1,0041	,4099	-2,4497	,0143	-1,8074	-,2007
Int_2	-1,3836	,4140	-3,3422	,0008	-2,1950	-,5722
Int_3	-,4483	,6695	-,6696	,5031	-1,7606	,8639

These results are expressed in a log-odds metric.

```
Product terms key:
 Int_1    :        Push      x        W1
 Int_2    :        Push      x        W2
 Int_3    :        Push      x        W3

Likelihood ratio test(s) of highest order
unconditional interactions(s):
        Chi-sq         df           p
X*W    13,1316      3,0000       ,0044
----------
    Focal predict: Push      (X)
          Mod var: Content   (W)
```

Personalized content only - base no distance (3b)

Blockage for personalization used three segments: fitness and health; home; college students.

Between-Subjects Factors

		Value Label	N
PushFator	0	No push	26
	1	Yes push	22
Segment	1	Fitness and Wellness	13
	2	Home	25
	3	College	10

The mean visit rate was higher (M=0.46) for users that did not receive the push compared to the ones that did (M=0.27).

Table 38 – Group Statistics

	PushFator	N	Mean	Std. Deviation	Std. Error Mean
Visit	No push	26	,46	,508	,100
	Yes push	22	,27	,456	,097

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									90% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Visit	Equal variances assumed	5,873	,019	1,344	46	,186	,189	,141	-,047	,425
	Equal variances not assumed			1,356	45,826	,182	,189	,139	-,045	,423

The average visit rates for app users that received a personalized location-based push notification was not significantly different between the treatment groups (t-test *p*-value = 0.182). Therefore, H3 is not supported.

H3	The degree of content personalization is positively related to store visits.

Discussion

Once customers were oriented to only leave the house for essential errands, window shopping in malls were impacted. According to the Brazilian Association of Shopping Tenants (ALSHOP, ESTADÃO, 2021), the malls are emptier and the shopping trips, shorter. Monthly visits dropped from 502 million in 2019 to 341 million in 2020. The time spent in shopping centers has also been reduced, from 1h30 to between 20 and 30 minutes.

One of the learnings concerns the format of data extraction from reports for field experiments. The format in which the reports are extracted from geodata companies does not necessarily match the format required for experimental analysis. Manual adjustment always increases the chance of errors and discourages learning. For real-time analysis to be more effective, it is recommended that the reports are previously validated by data analysts and managers with the perspective of generating insights, facilitating the transformation of data into knowledge.

Despite de 50/50 settings, the control group was much larger than the treatment group. The control group (no push) always records when the trigger is activated. However, for the treatment group (yes push) it depends on several factors, such as device connection problems, which end up making it too late to send the push when the system receives the information.

The initial idea was to measure changes in foot traffic as the mobile push notification campaign unfolded. Unfortunately, due to a number of unforeseen setbacks, the final numbers were away below predicted. This study acknowledges that there potentially might be debate about the causality of the claims. Given the limitations of the data from studies 2 and 3, some required methodological approaches to establish causality could not be performed. Some of the campaigns were underpowered because of insufficient sample sizes (personalized content). The experiment in study 4 solves the data issues by having similar sized experimental groups and random assignment to the treatment and control group allowing us to execute further experimental analyses.

7.
STUDY 4: online experiment

The proliferation of mobile and sensor technologies has contributed to the rise of location-based mobile advertising (GHOSE et al., 2019). However, despite this rise, offline shopping prevails (STATISTA, 2020). Hence, to analyze the effects of location and mobile message content on store visits, the study performed a randomized online experiment. Participants in two surveys received simulated smartphone push notifications, using 3×2 (neutral, branded, promotional; near and far) and 2×2 (personalized or not; near and far) between-subjects factorial designs, randomly assigned by the research platform. The experiment included five different industry categories and counted with 1.534 respondents.

Context

As study 2 and 3 advanced, the geolocation platform being used in the research was sold and, therefore, could no longer be used for field experiments after March, 2021. Hence, another path to deal with the location variable was needed. First, a pre-tested (n=7) was deployed analyzing the possibility of participants spontaneously downloading and sharing their Google Timeline Data. The participants received detailed instructions on how to download their timeline (see appendix Timeline Instructions) and a post interview was performed. All the respondents were unanimous in saying this procedure was extremely invasive. Therefore, the first step of the research was changed to a Timeline questionnaire (n=99), asking “Please list 10 commercial places you have visited in the past 30 days, other than your work or home”. The Qualtrics platform was used. There were 76 valid responses. Using MaxQDA software, the study proceeded with a frequency count. The most visited categories in the sample were supermarkets (n = 24) and drugstores (n = 17). The third category was an unexpected bakery category. Since people seemed to go to supermarkets, drugstores, and bakeries frequently without prompting, there was a risk that the choice of those categories would wash out the potential "pull" effect of the promotion. Regardless of the prompting, respondents had a chance go to there anyway, in a normal inertia path. Therefore, the study included a third different category, fast-food restaurants, a non-necessity category, to analyze the effects of mobile messages in store visits' intention. Following the sample results, for the personalized message, the choice was of fitness category (n=21) and pets category (n=27). The category choice followed Maity and Dass (2014) indication of low-consideration contexts. It also followed the findings of Bart et al. (2014). They applied a large dataset that featured 54 mobile display campaigns across three years to explore which type of product was best suited to the mobile display banner. Their analysis showed that the mobile display banner had a significantly positive effect on raising the customers' favorable attitudes and purchase intention for utilitarian products with a higher involvement, description under which pets products and fitness equipment fall.

Study 4a: 3x2 between-subjects factorial designs with location (near, far) and message content (control, branded, promotional). Industry categories: supermarket, drugstore, fast food.

Study 4b: 2x2 between-subjects factorial designs with location (near, far) and message content (control, personalized). Industry categories: pets and fitness.

H2a	Study 4a	For customers at a proximal distance, those who receive a promotional content are more likely to visit the store than those who receive a branded content.
H2b	Study 4b	For customers at a proximal distance, those who receive a personal content are more likely to visit the store than those who receive an impersonal content.
H3	Study 4b	The degree of content personalization is positively related to store visits.

Procedures

The following step of the study was the second part of the questionnaire. A designer was hired to draw 26 different screens the evoked smartphone real behaviors. The research chose to expose each subject to only one experimental treatment and to compare the measures between subjects exposed to different treatments (between -subjects or intersubjects) (HERNANDEZ et al., 2014). For that, the Qualtrics randomization tool was used.

Participants received simulated smartphones push notifications and a geolocation scenario. The study measured likelihood to visit as the extent to which participants had a favorable intention toward walking to the store (“How would you describe your chances of visiting [store x] in such context?” 1 = “very likely,” and 5 = “not likely”). The online survey was open for a month (Feb 10th till March 9th, 2021), during which 1.909 people clicked in the 3x2 experiment and 261 clicked in the 2x2 experiment link (149 fitness and 112 pets).

Participants were invited to the study through a professional Research Company mailing list, WhatsApp groups and the previous timeline questionnaire. The target group was Portuguese speaking smartphone users. 1.353 responses were deemed appropriate for the final sample to analyze in the 3x2 experiment (71% completion). Breakout response rate for study 4a, that used the mailing list:

Table 39 – Respondents WhatsApp and email

	Valid responses	WhatsApp	Email
Until Feb 28th	497	X	***
On March 1st	665	X	X
March 2nd till March 9th	191	X	X

For the personalized manipulation (study 4b), the questionnaire was sent to respondents that marked pets and fitness location on the Timeline research. Since the numbers of valid responses was below twenty per cell, the questionnaire was also sent to pets and fitness WhatsApp groups (i.e, gym goers and pet owners). From 237 respondents that clicked, there were 181 valid responses (70% completion). The study got only two responses from Amazon Mechanical Turk (Portuguese speaking respondents), which were discarded.

The data set for study 4 is available at: https://bit.ly/3dMONyM

Questionnaire and manipulation pre-test

The pre-test questionnaire was sent to respondents (n=14) for feedback, testing for comprehension, typing mistakes, time of response and images. Those responses were not considered in the study. Besides, in a second pre-test questionnaire, responses were tested for each experimental treatment. The study tested the stimuli that were to be manipulated – distance and message content. For distance (near vs. far) there were "near" and "far" images in 2 different samples, with a simple question that read "How far away is this place?", with answers ranging from 1 to 5. Then the study compared the averages to check if the difference was as expected. As a result, the far distance was increased from 650m to 750m. The intermediate distance was dropped. The same test was performed with mobile message content (branded, promotional, personalized and neutral). This step was important to ensure that manipulation was perceived by the respondents.

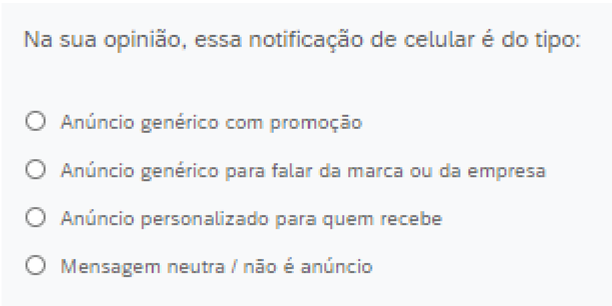


Figure 32 - Example of content manipulation pre-test

Manipulation Check

The experiment tested the distance manipulation by checking the respondents' perception regarding distance, with the question: "how much do you think the place shown is close to you", and answers ranging from 1 to 7. According to the Mann-Whitney test result, there is a significant difference of distance perception between near and far images ($p < .0001$).

Mann-Whitney Test

Ranks

	Distance	N	Mean Rank	Sum of Ranks
Map_Distance	Near	666	562,13	374380,00
	Far	687	788,36	541601,00
	Total	1353		

Test Statistics[a]

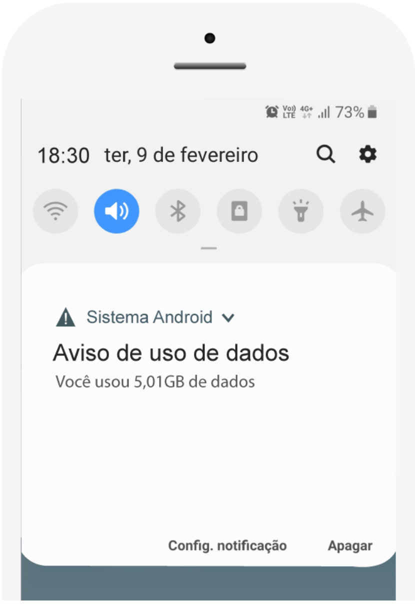
	Map_Distance
Mann-Whitney U	152269,000
Wilcoxon W	374380,000
Z	-10,981
Asymp. Sig. (2-tailed)	,000

a. Grouping Variable: Distance

Variables

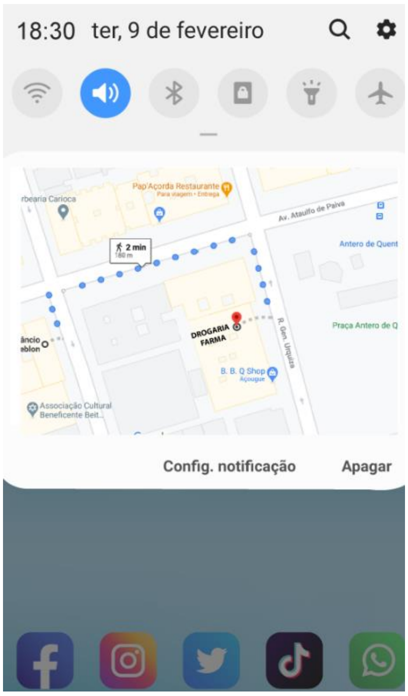
The dependent numeric variable is the intention to visit to the prompted offline location (scale 0 to 10). There are two independent categoric variables (distance and message content) with two treatments (near, far) and three treatments (branding, promotional, personalized), across different industry categories (blocks). For further details, check appendix e. For the geographical targeting, the study followed Luo et al. (2014) procedures: close distances less than 200 meters; medium distances between 200 and 500 meters, and far distances between 500 meters and 2 kilometers to the offline store. Such measure analyzes the distances people are willing to travel on foot to the store.

