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Digital inbound marketing: Measuring the economic performance of grocery e-commerce in Europe and the USA

Anett Erdmann[1,*], José M. Ponzoa[1]

ESIC Business & Marketing School, Camino Valdenigriales, s/n, 28223 Pozuelo de Alarcón, Madrid

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ABSTRACT

This research investigates the cost-result relationship of the Inbound Marketing actions used by grocery e-commerce. The analysis is based on the application of the Dorfman and Steiner (1954) model for optimal advertising budget, which is adapted by the authors to digital marketing and verified with empirical statistical analysis. Considering 29 leading companies in six countries over a time horizon of six years, an analysis of the mix of SEO and SEM techniques aimed at the attraction and conversion of Internet users to the web pages of their companies is carried out. The results confirm that e-commerce is optimizing Digital Inbound Marketing in line with the established model. Differences are identified depending on the type of format (pure player versus brick and mortar) and at the country level (UK and USA versus others).

1. Introduction

The market entry of pure players (PP), with its innovative management and marketing techniques (Philipp, 2013; Verhoef et al., 2019), has seen a revival in retailing. Click and mortar (CM) have adapted (or are adapting) processes associated with different areas of digital commerce: tangible and intangible services and resources (Cronin, 2016; Beitelspacher et al., 2012), logistics and product delivery (Hänninen et al., 2018), brand influence (Zarantonello and Pauwels-Delassus, 2015), product selection, presentation format and demand forecast (Boyd and Bahn, 2009; Cenamor et al., 2019; Chong et al., 2017), dynamic price setting (Petrescu, 2011; Cebollada et al., 2019), and management of offers, promotions and recommendations by other users (Chong et al., 2016; Breugelmans and Campo, 2016).

Digital Inbound Marketing (DIM) has also been studied in the marketing literature from a perspective that contemplates its conceptualization, its different techniques, its function within the marketing system in general, and its own application or management (Bleoju et al., 2016; Halligan and Shah, 2009; Hernández et al., 2010; Opreana and Vinerean, 2015; Vieira et al., 2019; Patrutiu-Baltes, 2016).

Hence, digitalization of marketing fuels the buying process in all its stages (Dahiya, 2018), from attraction to loyalty (Baye et al., 2015; Seitz et al., 2017; Jun et al., 2014; Melis et al., 2015), but concrete analytical guidance is sparse. In particular, regarding the optimization of investment in advertising and marketing, which has been addressed by several authors (Bagwell, 2007; Corfman and Lehmann, 1994; Cooper and Nakanishi, 1988; Eryigit, 2017; Kienzler and Lischka, 2015; Wierenga, 2008), the nature of DIM changes the cost structure of advertising and marketing (Frohmann, 2018). The techniques of SEM, backlinks (in the form of external links), and display require an explicit marketing expense (Goldfarb, 2002). The amount of the budget to be invested by the marketing department depends mainly on the selected Internet media type in which it is advertised, type of content (video, image, text), characteristics (size, position on the website), selected keywords, and the obtained website visits ("performance-based") for the e-commerce (Melis et al., 2015; Halbheer et al., 2014). SEO and backlinks (in the form of internal links) involve internal costs generated from the company's own structure (Ziakis et al., 2019).

This triggers our research question on how the standard theory of optimal advertising can be used in the digital environment understanding its performance and optimal composition and whether we see this reflected in firm behavior. That is, our goal consists of analytically exploring the relationship between DIM and performance in terms of economic efficiency analysis (Green, 2008).

Concretely, in the environment of grocery e-commerce (GE) and from a classic economic perspective of evaluation of the optimal marketing budget of Dorfman and Steiner (1954), which has been adapted

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* Corresponding author.
E-mail addresses: anett.erdmann@esic.edu (A. Erdmann), josemanuel.ponzoa@esic.edu (J.M. Ponzoa).

[1] Authors are listed alphabetically, and all authors contributed equally.

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by the authors of this research to the nature of digital marketing, an analytical model is proposed which allows to optimize the investment in marketing based on a marginal analysis and respond to a fundamental question in DIM: the analysis of its economic performance. The model accounts for conversion as well as the cost structure of DIM techniques and therefore goes beyond just focusing on the sales outcome and allows to address efficiency (desired result at minimum costs).

In the context of GE, using search traffic data, we conduct an econometric analysis to test the hypothesis that the firm behavior of the leading grocery e-commerce meets the established economic optimality of DIM.

Additionally, with the purpose of revealing possible differences across firms and the state of the question on DIM performance in Europe and the USA, the following three objectives are established: First, measurement of the efficacy (desired result) of the DIM in terms of visits (capture) of users to e-commerce and in terms of sales volume (conversion) achieved by e-commerce and representation of the conversion technology of a firm. Second, measurement and analysis of the variable cost structure of DIM and possible cost advantages. Third, analysis of firms, in terms of standard performance criteria (like conversion advantage and cost advantage) and the introduced DIM-efficiency measure, as cost — marketing efforts optimization relationship, which is presented using position mapping. This comparative analysis allows us to describe the observed differences regarding the way in which PP and CM optimize their investments in DIM.

Given the percentage of the marketing budget invested in DIM by digital business managers, which, according to Statista (2019), is more than 70 percent, implications for management are considered equally relevant. We provide operational conclusions for data-based marketing managers in terms of mixing digital advertising and positioning through Search Engine Optimization (SEO) and Search Engine Marketing (SEM) to optimize digital marketing costs.

The analysis of the optimal DIM mix of SEO and SEM oriented towards the generation of website traffic is conducted for a total of 29 leading grocery e-commerce firms in Europe (UK, France, Germany, Netherlands, and Norway) and the USA over a time horizon of six years (2014 – 2019) at a monthly level to evaluate the relationship between DIM and economic performance.

Data on organic positioning and paid positioning are extracted from the web analytics tool SEMrush (2019), to construct the main dataset for the study. Originally used by companies and digital media planning agencies, the tool has recently found application by academic researchers in the field of digital marketing (Huang et al., 2019; Huang and Shih, 2019). Complementary data on online sales generated by each of the e-commerce companies is provided by the LZRetailytics (2019) database and EcommerceDB (2019).

Considering grocery e-commerce in particular, “Food retail business or food retailing is a collective term for retailers, which primarily carry food products in their assortment” (Seitz et al., 2017, p. 1244), especially fast-moving consumer goods (FMCG), which have been studied in this sense by several authors (e.g. Kureshi and Thomas, 2019; Barile et al., 2018; Elms et al., 2016; Wilson-Jeanselme and Reynolds, 2006) and is considered a strategic sector of the retail assortment due to the loyalty and the reiteration of purchase it generates among customers (Sieira and Ponzoa, 2018). Grocery e-commerce is a subset of this retail segment with the integration of internet technology reflected in different online business formats, which has become an integral part of the grocery industry in some countries (e.g., Kureshi and Thomas, 2019). The most common formats observed are websites of retailers born on the web (pure players) and those of a physical nature that have incorporated e-commerce as a business unit (brick and mortar initially, click and mortar today) or offer a click and collect format (Bleoju et al., 2016; Davies et al., 2019).

The transformative process in which the retail sector is immersed goes through digitalization, a megatrend that affects both digital and physical commerce (Bleoju et al., 2016). In this sense, today, an establishment that only has one type of format or sales channel may not be competitive, since multichannel is becoming one of the strategic factors from which business is derived (Breugelmans and Campo, 2016). A clear tendency exists to mix the physical and virtual store, thus making digitalization and virtualization intermingle (Hänninen et al., 2018). This phenomenon is especially significant in grocery, with marketing managers facing different challenges, including: digitalization without denaturing the product or removing its healthy or fresh features (communication challenge), delivering the product at the consumer's house in optimal conditions (logistical challenge), and continuously adapting the sale of food and drink to demand (customer behavior), especially in formats, product development or the combination of items directed at different consumer segments.

