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LET'S (RE)LOCATE DIGITALLY: SPATIAL COMPETITION FOR USERS' ENGAGEMENT IN THE SOCIAL MEDIA SPACE

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Abstract

Online social environments provide attractive platforms for firms to connect and engage with consumers. The objective of this paper is to optimize marketing efforts by brands to improve engagement and market share in social media. To this end, we define and conceptualize the digital social media space using the concepts of homophily and social distance. For quantification purposes and a more tangible practical implementation we build on Huff's retail gravity model, which is transposed to the social media space. The model allows the calculation of the expected engagement and social media market participation at the brand level, based on the positioning of the brand and its' competitors and the distribution of consumer activity in different social media, thus enabling the optimization of marketing efforts through digital (re-)location. The model is applied to leading brands in the athletic footwear market to test its robustness.

Keywords: *Social media, homophily, social distance, Huff model, digital marketing optimization.*

JEL Classification*: L1, L2, M3*

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1 INTRODUCTION

Social media has become an important space for firms to interact with potential and current customers (Alalwan et al., 2017; Wang et al., 2019), and is further gaining importance, evidenced by people spending on average 2h 27m in social media each day and a total of 4.62 billion social media users worldwide (Hootsuit, 2022). In essence, social media has woven itself into an integral part of people's lives, playing a crucial role driving customer engagement and shaping the competitive dynamics between firms in an environment where firms use a variety of social media platforms (Dwivedi et al., 2023). This is particularly evident in the realm of social commerce, with a large part of online sales occurring via social media channels. These platforms enhance customer engagement especially through socialization and personalization (Phan et al., 2020), and research has emphasized that companies should use social media marketing strategically to effectively connect with their target audience (Dwivedi et al., 2023). In practice, we observe that firms are increasing their marketing effort and investment in social media, with advertising spending in social media reaching $US 130.24 billion worldwide in 2022, with a predicted growth potential of more than 200% in the next six years (Statista, 2022). This highlights the economic relevance of the optimization of firms' activity in social networks and implies a new dimension of competition for user engagement with firms or brands. To date, 97% of the Fortune 500 companies and 71% of small and medium enterprises are active in at least one social network (Hootsuite, 2022; Porteous, 2021).

The study of digital competitiveness in the realm of social media is pivotal for understanding the maturity of the digital transformation landscape the intellectual capability of digital innovation (Kő et al., 2022). The literature has identified a variety of strategic actions (e.g., market entry and repositioning) and tactical actions (e.g., marketing effort in terms of selective communication) to boost a digital competitive advantage, identifying key concepts how digital technologies enable a competitive advantage, such as connectivity, integration and applicability (Saura et al., 2022). However, to the best of our knowledge, there is a lack of research on how interactions between brands and users take place in the competitive social media space.

In this context, social media analysis is becoming increasingly important from two perspectives: first, for a deeper understanding of the company's customers and the relationship that the brand has established with them (Garg et al., 2020; Valenzuela-Fernández, Barajas & Villegas Pinuer, 2023). Secondly, with the aim of optimizing marketing expenditure and response to competitors' social media activities (Nian & Sundarajan, 2022; Huo et al., 2020). When evaluating the performance of digital marketing activities in different channels or platforms, Marketers usually consider a set of digital marketing key performance indicators (KPIs) to assess the historical evolution and for competitive benchmarking (Saura, 2021; Iacobucci et al., 2019). These outcomes, based on aggregated historical behaviour of users, can easily be obtained from professional web analytics tools (SemRush, 2022; Ponzoa & Erdmann, 2021). However, there is a lack of explanation of how KPIs – such as engagement, reach and impressions in social media – arise, which requires modeling the outcome as a result of the distribution of users in these networks and their behavior towards the firm.

In a physical market with intense competition, the marketing strategy of customer attraction is recognized as a crucial determinant of market share (Bell, Keeney, & Little, 1975; Kotler, 1984). Spatial competition for consumer attraction is formalized in location models that rely on factors such as attractivity and distance to the firm (Appelbaum & Cohen, 1961; Appelbaum, 1966; Huff, 1963), which have been extensively applied in the physical world (Latruwe et al., 2022; Ogryzek et al., 2022; Zheng et al., 2020; Wang et al., 2016). Social media provides another dimension and space for social connections and interactions (Lim, 2014), however, models of customer attraction considering spatial competition are sparse. There is a lot of research on how to improve success in social media based on aggregated metrics, especially engagement measures (Rogers, 2018). Exploring how these metrics arise, research on social media networks has mainly focused on modeling peer-to-peer relationships (Boguña et al., 2004), as the original purpose of social media connecting people. Recently, a spatial consciousness of social connections has arisen, centered around people's geotagged activity, the engagement of power, and employing spatial concepts in the context of network societies (Leighton & Saker, 2017; Lim, 2014). At the same time, there is an increasing interest in leveraging available data on users' behavior for the strategic planning of digital marketing activities (Mačiulienė & Skaržauskienė, 2020; Saura, 2021), and the consideration of social media as a digital market (OECD, 2022).

The objective of this paper is to optimize marketing investment in social media spaces with the aim to improve engagement and social media market share. For this purpose, we develop a conceptualization of the digital social media space as a dimension of interaction between users and brands and the setup of a simple spatial competition model which allows explaining the brand's attraction area in social media, its expected engagement and the social media market share of the firm; based on the principle of homophily and liminality (McPherson et al., 2001; Van Gennep, 1960; Turner, 1974) and the concept and application of social distance (Akerlof, 1997; Boguña et al., 2004; Talaga & Novak, 2020; Mao et al., 2010). Considering the activity of a brand in several social media networks simultaneously, competing for the interaction of users, we build on the Huff model (Huff, 1963), which is transposed to the digital social media space. For a given marketing effort in social media, in terms of the frequency of posts, and the activity of a sample of users of these networks, the model allows to delimit social media trade areas for the firm, predict the expected engagement and the firm's social media market share in each network.

The model is applied to the athletic footwear market and its three leading brands in Spain: Nike, Adidas and Puma (Statista, 2022a). This market is especially interesting given the growth potential of 60% from 2021-2025 and the high brand awareness for fashion items (Statista, 2022b; Statista, 2022c). The selected social media markets are Instagram with Tik Tok and Instagram with Twitter, with Instagram being the social media where 62,3% of users enter with the purpose to follow or research products and brands, and most users are simultaneously active in Tik Tok or Twitter (Hootsuit, 2022). The firm activity in these networks is extracted using professional social media analytics tool and the sample of user behavior for our study comes from a survey realized among young adults. Initial results show it is not possible to have a “one-size” fits all model for brands in social media management, and that it is important to manage closed groups and by-invitation to maximize engagement.

