Discovering synergies and conflicts in online and offline in-store engagement

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Abstract
Brands expect that greater physical in-store engagement will reduce visits to competitors. However, if customers are simultaneously engaged virtually, where the visible enthusiasm on social media platforms can also proliferate competitor visits, the combined effect of dual engagement becomes more difficult to predict. Do online and offline indicators of engagement with the same physical space, at the same time, act (i) in synergy or conflict to (ii) improve or diminish a brand’s competitive position? The emergence of simultaneous interactive platforms demands a broader assessment of the impact of multi-channel engagement. The current paper illustrates an observational study integrating six databases drawing from Twitter, Yelp, GPS movement data, Census, US business database from the Restaurant Industry, and Brand Websites to demonstrate how engagement metrics derived from (i) physical movement inside 773 US store locations and (ii) social media activity inside the store interact to affect future customer visits to competitor stores. We find that cannibalization is more likely in Dine-In stores, whereas convergence more likely among Drive-Thru stores. The model presented in this paper can be used to test the validity of engagement measures, supplement primary research to moderate store operations, as well as discover the effectiveness of different store formats.

Keywords In-store engagement · Social media · Dwell time · Media synergy · Competitor spillovers · Negative binomial regression

Introduction
When retail managers consider promoting their store, they include both physical and virtual channels to engage their customers. One assumes that both channels will drive convergent outcomes such as visits and sales. However, is it possible that one channel dilutes or reverses the effect of the other? Omnichannel environments have disrupted brand positioning strategies. While many physical establishments are moving online, native-digital brands are also acquiring physical space (McGee 2018). Brands are struggling to reconstruct the physical and digital boundaries within which they can effectively prioritize resources and engage with their clientele. Shopping moving online has particularly impacted the retail trades. The physical disruptions caused by Covid-19 have increased curbside pickups, deliveries and buy online pick-up in store (BOPIS) at the expense of face-to-face engagement with stores (Briedis et al. 2020). Retail brands, originally positioned as physical spaces to connect consumers, are encouraging mobile interactivity on store premises to compete virtually with rivals and reconsidering their place within the new channel preferences. This presents them with a dilemma.

In one instance, retailers are trying to increase time spent in the store. Digital cameras and sensors tracking the flow of physical traffic assess whether dwell time is leading to customer satisfaction and retention. Some studies find that increases in average dwell time by 1% correspond to an increase in sales by 1.3% (Biggar & McAdams 2016). Similarly, some retailers are encouraging “slow shopping” to increase time spent inside the store because sitting down in a lounge on the retail space can increase shopper’s spending...
by 40% (Byron 2015), and introducing a mobile charging spot increased dwell time by 2.3x, increasing amount spent at the register by 1.47x (Weinberg 2018). Pre-Internet, marketers could simply use dwell time to estimate how engaging the in-store experience was, design atmospheric cues to enhance and utilize this duration to increase loyalty and reduce co-visits to competitor stores, also known as competitor spillovers.

However, with the diffusion of mobile Internet, customers are simultaneously absorbed by the Internet while inside stores. Consumers upload an average of 42 million images, “like” posts 1.65 billion times a day on a single platform: Instagram, and tweet 500 million times every day (Brain 2017; Smith 2020). Many of these interactions take place while people are engaged in physical activities. Foursquare reports almost 9 million “check-ins” daily, while users are out dining, shopping, and traveling (Jan Kamps 2016). This leads to several complex scenarios while measuring engagement with dwell time and social media activity. First, this hyper-engaged environment causes “inattentional blindness” (Mack and Rock 1998), which implies a loss in visual perception of physical stimuli, including store atmospherics. Hence, the duration of customer stay in the store may not be an effective indicator of store engagement if customers are disengaged from physical atmospherics. Second, metrics generated from social media used on store premises may be more representative of users being conspicuous rather than engaged if they are not physically engaging with the store experience. Overall, we address the following question: Do online and offline indicators of engagement with the same physical space, at the same time, act (i) in synergy or conflict to (ii) improve or diminish a brand’s competitive position? Implicit within the cannibalization-convergence question is the type of engagement-related outcome that indicates a brand’s position visa-a-vis competitors. In the current paper, we study effects on competitor spillovers, or co-visits to competitor stores, which can be accelerated by social media engagement and publicity agnostic of the valence of the message. Hence, in order for brands to optimally allocate resources toward physical and virtual engagement, marketers need to assess the cross-impacts (cannibalization, convergence) of engagement indicators of customers simultaneously engaged in both platforms.