The evolutionary process of e-commerce and marketplace in relation to the inclusion of new product categories (Boyd and Bahn, 2009) is assumed to incorporate grocery into its assortment. It is worth mentioning that the literature regarding the evolution of online grocery sales is heterogeneous. While some sources report a slow increase for general e-commerce (between 1% and 3%), others provide larger magnitudes up to 7% (eMarketer, 2019; Statista, 2019; Eurostat, 2019; EcommerceDB, 2019). For the respective online sales of food and drinks, the analysis shows a flat evolution over time that contrasts with the rest of the categories. In terms of sales participation, depending on the source and period analyzed, the results vary between 1% (in the case of general e-commerce) and 40% (in the case of e-commerce with a clear bias in the sale of grocery). The process of maturing electronic commerce, its penetration as a purchase option for younger audiences (Kureshi and Thomas, 2019), and the search for differential value in the assortment make it one of the key categories. Moreover, this evolution has been fast-forwarded through the recent Coronavirus disease (COVID-19) pandemic when many consumers were triggered the first time to buy groceries online (Statista, 2020; Coresight Research, 2020).

The strategic nature, its transformative process, and the challenges the firms face make e-commerce grocery an area of particular interest for academics and marketing professionals.

The results confirm that e-commerce is optimizing Digital Inbound Marketing in line with the established model and identifies differences across countries and by the type of firms. Emphasis is placed on the marginal analysis for the use and readjustment of the set of DIM techniques, which in general depends on the starting point of the company. As the analysis is not constant, it has to adjust to the individual situation of each company to identify the investments in DIM with the highest return (individually and as a mixture of techniques). In this sense, we are not looking for a single governing rule based on competition, but rather individual adjustment guidelines based on an optimization condition. In this process, three main components are discussed: the management of the technology on which SEO and SEM techniques are based, the opportunity cost derived from the market entry, and the different customer management strategies applied between the marketing managers of the retail companies of the pure player and click and mortar retailers.

2. Literature review

Within the context of data-driven retail management of e-commerce websites, we systematically survey the literature on optimal digital marketing actions within a conceptual framework of the stages of the online buying process—from attraction to loyalty—under the roof of the optimization of the marketing budget, which is illustrated in Fig. 1 (This framework lays out the basis for the methodological design of the analysis, explained in detail in section 3).

That is, the research relates to both marketing literature on the buying process and the economic literature on return and analytical models of optimization within the digital environment. Table 1 provides an overview of the most relevant preceding studies and the

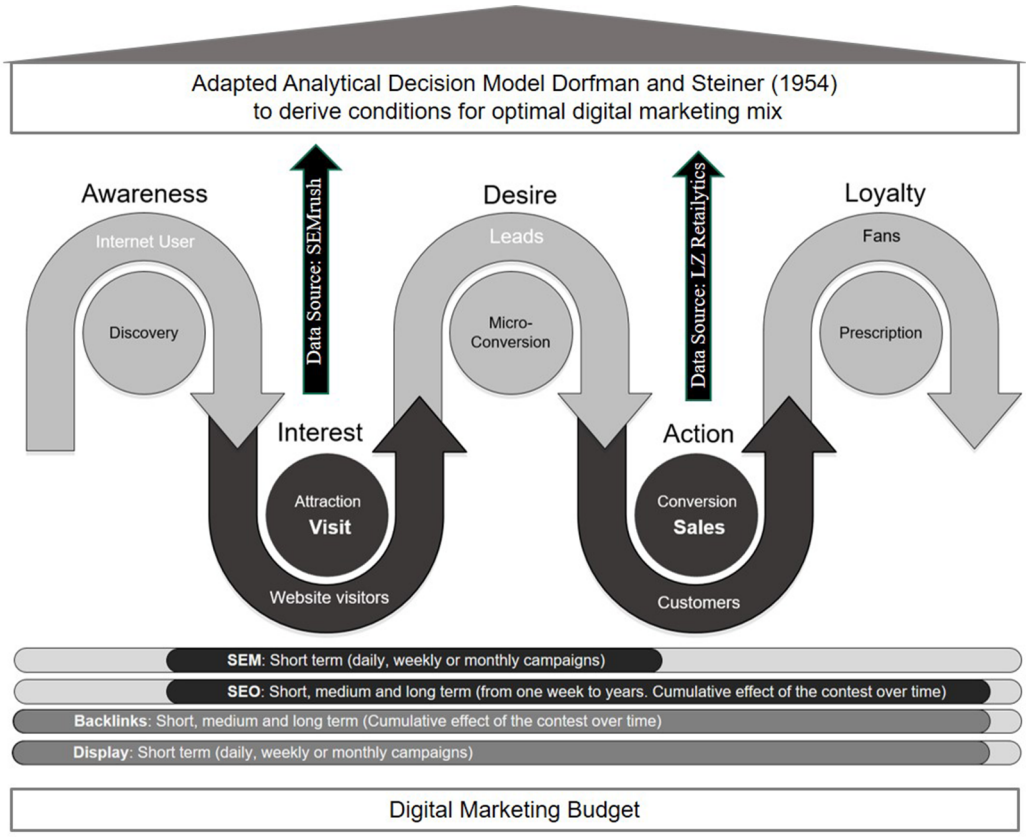

Figure 1. Digital Inbound Marketing: Measuring marketing activities and economic results

positioning of our research, which are explained in detail in the following within the conceptual framework.

Considering the current level of development of the information system of firms, an important part of the communicative interactions of users with firms' websites can be measured (Molodchik et al., 2018; Opreana and Vinerean, 2015; Sandvig, 2016; Seitz et al., 2017). The concept of service-dominant logic (SDL) is restructuring the vision of research and business practice. Transactional interactions are likely to be used for service optimization, with customer orientation being a critical operant resource that can lead to superior market performance of retailers, especially when leveraging different operant resources in the supply chain (Beitelspacher et al., 2012). A concrete example of a customer-oriented service-based resource is providing a direct link from the corporate website homepage to the e-commerce site of the firm, which is still observed with a certain delay in some concrete markets for food and beverage products (Festa et al., 2019).

E-commerce retailers should take advantage of the amount of data available to optimize their web activity (Barile et al., 2018) and consider that their competitors will also do so (Croll and Yoskovitz, 2013). There is a need for a systematic process to define and readjust the use of new digital marketing techniques (Goldfarb, 2002; Clarke and Jansen, 2017). Retail is one of the sectors in which digitalization has had the greatest impact. For their strategic decision-making, the marketing managers of the sector require precise studies of consumer behavior that consider cross-platform access to their sales channels (Hänninen et al., 2018). It is possible to identify and control KPIs and business indicators through new digital tools and measurement techniques for audiences on the website, both as quantitative (Saura et al., 2017) and qualitative analysis (Aulkemeier et al., 2016). This implies a new way of management, in which fast and precise access to information plays a fundamental role (Breugelmans and Campo, 2016).

For the analysis of traditional marketing, there are several analytical models of decision-making regarding marketing expenses. One of the best known is the Dorfman and Steiner (1954) model, based on a marginalist analysis with a microeconomic approach. Concretely, their analytical model shows that if the demand is sensitive to advertising, the optimality condition for maximizing profits is based on the marginal return, and the marginal cost of an additional dollar spent on ads, which has established as a fundamental theory in management and industrial organization (Wierenga, 2008; Froeb et al., 2018; Bellflamme and Peitz, 2015; Bagwell, 2007). Considering the marketing literature, after the publication of the fundamental theorem of Kotler (1967), which proposed a proportional relationship between the marketing effort and the sales or market share, a wide variety of methods – theoretical, econometric or rules of thumb – emerged with the objective to improve the efficacy of marketing actions and the allocation of the marketing budget (Jones, 1990; Corfman and Lehmann 1994).