The research contributes to the optimization of marketing efforts in social media within a competitive landscape. Competition analysis for social media positioning as a basis for the marketing strategy, is in general reduced to aggregated performance measures, in the form of static position mapping for benchmarking. While from an economic perspective, competition analysis usually builds on reaction functions, which allows the derivation of the best response given the behavior of others. A joint consideration of the positioning of competitors within the digital social media space and the spatial distribution of users' activity in this space, allows for repositioning in terms of marketing effort in social media activity, with the purpose of business growth, given that social media interaction between brand and users is understood as a liminary stage to business outcomes.

The structure of this paper is organized as follows: Section two introduces the essential elements required to conceptualize the digital social media space, with a focus on consumer-brand engagement, and the roles of homophily and social distance in the digital territories. In

section three, we adapt the traditional retail model to the digital context, based on the previously defined space. Section four presents a concrete data application to describe the digital social media space and optimize brand locations within this space through a simulation analysis of relocation possibilities. Section five discusses both theoretical and managerial implications, while section six concludes the paper, highlighting its contributions and providing suggestions for future research.

2 BACKGROUND LITERATURE

The use of social media in marketing, as part of a firm's digital marketing strategy, focuses on establishing a dialogue between consumers and firms. While there has been extensive research on consumer behaviour in this context (e.g., adoption by customers, information source, electronic word of mouth) and increasing work on marketing management of social media (e.g., advertising activity, brand issues, customer relationship management), with Alalwan et al. (2017) providing a comprehensive review, the competitive environment within and across social media ecosystems has so far received little attention.

2.1. Social media activity by firms

Social media today is a vital marketing and communications channel for businesses, organizations and institutions, and brands have been relying on social media to get close to their audiences since the introduction of Youtube and Facebook in 2007 (Appel et al., 2020), in turn enhancing awareness and disclosing relevant information (Nian & Sundaraja, 2022) and ensuring a higher sense of unity (Ata et al., 2022) - thus belonging. Early studies of social media activity indicate that companies and brands used social media primarily to achieve brand objectives related to attraction of new customers in business to business (B2B hereafter) e-commerce (Michaelidou et al., 2011) and business to consumer (B2C hereafter) e-commerce (Campell, Wells & Valacich, 2013). Prior research examined the usefulness of social media for marketing purposes, confirming the important role social interactions had on driving sales (Stephen & Galak, 2012). Firms are interested in using social media platforms like Twitter in order to establish a conversation with their stakeholders and the call for interactions through likes, shares, comments is most common and effective to establish this conversation (Miguel-Segarra, Rangel, & Monfort, 2023).

2.2. Social media activity by users

Billions of people are using social media to share information and make (and strengthen) connections – arguably, it is the primary domain in which they receive information about the world around them and share content and aspects of their lives with others (Appel et al., 2020). In the context of consumer/brand relationships, this is called consumer brand engagement (CBE), a term that includes cognitive processing – namely thinking about the brand and wanting to learn more about it, affection – positivity and optimism around the brand; and activation – usage and purchase (Hollebeek & Chen, 2014). Customer engagement (CE) was originally defined as a psychological state, that is "the concept of CE, which reflects customers' interactive, co-creative experiences with other stakeholders within focal service relationships" (Brodie et al., 2011, p. 6), meaning interaction with the brand. This definition builds on original work by Hanna et al. (2011), which suggested that social media needed to be conceptualized and understood as an integrated system, an ecosystem of sorts. Customer engagement behavior, particularly in the context of social media, has been a focus of research, with studies highlighting its multifaceted nature, with humanity and lived experience at the heart of these networks of people (Dwivedi et al., 2023).

2.3. Interaction in social networks: the concepts of homophily and social distance

One of the advantages of the digital world is its absence of boundaries: "Unlike the physical world in which we live, digital spaces present an abundance of new and uncharted terrain that is being constantly discovered, mapped and territorialized" (Gustche & Hess, 2020, p.2). This unique characteristic of the digital world makes it difficult to delimit digital spaces, yet spatial information is critical because nearly all human processes are spatially situated (Boeing, 2019). Mapping digital spaces requires a holistic approach that spans several disciplines and takes into consideration different concepts. The core concepts setting the scene are homophily (McPherson et al., 2001) and social distance (Akerlof, 1997).

In their thorough survey of homophily, McPherson et al. (2001) argued its important role as a key to the operation of all social networks (digital or otherwise), and a basic organizing principle. Simply defined, homophily is the propensity of similar agents to connect to each other (Talaga & Nowak, 2020). Because "similarity breeds connection" personal social networks tend to be homogenous with regard to certain characteristics, including behavior towards brands, known as value homophily, to refer to individuals who share values, attitudes and beliefs, and has been a core concept for value-led segmentation (McPherson et al., 2001). Similarity between individuals also produces niches of localized positions within social spaces and, as distance grows away from these nodes, homophily decreases and subsequently dissolves. This results in a core-periphery type of pattern, with a central group of closely related individuals who are connected to each other and far from another group. In turn, homophily will have a positive influence on community commitment, as described by Wang et al. (2019).

The essence of this pattern sits at the heart of the social distance model (Ackerlof, 1997). This type of gravity model improves on elements status and conformity by adding a further layer in the form of generalization, namely: individuals in a social space have an "inherited" position, and trade with other players will be a function of the difference in these initial positions. Naturally, individuals who are initially close will interact more strongly than those who are socially distant, who will show little interaction. Externalities are important when individuals try to move closer together, an example of conformist behaviour (Ackerlof, 1997). The closest two individuals are in a social space, the more interaction between them, thus an underlying incentive to conform. This feature was later named value homophily (Talaga & Novak, 2020). Ethnographical and biographical sketches were critical to discern the process of social interaction (Ackerlof, 1997, p.1007). For ethnographers and anthropologists, this conclusion is explained using the concept of liminality. Van Gennep´s (1960) original text referred to liminality as a state of "in-between-ness" in the study of rites of passage. Turner (1974) later argued that transitions are meaningful for individuals because each new state awaits a new identity, introducing the liminoid term to refer to individual willingness to participate in the experience. In social spaces, each liminal stage brings you closer to a cluster of conforming individuals with high degrees of homophily. In digital spaces, purchase intention is a liminal stage that separates clearly to very different identities: client and non-client of a brand. Inherited positions will be explained in terms of relationship to the brand, with the purchase act being the moment of incorporation to the brand, and the shopping cart the moment of transition. Limonoid phenomena in social media have been studied for Twitter (Herwig, 2009) and tourism in Instagram (Conti & Cassel, 2019).