A: Control Condition



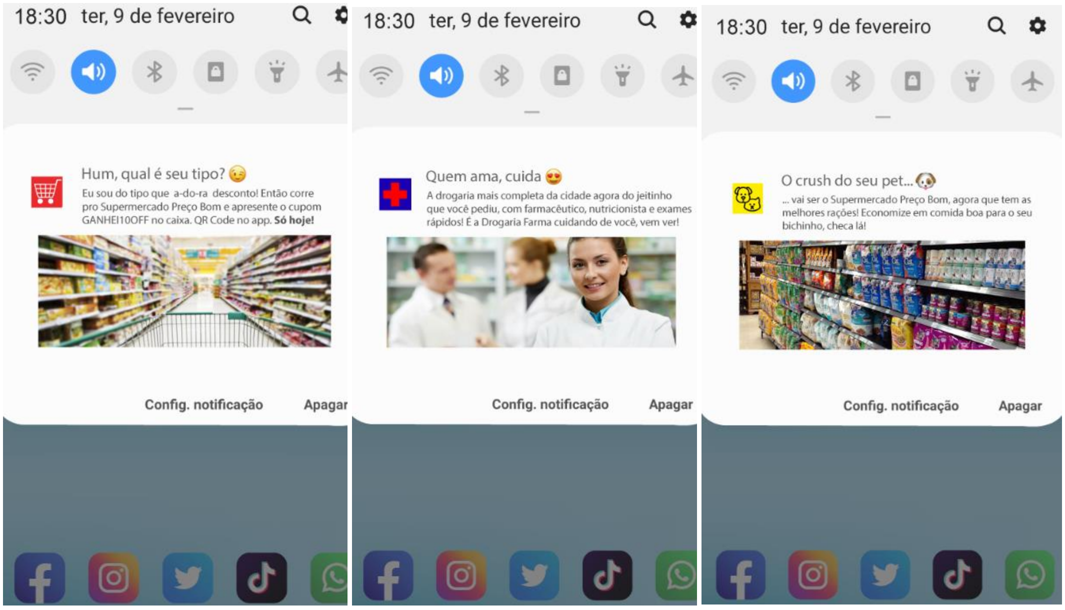
B: Exposed Condition

A: Near



B: Far

A: Promotional B: Branded C: Personalized



To absorb the fear of missing out effect, message with coupons should have a short expiration rate. Hence, the promotion is for a discount voucher valid only on the day of the offer. The promotional message read "*What is your type? I am the I love discount type. So, run to the supermarket and present the coupon WIN10%OFF at the cashier. QR code in the app. Today only!".* Mobile coupons have a perishable character: unlike traditional coupons, m-coupons do not seem to be stored and redeemed later (DANAHER et al., 2015). The branded messages referred to store qualities. For instance: "*Who loves, takes care. The most complete drugstore, now the way you asked for, with pharmacist, nutritionist and quick exams. The Drug Farma takes care of you, come see*". The personalized messages referred to pet food and to fitness outfits, since the respondents referred to going to related places in the past 30 days (personalization through geobehavior targeting).

Controls

To control for possible other effects, the study also tested for age, gender, and income levels. Other possible covariables were online and offline frequency of purchase regarding the category (pets, fitness, supermarket, drugstore, and fast food), as well as push notification perception. The questionnaire also included a question regarding daily walking habit. The control variables were measured and analyzed as co-variables in the two-way ANOVA factorial analysis. Another possible covariable is prior visit to the offline sites (customer vs not customer / buyers and non-buyers). This was considered only in the personalized message content questionnaire. Other covariates can relate to demographics (inferred residence, inferred place of work) and analytics results, such as views and clicks, but those were not used in this study. There were two possible roads of action: predefining the customer profile prior to the message trigger or analyzing the profile afterwards. This study looked at participant's profile afterwards. Demographic traits may also play a role in the effects, however, due to the LGPD (Data Protection General Law), its analysis was limited.

Results and Discussion

Study 4a and 4b included two-way ANOVAs (Analysis of Variance) with message content and location as between-subject factors. The two-way ANOVA test the effect of multiple groups of two independent variables on a dependent variable and on each other.

Table 40 - Sample Descriptive Statics online experiment Study 4a

		Count	%
Gender	Male	822	60,8%
	Female	517	38,2%
	Other	9	0,7%
	rather not answer	5	0,4%
Age	Under 16	1	0,1%
	16 to 24	66	4,9%
	25 to 34	425	31,4%
	35 to 44	441	32,6%
	45 to 60	283	20,9%
	Over 60	135	10,0%
	rather not answer	2	0,1%
Monthly Family Income	up to R$ 2.090,00 (USD 360)	102	9,3%
	R$ 2.090,01 to R$ 4.180,00	208	19,0%
	R$ 4.180,01 to R$ 10.450,00	340	31,1%
	R$ 10.450,01 a R$ 20.900,00	205	18,7%
	over R$ 20.901,00 (USD 3.600)	125	11,4%
	rather not answer	114	10,4%

The descriptive statistics present a well distributed sample, with respondents of different incomes, gender, and ages. On average, the respondents walk 643mts per day, meaning that walking to store should not be an issue, as proposed by the introductory question (see appendix).

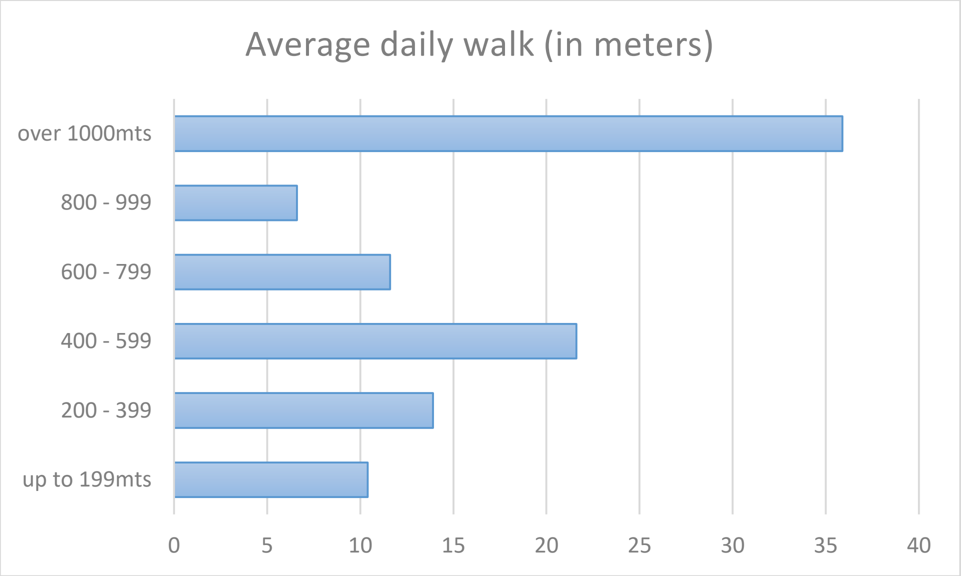


Figure 33 – Average daily walk

Table 41 - Descriptive Statistics Study 4b

		Count	Column N %
Age	Under 16	1	0,6%
	16 to 24	2	1,2%
	25 to 34	70	41,4%
	35 to 44	69	40,8%
	45 to 60	22	13,0%
	Over 60	5	3,0%
	rather not answer	0	0,0%
Gender	Male	63	37,3%
	Female	106	62,7%
	Other	0	0,0%
	Rather not answer	0	0,0%

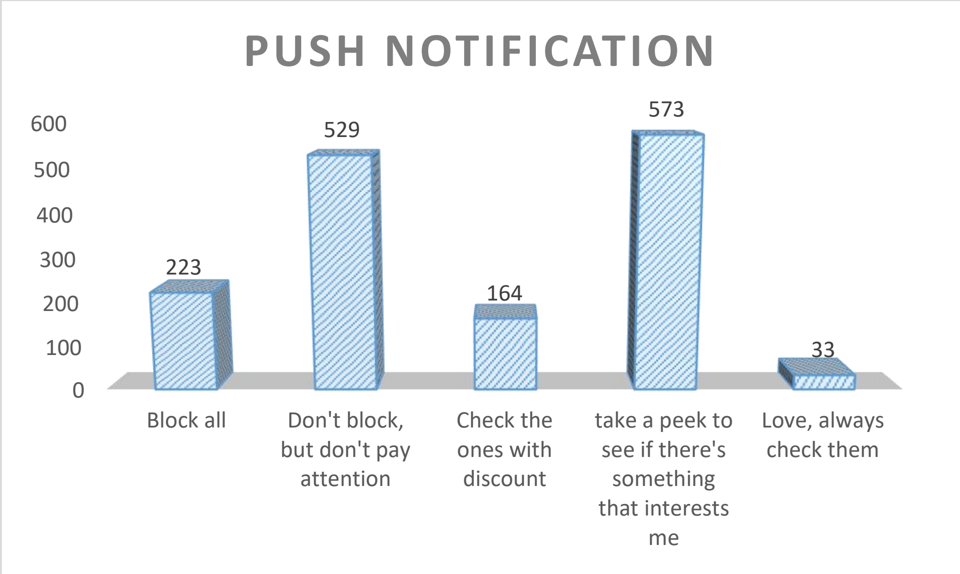


Figure 34 – Push notification

From a total of 1.522 respondents, only 15% mentioned blocking push notifications. However, 35% said they don't block, but they do not pay attention either. If both are considered, that means half of the respondents do not follow push notifications. However, most of the respondents (38%) declared to take a peek to see if there was something interesting.

Study 4a Experimental Design 2x3

		Message		
		control	branding	promotional
		Count	Count	Count
Distance	Near	198	226	242
	Far	228	233	226

All groups have more than twenty valid responses per cell.