With the digitalization of marketing, the relation between effort and sales is used to analyze the conversion rate (Moe and Fader, 2004) and the allocation and interaction of resources used in the offline and online channels (Wiesel et al., 2010; Banerjee and Bhardwaj, 2019). The study by Wiesel et al. (2010) offers an empirical example of how different online and offline marketing activities (Flyer, AdWords, Discount, etc.) affect purchase funnel metrics. Their findings help firms in the decision of allocating resources from a sales perspective, considering the response of one activity on the other, and interestingly find that online funnel metrics have a unidirectional effect on offline funnel metrics. Similarly, Breugelmans and Campo (2016) empirically identify for the largest online grocery retailer in the UK, an asymmetric cannibalization effect of promotions in the online channel on the offline channel. These studies emphasize the need to optimize the resource allocation in online marketing, controlling continuously for an optimal response in terms of investment adjustment.

Regarding DIM, and specifically in the stages of attraction and conversion, there have been multiple approaches with different focuses

Table 1
Research contribution embedded in the literature on DIM.

Papers	Inbound Marketing		On-line (Off-line)	Retailing	E-commerce	Analytical Approach of DIM			Profit	Contributions
	Attraction	Conversion	Marketing Mix	Brick & Mortar		Conversion	Costs	Efficiency		
Dorfman and Steiner (1954)				✓		✓	✓	✓		Classic economic model of optimal marketing budget evaluation.
Fedoseeva et al. (2017)					✓	✓	✓		✓	Test of economic theory to analyze mixed evidence on observed price dispersion online in the food industry.
Saura et al. (2017)	✓	✓			✓	✓	✓		✓	Study of almost 400 academic articles based on quantitative metrics to identify the most relevant metrics.
Moe and Fader (2004)	✓	✓			✓	✓				Dynamic conversion in e-commerce: phases and methods used.
Seitz et al. (2017)	✓	✓			✓	✓				Grocery shopping online from the consumer perspective in Germany
Halbheer et al. (2014)	✓	✓								Theoretical model based on Dorfman and Steiner (1954) to analyze the optimal strategy of paid content, sampling, and free content for digital information goods.
Verhoef et al. (2019)			✓		✓	✓	✓	✓	✓	Multidisciplinary discussion on required performance metrics, growth strategies, etc. and observed patterns for fast-growing digital business.
Bleoju et al. (2016)	✓	✓	✓	✓	✓	✓				Analyze the use of Inbound versus Outbound marketing techniques by pure online players and traditional firms.
Wiesel et al. (2010)	✓		✓	✓	✓		✓		✓	Estimation of the profit effects of selective marketing online and offline purchase funnel metrics.
Melis et al. (2015)			✓	✓	✓	✓	✓	✓	✓	Econometric consumer choice model for online grocery decision based on multichannel preferences and experiences.
This paper	✓	✓	✓		✓	✓	✓	✓	✓	Marginal analysis to evaluate the economic performance of digital inbound marketing techniques for grocery e-commerce.

of analysis. Considering the literature on attracting search traffic (organic or paid), many studies have focused on paid traffic, which motivated Baye et al. (2015) to explicitly analyze organic traffic through SEO for 759 online retailers, confirming the importance of SEO strategies in attracting consumers to retailers' e-commerce websites, in particular, the benefits of rank improvement and brand awareness. Saura et al. (2017) conduct a study to understand digital marketing based on the identification of the ratios and metrics used in the professional world. The authors highlight the benefits of web analytics for digital marketing depending on the context, instead of a general rule. Concretely, in a systematic review focused on SEO and SEM techniques, they identify the most relevant KPIs to control efficacy of DIM: conversion rate, user differentiation between new and returning visitors, type of traffic source, and keyword type and ranking. Since a successful DIM strategy needs to be both effective and efficient, in the present paper, we focus on efficiency, in the context of a contraction model where advertisers pay when the ad is clicked (pay-per-click (PPC)), and consider both paid and organic search traffic.

Seitz et al. (2017) center their study on the consumer interest in the German grocery market and empirically identify, from the perspective of practical application, the consumer type and incentives of attraction to the website, which allows to differentiate digital marketing content and actions by consumer groups. Concretely, they find that working mothers and young professionals show a significantly higher interest in online grocery shopping than other groups and the most important reason is convenience (independence from opening hours, easy ordering, no queueing, time saving) while the main obstacle was the lack of trust in grocery e-commerce and digital marketplaces. Such preceding studies show that the observed search traffic stems from a variety of heterogeneous consumer interests that can be explicitly targeted. If it comes to the specific content of interest, Halbheer et al. (2014), examine the optimality ratio of offering free samples to disclose quality and offering paid content only, within the Dorfman and Steiner (1954) framework. The authors conclude that the optimal decision depends on the sensitivity of consumers' quality expectations with respect to free samples, reflecting the trade-off between market expansion through learning and cannibalization of their own sales.

With the aim to make data on search traffic useful to forecast technological adaptation in terms of sales volume, Jun et al. (2014) use a time series analysis based on keywords used. The authors were able to identify that branded keywords can be used for predicting the purchase behavior of website visitors. Another study that models conversion in detail, rather than providing only aggregated measures, is Moe and Fader (2004). They propose and estimate a structural model on the purchase probability based on clickstream data of Amazon, differentiating by shopper motivation (directed buyers, search visitors, hedonic browsers, and knowledge-building visitors). The authors highlight the dynamics of the individual purchase-threshold of consumers, which for returning consumers may diminish over time due to a higher frequency of visits before making the purchase decision but at the same time may increase due to prior positive purchase experience.

These studies show once more that search traffic can be exploited to measure performance and increase understanding of the purchase process. However, since these papers focus on the demand side in terms of consumer attraction, their objective differs from our paper as we focus on economic optimality in terms of the minimization of digital marketing costs for a given sales objective.

The process of customer engagement is reconsidered by Bowden (2009) and Naumann and Bowden (2015), extending the understanding of customer engagement to a variety of brand-focused activities and suggesting new measures of loyalty (as a crucial outcome of engagement) in terms of satisfaction, affective commitment or rapport. Melis et al. (2015) empirically analyze the optimal store choice with a focus on loyalty. Differentiating between variable and fixed shopping utility, they find that online shopping choice is initially determined by

the preferred offline retail brand, but with the online experience, the online store loyalty dominates the consumer choice online. On the other hand, as mentioned earlier, the work by Moe and Fader (2004), suggests a dynamic and ambiguous result of loyalty on the conversion rate. These dynamics of decision-drivers in the online grocery choice of consumers can be regarded as an indication that optimal digital marketing choice is also relevant at the loyalty stage and suggests a continuous readjustment of marketing techniques.

From a cost perspective, the main challenge of the home delivery business model are the high delivery costs in the "last mile" (shipping costs from the local platform to the consumer's home or work) and the high expectations of consumers on the Internet in terms of fast and correct delivery on time. Zissis et al. (2018) study possible collaboration between companies in urban areas to manage the distribution challenges of last-mile delivery. All this reduces the profit margin in the online segment (Suel and Polak, 2017).

Considering the costs associated with marketing techniques or attraction of potential consumers, Reinares and Ponzoa (2008) analyze the optimization of the marketing budget based on the cost of contact through different direct marketing channels (mailing, email, telemarketing, and SMS). However, in the literature on digital marketing techniques, the cost as profit driver is in general neglected or considered in isolation in the context of a contraction model where advertisers pay when the ad is clicked (Saura et al., 2017).

Finally, considering the evolution of the marketing mix, Jackson and Ahuja (2016) provide an overview of the increased relevance of customer-centric marketing in a changing technological environment, that provides new analytical tools, automatization of the sales force, and data mining. In this context, the authors suggest to move away from a marketing-mix understood as "demand-impinging instruments", but instead redefine it towards a set of adjustable tools to gain competitive advantage and maximize profits in the long run. From the beginnings of the application of the DIM techniques, new marketing metrics and data access the marketing landscape has changed and is still changing considerably, with the new resources being beneficial to firms as well as to customers. Digital marketing research related to electronic commerce identifies digital platforms as the most outstanding digital growth strategy (Verhoef et al., 2019). In this line, Cenamor et al. (2019) analyze the effect of selling through digital platforms, for example, in the marketplace Alibaba (www.alibaba.com), identifying the performance implications for firms and the creation of competitive advantages. These business-to-consumer platforms imply changes in the cost structure of digital marketing (although different from pure e-commerce), shifting advertising costs from the marketing or advertising budget to transaction fees or provision (Frohmann, 2018).