In this context of trying to understand how people move in a spaces like social media networks, which have no geographical dimension, inherited positions can change their meaning through liminality as one moves into new territories, since individuals in digital spaces are frequently creating or reinforcing connections to "place" through mediated experiences. The correct term for this is "placeification", defined as the transformation of digital spaces into places of meaning and significance (Gustche & Hess, 2020), particularly if there is strong assortative mixing (Boguña et al., 2004). When applied to brands, an Instagram account is a digital space to which a client feels a connection and provides some form of status or conformism, as described by Akerlof (1997). This connection transforms into a "sense of place", for they offer some degree of familiarity, emotional or social connection. Through placeification, therefore, brands and audiences (clients and non-clients alike) can adopt online roles that in turn shape the formation of digital territories with their own rules and social mechanisms (Gustche & Hess, 2020). This particularity is enhanced when social media influencers are included, given their content creation is critical for boosting brand credibility and bringing in a more homogeneous set of fans (Ata et al., 2022), arguably a way to increase homophily. To sum up, the conversational interaction of firms with potential customers in social media networks creates a digital space with the location of the actors being crucial for connection. Homophily between users and brands - as a degree of similarity - increases the likelihood of interaction (McPherson et al., 2001), while social distance is inversely related to the likelihood of interaction (Talaga & Nowak, 2020), i.e. two opposing forces that determine their interactions. Moreover, consumers and brands are just two different types of users for which the homophily relation applies, and the connection between consumers and brands is known as engagement (Hollebeek et al., 2014). Therefore, homophily is expected to increase engagement, which leads us to set up the following proposition:

Proposition 1: The interaction between a brand and users in digital networks can be conceptualized using the concepts of homophily and social distance. Engagement is more likely to occur with a high level of homophily and a low level of social distance between users and brands.

The outcome of these interactions as suggested by the literature, measured through the engagement of users with the brand based on the concept of homophily and social distance is illustrated in Figure 1 and summarized in Table 1.

2.4. Measuring and modelling interactions between brands and users in social media

The fact that social location also has a geographic dimension has made it possible to measure social proximity: individuals at short distances will have a larger probability of being related (beyond homophily), while individuals at longer distances will relate to a lower probability. Thus, individuals are likely to establish social connections with acquaintances with a probability that decreases with their relative social distance defined on the metric social space, making it possible to build a network of acquaintances (Boguña et al., 2004). This underlying assumption gave rise to the social distance attachment model (SDA), through which it is possible to generate networks with an expected average node degree at any level of homophily and represent any social organization as a complex graph (Boguña et al., 2004). Location data have been used to bridge the gap between the physical and digital worlds to obtain a deeper understanding of preferences and behaviors of online users. The premise is that social network structures are directly linked to the geometry of the social spaces they are embedded in (Talaga & Novak, 2020). Connections and interactions between users tied to specific locations has given rise to another mathematical approach, Location-Based Social Networks (LBSN), introduced by Bao et al. (2015). Information is retrieved from users who share their locations and location-related content (e.g., a geo-tagged photo). LBSN models when applied have confirmed earlier work in the sense that user-user distance impacts similarity (the underlying premise of homophily), user-location distance will influence the likelihood that a user will be interested in the location (Bao et al., 2015).

Considering a competitive environment, Gascón et al. (2017) stated that the challenge for firms operating in social media is to choose in how many networks to participate and how active to be. Once decided in which social media spaces to enter, the assessment of the outcome of the marketing effort is in general realized based on quantitative success metrics (Gräve, 2019), with the most highlighted KPIs in the literature being the volume (followers), measurement of interactions (engagement), measures of monetary and non-monetary costs, or measurements of opinions (sentiment analysis), which is often used for a competitive benchmark. Those aggregated metrics can easily be accessed through professional web analytic services (e.g., SEMRush). Reaction to competitors' performance on social media, however, is at an early stage (Huo et al., 2020). The activity or marketing effort realized by a firm and its competitors is a key variable in many marketing models to determine the effectiveness and return of customer attraction. Kotler’s (1984) fundamental theorem posits that the attraction of consumers and the resulting market share is proportional to the firm's marketing effort, with the proportionality depending inversely on the total marketing effort by its competitors. Applied to the digital social media space, this suggests that the intensity of the firm's activity as well as the activity by rivals in particular networks determine the firm's social media market participation.

Attractiveness of the firm, that is the attraction that the consumer feels towards the brand, is another key aspect when considering competition elements in the marketing activity, and is the basis of market share attraction models, as introduced by Bell et al. (1975). In the general model, the attraction towards a brand, relative to the attraction towards the brands of competitors, determines the firm’s market share. Accounting in this context for the spatial nature of a firm's positioning, with respect to potential customers as well as competitors, allows determination of the area of influence from where the firm draws consumers. The concept of trade areas has its origin in marketing geography, introduced by Appelbaum and Cohen (1961), with trade areas containing the firm's current and potential customers, as the source of business and economic outcome for the firm. At the core of the definition of a trade area is the type of locations, the size of the store, and the retail structure and associations, which can vary over time as shopping habits change or competitors and the type of locations change and affect the retail-gravitation power. The shape of the trade area depends on the assumptions on the movement of customers (accounting for street patterns or moving straight as the crow flies). Appelbaum (1966) introduced a simple model of the trade area of a store, which is determined by the store site and location 'spotting' of customers on a map. In its simplest form, assuming that all spaces on the map provide the same customer value (without using supplementary data on customers), the trade area is a circular area around the store location, with the attracted customers being the number of spotted people within the defined circle. Establishing different radius of the trade circle, the trade area can be differentiated in primary, secondary and tertiary zones. Following this ring model, as trade rings are further away from the store location, the percentage of sales drawn from this area decreases. For each zone, the average weekly sales per capita are determined (using customer survey data), which multiplied by the number of spotted customers in the zone provide the sales potential to be derived from the area. Considering the total potential sales in a trading area, allows to determine the market share the store derives from a spatial area and assess the sales potential for new sites (evaluating relocation opportunities, trading of increase in revenues and profit against associated investment of relocation). In this framework, attractivity of a store becomes an important attraction factor. As stated by Appelbaum (1966, p. 136), "a firm's public acceptance (image) can and generally does vary from one region to another," that is, stores with different acceptance (attractivity) and similar market potential will derive different sales per capita. Likewise, Appelbaum and Cohen (1961) stated that the personality of a store is expected to affect the extension of the trade area. These models have been extended and adopted, with the Huff (1963) model being the most common approach to the delimitation of trade areas, built on gravity-based probabilities of customer attraction. This approach has found several extensions using new data types (Baray & Cliquet, 2006; Wang et al., 2016) and has been implemented in professional tools of geographic business data analysis for mapping purposes and identification of catchment areas, e.g., GIS (Cui et al., 2012). The Huff model, a statistical model developed by the geographer David Huff (1963), is used to predict the likelihood of an action or event to happen at a particular location (e.g purchase/patronage by a particular consumer), given the spatial distribution of features and events in the surroundings of the considered location. This allows assessment of the competitive position of a firm and evaluation of repositioning opportunities. Concretely, the probability of customer attraction is modeled based on the attractivity of the store (commonly measured as the size of the commercial facility) and the physical distance with respect to customers using a gravity approach. In this framework, consumers' sensitivity with respect to distance and attractivity of the store can be assumed or estimated (Huff, 2003). These models have found broad application for the positioning of brick-and-mortar stores in the physical world. Given new behavioral patterns of customers and information on customers' use of social media, social media data have turned out useful to project behaviour (e.g., users' activity in Twitter) on the geographic space to detect spatial patterns (Adan et al., 2014; Laylavi et al., 2016), and Wang et al. (2016) suggest using this information for the delimitation of trade areas.