Table 42 – Study 4a experimental design 2x3

				Message		
				control	branding	promotional
				Count	Count	Count
Distance	Near	Category	supermarket	69	82	76
			drugstore	56	71	78
			fastfood	73	73	88
	Far	Category	supermarket	85	76	75
			drugstore	70	79	76
			fastfood	73	78	75

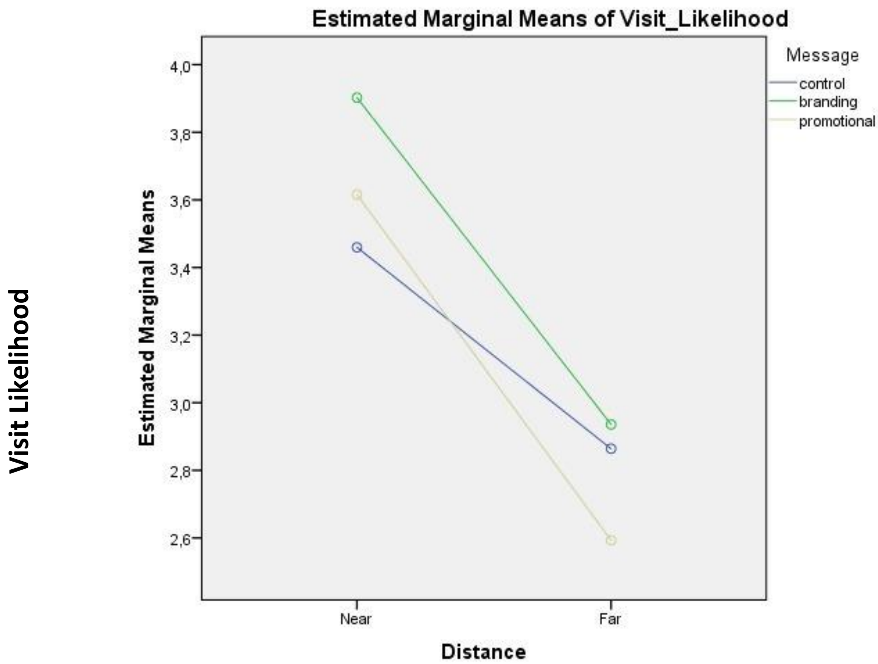


Figure 35 – Interaction effect distance and message content

Table 43 - Interaction between message content and location for intention to visit for all categories.

		Message		
		control	branding	promotional
Distance	Near	3,46	3,90	3,62
	Far	2,86	2,94	2,59

Null hypothesis:

The means of all distance groups are equal

The means of all mobile message content groups are equal

There is no interaction between distance and mobile message content groups

Table 42 shows that the influence of the push notification on intention to visit the store differs significantly (p<.001) for all message contents, depending on where the push notification is sent (distance). Promotional push notifications sent far from the store induce a low intention to visit (M = 2.59). On the other hand, branded push notifications sent closer to the store induce a higher intention to visit (M = 3.90). Figure 42 shows the illustrated graphs of the interaction effect. There is no significant interaction effect between message content and location.

However, there is a significant interaction effect between message content and respondents' relationship with push notification (p < .001). Intention to visit is higher (M=7,25) for respondents that love push notifications compared to participants that don't block but don't pay attention either (M = 2,63).

Table 44 – Duncan test for visit likelihood and push notification

Visit_Likelihood

Duncan[a,b,c]

PushNotification	N	Subset 1	Subset 2	Subset 3
Block all	209	2,17		
Dont't block, but don't pay attention	478	2,63		
take a peek to see if there's something that interests me	493		3,84	
Check the ones with discount	145		3,85	
Love, always check them	28			7,25
Sig.		,289	,984	1,000

Means for groups in homogeneous subsets are displayed.
Based on observed means.
The error term is Mean Square(Error) = 9,297.

a. Uses Harmonic Mean Sample Size = 97,057.

b. The group sizes are unequal. The harmonic mean of the group sizes is used. Type I error levels are not guaranteed.

c. Alpha = ,05.

Table 45 – Tests of Between-Subjects Effects

Tests of Between-Subjects Effects

Dependent Variable: Visit_Likelihood

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	1585,491[a]	17	93,264	10,025	,000
Intercept	6844,818	1	6844,818	735,777	,000
Message	28,592	2	14,296	1,537	,215
Distance	271,270	1	271,270	29,160	,000
Message * Distance	12,677	2	6,339	,681	,506
Message * PushNotification	1294,361	12	107,863	11,595	,000
Error	12419,303	1335	9,303		
Total	28087,000	1353			
Corrected Total	14004,794	1352			

a. R Squared = ,113 (Adjusted R Squared = ,102)

b. Computed using alpha = ,05

				Message		
				control	branding	promotional
				Visit_Likelihood	Visit_Likelihood	Visit_Likelihood
				Mean	Mean	Mean
Distance	Near	Push Notification	Block all	2,58	2,49	2,16
			Don't block, but don't pay attention	3,89	3,10	2,67
			Check the ones with discount	2,94	4,86	5,20
			take a peek to see if there's something that interests me	3,45	4,47	4,64
			Love, always check them	5,33	10,00	8,00
	Far	Push Notification	Block all	2,09	1,83	1,87
			Don't block, but don't pay attention	2,51	1,69	2,12
			Check the ones with discount	3,44	2,96	3,96
			take a peek to see if there's something that interests me	3,21	4,09	2,73
			Love, always check them	6,00	6,75	6,75

Also, there is a significant difference in visit likelihood means when offline shopping behavior for the category is considered. A *post hoc* Duncan test also confirmed significant differences ($p < 0.001$) between the mean ratings of visit likelihood for different offline shopping behaviors in the category.

Table 46 - Duncan test for offline shopping behavior

Visit_Likelihood

Duncan[a,b,c]

OfflineShoping	N	Subset 1	Subset 2	Subset 3
Never	238	2,04		
Every 15 or 30 days	683		3,17	
At least once a week	432			3,97
Sig.		1,000	1,000	1,000

Means for groups in homogeneous subsets are displayed.
Based on observed means.
The error term is Mean Square(Error) = 9,702.

a. Uses Harmonic Mean Sample Size = 375,910.

b. The group sizes are unequal. The harmonic mean of the group sizes is used. Type I error levels are not guaranteed.

c. Alpha = ,05.

Table 47 shows that the influence of the age variable on intention to visit the store ($p<.05$). Younger people (16-24) are more likely to visit the store. The categories rather not answer and under 16 discarded for the analysis since they had fewer than two cases.

Table 47 – Tests of Between-Subjects Effects including Age

Dependent Variable: Visit_Likelihood

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	435,422[a]	7	62,203	6,165	,000
Intercept	9214,024	1	9214,024	913,179	,000
Message	21,053	2	10,527	1,043	,353
Age	155,279	4	38,820	3,847	,004
Distance	243,818	1	243,818	24,164	,000
Error	13540,851	1342	10,090		
Total	28051,000	1350			
Corrected Total	13976,273	1349			

a. R Squared = ,031 (Adjusted R Squared = ,026)

Table 48 – Duncan test for visit likelihood and age

Visit_Likelihood

Duncan[a,b,c]

Age	N	Subset 1	Subset 2
45 to 60	283	2,80	
Over 60	135	2,92	
35 to 44	441	3,29	
25 to 34	425	3,36	
16 to 24	66		4,44
Sig.		,150	1,000

Means for groups in homogeneous subsets are displayed.

Based on observed means.

The error term is Mean Square(Error) = 10,090.

a. Uses Harmonic Mean Sample Size = 162,797.

b. The group sizes are unequal. The harmonic mean of the group sizes is used. Type I error levels are not guaranteed.

c. Alpha = 0,05.

There is a significant difference in visit likelihood means when income levels are considered ($p < .001$). The visit likelihood is higher (M=3,69) for medium-low income levels (between 2 and 4 monthly minimum wages). However, there is no significant interaction effect between message and monthly family income ($p > .05$). No significant effect was noticed for gender.

Table 49 – Duncan test for visit likelihood and monthly average income

Visit_Likelihood

Duncan[a,b,c]

Monthly_Family_Income	N	Subset 1	Subset 2	Subset 3
over R$ 20.901,00 (USD 3.600)	125	2,54		
rather not answer	114	2,83	2,83	
R$ 4.180,01 to R$ 10.450,00	340	3,09	3,09	3,09
R$ 10.450,01 a R$ 20.900,00	205	3,12	3,12	3,12
up to R$ 2.090,00 (USD 360)	102		3,55	3,55
R$ 2.090,01 to R$ 4.180,00	208			3,69
Sig.		,145	,068	,127

Means for groups in homogeneous subsets are displayed.

Based on observed means.

The error term is Mean Square(Error) = 9,877.

a. Uses Harmonic Mean Sample Size = 153,050.

b. The group sizes are unequal. The harmonic mean of the group sizes is used.

Type I error levels are not guaranteed.

c. Alpha = ,05.

Tests of Between-Subjects Effects

Dependent Variable: Visit_Likelihood

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	356,832[a]	18	19,824	1,959	,010
Intercept	9063,626	1	9063,626	895,625	,000
Message	35,872	2	17,936	1,772	,170
Distance	91,296	1	91,296	9,021	,003
Message * Monthly_Family_Income	223,389	15	14,893	1,472	,108
Error	10878,880	1075	10,120		
Total	22185,000	1094			
Corrected Total	11235,712	1093			

a. R Squared = ,032 (Adjusted R Squared = ,016)

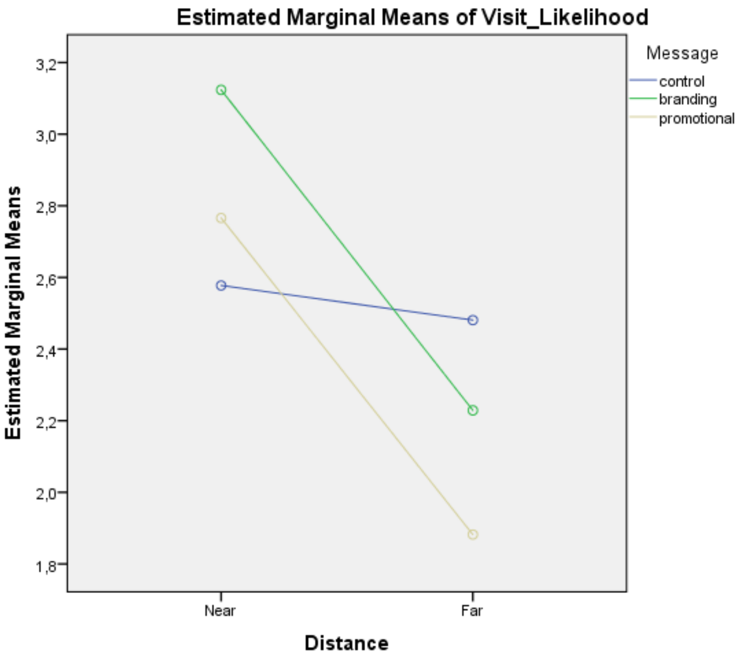


Figure 36 - Interaction between message content and location for intention to visit considering gender and income levels.

When the study considered the category blocks for the push notification on the likelihood to visit, the effects for the supermarket category were significantly different, according to the Duncan test results in Table 49. Therefore, on the sequence, the study tested for supermarket respondents only.

Table 50 – Duncan test for industry categories

Visit_Likelihood

Duncan[a,b,c]

Category	N	Subset 1	Subset 2
drugstore	430	2,85	
fastfood	460	3,12	
supermarket	463		3,67
Sig.		,201	1,000

Means for groups in homogeneous subsets are displayed.
Based on observed means.
The error term is Mean Square(Error) = 10,081.

a. Uses Harmonic Mean Sample Size = 450,496.
b. The group sizes are unequal. The harmonic mean of the group sizes is used. Type I error levels are not guaranteed.
c. Alpha = ,05.

Results for Supermarket Category

Univariate analysis of variance (ANOVA) was performed to test the statistical significance of distance and message content for the supermarket category only.