Prior research on media synergy and simultaneous media use (Assael 2011) has addressed the distraction caused by different device platforms. However, there has been limited acknowledgment of physical environment as an alternate “medium” or research on how physical environment and virtual media influence each other. This leads us to two related research questions. One, do physical and virtual engagement metrics cannibalize or converge in terms of their influence on engagement-related outcomes? Two, what contextual factors can cause variations in the above effects? In the following sections, we describe the multi-platform environment characterized by simultaneous engagement including in-store dwell time and crowdedness as indicators of physical engagement, and Situated Engagement, Virality, and Network Reach of in-store tweets as indicators of virtual engagement. To answer the questions posed previously, we integrate data from social media, review websites, the Census, and GPS tracking of between-store movement among coffee shops to examine the cannibalization-convergence effects of in-store physical and social media activity on competitor spillovers. Our findings show that the answer to the above questions varies by brand and retail format. Managerial implications are discussed for brands, relative effectiveness of platforms on their target audiences, and unintended outcomes of positive engagement.

**Split-attention environments**

Traditionally, retailers used in-store promotions (Grewal et al. 2017), immersive technologies (Scholz and Smith 2016), and store atmospherics (Spence et al. 2014) to enhance customer engagement inside their stores. Engagement has been defined as the process of a consumer achieving positive self-control over his/her consumption experiences (Calder et al. 2016), which is reflected in non-transactional behaviors such as recommending the brand, writing blogs, posting comments (Zhang et al. 2017). Increased engagement helps build affective commitment and shopper satisfaction and elevates the likelihood of repurchase and shopper loyalty (Thakur 2016). Thus, despite being non-transactional, engagement helps predict transactional outcomes.

However, mobile usage inside the store exerts complex influences on shoppers’ attention processes leading to diverse shopping outcomes. It can enhance a customer’s engagement with the shopping experience by price-checking, or accessing shopping lists (Sciandra 2015). In the short term, customers using a mobile device inside the store are seen to take longer paths to checkout, accompanied by more unplanned spending, thus benefiting the store (Hui et al. 2013). Similarly, augmented reality apps help shoppers explore and discover new experiences (Dacko 2017; Poushne, and Vasquez-Parraga 2017). However, in-store mobile Web access is also used for showroooming, i.e., scanning inventory and prices to find better deals for similar products online and for making virtual purchases from competitors’ Web sites while on store premises (Rapp et al. 2015). There are considerable dangers in terms of limitations on visual attention and inattentional blindness due to mobile phone use (Briem and Hedman 1995; Sciandra 2015; Strayer and Johnston 2001). This can render ineffective the efforts made
by retailers to engage customers with their promotional material.

The above scenario raises the classic cannibalization-convergence question that has been debated in the integrated marketing communication and advertising literature (Assael 2011), about whether simultaneous media use leads to positive or negative synergies (Enoch and Johnson 2010), i.e., leading to media supplementing or diluting each other’s effectiveness. Since the human attentional system is strictly limited, the quality of attention is clearly important to track or monitor (Hassoun 2014) for managers. In contrast to decades of prior research which followed silo or within-media approaches to assess media effectiveness (Schultz et al. 2012), managers need to acknowledge that consumers access and process media forms holistically and simultaneously (Naik and Peters 2009), so that they can better allocate resources to optimize ROI. Adding to the above is furious acceleration in the race for digital marketing, which has seen increasing pressure for response speed, thus leading managers to rethink about traditional measurement methods. Time-consuming surveys, in-depth interviews, and dispersion in response quality have pushed marketers toward increasing reliance on tools that can be observed continuously and analyzed as real-time dashboards to generate warning signals. As a result, marketers have deviated from traditional “planned” media placements, to an “agile marketing” real-time orientation in which they seek to seamlessly monitor customer engagement levels and detect trigger events that might cause changes in customer relationships (Malthouse et al. 2019). In the following section, we discuss measures of physical and virtual engagement, competitor spillovers, and contextual factors that can cause variations in the cannibalization-convergence outcomes.