Note that the relationship between distance, attractiveness and patronage of a store in a physical environment works in the same way (based on the corresponding physical forces) as the relationship between social distance, homophily and engagement in digital space (Fig. 1). Therefore, we set up the following proposition:

Proposition 2: The concepts of homophily and social distance allow to transpose the traditional retail gravity model to the digital space, which allows to optimize the brand's position in social media (similar to firms optimizing location and influence in the physical world).

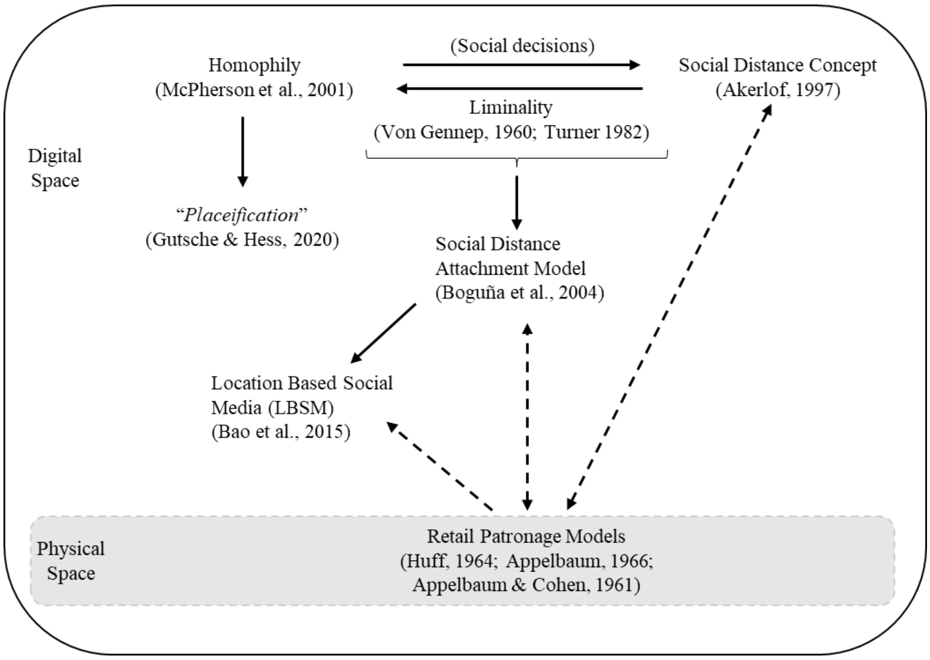

Fig. 1 – Concepts Inherent to the Definition of Digital Space. Source: own research

Tab. 1 – Summary of Concepts. Source: own research

Authors	Title	Approach	Core Contribution	Number of citations (WOS)	Number of citations (Google Scholar)
McPherson et al. (2001)	Birds of a Feather: Homophily in Social Networks	**Literature Review**	Definition of homophily, identification of the types and patterns of homophily.	9,240	21216
Akerlof, (1997)	Social Distance and Social Decisions	**Empirical**: Social Distance Concept	Individuals in social spaces have 'inherited' positions and trade with other individuals will be a function of the difference in these initial positions. Discussed status vs. conformist behaviour and included ethnographic work to validate his model.	562	1993
Boguñá et al., (2004)	Models of Social Networks based on	**Empirical**: Social Distance Attachment	Social connection as a function of their relative social distance is defined on the metric social space. Represented homophily in a node graph and argued	490	849

	social distance attachments	Model (SDA)	for clustering and positive assortative mixing.		
Huff, D.L. (1963)	A probabilistic analysis of shopping center trade areas	**Empirical** Retail patronage model	Development of a probabilistic gravity model to measure retail patronage in a geographic (physical) space.	411	1262
Bao et al., (2015)	Recommendations in location-based social networks: a survey	**Empirical**: Location-based social networks (LBSN)	Bridged the gap between the physical and digital worlds using location data. Confirmed homophily and distinguished user-user distance, user-location distance and location-location distance.	355	565
Applebaum, (1966)	Methods for determining store trading areas and market equilibrium	**Descriptive:** quantitative	Presented an improved method for determining trade areas and market penetration of existing stores and an analog method for estimating potential store sales at a given location.	101	429
Gutsche & Hess, (2020)	Placeification: the transformation of digital news spaces into “places” of meaning	**Empirical**: qualitative	Introduced the term “placeification” – the process and practices by which digital spaces (in their case digital news spaces) transform into places of meaning and significance.	6	16

3 THE DIGITAL SOCIAL MEDIA SPACE: CONCEPTUAL FRAMEWORK AND MODEL

In the following, we build on the concepts and models introduced in the previous section, providing a conceptualization of the digital social media space and developing a model that allows optimizing the brand's positioning in this space in terms of the expected engagement with users.

3.1 Conceptualization of the digital social media space

It is possible to translate the presented concepts, in particular homophily and social distance, to brand-customer relations in digital networks. An attempt is made in Figure 2 below. Liminal stages occur as consumers (and communities) increase their commitment to the brand – the emotional brand state defined by Zhou et al. (2012), typically because they start following the brand itself but also because they join either closed groups (co-creation or otherwise) or are invited by the brand to form part of a closed community within the brand. Liminality in the traditional sense will entail some form of incorporation into new territories where homophily is high and placeification is intensified. This in turn has a positive influence on community commitment (Wang, Cao & Park, 2019).

The level of homophily and social distance between the brand and a potential consumer segment can be inferred from the stages the users are in at a given point in time and their activity in the respective social media (which can be measured through a survey of the target segment). That is, social distance and homophily are considered key variables that determine the likelihood of engagement with the brand; with engagement being one of the most important KPI for firms' social media performance (e.g., Shahbaznezhad et al., 2017). Given this conceptualization and the corresponding measurements, we study the positioning of a brand in a competitive environment.