The firm's beliefs about entry and positioning in the online market for grocery have been investigated by Kureshi and Thomas (2019). The authors identify, based on firm interviews, positive outcome beliefs in terms of business expansion and increased visibility and reputation, but also concerns about increasing and restructuring inventory management or increased costs for store helpers or computer assistants. Additionally, social and peer pressure with respect to customer expectations, suppliers, and rivals, drives the firm's belief in gaining first-mover advantage entering the online business, with no entry or exit cost. Given these positive and negative beliefs about the outcome of online market participation, the performance of market leaders in the sector may provide some guidance.

On the other hand, from a consumer perspective, Aponte (2015) identifies perceived security, privacy, risk, and website quality as determinants of consumer confidence towards e-commerce. All these studies reveal the existing uncertainty and importance in regards to the information structure and data-based decision in the new online business models.

The literature on strategic interactions between companies in digital transformation processes is sparse. The first research in this line has been conducted by Zutshi et al. (2018), estimating a management model based on game theory to identify the number of potential customers registered on the web ("online leads") that a company must achieve in order to compete efficiently in a market. In this context, the operational optimization of companies in terms of DIM techniques is considered fundamental for further steps of competition based strategies.

The literature that uses or verifies economic theories within the framework of digital transformation is still scarce. Fedoseeva et al. (2017) verify the economic theory that suggests that a market with better-informed consumers (able to compare prices online without incurring substantial opportunity costs) reduces price dispersion. Considering the retail sale of grocery on the Internet, these authors identify that there is no price convergence; that is, they conclude that there are still significant differences in the prices of online commerce. Similarly, the digitalization of the whole buying process triggers the question of whether firms meet the economic theory of optimal marketing spendings within a digital environment.

"The need for actionable knowledge" in the adaptation of digital marketing in this new market is emphasized by Bleoju et al. (2016), the closest paper to the present work, which provides practical insights on how to switch between a focus on inbound marketing and outbound marketing. Concretely, the authors identify based on a firm-level survey on the use of digital inbound and outbound activities, including firms with different degree of integration of internet technologies, that the combination of creating content and interaction commitment explains the propensity toward inbound marketing (while the combination of loyalty profiling and client interests are identified as causal for outbound marketing.) We complete this path for actionable knowledge focusing on DIM and when to switch between SEO and SEM techniques.

Finally, a multidisciplinary literature review by Verhoef et al. (2019) reveals that the digital transformation of incumbents (in general traditional brick and mortar firms) is especially relevant in terms of redefining value-creation, investment in new resources and analytical capabilities. In this context, they state a variety of KPIs and intermediate results, which are important for fine-tuning the new business and observe that while traditional firms stick to financial profitability, pure digital firms focus on the growth of users, customers or sales. Likewise, Baye et al. (2015) find that pure online retailers receive, on average, 13% more organic traffic than their click and mortar competitors. Our paper investigates this difference between click and mortar and pure online firms further in terms of the economic efficiency of digital marketing as essential intermediate performance metrics.

Thus, based on the underlying mechanisms of the purchasing process online and the digitalization of marketing discussed in previous studies, we extend the literature on data-based marketing management, theoretically and evidence-based.

Our adaptation of a classical analytical framework for optimal advertising explicitly considers the structure of marketing costs online as profit drivers, neglected in the literature, which allows performance measure in terms of efficiency. Based on the model, the usability is verified based on search traffic data for leading firms in the sector. Additionally, we study the existence of differences in the use of DIM techniques between companies and, in particular, the difference between pure players and the new click and mortar players, in terms of performance measures and conversion technology and cost structure. The results provide implications for data-based management decisions on the adjustment of DIM techniques optimizing the marketing budget, in particular, the readjustment of SEO- and SEM-generated visits.

3. Method and research design

This article studies the development on the Internet of 29 leading e-commerce organizations in six different countries (USA, UK, France, Germany, Netherlands, and Norway) during a time horizon of six years

(2014 – 2019), comparing the use of DIM techniques of firms operating physical as well as virtual stores with retail companies born in the digital environment.

Four different paths or access routes to the website can be differentiated: (i) visits derived from search engines through paid positioning or SEM; (ii) access to the web of e-commerce from search engines through organic positioning or SEO; (iii) visits through media links, social networks, web pages or publications that include references and links that direct the user to the respective e-commerce websites (backlinks) and (iv) the visits derived from banners, interstitials, megabanners, billboards, skyscrapers, pop-ups or other graphic formats used to support Internet advertising (known by the generic term display ads).

From this starting point, we investigate DIM techniques used by e-commerce in the process of capturing Internet users or addressing them from free web browsing to their websites (see Fig. 1). In particular, this article focuses its research on SEO and SEM marketing techniques that make it possible to position e-commerce in web search engines.

In order to analyze the economic performance of these DIM techniques, the classic economic model of evaluation of the optimal marketing budget of Dorfman and Steiner (1954) is adapted to the nature of the DIM (Fig. 1).

Based on this analytical framework and in particular, the optimization condition to achieve allocative efficiency of the DIM effort, the behavior observed by the online grocery retailers is used to verify, using time series analysis, whether grocery e-commerce firms indeed optimize marketing effort in line with the model. In this context, we also analyze potential differences between click and mortar grocery e-commerce compared to pure players in terms of performance and positioning, in particular, the Internet access to different e-commerce and the corresponding marketing costs with the objective to achieve a certain level of consumer attraction at minimum costs.

Using the Attraction, Interest, Desire and Action (AIDA) model Fig. 1 proposed by American publicist Elias St. Elmo Lewis (cited by Barry, 1987), adapted to the digital environment by Rowley (2002) we propose a design of research based on two of the fundamental stages of the digital marketing funnel: the interest stage, which involves attracting the customer to the web (measured in number of visits) and the action stage, which involves converting the visit into purchases (measured in sales). The model has been updated by the authors of this article after including the commercial objectives, the marketing results, the inbound marketing techniques used and a new stage of loyalty (motivated by several studies on the impact of DIM on engagement and loyalty, discussed in section 2) within the process. The stage of attracting the consumer to the web through any of the marketing techniques is associated with explicit or implicit costs, which are analyzed together with the visits and sales generated in the proposed analytical model.

As shown in Fig.1, to obtain the information necessary to create the database of the study, sources referred to DIM (provided by SEMrush), and online sales (provided by LZRetailytics) have been used, both being analytic tools of wide acceptance and use in the academic as well as professional world.

3.1. Data collection and sample

The database LZRetailytics (https://www.retailytics.com/) provides the sales data for the analysis. This data source, provided directly by the German market research firm of the same name that is specialized in the grocery retail sector, has been used to identify for five European countries (UK, France, Germany, Netherlands, and Norway) a total of 23 leading grocery e-commerce firms (Tesco, Asda, E. Leclerc, Rewe, Ahold, among others) and Amazon (the world's leading e-commerce firm with a turnover close to 233,000 million US dollars, according to data of the company itself) and its corresponding grocery sales online. Firms have been selected based on sales in a decreasing order such that the joint market share covers at least 74% of the corresponding national grocery e-commerce market and provides a broad assortment that allows the purchase of a standard shopping basket (excludes pure frozen distributors, pet food stores, drugstores).

For the US market, the list of companies and sales data comes from EcommerceDB (https://ecommercedb.com/).

The web analytics tool SEMrush (2019), which has been used to extract the main data for this study, considers both SEM costs (positioning paid at the closing price provided by Google in a keyword auction) and SEO costs (an estimate based on an extrapolation based on the SEM cost of each keyword indexed by e-commerce on Google). In this way, and using data very close to the real investment made by companies, this study proposes a marginal analysis (Dorfman and Steiner, 1954) of the investment in DIM. This web analysis tool that has been used in several academic articles in recent years (Molodchik et al., 2018; Sandvig 2016; Huang et al., 2019; Huang and Shih, 2019). SEMrush allows, through its own algorithm, access to a large number of DIM indicators to be visualized through a dashboard. Based on a license provided by SEMrush for research purposes, we created a dataset for this study extracting the necessary variables for the considered e-commerce. By focusing the study on the economic efficiency of DIM with a focus on SEO and SEM, special attention was given to the web traffic generated and the corresponding costs of each of these techniques. The constructed panel dataset includes more than 1,600 observations per variable and about 10,000 records.