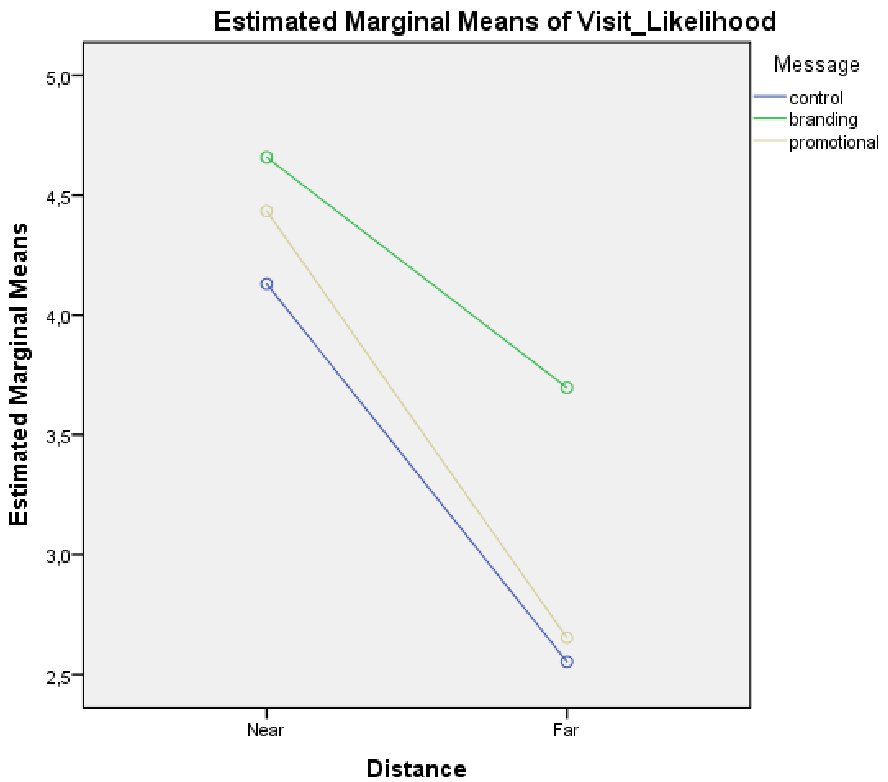


Figure 37 - Interaction between message content and location for intention to visit for supermarket

Tests of Between-Subjects Effects

Dependent Variable: Visit_Likelihood

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	322,780[a]	5	64,556	6,429	,000
Intercept	6268,703	1	6268,703	624,278	,000
Message	59,268	2	29,634	2,951	,053
Distance	238,899	1	238,899	23,791	,000
Message * Distance	14,144	2	7,072	,704	,495
Error	4588,974	457	10,042		
Total	11161,000	463			
Corrected Total	4911,754	462			

a. R Squared = ,066 (Adjusted R Squared = ,055)

Null hypothesis

The means of all distance groups are equal

The means of all mobile message content groups are equal

There is no interaction between distance and mobile message content groups

The null hypothesis for these tests is that there is no difference between different mobile message content with respect to likelihood to visit the store. Another null hypothesis is that there is no difference between proximity to store (location where the user receives the push notification) with respect to likelihood to visit the store. The results show a significant main effect of incentive on message content $(F(2;457)=2.951; p < .10)$

The p-value speaks to the credibility of the null hypothesis. A low p-value means the null hypothesis is less credible and unlikely to be true. If the null hypothesis is unlikely to be true, then it suggests that there is a difference in likelihood to visit the among different mobile message content and distance to store. It seems much more likely that the alternate hypothesis—namely, that distance and mobile message content make a difference— is true, for the supermarket category.

However, there is no significant interaction effect on message and distance. There is no support for H2a, since for customers at a proximal distance, those who receive a branded message are more likely to visit the store than those who receive a promotional message. Besides, the further the distance, the more influential the message content type is. Figure 44 also shows that the influence of the message content on intention to visit differs significantly depending on the location it is sent.

Results for Supermarket Category with offline purchase behavior

Tests of Between-Subjects Effects

Dependent Variable: Visit_Likelihood

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	364,169[a]	7	52,024	5,234	,000
Intercept	1417,631	1	1417,631	142,636	,000
Message	58,560	2	29,280	2,946	,054
Distance	241,972	1	241,972	24,346	,000
Message * Distance	19,290	2	9,645	,970	,380
DailyWalk	3,803	1	3,803	,383	,537
OfflineShoping	42,110	1	42,110	4,237	,040
Error	4273,678	430	9,939		
Total	10771,000	438			
Corrected Total	4637,847	437			

a. R Squared = ,079 (Adjusted R Squared = ,064)

Table 51 – Tests of Between-Subjects Effects daily walk and offline behavior

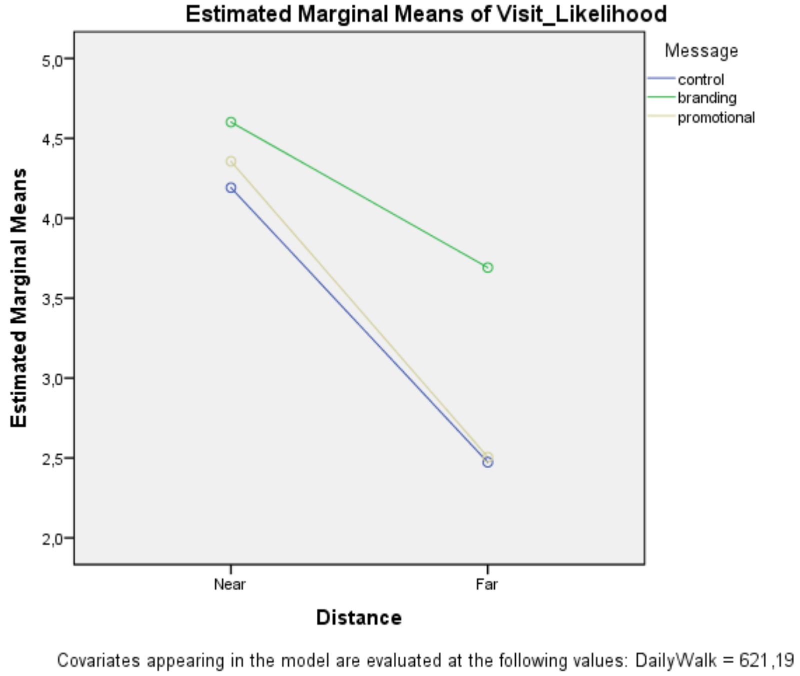


Figure 38 - Interaction between message content and location for intention to visit for supermarket category, considering daily walk, and offline purchase behavior.

Study 4b Experimental Design 2x2 Personalized

Table 52 - Experimental set-up (study 4b)

		Message	
		control	personalized
		Count	Count
Distance	Near	42	50
	Far	40	49

				Message	
				control	personalized
				Count	Count
Distance	Near	Category	pets	14	23
			fitness	28	27
	Far	Category	pets	19	20
			fitness	21	29

An Analysis of Variance (ANOVA) was performed to test the statistical significance of distance and message content across categories. The results are shown in Table 53. Levene's tests indicated no violation of the homogeneity of variance assumption.

Levene's Test of Equality of Error Variances a

Dependent Variable: Visit_Likelihood

F	df1	df2	Sig.
1,485	7	173	,175

Tests the null hypothesis that the error variance of the dependent variable is equal across groups.

a. Design: Intercept + Distance + Message + Distance * Message + Category

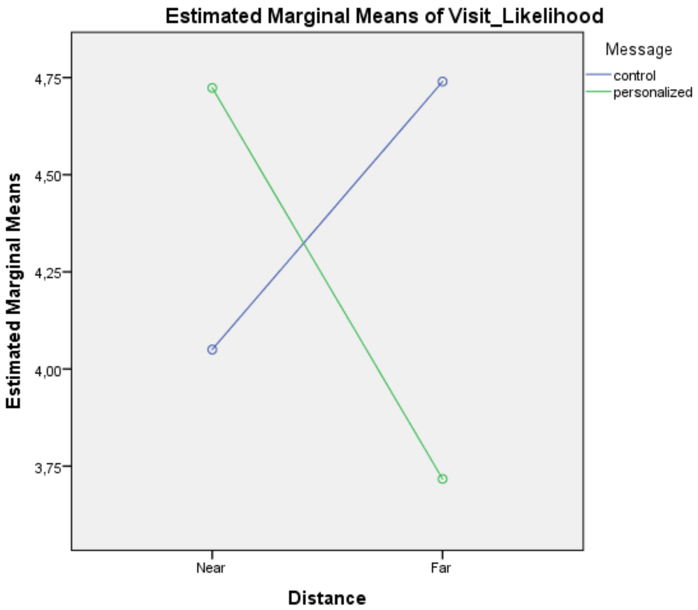


Figure 39 – Interaction effect distance and personalized message

Table 53 - Interaction between message content and location for intention to visit for pets and fitness.

				Message	
				control	personalized
				Visit_Likelihood	Visit_Likelihood
				Mean	Mean
Distance	Near	Category	pets	2,57	5,22
			fitness	4,89	4,33
	Far	Category	pets	5,00	3,15
			fitness	4,52	4,17

Table 54 – Tests of Between-subjects Effects for distance and message content

Tests of Between-Subjects Effects

Dependent Variable: Visit_Likelihood

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	40,994[a]	4	10,248	,894	,469
Intercept	3240,340	1	3240,340	282,730	,000
Distance	1,122	1	1,122	,098	,755
Message	1,365	1	1,365	,119	,730
Distance * Message	31,932	1	31,932	2,786	**,097**
Category	7,469	1	7,469	,652	,421
Error	2017,117	176	11,461		
Total	5454,000	181			
Corrected Total	2058,110	180			

a. R Squared = ,020 (Adjusted R Squared = -,002)

Since the means difference was very different across categories, the study also tested for other covariates that could influence the effect, such as online and offline shopping frequency. The purchase frequency seems to affect intention to visit, regardless of the message content or the distance, when it comes to personalized message content.

Table 55 - Tests of Between-subjects Effects: distance, content and offline shopping behavior

Tests of Between-Subjects Effects

Dependent Variable: Visit_Likelihood

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	196,410[a]	8	24,551	2,398	,018
Intercept	1264,596	1	1264,596	123,529	,000
Distance	2,625	1	2,625	,256	,613
Message	6,293	1	6,293	,615	,434
Distance * Message	28,055	1	28,055	2,741	,100
Category	15,189	1	15,189	1,484	,225
OfflineShoping	136,867	2	68,434	6,685	**,002**
Message * OfflineShoping	14,367	2	7,183	,702	,497
Error	1637,956	160	10,237		
Total	4936,000	169			
Corrected Total	1834,367	168			

a. R Squared = ,107 (Adjusted R Squared = ,062)

The study applied the Tukey test and the Duncan procedure for the comparison of pairs of mean, from where the difference between participants that had the offline shopping habit was distinguished from the ones that did not.

Visit_Likelihood

	OfflineShoping	N	Subset	
			1	2
Tukey B[a,b,c]	Never	44	2,86	
	Every 15 or 30 days	115	4,67	4,67
	At least once a week	10		6,10
Duncan[a,b,c]	Never	44	2,86	
	Every 15 or 30 days	115	4,67	4,67
	At least once a week	10		6,10
	Sig.		,060	,135

Means for groups in homogeneous subsets are displayed.
Based on observed means.
The error term is Mean Square(Error) = 10,353.
a. Uses Harmonic Mean Sample Size = 22,827.
b. The group sizes are unequal. The harmonic mean of the group sizes is used. Type I error levels are not guaranteed.
c. Alpha = ,05.