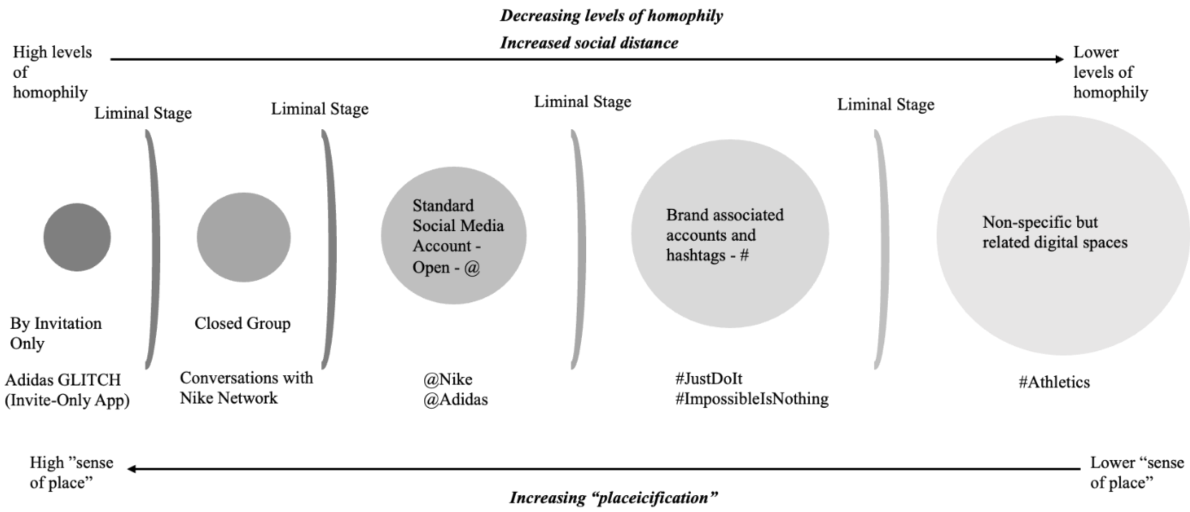

Fig. 2 – Brand-Customer Relations in Digital Networks. Source: own research.

3.2. Patronage of brands in the digital social media space: A gravity-based probability model

For the assessment of the brand's positioning in the digital social media space, we make use of the traditional Huff (1963) retail model, which we transpose from the physical to the digital social media space, based on the logic of the previously outlined concept of social distance and attraction in the digital social media space. The logic of applying spatial economic models to alternative spaces is not new. For instance, Hotelling's model of product differentiation was initially applied to the geographic differentiation on a horizontal line (e.g., ice cream store location at a beach), however, subsequently the model found application in the differentiation in the product space, becoming the basic model for product differentiation with a huge number of extensions or variations of the model framework (Hotelling, 1992), and recently has found also application in the digital context of competition between platform ecosystems to attract users (for smartphone apps) accounting for individual's preferences for a particular platform (Weonseek, 2020). Transposing the geographical understanding of distance to the social media space, the concept of social distance, as introduced by Boguña et al. (2004), becomes relevant. The connection probability between users (user u and user b) is inversely determined by the social distance (d_{ub}), with users at a shorter distance having a higher probability to be related, and the sensitivity to social distance depends on the degree of homophily (λ), which can be expressed in general terms as $p_{ub} = 1/\, f(d_{ub}, \lambda)$.[1] Given that brands are just a specific type of users of the network, the relevance of social distance also holds in the context of customer attraction, with the difference being that the focus of interest is one directional, from customer locations to the firm. The measurement of social distance can be understood as a multidimensional vector, or one-dimensional positioning (Boguña et al., 2004). Note that the understanding of distance effect on the probability of connections, as proposed by the authors, is in line with the Huff model, modeling attraction as well as a gravity model in terms of the distance and is analyzed using different sensitivity parameters of distance, here in terms of homophily.

Given the outlined framework, our model is defined as follows. The general digital social media space is defined as an S-dimensional space in a finite area, with S being the number of

[1] The notation used by Boguña et al. (2004) has been adapted to guarantee coherence in the model development based on Huff (1963). Concretely, we use λ (instead of α) as homophily parameter and individuals are directly referred to as users u and brands b (instead of ij).

considered social media networks, with users located based on their activity in each of the social medias. For simplicity, we focus on a two-dimensional space, that is a local digital social media space focused on the activity in two concrete social media. In this setting, let us consider a set $B = \{1, \dots, M\}$ of M brands, which are placed within the space according to their activity (m_{bs}) in the two social media networks, that is, at $m_b = (m_{b1}, m_{b2}) \in S$. Within the same space, a set $U = \{1, \dots, N\}$ of N users is assumed, which are distributed across the space given their presence (h_{us}) in the corresponding social networks, that is, showing an activity $h_u = (h_{u1}, h_{u2}) \in S$. The social distance between brand b and user u is measured by the vector d_{ub}, with the Euclidean length $\|d_{ub}\| = \sqrt{(h_{u1} - m_{b1})^2 + (h_{u2} - m_{b2})^2}$.

In this space, brands are assumed to compete for users' interactions, that is, users' expenditure of a limited number of clicks/likes/shares, which they use to spend on the respective social media space. Users' interactions with any brand are specified as $I_u = (I_{u1}, I_{u2}) \in S$.

The attractivity of a brand A_b is assumed to be exogenously given, or relaxing the assumption assumed not to be influenceable by a single user given the large number of users in the digital social media space. In it's simplest form, the attractiveness can be measured as the brand value. Alternatively, attractiveness can be measured as the size of the brand within the network regarding followers. Note that this is analogue to the size of a physical retail store, as used in the original Huff model.

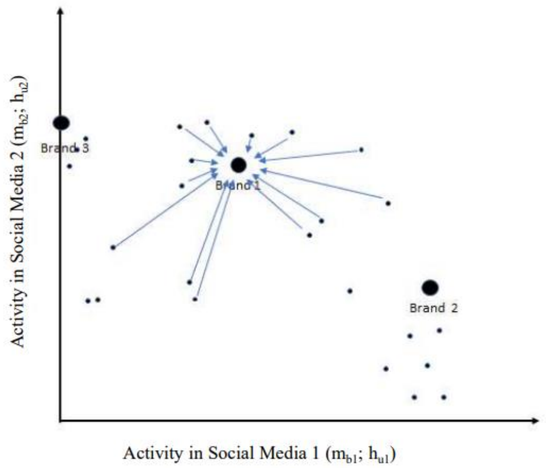

Fig. 3 – Customer spotting map in the two-dimensional social media space

Following Huff (1963) and in line with Boguña et al. (2004), given attractivity (an importance attribute in establishing a connection) and social distance as key elements for engagement, the probability that a user interacts with a brand within the defined social media space is defined as follows:

$$P_{ub} = \frac{A_b^\alpha / d_{ub}^\lambda}{\sum_{j=1}^{M}\left(A_j^\alpha / d_{uj}^\lambda\right)}$$

with λ being the homophily parameter, which captures the sensitivity with respect to the social distance, and α being the sensitivity parameter with respect to the attractivity of a brand.