For the purpose of replicability, it is considered necessary to state that SEMrush distinguishes between Domain Analytics (SEO, SEM, Backlinks, and Display data, based on keyword positions) and Traffic Analytics (clickstream data, by traffic source: Direct, Reference, Unpaid Search, Paid Search, and Access from Social Networks). In this work, we use the data from Domain Analytics, which provides direct cost estimates for SEM and estimated opportunity costs for SEO. The historical traffic data and monthly costs are available from January 2012. However, limited by the availability data horizon of economic data from the complementary database LZRetailytics, the horizon from January 2014 to December 2019 is considered. It is important to specify that from January 2018, SEMrush began to track additional mobile data; however, until April 2019, mobile traffic sources were merged and undefined. To extract data from a consistent time series on the website, we focus on monthly traffic from the computer and within the respective country.

For the analysis, we use the merged dataset at the annual level, and the created DIM-panel at the monthly level.

Table 2 summarizes the sample, with the countries ordered from highest to lowest by total sales in Food & Beverage e-commerce (according to Statista, 2019), indicating online sales and acquisition costs through SEO and SEM for 2018.

3.2. Economic framework

In general, a set of metrics (dashboard) are used to evaluate a particular marketing activity. Choosing the most relevant metric for decision making and control of objectives depends on the purpose of the analysis. For example, from a financial perspective, the return on investment (ROI) is usually used as a standard measure of profitability. Alternatively, from a commercial perspective, we could consider the advertising elasticity of demand (AED) as a measure of the efficacy of a given campaign. In this study, both approaches are considered using an economical approach with the objective of minimizing costs and/or maximizing profit.

Based on classical microeconomics, economic efficiency is defined as follows: “Producers are characterized as efficient if they have produced as much as possible with the inputs they have actually employed or if they have produced that output at minimum cost” (Green, 2008, p.100).

In the present study, we use the Dorfman and Steiner model (1954),

Table 2
The largest grocery e-commerce retailers in six countries and their sales and cost of Digital Inbound Marketing in 2018.

Country	Business nature	Grocerye-commerce(Retail group)	Website(s)	E-Commerce SALES 2018(Sales of Retail Group)	% Grocery E-Commerce*	DIM COST 2018(SEO y SEM)
EUROPE				*In EUR mn*		*in EUR mn*
UK	Click and mortar	Tesco	tesco.com	3.905,01	34,10%	21,74
UK	Click and mortar	Asda (Walmart)	asda.com	1.813,80	15,84%	76,50
UK	Click and mortar	Sainsbury's	sainsburys.co.uk	1.783,94	15,58%	38,11
UK	Click and mortar	Ocado	ocado.com	1.682,90	14,70%	5,42
UK	Click and mortar	Morrisons	morrisons.com	557,20	4,87%	15,22
UK	Pure online	Amazon	amazon.co.uk	87,03 (12.527,83)	0,76%	536,64
FRANCE	Click and mortar	E. Leclerc	e-leclerc.com; leclercdrive.fr	3.049,00	43,21%	13,68
FRANCE	Click and mortar	Auchan	auchan.fr auchandrive.fr auchandirect.fr	794,30 (1.439,83)	20,40%	244,31
FRANCE	Click and mortar	Carrefour	carrefour.fr	661,77 (720,78)	10,21%	26,30
FRANCE	Pure online	Amazon	amazon.fr	3,00 (4.111)	0,04%	199,5
GERMANY	Click and mortar	Rewe (Rewe Group)	rewe.de	195,00 (225,00)	32,16%	10,72
GERMANY	Click and mortar	Edeka (Edeka Group)	edeka.de	95,00 (198,00)	28,30%	7,08
GERMANY	Click and mortar	Metro AG	metro.de	48,00	7%	1,24
GERMANY	Pure online	Amazon	amazon.de	81,00	11,6%	777,54
NETHERLANDS	Click and mortar	Ahold Delhaize	ah.nl	422,22	48,35%	24,27
NETHERLANDS	Click and mortar	Jumbo	jumbo.com	296,20	34,62%	3,49
NETHERLANDS	Click and mortar	Plus Online (Plus Groep)	plus.nl	100,3 (108,61)	12,69%)	1,56
NETHERLANDS	Pure online	Amazon	amazon.nl	(8,61)		0,07
NORWAY	Click and mortar	Meny Nettbutikk		29,01	60,13%	
		Spar Nettbutikk	meny.no	12,82		1,83
		Joker Nettbutikk	spar.no	4,62		0,19
		(Norgesgruppen)	joker.no	(46,44)		0,25
NORWAY	Click and mortar	Vinmonopolet	vinmonopolet.no	30,79	39,87%	1,29
NORWAY	Pure online	Amazon	amazon.com	(67,2)	na	1,87
USA				*In US$ mn*		*In US$ mn*
USA	Pure online	Amazon	amazon.com	4.648 (197,36 bn)	9,61%	5.865,20
USA	Click and mortar	Walmart	walmart.com	2.126	6,39%	1.236,64
USA	Click and mortar	Kroger	kroger.com	965	3,12%	70,73
USA	Click and mortar	Target	Target.com	704	5,28%	877,71
USA	Click and mortar	Ahold	Foodlion.com	1.169	2,70%	10,88
USA	Click and mortar	Costco	costco.com	597	9,61%	357,03

Sources: Sales data from LZRetailytics (2019), EcommerceDB (2019) and Statista (2019). Cost data from SEMrush (2019). For Amazon we indicate the total retail sales since traffic can not be differentiated by product category.

* Market definition Grocery E-Commerce by LZRetailytics, excluding distributors of exclusively frozen goods, pet food and drugstores.

Some sales and cost data were not available in EUR and have been extracted in USD applying the average annual exchange rate reported by Statista (2019) to convert into EUR.

the workhorse of optimization of marketing spending, which is adapted to DIM techniques. A recent example of an application of the model is Halbheer et al. (2014), which analyzes the optimal strategy and advertising revenues for a given digital content strategy.

In the DIM context, with a focus on SEO and SEM, we define the profit of the company as follows:

$$\pi = p^{*}Q(p, V_{SEO}, V_{SEM}) - C(Q(p, V_{SEO}, V_{SEM}); V_{SEO}, V_{SEM})$$

where demand, and therefore sales, depends on the number of website

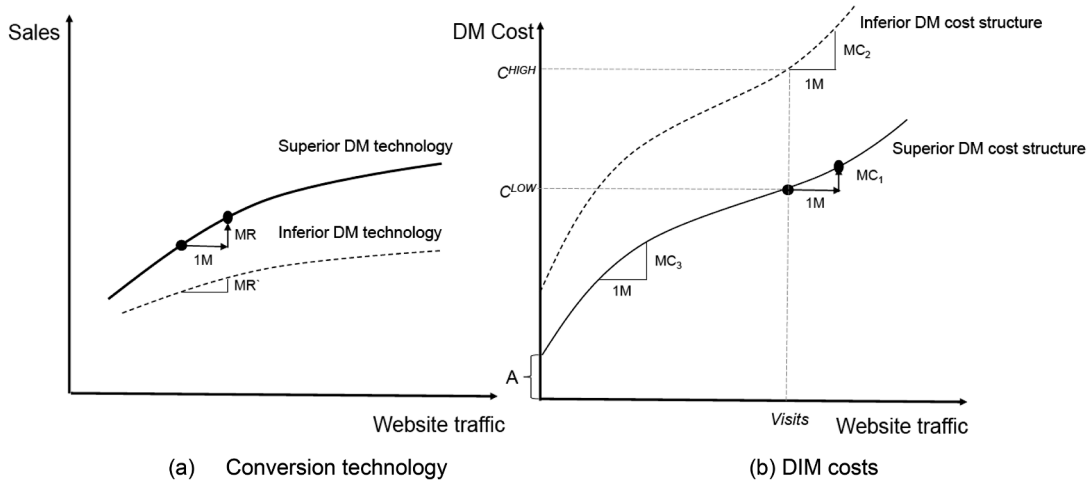

Figure 2. Conversion and Attraction Costs

visits generated and digital marketing costs depend directly and indirectly on the number of website visits. Thus, an important part of the cost structure of DIM is variable costs, instead of a fixed amount of advertising investment. We differentiate in visits generated by SEO (V_{SEO}) and visits attributed to campaigns through SEM (V_{SEM}).