Table 56 – Difference of means for offline shopping behavior in the category

Dependent Variable: Visit_Likelihood

OfflineShoping	Mean	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
Never	2,724	,504	1,729	3,720
At least once a week	5,875	1,033	3,836	7,914
Every 15 or 30 days	4,629	,301	4,035	5,224

Study 4a + 4b

In order to test the hypotheses 2a and 2b, considering the full set of content messages, two-way analysis of variance (ANOVA) was performed with database a and b combined to analyze the whole set of message content variation.

Visit_Likelihood

Duncan[a,b,c]

Message	N	Subset	
		1	2
promotional	468	3,12	
control	508	3,35	
branding	459	3,41	
personalized	99		4,25
Sig.		,346	1,000

Means for groups in homogeneous subsets are displayed.

Based on observed means.

The error term is Mean Square(Error) = 10,108.

a. Uses Harmonic Mean Sample Size = 244,127.

b. The group sizes are unequal. The harmonic mean of the group sizes is used. Type I error levels are not guaranteed.

c. Alpha = ,05.

Experimental diagram:

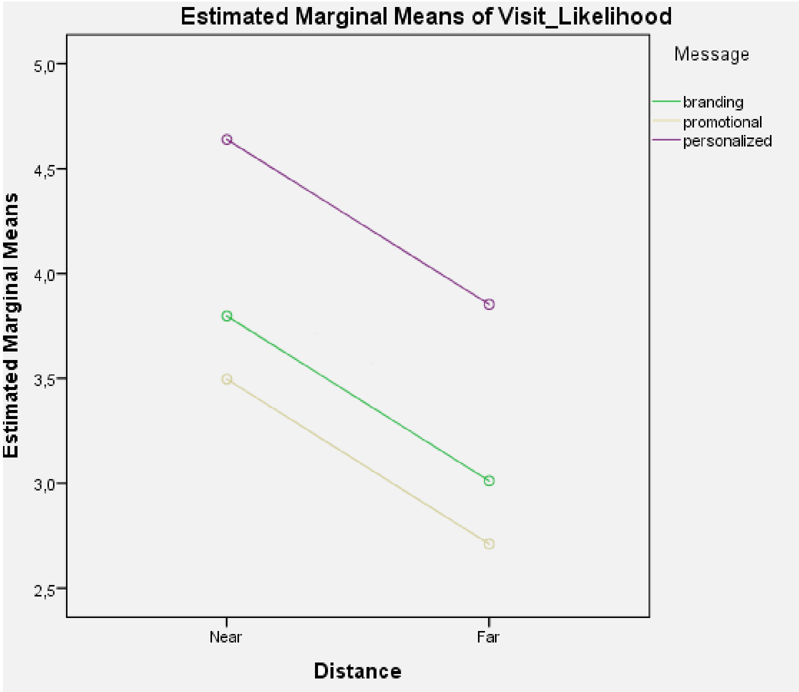


Figure 40 - Interaction between message content and location for intention to visit (all categories)

Preliminary Hypothesis diagram:

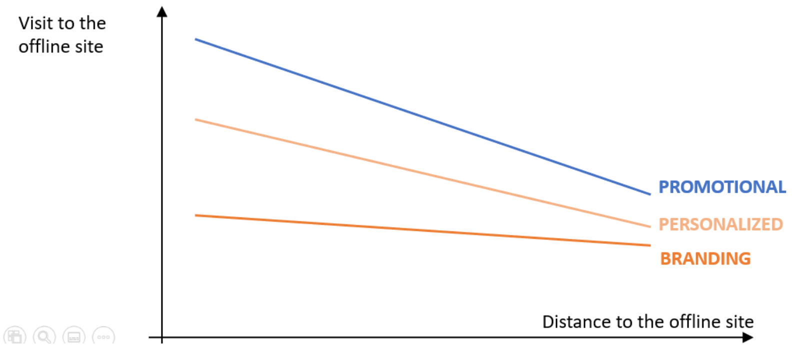


Figure 41 – Hypothesis diagram

This analysis support hypothesis H2b (for customers at a proximal distance, those who receive a personal content are more likely to visit the store than those who receive an impersonal content) and H3 (the degree of content personalization is positively related to store visits). However, it does not support H2b (for customers at a proximal distance, those who receive a promotional content are more likely to visit the store than those who receive a branded content). The visit likelihood does not increase over promotional messages.

H2a	Study 4a	For customers at a proximal distance, those who receive a promotional content are more likely to visit the store than those who receive a branded content. **DOES NOT SUPPORT**
H2b	Study 4b ✓	For customers at a proximal distance, those who receive a personal content are more likely to visit the store than those who receive an impersonal content. **SUPPORT**
H3	Study 4b ✓	The degree of content personalization is positively related to store visits. **SUPPORT**

Visit_Likelihood

Duncan[a,b,c]

Category	N	Subset			
		1	2	3	4
drugstore	430	2,85			
fastfood	460	3,12	3,12		
supermarket	463		3,67	3,67	
pets	76			4,13	4,13
fitness	105				4,48
Sig.		,432	,111	,184	,317

Means for groups in homogeneous subsets are displayed.
Based on observed means.
The error term is Mean Square(Error) = 10,108.
a. Uses Harmonic Mean Sample Size = 170,410.
b. The group sizes are unequal. The harmonic mean of the group sizes is used. Type I error levels are not guaranteed.
c. Alpha = ,05.

Table 57 – Duncan test for visit per industry category

			Message			
			control	branding	promotional	personalized
			Visit_Likelihood (mean)			
Distance	Near	supermarket	4,13	**4,66**	4,43	
		drugstore	3,88	3,03	2,63	
		fastfood	2,51	3,90	3,78	
		pets	2,57			**5,22**
		fitness	**4,89**			4,33
	Far	supermarket	2,55	3,70	2,65	
		drugstore	3,53	2,53	1,88	
		fastfood	2,59	2,60	3,25	
		pets	**5,00**			3,15
		fitness	**4,52**			4,17

This study proceeds with the work of Beeck and Toporowski (2017) regarding both location and content in mobile marketing. The authors pointed out that there had not been a research conducted about promotional texts that lack any monetary value. Therefore, the study included branded and personalized messages in the content variable.

The average treatment effect was the difference between the mean likelihood to visit store ratings in the exposed and control conditions. Given that participants were randomly assigned to conditions, a significant positive average treatment effect for a mobile push notification on a given metric indicates that the push was effective in improving that metric (in the case, offline visit likelihood). This study tested whether message content aspects at least partially explain differences in campaign effectiveness on the store intention to visit metric. The results indicate that location-based push notification can affect the intention to visit the store under the following circumstances: the closer the store, the higher is the mobile user likelihood to positively respond to the push notification, in line with previous studies. Besides, mobile users with a positive relationship to push notifications are more likely to visit a store due to this digital activation.

Regarding content, the results indicate a higher likelihood of visits for participants that receive a branded message compared to a promotional or neutral one (control condition), with a significant effect ($p < .05$). Yet, the message content effect appears to be highly dependent on category, since the effects were only significant for the supermarket category. High income classes are less influenced by push notification regarding intention to visit the store. Lower and medium classes respond better.

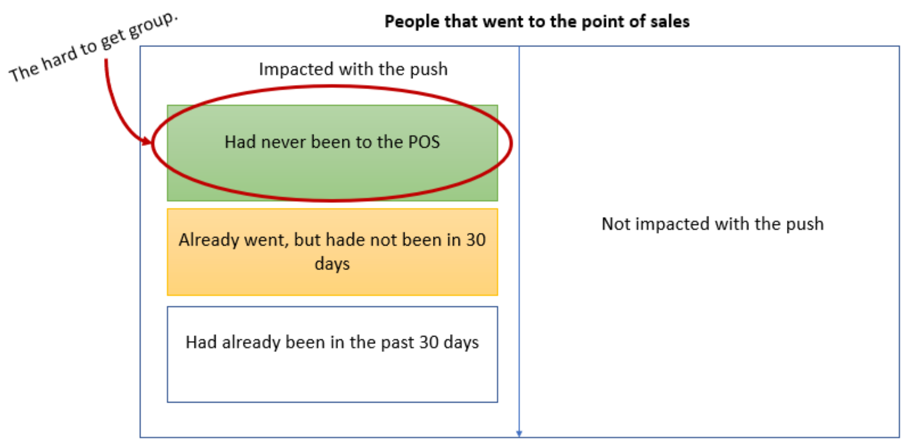


Figure 42 - Behavioral targeting in mobile communication

The offline geobehavior also presented a positive effect on visit likelihood. As a managerial recommendation, it seems very hard to convince a person that does not have an usual offline behavior to engage in a O2O process with a push notification. However, there seems to be a higher chance to increase the frequency of those that already demonstrate some offline behavior (i.e, from once a month to every week). That aspect can be further explored in future studies.

Driving people to stores with the use of digital content is a complex, multifaceted topic. It has been a few years since marketeers are searching for ways to use mobile advertising effectively (BART & STEPHEN, 2014). Many companies, however, approach mobile advertising with a “spray-and-pray” mentality—that is, placing advertisements without any sense of how effective they will be. Each new effort is an improvement from such path.

8.
GENERAL DISCUSSION AND CONCLUSIONS

E-commerce sales increased in a two-digit growth rate over the past years, strengthening mobile representativeness, regarding both advertising and sales. Despite mobile growth, the majority of retails sales is still concluded in brick-and-mortar stores (APP ANNIE, 2020; WEBSHOPPERS, 2021). Little is known about the role mobile content plays on this cross-channel perspective. Academic research in Mobile Marketing lags studies regarding the effects of mobile efforts in offline behavior, under the O2O perspective (LAMBERTON & STEPHEN, 2016; BEECK & TOPOROWSKI; 2017; CHIANG et al., 2018).

Therefore, the purpose of the research was to analyze which visual and textual features of push online mobile messages generate more visits to brick-and-mortar stores, which was accomplished. 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.

The effectiveness of Mobile Marketing is guided by the principle of context - taking the right action in the right place at the right time. In a scenario where most of our digital minutes happen on mobile platforms, it is a matter of survival to have mobile-focused planning that embraces the potential of new technologies such as geolocation and geo behavioral targeting. For that, the research built on the literature of contextual marketing and behavioral advertising to posit that the geolocation mobile promotion directed to the customer once he approaches the store increases the chances of a positive response to the communication. It also posits that the effect would be moderated by the type of message, promotional, branded, or personalized. The main assumption behind the study is that the type of content and the geolocation data increase store visits. Context and convenience as the primary drivers of the effect (visits to the offline point-of-sale), considering that context and convenience are represented by geolocation and message content. That provides the base for a mobile model for companies enhance customer store visits via mobile.

8.1. Theoretical and Managerial Contributions

The research consisted of a qualitative study, a secondary data study, field experiments and an online experiment. The research used a mixed-method approach to assess knowledge on mobile promotions and offline behavior, in a cross-channel perspective. 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. Hornik et al. (2017) had highlighted that consumers respond to emotional appeals more favorably than to rational appeals, which this research reinforced.