Hence, given the probability of connection between the brand and users over the local digital social media space, allows delimination of the social media trade area of the brand, and considering the number of interactions of users in the space (at the individual level or by spatial clusters) allows determination of the total expected engagement that a brand b derives from a particular social media network as follows:

$$EE_b = \sum_u P_{ub} * I_u$$

Note that this is analogue to the expected expenditure in the traditional Huff model. However, here, brands are not competing for revenues but engagement, as a liminary stage towards business realizations. Finally, the brand's social media market participation in a particular social media network is defined as follows:

$$s_b = \frac{EE_b}{\sum_u I_u}$$

Furthermore, additional knowledge on the users' perceived value of the brand V_ub and the corresponding value distribution over the space, allows to calculate the potential value to be captured by the brand, at a particular location in the digital social media space. Whether to maximize the total expected engagement or the total expected potential value by engaged users is a strategical question (analogue market penetration or revenue maximization). Table A1 in the appendix summarizes the notation of space, variables and parameters used in the gravity-based probability model of engagement in the digital social media space.

4 APPLICATION OF THE MODEL TO THE ATHLETIC FOOTWEAR MARKET

4.1. Data

To provide an example of the proposed approach to determine the market participation of brands in social media networks and evaluate the possibilities of relocation within the digital social media space, we apply the model to the athletic footwear market, which is clearly dominated by a few brands and is a growing market worldwide, registering in 2022 revenues of m$US 60.853, which are expected to reach m$US 76.892 in 2025 (Statista, 2022b, 2022c). Concretely, we focus on the three leading sporting goods companies in Spain, namely Nike, Adidas and Puma (Statista, 2022a).

Social media networks have been selected based on their popularity and main activity purpose. For the two-dimensional space, we analyze Instagram and TikTok and, alternatively, Instagram and Twitter. Instagram has been chosen as the principal network, given that 62% of users indicate that the main purpose for following is researching brands and products (Hootsuit, 2022). Furthermore, the report reveals that the use of TikTok is mostly for fun, while Twitter is for news, but they are frequently combined with the use of Instagram and, in both combinations, covering approximately 80% of Spaniards.

Individual user data on the social media activity of potential consumers was collected through an online survey targeting young adults (76% aged 16-24, 23.52% aged 25-34) using a questionnaire between November and December 2022. Only surveys that were fully completed (all questions answered), leading to a second wave of information gathering in January 2023. The survey used frequency scales to measure users' activity on the networks in general (in terms of frequency of entry and time spent on the selected social media and interactions on the networks, differentiated by likes, comments, shares and posts), as well as brand-related interactions on the network. Table 2 provides an overview of the general behavior of the respondents. Table A2 in the Appendix details the items used in the questionnaire. Data on the social media performance of brands have been manually extracted from social media and complemented with data from the professional social media analytics tool Rival IQ (2022). The extracted data are aggregated data at the brand level. Table 3 provides the attractiveness of the brand in social media in terms of size (followers), the activity of the brand (posts per week), and the connection between the brand and users (engagement). Note that the leading brand in terms of size and activity differs across social media networks. The web-extracted data and survey results were consolidated into a singular database within Excel, and the gravity model was calculated creating an Excel macro.

Tab. 2 –
Users' general activity in social media

Average / Users' behaviour	Social media network	Instagram	Twitter	Tik Tok
Network				
Contacts		1282	118	193
Follow		507	119	141
Follow_Brands		11,2	1,3	3,4
Activity (frequency)				
	Access (per day)	**13,51**	**2,71**	**7,85**
	Interact	15,88	5,37	16,25
	Like (per session)	14,72	4,54	15,23
	Comment (per sessio	4,58	1,99	4,58
	Share (per sessione)	6,25	3,06	9,17
	Create (per day)	1,09	0,77	1,04
	Time (hours/day)	1,58	0,91	1,86

Tab. 3 –
Brands' performance in social media.

Source: own research

Brands' performance	Social media network	Instagram	Twitter	Tik Tok
Nike				
Entry data		nov-11	nov-08	
# Followers		264M	5.1M	3.5M
Total # Posts / # Tweets / # Sent Likes		1043	392.1K	10.9M
Posts (per week)		**8,5**	**-**	**0**
Adidas				
Entry data		jan-12	may-11	
# Followers		27M	4.3M	3.8M
Total # Posts / # Tweets / # Sent Likes		902	15.7K	20.9M
Posts (per week)		**3**	**1,75**	**2,1**
Puma				
Entry data		sep-11	jun-09	
# Followers		13M	1.9M	3.6M
Total # Posts / # Tweets / # Sent Likes		3486	73.1K	25.1M
Posts (per week)		**3,75**	**15,25**	**3,0**

4.2. Results

Results for the application of the proposed model to the footwear market are presented below in Figure 4 (Brand-customer relationship by homophily) and Table 4 (Expected outcome and assessment of relocation possibilities). The most relevant finding is that homophily is very different for each brand despite the social media network used, even if all three rely primarily on Instragram. Levels of homophily remain relatively low for all brands, with the bulk of interactions in brand associated hashtags and accounts. Nike and Adidas achieve better homophily patterns than Puma, particularly in Instagram but also in Twitter (Nike) and Tik Tok (Adidas). However, Adidas manages a relatively larger proportion of customers in either closed communities (14,9%) or by-invitation only communities (14,8%). This fact suggests Adidas is the brand that best manages placeification (Gustsche & Hess, 2020), conformity (Ackerlof, 1997) and positive assortativity (Talaga & Novak, 2020) and it does so in every social network it is present in. One could argue, therefore, that Adidas followers show higher levels of homophily overall than either Nike or Puma, despite Nike showing some efforts in Instagram (3,7% in closed groups) and Puma in Tik Tok (1,9%). Liminoid phenomena are also evident, with individuals clearly choosing to belong to the group in which they place themselves, in itself evidence for placeification. These results suggest it is not enough to apply a "one-size fits all" fits all strategy for brand activity per network in their different social media accounts. Instead, brands need to consider the social media space as inclusive of these different activities if they are to take advantage of real behavior, which implies knowing users's social media location as a whole. Since positions are inherited, as discussed by Ackerlof (1997) and liminoid processes are in place, brands should take really care as to how they want to manage each community, instead of relying on conversion across liminal stages. We will discuss the managerial implications for this later on in this paper.