This process of transformation of visits into sales is illustrated conceptually in Fig. 2(a). In this sense, a superior "conversion technology" is understood as converting 1M additional visits in more additional sales (Marginal Revenues, *MR*) than an inferior technology (with Marginal Revenue, *MR'*).

The costs are the sum of the production costs (depending on the quantity sold online) and the DIM costs, which are mostly based on performance and, therefore, are directly associated with the visits generated to the website. We could additionally include a fixed amount of investment in advertising (A) as in the classic model, which can be omitted for simplicity. Since the visits generated by different DIM techniques have different costs, we differentiate between the explicit costs associated with SEM traffic (C_{SEM}) and the implicit costs associated with SEO (C_{SEO}).

The relevant costs for the company are the variable costs (explicit or implicit). Here, in order to readjust the marketing-mix of grocery e-commerce, in particular, the relevant costs are the variable economic costs of the DIM:

$$Variable\ costs = VC(Q) + \underbrace{Variable\ costs\ of\ DIM}\, ac_{SEO}\ V_{SEO} + ac_{SEM}\ V_{SEM}$$

ac_{SEO} and ac_{SEM} are the average costs per visit for the corresponding DIM technique.

The number of total visits the company aims to generate from different traffic sources is subject to the available DIM budget:

$$DIM\ \ budget = ac_{SEO} V_{SEO} + ac_{SEM} V_{SEM} + A$$

Note that a low average cost of either technique implies a competitive advantage for the firm.

Fig. 2 (b) illustrates the relationship between visits and the corresponding marketing costs of website traffic attraction. Note that the cost of generating additional traffic of 1M visits (Marginal cost, *MC*) may depend on the level of the website traffic of the firm as well as on the cost structure relative to competitors.

Given the individual conversion and cost structure of a firm, there is no general rule but a firm specific optimality condition, determined by the marginal cost and marginal return of additional website traffic:

$$\frac{MC_{SEO}}{MC_{SEM}} = \frac{MR_{SEO}}{MR_{SEM}}$$

3.3. Empirical approach to analyze optimal DIM-Mix

The empirical literature on evaluating the operation of the firm above minimum costs in a Debreu-Farrell style (Green, 2008) differentiates in technical efficiency (here: conversion of visits into sales) and allocative efficiency (here: misallocation of advertising budget; i.e., using SEO and SEM in the wrong proportion). This approach requires the estimation of the process of generating sales from different marketing techniques and the estimation of the cost function. At this point, we acknowledge this approach of empirically estimating efficiency in a structural way, which inspired our analytical approach but is not required here. In the interest of brevity, we abstain from a more extensive review of this type of analysis.

Instead, given the availability of cost data at the disaggregated level (costs for SEO, costs for SEM), we can directly test the optimality condition. Here we use the identifying assumption that marginal revenues per visit are independent of the traffic source (imposed by the availability of sales data at the annual level only). The marginal cost can be calculated directly from the data as the ratio of discrete changes in costs and visits between the two following months. Other studies that use directly available cost information (which, for most industries, is from their own information) for statistical testing or empirical analysis come from the electricity industry, and consider the estimation of markup (Wolfram, 1999) or the poor performance of NEIO estimates versus the use of actual marginal costs data (Kim and Knittel, 2006).

The variable that measures the discrepancy from optimality is calculated for each firm at a monthly level for 72 periods.

We investigate this hypothesis graphically and econometrically. Time series analysis is used to check the hypothesis of optimization based on the discrepancy from optimization as a random variable that should follow a white noise process (e.g., Zhang, 2016; Zhang et al., 2019).

$$Discrepancy\ from\ optimality: \ d_{it} = MC_{SEO,it} - MC_{SEM,it} \overset{H_0}{\sim} WN$$

Note that higher values imply an inefficient DIM-mix while low values suggest the firm operates close to the minimum possible DIM spending for a given objective of website visits or sales.

However, the absolute discrepancy from optimality doesn't allow comparison across countries. Hence, in order to make the measure comparable across firms and markets, we set up a *DIM-efficiency measure*, reformulating the discrepancy from optimality in relative terms and normalized as follows:

$$DIM - efficiency: rd_{cit} = 1 - \left(\frac{d_{cit}^2}{\sum_{i \in C} d_{cit}^2}\right) \in [0, 1]$$

with $C = \{UK, France, Germany, Netherlands, Norway, USA\}$and $c \in C$.

Note that this transformation of the discrepancy from optimality is analogous the error formulation in the ordinary least square approach and has been chosen for the following properties:

I. Account for the total deviation in a market, without positive and negative deviations compensating each other.
II. Relative measure, which allows us to rank firms within a country according to their DIM-efficiency.
III. Normalized metric within the Interval [0,1], with rd = 1 implying that the firm operates completely efficient while rd→0 implies a misallocation of DIM effort, which is a waste of the advertising budget.

Apart from the presented measures of DIM-efficiency, we consider average KPIs in terms of average costs per visit (ACPV) and average sales per visit (ASPV), measuring potential cost advantage and advantage in conversion technology, respectively. Finally, we analyze the positioning of the firms given these metrics in national and global contexts.

4. Results

4.1. Descriptive analysis

First, we consider the efficacy in terms of the technical ability of firms to generate sales and the associated costs on a visit-by-visit basis to the website. Appendix A provides the graphical representation of an estimated visits-sales relationship that captures the company's conversion technology and the cost structure in terms of the relationship visits – DIM costs at the country and company levels. Note that the positive relationship between online sales and website visits, as well as variable DIM costs and website visits, is in line with the model assumptions (Fig. 2). Moreover, many of the firms show a concave sales function, suggesting a diminishing conversion rate as website visits increase.

Table 3 presents the DIM-efficiency measures based on the adapted Dorfman- Steiner approach, as well as average revenues per visit (ARPV) and average costs per visit ($ACPV_{SEO}$ and $ACPV_{SEM}$). The data are reported for 2018, as the latest available complete data for sales and search traffic with the associated costs, with the purpose of a descriptive comparison of the state of the market leaders (the relation holds in a similar way for previous years).

Three interesting observations are apparent:

I. The pure player shows the highest DIM-efficiency in almost all considered countries.
II. The existence of differences across countries in the level of DIM-efficiency. UK grocery e-commerce retailers optimize the DIM-mix, minimizing the advertising budget, which is in line with the model. Likewise, US firms show a high level of optimal resource allocation.
III. The cost advantage in SEO in terms of average DIM-costs per visit is, in general, held by the national market leader in grocery e-commerce. There is no clear ranking detected for SEM costs.

4.2. Model verification

In the econometric analysis, we consider the time series of a firm's discrepancy from the optimal marketing budget for SEO and SEM activities and test whether the observed firm behavior is in line with the proposed model.

Appendix B (left column) plots the evolution of the absolute measure of DIM-efficiency by country and firm. The ADF test suggests the discrepancy from the optimality condition is a stationary, random variable with an expected value close to optimality. Further, the correlogram and Ljung Box test do not allow us to reject the hypothesis of independence (no autocorrelation) of meeting the condition each period.

Hence, our hypothesis has been confirmed, that is, the observed firm behavior is in line with the adapted Dorfman-Steiner model, with fluctuations around the optimal value in DIM adjustment.