In the qualitative study, interviews were conducted with C'level managers and experts from the digital industry involved with mobile promotion. The results led to a more complex question after all. Does context matter in mobile promotions? How does it matter? The real deal behind mobile promotions goes beyond geolocation – it refers to context. Both message content and geolocation are important pillars of context. It is about understanding when, where and how to talk to consumers, in a way that actually matters to then – the so-called relevance. For now, the smartphone is the main device that provides the ubiquity this process requires. The app download is a sign that the consumer trusts the company. It is the happening of the "brand in the hand" marketing era, as Sultan & Rohm had put it some years ago (2005).

The qualitative study also revealed the broader aspects of contextualization concept compared to personalization in the mobile context. The first digital moves allowed marketeers to personalize; now mobile data allows to contextualize. That implies that geolocation is just part of the equation. It is necessary to rescue behavior data and add to geolocation, assembling the data puzzle. 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 to 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 Case, brought by one of the interviewees, for example, messages like "Your mother deserves the best" generated more engagement than others like "Have you bought a gift for mom yet?". This remark from the qualitative study is aligned with the results from study 1, favoring messages with an emotional branded appeal.

Study 1 was a text and image analysis of real mobile message content from mobile campaigns that ran from November 2018 until March, 2019, using computer vision, machine learning and image detection applications. 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. Study 1 showed that the presence of a person in the add has a positive effect on visits, regardless of the add's appeal. According to the study results, an add displaying a person / people tends to drive (6,67%) more visits to the offline point of sale than one with no person. Nonetheless, only 17% of the ads from the campaign sample displayed a person.

Studies 2 and 3 were field experiments with message content and distance as factors. Whist most studies use "intention to redeem" as a dependent variable, the field experiment used actual consumer behavior performance data (mall visits from app users). As in Högberg et al.(2020) experiment, this cooperation between the tech company and the mall allowed the research to use a field experimental approach for causal inferences regarding psychological mechanisms and their effect on behavior generalized beyond the laboratory.

Study 4 was an online experiment with 1534 respondents, with distance and message content as factors, and likelihood to visit as the dependent variable. The results indicate that location-based push notification can affect the intention to visit the store under the following circumstances: the closer the store, the higher is the mobile user likelihood to positively respond to the push notification, in line with previous studies. Besides, mobile users with a positive relationship to push notifications are more likely to visit a store due to this digital activation. The effects of location-based push notification on likelihood to visit the store are higher for younger people (16-24) and lower income classes. The offline geobehavior also presented a positive effect on the likelihood to visit the store. As a managerial recommendation, it seems hard to convince a person that does not have a usual offline behavior to engage in a O2O process with a push notification. However, there seems to be a higher chance to increase the visit frequency of those that already demonstrate some offline behavior (i.e, from once a month to every week). That aspect can be further explored in future studies.

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.

The first key seems to be balancing the optimal frequency and relevance of the push notification to the consumer, understanding when they are most likely to engage with the message and what is the ideal message for each moment. Given a decision to invest in mobile push notifications, marketers can have a better sense of how their mobile message content should be positioned in a campaign to maximize effectiveness (i.e.,which elements of the content should they). The set of studies (secondary data, field and online experiment) demonstrated that branded mobile content has a significant and positive relationship with store visits.

Mobile notifications are an actual behavior changer when people have so many choices. Companies can improve the app experience and improve the customer journey experience by using location data for personalized communication. The goal is to improve response rates with targeting based on the real-time geographic proximity. The location sensitivity of smartphones is an important tool for marketing managers. It works to nudge consumers offering convenience and personalization and respecting privacy at the same time.

Mobile devices allow to track behaviors, both digital and offline, hence expanding the comprehension of the customer path and allowing for more precise clusterization. Regarding customer journey, it helps generating qualified leads and creating real business opportunities. Besides, opportunities are presented to engage app users with push notifications. Consumers have countless interactions with their mobile phones, like texting family and friends, dropping a quick work email while waiting in line, or posting a funny Tik Tok video to make friends laugh. They are not necessarily looking to engage with brands at those moments. And if a brand tries to butt in with a message? Swipe, it is just disruptive. But in other moments, consumers can be open to the influence of brands. These are the moments when marketers want help making decisions (THINK WITH GOOGLE, 2020). These are the moments when mobile promotion can help the shopper engage the funnel. Understanding these moments is understanding the customer context and journey. Under such perspective, interacting with a message via mobile needs to be relevant to the consumer context. Indeed, as study 4 demonstrated, customers that prefer online shopping to offline shopping are less likely to respond to store push notifications.

However, although these targeted notifications have the power to increase brick-and-mortar shopping experiences, personalization can backfire, and this is an important issue that deserves future attention on research. Of particular relevance, highly personalized notifications can rouse consumer privacy concerns (AGUIRRE et al., 2015; KIM et al., 2019). Indeed, retailers should be aware of the privacy concerns preventing some customers from using mobile stimuli (BEECK & TOPOROWSKI, 2017). Risk avoidance (PANTANO & PRIPORAS, 2016) and lack of trust play an important role in limiting the consumer’s acceptance of the mobile shopping technology and it might extend to their willingness to accepted targeted push-notifications. This is a managerial challenge regarding person-level data and bringing one-to-one-marketing campaigns to life.

Dynamic mobile ads require more than geolocation data. Marketeers and retailers can use location data to go beyond proximity marketing. Instead of trying to reach consumers the moment they approach a location, other focus can be reengaging infrequent visitors, finding new customers with similar profile or rewarding loyal ones. Managers can learn more about customers by analyzing their geobehavior. However, that requires investing resources in BI and data pool. Regarding to that, a challenge may be the so called walled gardens, closed data environments like those of Apple and Google, that make it difficult to analyze results across all media channels. Both are working on anti-tracking features that will impact advertising partners. The focus is migrating from individuals to groups of people with similar interests.

8.2. Limitations of the studies

A number of limitations and concerns are associated with the chosen research method and the research itself. Regarding the qualitative study, the main limitation is related to the verification of the study and the impossibility of generalization of the obtained data. A limitation of the experiment method is the trade-off between internal validity and external validity. Controlling concomitant variables in the field is a challenge. Future studies can include more variables that may also affect store visit than the ones considered in the proposed model.

Regarding the research itself, a main limitation was that the focus of the research was geolocation in times of the unpredictable Covid pandemic. People were oriented to stay in their homes and any advertising stimulating going to stores was to be avoided. Therefore, the field study was postponed a few times and at the end, was performed with much smaller numbers than predicted. 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.

8.3. Future Research

A 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.

Cross-cultural differences affecting mobile communication can be a fruitful research avenue. Gupta and Arora (2017) pointed out that the reasons to adopt mobile shopping are very context specific and may vary across countries. Different contexts require distinguished mobile strategies. Indeed, in India, the majority of consumers used mobile shopping with the "cash on delivery" option, whereas in Italy, they opted for in-store pickup delivery (PANTANO & PRIPORAS, 2016). The results indicated that the likelihood to visit the store with the mobile push was higher for lower income levels, but that might be due to the strong social inequality of the country of the research.

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). Further interviews with telecom players could also add interesting insights. 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.

8.4.
Concluding Remarks

Mobile is a digital paradigm shift in retail, a key tool to enhance the consumer experience in physical stores. Retailers should be ready to adopt a mobile mindset if they want to execute a successful cross-channel strategy. The consumer lives a journey in which he passes through multiple channels and points of contact, with the mobile as the hub of this process. Thus, the approach should be increasingly multimedia and cross-platform, taking advantage of the synergies that the mobile offers with the other channels. 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, further 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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APPENDICES

Appendix a - Study 1 t-tests and mean differences

		VTR
		Mean
ShowPrice	no	8,87%
	yes	3,36%
ShowDiscount	no	10,29%
	yes	4,83%
PurchaseAppeal	no	10,83%
	yes	4,59%
ShowAddress	no	8,38%
	yes	6,06%
BrandingAppeal	no	4,59%
	yes	10,83%
Person	no	7,22%
	yes	13,89%
Animal	no	8,23%
	yes	23,44%
Wording black	no	10,11%
	yes	4,06%
Wording discount (s)	no	9,90%
	yes	3,31%
Wording no	no	9,23%
	yes	4,48%
Wording Participate	no	8,18%
	yes	9,36%
Wording Store (s)	no	8,82%
	yes	6,82%

Means difference table

Since “animal” and “address” were present in less than 1% of the cases, they were not considered in the analysis. “Show price” and “show discount” were used to categorize “purchase appeal”.

t-test log VTR and Branding Appeal

Group Statistics

	BrandingAppeal	N	Mean	Std. Deviation	Std. Error Mean
LN_VTR	0	248	,8034	1,18973	,07555
	1	377	1,6354	1,36507	,07030

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
LN_VTR	Equal variances assumed	1,731	,189	-7,838	623	,000	-,83205	,10616	-1,04052	-,62359
	Equal variances not assumed			-8,063	576,184	,000	-,83205	,10320	-1,03475	-,62936

Test of Homogeneity of Variances

LN_VTR

Levene Statistic	df1	df2	Sig.
28,454	1	623	,000

ANOVA

LN_VTR

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	17,322	1	17,322	9,496	,002
Within Groups	1136,505	623	1,824		
Total	1153,827	624			

t-test log VTR and person

Group Statistics

	Person	N	Mean	Std. Deviation	Std. Error Mean
LN_VTR	0	519	1,2300	1,26164	,05538
	1	106	1,6736	1,72373	,16742

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
LN_VTR	Equal variances assumed	28,454	,000	-3,082	623	,002	-,44362	,14396	-,72632	-,16091
	Equal variances not assumed			-2,516	128,921	,013	-,44362	,17634	-,79252	-,09471

t-test log VTR and wording (Black)

Group Statistics

	Black	N	Mean	Std. Deviation	Std. Error Mean
LN_VTR	,00	444	1,5515	1,34356	,06376
	1,00	181	,7012	1,20454	,08953

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
LN_VTR	Equal variances assumed	1,180	,278	7,390	623	,000	,85037	,11508	,62438	1,07636
	Equal variances not assumed			7,736	370,196	,000	,85037	,10992	,63423	1,06651

t-test log VTR and wording (discount / discounts)

Group Statistics

	Desconto_s	N	Mean	Std. Deviation	Std. Error Mean
LN_VTR	,00	479	1,4485	1,44280	,06592
	1,00	146	,8352	,89708	,07424

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
LN_VTR	Equal variances assumed	21,428	,000	4,857	623	,000	,61336	,12629	,36536	,86135
	Equal variances not assumed			6,178	390,202	,000	,61336	,09929	,41815	,80856

t-test log VTR and wording (no)

Group Statistics

	Não	N	Mean	Std. Deviation	Std. Error Mean
LN_VTR	,00	510	1,3625	1,43786	,06367
	1,00	115	1,0514	,90042	,08396

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
LN_VTR	Equal variances assumed	23,502	,000	2,223	623	,027	,31104	,13993	,03625	,58584
	Equal variances not assumed			2,952	263,294	,003	,31104	,10537	,10356	,51853

t-test log VTR and wording (store / stores)

Group Statistics

	Loja_s	N	Mean	Std. Deviation	Std. Error Mean
LN_VTR	,00	480	1,3653	1,33447	,06091
	1,00	145	1,1064	1,42731	,11853