For the model estimation and in order to keep it simple, we focus on only two social media platforms, Instagram and Tik Tok, Table 4 below provides the location-based outcome in terms of the expected engagement and the social media market participation of each brand. In order to assess relocation effects, we conduct a simulation analysis considering exemplarily three scenarios: an increase of 100% of activity in two networks (Instagram and TikTok); an increase of 200% in activity; and maximization of expected engagement to be drawn from the space. The homophily parameter is set at λ=2, analogue to research in physical spaces. A sensitivity analysis with respect to lambda follows, which suggests results are robust with respect to the parameter specification. Results once again prove the advantages gained by Adidas in all three scenarios given its management of homophily and social distance. Scenarios 1 and 2 already provide an increase in social media market share for Adidas vs. Nike and Puma, and this refers almost exclusively to increasing current posts per week – moving from 3 to 6 (Scenario 1) and 3 to 12 (Scenario 2), assuming the same rate of expected engagement as currently. However, maximization of engagement taking into account the brand-customer relations in Figure 4 is what really makes a difference, and it is then that Adidas really steals market share from Nike. If a brand can increase the number of customers with high levels of homophily, as is evident in groups by invitation or closed groups, maximizing engagement in those groups dramatically increases social media market share. The reason for this lies in the concepts outlined before, namely social distance – since trade is a function of initial positions – and placeification, since higher degrees of homophily imply increased meaning and significance.

Fig. 4 – Brand-customer relationship by homophily and social distance. Source: own research.

Tab. 4 – Expected outcome and assessment of (re-)location possibilities

	Instagram			Tik Tok		
Expected KPI	Adidas	Nike	Puma	Adidas	Nike	Puma
Current activity (post per week)	3	8,5	3,75	2,1	0	3,03
→Expected Engagement (by user per week)	0,13	1,30	0,06	0,21	0,00	0,20
→Expected Social Media C3-Market Participation	8,53%	87,42%	4,05%	50,97%	0,00%	49,03%
Simulation of "relocation" in the digital social media space						
ADIDAS	Adidas	Nike	Puma	Adidas	Nike	Puma
Increase activity by 100% in both networks	6	8,5	3,75	4,2	0	3,03
→Expected Social Media C3-Market Participation	8,91%	87,05%	4,04%	52,31%	0,00%	47,69%
Increase activity by 200% in both networks	12,0	8,5	3,75	8,2	0	3,03
→Expected Social Media C3-Market Participation	9,76%	86,24%	4,00%	55,08%	0,00%	44,92%
Maximize Engagement	168,4	8,5	3,75	51,0	0	3,03
→Expected Social Media C3-Market Participation	42,03%	55,39%	2,58%	79,1%	0,0%	20,9%
Sensitivity analysis with respect to the homophily paramtere (λ)						
λ = 2 (default)	8,53%	87,42%	4,05%	50,97%	0,00%	49,03%
λ = 3	8,38%	87,61%	4,01%	50,78%	0,00%	49,22%
λ = 5	8,11%	87,95%	3,94%	50,39%	0,00%	49,61%

A limitation of the analysis is the restriction to the three largest brands. It would also be interesting to calibrate the homophily parameter for the different levels of interaction with the brand (Fig. 2), which is in line with Wang et al. (2016) who differentiate between the behavior of potential customers in the space in their calibration of the sensitivity parameters between the behavior of potential customers in the space, but this is left for further research.

5 DISCUSSION AND MANAGEMENT IMPLICATIONS

5.1 Theoretical implications

The social media landscape of a brand has traditionally been defined implicitly using metrics on users' activity and customer spotting in the respective social media, without a clear definition or delimitation of the space. This paper goes beyond general counts of user patronage within a particular social media platform but provides a spatial approach based on a well-defined brand-customer relationship in an S-dimensional digital market: the transposing of the gravity patronage model to the digital social media world. In doing so it helps delimitate trade areas in a boundless environment such as the digital space. Extensions or adoptions of Huff-like models for the study of patronage behavior of customers have long time focused on the type and number of attributes (Gautschi, 1981), followed by software solution for business implementation (Cui et al., 2012), new analytical methods like mathematical morphology to delimitate trade areas (Baray & Cliquet, 2006) or new data sources (Wang et al., 2019). While simple spatial customer attraction models in the physical space are often based on the strong assumption that the world is a plane, ignoring infrastructure and natural barriers, at the first glance this is not an issue in the digital social media space. However, accounting for the network connections between users, the 'digital connection infrastructure' is relevant (e.g., Boguña et al., 2004). Hence, for further research, we are considering the flexibilization of the 'plane space' assumption accounting for the network structure between users.

The concept of homophily in social networks explains the propensity of consideration of a brand, becoming a key concept in the understanding of social media performance outcomes (e.g., Mao et al., 2010; Wang et al., 2019). Previous literature has studied a variety of actions that can connect the brand with users in social media (Alalwan et al., 2017), and has emphasized the brand identity and its competitive features as crucial for brand strategies to appear approachable and connect with consumers (Khan & Mujitaba, 2023). The proposed conceptualization of possible interactions between users and brand, based on the homophily argument, suggests a gravity pattern in the attraction of users. Moreover, in line with Boguña et al. (2004), homophily determines the sensitivity of a relation with respect to the social distance. Both arguments suggest the use of a gravity approach to the analysis of social media performance given the activity of the brand, which has been implemented in this study. Furthermore, in the context of social commerce, socialization - defined as the strength of interaction between users in the network and identified as a crucial dimension of social commerce (Phan et al., 2020) - is expected to be enhanced by a higher degree of homophily. That is, the relationship between social commerce and brand engagement is anticipated to be even stronger if the brand optimizes its location in the digital social media space, as proposed in the model presented.

The study also takes a step forward by demonstrating that the inherited positions described by Ackerlof (1997) consolidate placeification (Gustche & Hess, 2020). This makes it more relevant to divert attention from conversion rates to maximization of engagement in these inherited positions, since it is at this level that most positive assortativity is taking place (Talaga & Novak, 2020) and possibly also higher levels of influence (Ma et al., 2010). This paper also contributes to the literature of spatial repositioning. The consideration of the time dimension, respective competing store positioning, was already discussed by Appelbaum and Cohen (1961), with the warning to watch out for a possible adverse effect on the store's trading-area boundaries and market penetration. Recently, the mapping of the dynamics of market structure has found increasing interest in marketing and operation research, with the identification of dynamic patterns (trajectories of firms) allowing insights to be derived on firms' repositioning strategy (Matthe et al., 2022). At the same time, a variety of professional mapping tools have emerged (e.g., Carto, PowerBI), which increasingly focus on the representation of the customer value. The assessment of repositioning in the digital social media space provides a new dimension for these considerations.

Note that the conceptual framework and model presented in this article align with the insights provided by Saura et al. (2022). This alignment addresses each of the identified pillars necessary for leveraging digital technology to enhance competitiveness. These pillars include the creation of a competitive advantage, characterized by optimal positioning in the digital social media landscape; integration, which involves the coherent management of brand presence across various social media platforms; connectivity, focusing on the frequency of connections and the homophily in user-brand relationships; and applicability, offering a model with practical implications. Particularly, in light of social media's role in fostering dialogue between firms and users (Dwivedi et al., 2015), this paper contributes to the integration of communication and marketing analytics within the realm of digital competition.