4.3. Positioning

The descriptive analysis of the time series reveals that some firms show much more volatility in meeting the efficiency criteria than others (heteroskedasticity). To be precise, we find that:

I. Pure players show less volatile behavior compared to click and mortar firms in the adjustment of the DIM-mix.

Appendix B (right column) expresses the positioning of the firms in terms of cost advantage, conversion advantage, and DIM-efficiency. (For all European countries and firms, the revenues and cost measures are in Euros, while results for the US are reported in dollars). While the average measures are assigned to the axis, the marginal approach in terms of DIM-efficiency is captured by the size of the corresponding circle, with a larger circle implying a more efficient DIM-mix. Here we pay particular interest to the comparison with the pure player, which is represented with dashed lines. Complementarily, a global positioning of all considered firms is provided.

II. In general, the market leader positions in the upper left corner and the pure player in the lower right corner. While the market leaders are highly positioned in terms of revenues per visit and show a cost advantage, the retailers born in the digital environment are most efficient in terms of DIM-mix.
III. In Norway, where there is no pure player with direct market presence, click and mortar firms show a relatively high cost per visit compared to other markets where physical retailers face direct competition from pure players.

We observe in the data that some grocery retailers are gaining market share through their online sales, and in some cases, even position themselves in the online sales ranking in front of traditional industry leaders.

In order to understand which metrics have been the drivers of this evolution, we present the dynamic evolution of the positioning strategy of the new grocery retailers and the pure players with arrows for different years (Appendix D), showing in different shades of gray the countries included in the study and the retailers analyzed in each one of them. The relationship between customer attraction and sales achieved in the different retailers, and the relationship between PP and C&M (represented by Amazon) can be observed.

The repositioning of the firms suggests that:

IV. In Europe, traditional, established retailers are generating fewer sales from the received website visits than earlier, and at the same time, show an increase in DIM costs per website visit.
V. The pure players, in turn, start operating with high DIM costs per visit and gradually increase the average sales per visit and decrease cost per visit. At any time, they operate very close the optimal marketing-mix from an economic perspective, minimizing advertising costs for a given sales objective.

The conversion technology and cost structure of the firms suggest the following:

VI. For the considered European grocery retailers:
    a. The technology and cost structure for digital marketing is firm-specific. The marginal revenues and marginal costs associated with 1K or 1M more visits differ across firms and depend on the level of visits.

Table 3
Performance analysis: Measurement and optimization of the e-commerce budget in Digital Inbound Marketing (DIM).

Country	Grocery e-commerce	Average Revenues per visit	Average Cost per visit 2018 in EUR		Optimal DIM-mix (absolute discrepancy)	Optimal DIM-mix (DIM-efficiency)
		$\frac{Revenues\ Online}{V_{SEO}+V_{SEM}}$	$\frac{Cost_{SEO}}{V_{SEO}}$	$\frac{Cost_{SEM}}{V_{SEM}}$	$d=\lvert\frac{\Delta Cost_{SEO}}{\Delta V_{SEO}}-\frac{\Delta Cost_{SEM}}{\Delta V_{SEM}}\rvert$	$rd\in[0,1]$
EUROPE (in EUR)						
UK	Tesco	13,75	**0,08**	0,34	17,38	**0,03**[+]
UK	Walmart (Asda)	8,76	0,38	0,23	0,77	**1,00**
UK	Sainsbury's	16,52	0,36	0,20	2,91	**0,97**
UK	Ocado	124,65	0,40	0,40	0,76	**1,00**
UK	Morrisons	12,2	0,34	0,11	0,29	**1,00**
UK	Amazon*	7,76	0,34	0,40	0,38	**1,00**
FRANCE	E. Leclerc	7,58	**0,12**	0,08	0,51	**0,78**
FRANCE	Auchan	1,59	0,24	0,29	0,12	**0,99**
FRANCE	Carrefour	8,25	0,30	0,29	0,93	**0,25**
FRANCE	Amazon*	4,54	0,24	0,28	0,12	**0,99**
GERMANY	Rewe	5,06	0,33	0,32	0,36	**0,65**
GERMANY	Edeka	3,48	0,26	0,16	0,37	**0,62**
GERMANY	Metro	5,74	0,15	0,07	0,04	**1,00**
GERMANY	Amazon*	0,04	0,34	0,35	0,31	**0,73**
NETHERLANDS	Ahold Delhaize	5,02	0,29	0,14	0,27	**0,84**
NETHERLANDS	Jumbo	15,86	0,19	0,14	0,62	**0,17**
NETHERLANDS	Plus	13,56	0,21	0,19	0,01	**1,00**
NETHERLANDS	Amazon*△	135,95	**0,03**	-	-	-
NORWAY	Meny	4,55	**0,30**	0,00	0,38	**0,74**
	Spar	10,62	**0,21**	0,00	0,17	**0,91**
	Joker	7,59	**0,30**	0,33	0,30	**0,56**
NORWAY	Vinmonopolet	7,96	0,33	-	-	-
NORWAY	Amazon*●	12,83	0,36	0,75	0,27	**0,78**
USA (in US$)						
USA	Amazon*	0,59	0,74	0,73	0,43	**0,97**
USA	Walmart	1,12	**0,66**	0,21	1,61	**0,64**
USA	Kroger	12,57	0,92	0,53	1,20	**0,80**
USA	Target	0,72	0,90	0,60	1,17	**0,81**
USA	Ahold	93,07	0,87	**0,00**	0,88	**0,89**
USA	Costco	2,13	1,27	1,18	0,85	**0,90**

Notation: The marginal cost cannot be calculated when the firm does not generate any traffic through SEM activities during the two following years.
* Amazon reported data are for the retailer in total, not the grocery segment.
● Amazon has no own website. Shipping of some products from Amazon.com.
+ Outlier in 2018. In general, Tesco shows a high DIM-efficiency (2019: 0,00).

b. The data suggest that market leader(s) use a superior conversion technology.
c. In general, market leaders(s) work with a DIM cost structure that is lower than competitors.

VII. For the considered US grocery retailers:
a. The DIM cost structure seem to be similar across firms, such that the difference in marginal costs depends primarily on the level of generated visits where the firm operates.

5. Discussion

DIM efficiency allows to quantify the trade-off of the allocation of the marketing budget to SEO and SEM exploiting search traffic data, which complements the existing dashboard of firm specific KPIs or rules online (Saura et al., 2017), the isolated optimization of SEO (Baye et al., 2015) or SEM (Balseiro and Gur, 2019) and interrelations between online and offline promotions (Breugelmans and Campo, 2016).

The difference between pure players and click and mortar players in managing DIM is supposed to be driven by the origin of the firms. Entering the online market, brick and mortar firms behave as though in the offline world. Note that this observation is analogue the first experience of consumers buying online and taking as reference their behaviour offline with respect to their favourite brick and mortar brand (Melis et al., 2015) and the successive adaptation of behaviour online (Moe and Fader, 2004). Hence, as CM firms become more experienced in DIM the differences are expected to vanish.

This evolution seems to be speed up by the market presence of PP in the country, which may be considered a potential threat by incumbent brick and mortar firms. Accomodating the new rival in the country implies a potential loss of sales, but profit effects may be mitigated (or even avoided) by decreasing the necessary advertising budget and hence contribute to stay competitive through DIM optimization.

A further accelerator of the evolution towards DIM implementation and optimization, combining the two previous arguments, is supposed to be the current Covid-19 pandemic. As outlined in the introduction, especially in the grocery industry online sales have started to skyrocket. This provides the firm with plenty of experience, and at the same time all retail firms have speed up the digital transformation implying “new players” in the online market.

With experience on the firm- and consumer-side, that is, a consolidated e-commerce in the grocey industry, also differences in the DIM cost structure across firms are expected to vanish, as we see it already in the US market. Likewise, in terms of the conversion at a visit by visit basis, the considered pure players, born in the USA, show a lower rate, which is

interpreted as a result of diminishing returns in the sense of the established model as website traffic increases. This is coherent with the findings in the literature that pure players show a higher organic traffic share than brick and mortar firms (Baye et al., 2015).