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
LN_VTR	Equal variances assumed	2,926	,088	2,014	623	,044	,25887	,12854	,00644	,51130
	Equal variances not assumed			1,943	225,367	,053	,25887	,13327	-,00374	,52148

t-test log VTR and wording (participate)

Group Statistics

	Participe	N	Mean	Std. Deviation	Std. Error Mean
LN_VTR	,00	531	1,2111	1,41796	,06153
	1,00	94	1,8370	,78229	,08069

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
LN_VTR	Equal variances assumed	36,511	,000	-4,167	623	,000	-,62593	,15021	-,92090	-,33096
	Equal variances not assumed			-6,168	219,603	,000	-,62593	,10147	-,82592	-,42594

t-test log VTR and wording (valid)

Group Statistics

	VALID	N	Mean	Std. Deviation	Std. Error Mean
LN_VTR	,00	492	1,3292	1,39606	,06294
	1,00	133	1,2166	1,21712	,10554

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
LN_VTR	Equal variances assumed	2,901	,089	,848	623	,397	,11266	,13293	-,14837	,37370
	Equal variances not assumed			,917	234,613	,360	,11266	,12288	-,12943	,35475

t-test log VTR and wording (consult)

Group Statistics

	CONSULTE	N	Mean	Std. Deviation	Std. Error Mean
LN_VTR	,00	521	1,3240	1,36490	,05980
	1,00	104	1,2113	1,33655	,13106

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
LN_VTR	Equal variances assumed	4,153	,042	,772	623	,440	,11276	,14609	-,17413	,39965
	Equal variances not assumed			,783	149,068	,435	,11276	,14406	-,17190	,39742

t-test log VTR and wording (valid)

Group Statistics

	CONSULTE	N	Mean	Std. Deviation	Std. Error Mean
LN_VTR	,00	521	1,3240	1,36490	,05980
	1,00	104	1,2113	1,33655	,13106

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
LN_VTR	Equal variances assumed	4,153	,042	,772	623	,440	,11276	,14609	-,17413	,39965
	Equal variances not assumed			,783	149,068	,435	,11276	,14406	-,17190	,39742

t-test log VTR and wording (promotion)

Group Statistics

	Promoção	N	Mean	Std. Deviation	Std. Error Mean
LN_VTR	,00	512	1,3471	1,36397	,06028
	1,00	113	1,1159	1,33031	,12514

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
LN_VTR	Equal variances assumed	,236	,628	1,638	623	,102	,23118	,14114	-,04600	,50835
	Equal variances not assumed			1,664	168,018	,098	,23118	,13891	-,04305	,50540

t-test log VTR and wording (new)

Group Statistics

	NOVO	N	Mean	Std. Deviation	Std. Error Mean
LN_VTR	,00	520	1,3246	1,36923	,06004
	1,00	105	1,2093	1,31431	,12826

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
LN_VTR	Equal variances assumed	,001	,975	,792	623	,428	,11530	,14553	-,17048	,40109
	Equal variances not assumed			,814	153,105	,417	,11530	,14162	-,16448	,39509

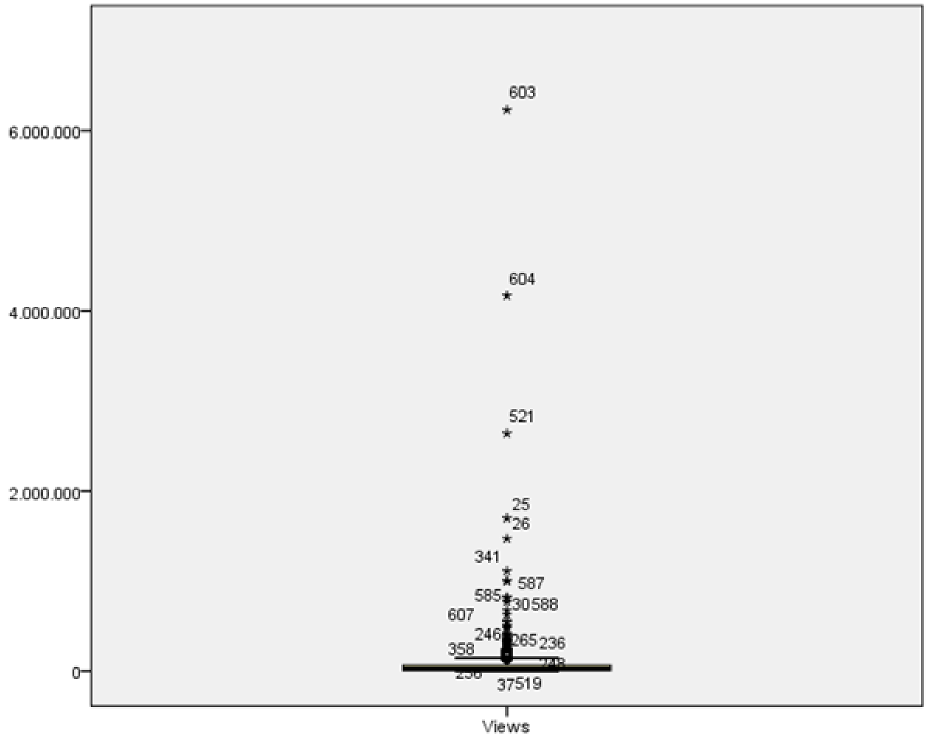
Dependent Variable: LN_VTR

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	228,748[a]	17	13,456	8,829	,000
Intercept	21,532	1	21,532	14,128	,000
BrandingAppeal * Person	,326	1	,326	,214	,644
ShowPrice * ShowDiscount	,000	0	.	.	.
Person * ShowDiscount	,114	1	,114	,075	,785
Person * ShowPrice	,881	1	,881	,578	,447
Black * Participe	21,517	1	21,517	14,118	,000
ShowDiscount * Black	,023	1	,023	,015	,903
Desconto_s * Não	17,432	1	17,432	11,438	,001
ShowPrice * Desconto_s	1,152	1	1,152	,756	,385
ShowDiscount * Não	10,705	1	10,705	7,024	,008
BrandingAppeal * Participe	,515	1	,515	,338	,561
BrandingAppeal	,000	0	.	.	.
Person	,239	1	,239	,157	,692
ShowPrice	3,079	1	3,079	2,021	,156
ShowDiscount	3,129	1	3,129	2,053	,152
Black	3,398	1	3,398	2,230	,136
Desconto_s	6,803	1	6,803	4,464	,035
Não	,764	1	,764	,501	,479
Participe	31,038	1	31,038	20,366	,000
Error	925,079	607	1,524		
Total	2218,637	625			
Corrected Total	1153,827	624			

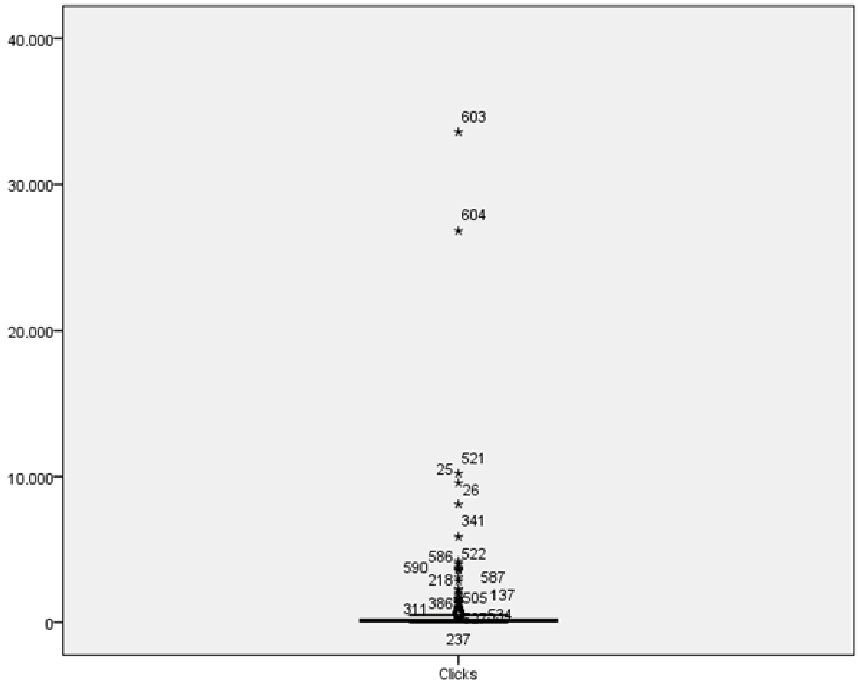
a. R Squared = ,198 (Adjusted R Squared = ,176)

Study 1 – Analysis of Covariance (ANCOVA)

Appendix c - Study 1 complementary data



Box-plot variable Views



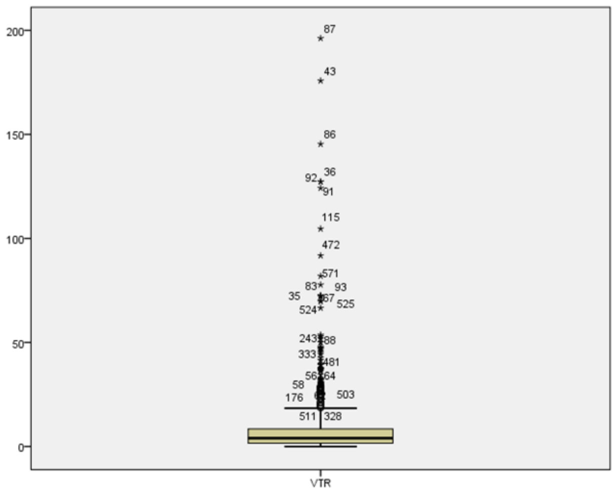
Box-plot variable Views Clicks

Correlation Matrix

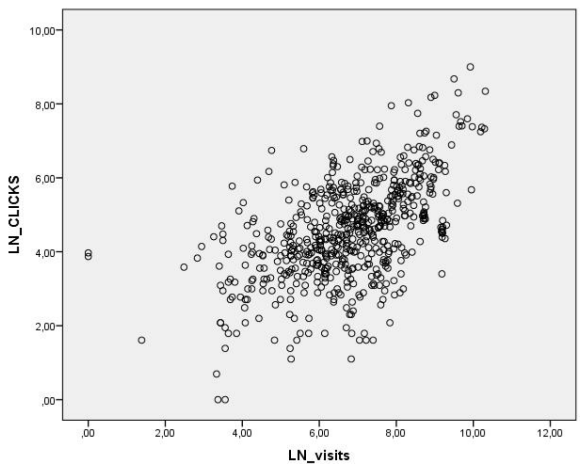
		LN_visits	LN_CLICKS	LN_VTR	LN_CTR
LN_visits	Correlação de Pearson	1	,548**	,527**	-,207**
	Sig. (bilateral)		,000	,000	,000
	N	625	625	625	625
LN_CLICKS	Correlação de Pearson	**,548****	1	-,373**	-,028
	Sig. (bilateral)	,000		,000	,482
	N	625	625	625	625
LN_VTR	Correlação de Pearson	**,527****	-,373**	1	,114**
	Sig. (bilateral)	,000	,000		,004
	N	625	625	625	625
LN_CTR	Correlação de Pearson	-,207**	-,028	,114**	1
	Sig. (bilateral)	,000	,482	,004	
	N	625	625	625	625