5.2 Management implications

Social media activity is associated with costs for the firm, and a high return depends on the value assessment by the customers who are exposed to or interact with the firm's activity. On the other hand, consumers differ in their intensity of use of different social media platforms, which directly impacts brand attractiveness. Hence, a lower social media activity in a digital space with high-value customers can yield lower costs and/or higher revenues than a higher investment in social media channels in other digital spaces. When considering the profitability of marketing spendings to attract customers, a variety of structural models have been proposed from an economic perspective (Bagwell, 2007). The analysis based on a gravity model helps question whether increases in user engagement justify increased investments in activity and whether these improve social media market penetration for a given brand in relation to its competitors, particularly if liminality concepts are ignored, given homophily. The answer depends on the objective that needs to be maximized and the current positioning of competing brands, as Appelbaum and Cohen (1961, p. 100) discussed: “a powerful competitor who overbuilds can ruin others. A weak competitor who miscalculates can ruin himself.” It is clear from this study that there are two main forms of miscalculation: (1) assuming all social networks work in the same way and for all brands and (2) ignoring the personal choice of customers in terms of how much engagement they themselves are willing to engage in, which determines social distance and enhances placeification. Management emphasis on conversion at all costs ultimately jeopardizes the understanding that maximization of engagement happens in these inherited positions and that a previous mapping of distribution of clients into the different groups is critical to increase penetration. This finding is consistent with previous studies that look at how social media analysis aids an indepth understanding of an organization's customers and the relationship established with them by the brand (Garg et al., 2020; Valenzuela-Fernández, Barajas & Villegas Pinuer, 2023). Thus, evaluating the profitability of using a certain social media channel, to earn the attention of potential consumers and attract customers needs to consider both the distribution of different consumer types in the considered channels, the distribution of customers into different clusters of homophily and the positioning of rival firms.

In planning attractivity and activity of the brand in the social media space, it is also necessary to anticipate regulatory changes. For instance, boosting the size of an e-commerce through the social media positioning, can imply crossing established thresholds which activate the firm being subject to regulations (e.g., gatekeeper definition by the Digital Market Act). On the one hand, the presence and activity of different firms of the same industry in relevant social media markets is supposed to have a direct impact on customer attraction, which gives rise to specialized professional profiles of social media management. The presence and activity of potential customers in social media determines the likelihood to be exposed to information from the firm, which increases as the intensity of use/activity is close to the firms' activity (close in terms of relative importance of a particular platform and the intensity of use).

Last but not least, the existing literature has emphasized the capacity of digital technologies to enhance a firm's performance, noting that smaller firms often encounter more substantial challenges in implementation (Kő et al., 2022). The conceptual framework proposed in this paper leverages digital information for optimal location selection, without the need for costly resources and minimizing associated risks. This approach can be executed utilizing advanced data analysis skills in Excel, thereby facilitating an increase in digital competitiveness also for small and medium-sized enterprises.

6 CONCLUSIONS AND SUGGESTIONS FOR FURTHER RESEARCH

This study is pioneering in its approach to conceptualizing the digital social media space, utilizing well-established frameworks from diverse disciplines and resulting in a comprehensive and interdisciplinary perspective that takes into account homophily, social distance, and liminality. This perspective has proved useful in understanding and anticipating the interaction between brands and their social media consumers, based on their respective positions in relation to the brands with which they engage. This is a significant contribution as prior research has predominantly focused on aggregated measures of engagement without clarifying the process of how engagement is established. Our secondary contribution entails the adaptation of conventional spatial patronage models from physical to digital spheres within the social media space, indeed it is the first time a Huff-like model has been applied to a digital space. This paper introduces a bespoke spatial competition model created for (boundless) digital spaces beyond traditional spatial models that use geographical locations, with the ultimate objective of assessing whether marketing efforts can be optimized in terms of improved engagement and market share. For this reason, we have chosen to keep it simple, focusing on a two-dimensional setting that considers a local social media space with only two social media platforms (Instagram vs. Tik Tok; Instagram vs. Twitter).

The need to keep it simple at this moment in time helps stress the important contribution we are making to existing research. However, it also provides future research opportunities, like extending the study to a higher dimensional space. An additional improvement would be to address the content or purpose of particular social media activity of brands and qualitative differences between them, since the study has focused exclusively on the quantitative measure of the firm's activity. Following recent work presented by Valenzuela et al. (2023), it may be worth separating B2B and B2C. Further research should also compare the expected results based on the sample with the observed outcomes in order to calibrate the homophily parameter and the sensitivity of attractiveness. Furthermore, a challenge in the precise implementation of the model is the measurement of observed engagement, which seems to differ for some brands considerably depending on the professional social media analytics tool that is used. Finally, to keep it simple, we have focused on homophily and social distance as determinants of engagement. However, some authors have argued that homophily operates in parallel to other processes (Newman et al., 2001). For instance, social influence has been found to explain more the timing of purchase while homophily explains more the choice (Mao et al., 2010). Therefore, accounting for social influence is expected to provide additional insights and gives rise for further research.

The presented patronage model for the digital space of social media assists in evaluating brands' marketing efforts concerning expected engagement and social media market share. It also permits the assessment of (re-)location. After putting it into practice in the athletic footwear industry, we spotted variations in the degree of homophily in the different social media and among brands. In this context, our simulation demonstrates how relocating a brand's social media positioning can enhance its digital competitiveness and increase expected user engagement and market participation on social media. Further investigation of homophily within specific communities can facilitate understanding of content and purpose of different brands in social media. Expanding the study to higher dimensional spaces will bolster findings and facilitate comparison between expected and observed outcomes for effective adoption by brands. In summary, this paper offers new opportunities for research in optimizing social media marketing efforts.

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Appendix

Table A1. Summary of the model notation

Notation	Description
s	Social media $s \in S = \{1,2\}$
u	User $u \in U = \{1, \dots, N\}$
b	Brand $b \in B = \{1, \dots, M\}$
λ	Homophily parameter, which determines the sensitivity of a potential interaction between users and the brand based on the social distance
α	Sensitivity parameter for the overall attractiveness of the brand in relation to the size of the brand.
d_{ub}	Social distance between user *u* and brand *b*
h_{us}	Activity of user *u* in social media *s*
m_{bs}	Activity of brand *b* in social media *s*
For each social media space *s:*	
I_u	Interaction of user *u* with any brand (endowment of interactions given the users' activity and time constraint)
A_b	Attractivity of brand *b* (e.g., number of followers)
P_{ub}	Probability of interactions between user *u* and brand *b* (probability of engagement)
EE_b	Expected engagement that brand b can achieve, given its position in the digital social media space
s_b	Social media market participation of brand *b*