Currently we are also observing pure players becoming click-and-mortar players (example Amazon), such that it would be interesting in the future to follow up whether the PP keep on advertising at a stable DIM efficiency level or whether the brick and mortar business implies more idiosynchratic shocks.

6. Concluding remarks, managerial implications, and future research

6.1. Academic contribution

The application of marginal analysis to the optimization of the DIM budget depends on the identification of marginal costs, where three main challenges arise:

I. The requirement to identify, in addition to explicit costs, the opportunity costs. This is especially relevant in the case of SEO, for which an explicit variable cost (or direct cost) cannot be attributed - or simply through indirect labor and structural costs. However, from an economic perspective, we argue that website traffic generated from SEO could be alternatively generated through a paid search and, therefore, implies an implicit cost (opportunity cost), which is estimated through software solutions such as SEMrush and should be considered in the optimization of the use of DIM techniques.
II. Consider that DIM activities may have a fixed component and a variable component (cost per click or access to a link) that should be separated from the total advertising budget (Hu et al., 2016; Phippen et al., 2004).

The use of an optimization model for the DIM cost is influenced by three main components, in addition to the choice and application of the economic control and measurement model. These components can be deduced from the analysis of the results:

III. The knowledge and management of the technology on which SEO and SEM techniques are based, influenced by the application of keyword search algorithms in search engines, and, in general, by the Internet ecosystem. The fact that PPs obtain a competitive advantage in the efficient application of DIM techniques with respect to CM indicates a better management knowledge of DIM techniques and, therefore, their better application. It is known that innovation and technology adoption, unlike other sectors, has never been one of the main assets of traditional retailing (now CM), greatly influenced by its strong investments in infrastructure and direct customer service through people. This attitude of departure has influenced a lower initial predisposition to investment in technology applicable to e-commerce in professional profiles capable of applying it and in digital marketing budgets assigned for this purpose.
VI. The opportunity cost derived from market entry. The PP boosted e-commerce, to which the CMs joined some time later. Although the study presents a time horizon of six years of e-commerce activity, the commitment of companies in terms of investment in SEO and SEM positioning has been uneven. Our conjecture is that this is due to the need to apply applicable resources and the slowness with which SEO investments begin to deliver results. While PPs have been very clear from the beginning that positioning keywords through content is crucial for the future development of e-commerce in terms of opportunity cost, the BMs have been slow to understand the process of the accumulating value of marketing (in number, type, and position of keywords in search engines). The fact that in the US and the UK (markets with a higher e-commerce penetration rate), this fact is more present confirms this opportunity cost.
V. The strategy of customer management by marketing managers in the application of DIM techniques has been unequal between CMs and PPs. In the case of PP, and in a very special way in the case of Amazon, its tendency has been to push the client towards more advanced stages (which is reflected in a high but efficient cost per visit): action and loyalty influencing the generation of customer databases, repetition of purchase, increase in average value per purchase, and recommendation to third parties. These are strategies and processes that are very present in direct sales. In contrast, physical retailers (present in the study through the CM) seem to have chosen to replicate themselves on the internet through e-commerce using the strategy followed in physical commerce in order to influence the attraction of clients and to influence sales. Both behaviors (PP versus CM) have a direct impact on the way in which the DIM is set up.

Appendix C presents the global perspective of economic performance of DIM implementation.

6.2. Managerial implications

The optimization of investment (in terms of marketing) or cost (in economic terms) of marketing actions based on the established objectives of the firm is one of the main concerns of marketing managers. In fact, good professional marketing practice is often associated with its efficacy (achievement of objectives, mainly sales, regardless of cost) and efficiency (in terms of the relationship between costs and results).

This study provides new information and raises questions for reflection for marketing professionals regarding the following issues:

I. DIM is explored and focuses on two of its key techniques: SEO and SEM. This analysis allows a comparative description of the market situation of the countries included in the study. It offers, in this sense, an intentional outlook based on data on the situation of grocery e-marketing in general and on the situation of the DIM in particular.
II. A reflection on decision making in marketing in DIM and its future impact can serve as a reference to markets with lower levels of development.
III. The need to apply analytical models of econometric control of investment in DIM, based on the large amount of data available, and proposes a specific model of marginalist analysis, which is replicable by the company.
IV. The study is based on professional tools and databases (SEMrush, LZ Retailytics, and EcommerceDB); in this same sense, it highlights the functionality of these solutions and proposes their use through this research design.
V. From the theoretical questions outlined in the previous point, conclusions of application in business praxis can be derived, due to the novelty of the study and its own foundation in business reality. Deductible management implications of this research are issues such as:
    a. The company's disposition of the appropriate planning and control tools of DIM.
    b. The recruiting of professional people (internal or external) capable of optimizing investments in SEO and SEM.
    c. The importance of considering the opportunity cost that can be derived from highlighted positions in web search engines and their subsequent generated access to e-commerce.
    d. The need for managers of the e-commerce portals to have a clear, strategic focus on the part of the conversion of generated website visits into sales.
    e. The interest in generating customer databases from which to establish direct relationships with customers.
VI. The model can serve as a starting point for software development

companies, in a complementary way to the metrics that are already provided, allowing to facilitate cost-dynamic DIM readjustment solutions.

6.3. Limitations and futures research

One of the main limitations of the study is of technical origin. The use of external databases to the data sources of the companies included in the study may introduce error margins between the actual data and those recorded by the tracking tools (SEMrush in this study).

According to information provided by SEMrush (2019), there are differences between information registered by the tool when processing millions of network interactions and the interactions registered on the server itself, which hosts the web (the computer code) that supports the e-commerce. However, since it is such a high volume of information, and without being able to verify the difference between one data source and another in this research, a very high level of statistical validity is assumed without indecency, or with minimal impact on the results.

The data provided and used to identify e-commerce sales volume and the market share of grocery e-commerce come from different sources for the European (LZRetailytics, 2019) and American (EcommerceDB, 2019) market. Both databases are based on obtaining information through annual reports from retailers and e-commerce and may apply a broader or narrower market definition. While this may have implications for the identification of the respective market leaders covering the established cumulative market share to ensure representativeness, the advantage of using data from local market experts is an expected higher level of precision in the data and complementary information. Moreover, being able to access online sales data on a monthly basis and differentiating by the traffic source would allow us to accurately estimate the marginal effect of additional visits on revenues and disregard the identification assumption that the conversion is independent of the source of web traffic.

With regard to future research lines focused on the economic performance of digital marketing, the possibility of applying similar studies to the use of other DIM techniques, such as display (or advertising in the networks) or backlink (or generation of links from social networks, blogs and other content support on the Internet), in which case it would imply accounting for incomplete information on private costs of companies regarding these Backlink and Display techniques.

Finally, it would be desirable to contemplate the interaction between companies in terms of best response based on game theory, within the framework of the analysis of economic efficiency of the DIM-mix and the richness of the available data with respect to the measurement of DIM. The motivation, results, and contribution of the study converge on the idea of providing a new step in the improvement of marketing decisions made in the digital environment.

CRediT authorship contribution statement

Anett Erdmann: Conceptualization, Methodology, Formal analysis, Data curation, Writing - original draft, Writing - review & editing. **José M. Ponzoa:** Conceptualization, Visualization, Writing - original draft, Writing - review & editing.

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Supplementary materials

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ANETT ERDMANN PhD in Economics, Master in Economic Analysis. Senior Lecturer at ESIC Business & Marketing School, Head of the bachelor's degree in marketing at ESIC Business & Marketing School. Research on strategic firm behavior and economic analysis of marketing actions within the digital economic environment.

JOSÉ MANUEL PONZOA CASADO PhD in Marketing, Fellow of HEA, Certified university professor by the Spanish Academic Authorities. Senior Lecturer in the Marketing Department at ESIC Business & Marketing School, Head of the Marketing Department at ESIC Business & Marketing School. Investigating the current function of marketing within the digital economy.