**. A correlação é significativa no nível 0,01 (bilateral).

Correlation Matrix



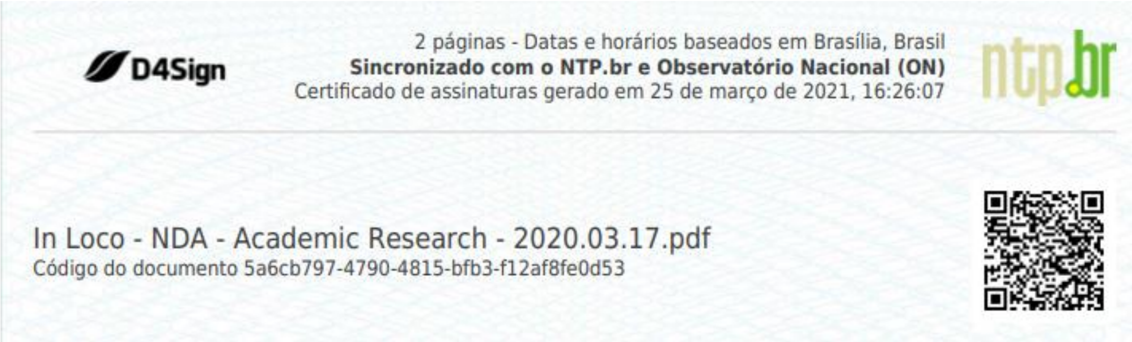
Box-plot variable Visit Through Rate (VTR)



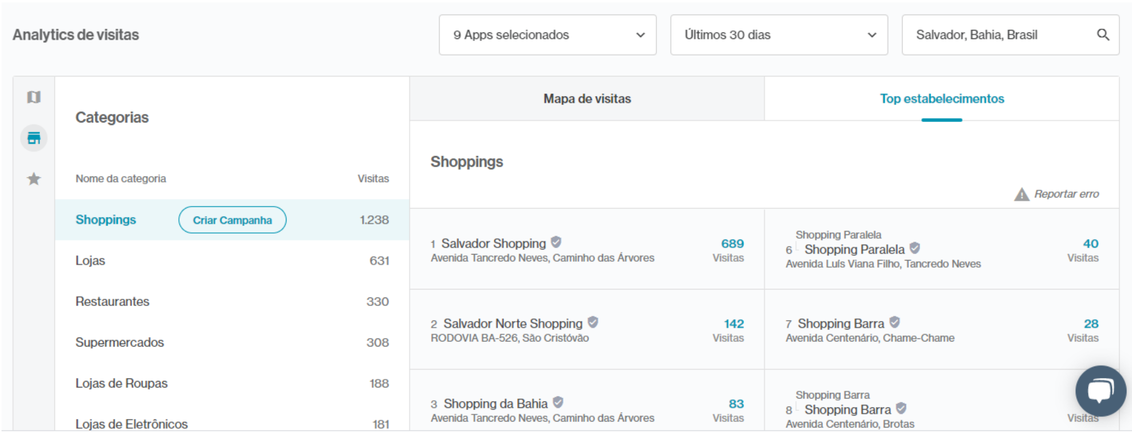
Scatterplot Visits and clicks

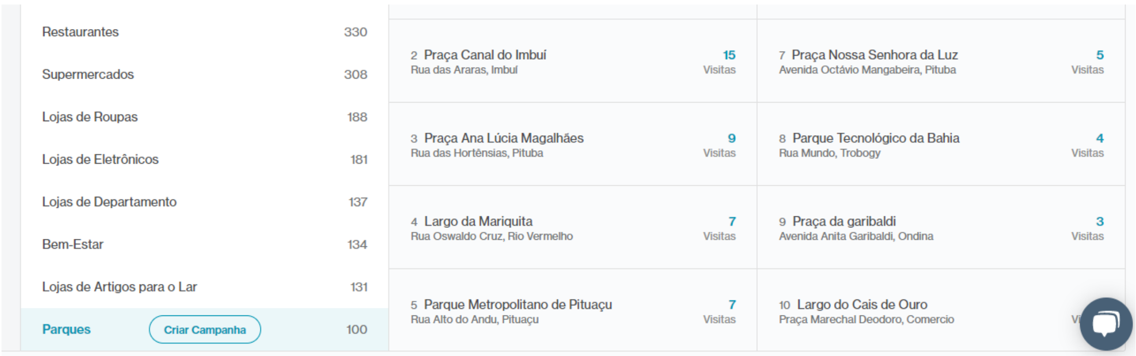
Appendix d – Studies 2 and 3

Technical Cooperation Term and Non-disclosure agreement



Access to the system granted by the involved companies:

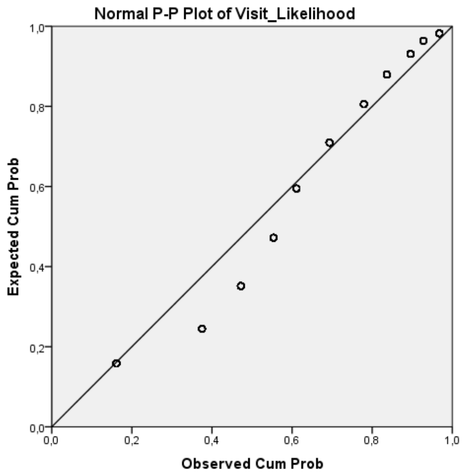




Appendix e - Study 4 ANOVA assumptions

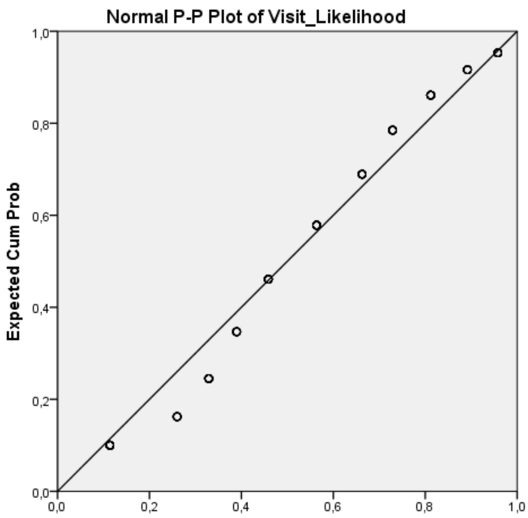
The assumptions of a two-way ANOVA are: the dependent variable is continuous; the independent variables are categorical, independent groups; sample independence; variance equality and normality. Therefore, the study tested for normal distribution (see below). The normality of the cases was confirmed by means of probability plots to evaluate the skewness of a distribution.

Visit_Likelihood



Normality test for study 4a

Visit_Likelihood



Normality test for study 4b

Variables	**Type of variable**	**Categories / Scale**
Location	Nominal	Map near Map far
Message content	Nominal	Message control / neutral Message branding Message promotional
Message content	Nominal	Message control / neutral Message personalized
Industry Category	Nominal	Supermarket Drugstore Fast food
Industry Category	Nominal	Pets Fitness
Visit likelihood **	Scale	0 to 10 (0 not likely; very likely)
Perceived distance	Ordinal	1 a 5 (1 very close; 5 very far)
Online shopping for the category	Nominal	Never At least once a week Every 15 or 30 days
Offline shopping for the category	Nominal	Never At least once a week Every 15 or 30 days
Push notification	Nominal	Block all of them Don’t block but don’t pay attention Just look at the ones with discount Check sometimes to see if there is something that interests me Love, always check them
Gender	Nominal	Male Female Other Rather not answer
Age	Ordinal	Under 16 16 to 24 25 to 34 35 to 44 45 to 60 Over 60 Rather not answer
Daily walking distance	Scale	from 0 to 1000 mts
Monthly family income	Ordinal	up to R$ 2.090,00 (USD 360) from R$ 2.090,01 to R$ 4.180,00 from R$ 4.180,01 to R$ 10.450,00 from R$ 10.450,01 to R$ 20.900,00 over R$ 20.901,00 (USD 3.600) rather not answer

Study 4a and 4b variables

Appendix f - Study 4 supermarket category

Results for Supermarket Category with offline purchase behavior

Levene's tests indicated no violation of the homogeneity of variance assumption.

Dependent Variable: Visit_Likelihood

F	df1	df2	Sig.
1,081	11	426	,375

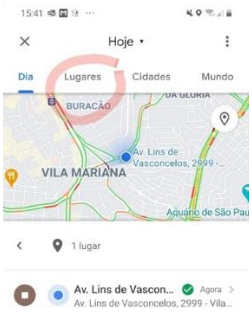
Tests the null hypothesis that the error variance of the dependent variable is equal across groups.
a. Design: Intercept + Message + Distance + Message * Distance + DailyWalk + OfflineShoping

Levene's Test of Equality of Error Variances

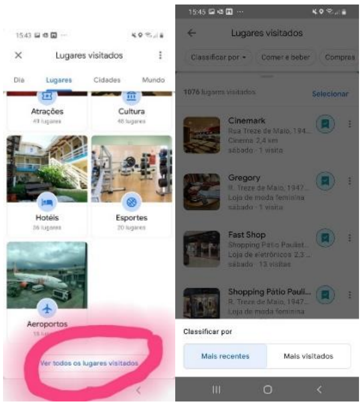
Appendix g - Study 4 Google Timeline Instructions

Para puxar a lista de lugares:

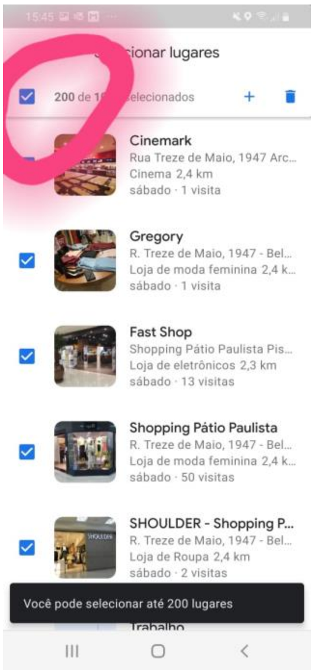
1. No seu smartphone ou Tablet **Android**, abra o app **Google** Maps .
2. Toque em sua foto do perfil ou inicial Sua linha do tempo .
3. Clique em Linha do tempo .
4. Clique em Lugares



5. Na tela de Lugares, role até o final e selecione “Ver todos os lugares visitados”

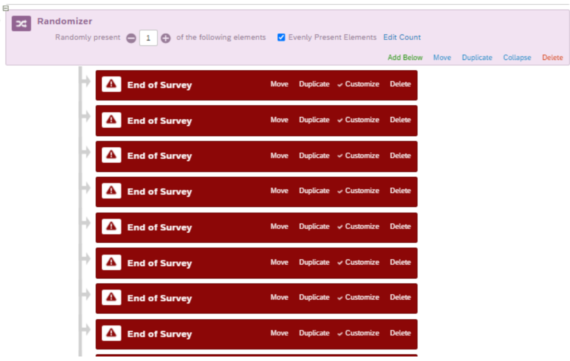


6. Cheque se está classificado por “Mais recentes”
7. Clique em selecionar lugares



8. Selecione todos (ele só vai aceitar selecionar 200, tudo bem)
9. Clique em +
10. Crie uma nova lista Compartilhada e me mande o link por favor

Appendix h - Study 4 questionnaire



Qualtrics randomizer for each one of the 26 versions of the questionnaire

Introduction

QR Code for one of the 26 versions of the questionnaire