### Outcomes of physical and virtual in-store engagement: a conceptual framework

Overall, the effects of physical and virtual in-store engagement on competitor spillovers are expected vary by brand and retail store format. More detailed descriptions of different variables are provided below (Fig. 1).

#### Physical and virtual engagement

One of the most common indicators of physical engagement is **Dwell Time**. How long shoppers stay inside a retail outlet is found to indicate how much money they spend on store premises (Biggar and McAdams 2016), analogously to the way time spent on a Website is expected to demonstrate how engaged a user or shopper is with the space. Time and distance traveled within a store are also correlated with unplanned purchases (Hui et al. 2013). However, dwell time can also be a product of delay or wait time, which does not lead to customer satisfaction. Dwell time needs to be understood and interpreted in combination with **crowding** (Hui and Bateson 1991). While retail crowding can be viewed as a construct that reduces perceived control over the environment and customer satisfaction, increased crowds can also be an indicator of a store being popular or “happening” and yield positive sentiments about the store. Hence, dwell time and crowding are both indicators of store engagement, but their effects on engagement-related outcomes, such as loyalty, can be complex depending upon the context of occurrence.

In addition to physical engagement, virtual engagement can be assessed from the content of the posts generated from store premises. While the engagement implicit in shopper posts can be measured by the enthusiasm, frequency of occurrence and elaboration of the message (Dwivedi 2015), timeliness (synchronicity of message with context) are also critical (Borah et al. 2020). Though most sentiment extracted from social media posts is agnostic with respect to the physical context of the

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**Fig. 1  Conceptual framework**
post, research on WOM contiguity effects (Chen and Lurie 2013) demonstrates that the contiguity between post and experience enhances the value of opinions shared. Therefore, “situated” engagement metrics, generated from inside the premises of the store, should be a strong indicator of in-store engagement. Similarly, the extent to which posts go viral or are liked, shared, or retweeted can also indicate engagement. The extent to which posts about a store become visible is also determined by the number of followers a tweeting shopper has, and how frequently the shopper posts about the store. Thus, this extended Network Reach can also become an indicator of virtual engagement for a store.

**Competitor spillovers and context**

How is physical and virtual engagement likely to affect competitor store visits? And why are competitor store visits relevant? Most engagement metrics are known to predict loyalty, but in several product categories, customers are loyal to repertoires of brands rather than single brands (Sharp et al. 2002). Traditionally loyalty implied dyadic relationships with single brands, but customers are also seen to demonstrate “flings” and “flirtations” with competitor brands (Consiglio et al. 2018). While positive word-of-mouth tends to indicate customer satisfaction, retention, and loyalty, the enthusiasm underlying such experiences can also lead customers to seek more variety among associated brands or competitors. As promotional messages are processed by interconnected associative networks, thoughts about a focal brand can trigger cognitions about related abstract concepts and competitor products (Sanchez et al. 2020). Thus, promotion of one brand can make consumers think of competing brands that have not been advertised (Anand and Shachar 2011).

As a result, even positive engagement can inadvertently drive more competitor spillovers (Sahni 2016) or greater competitor visits for stores located in regions with high competitor density. In contrast, positive engagement can lead to lesser competitor spillovers in regions where such options do not exist (Sanchez et al. 2020). Thus, as we will see, the indicators of virtual and physical engagement potentially share a complex relationship with competitor spillovers depending on the context of occurrence of the stores. In the remaining part of the manuscript, we explore this relationship for two brands of coffee shops with Dine-In and Drive-Thru retail formats. Dine-In stores are usually located in urban centers with high-density presence of competitor stores, whereas Drive-Thru coffee shops are in regions where fewer competitors exist.

**Brands and their audiences**

While Starbucks targets age groups from 18 to 44 and mostly higher income professionals, Dunkin Donuts clients are mostly working people and students, looking to “grab-and-go”. Dunkin stores generally have little room for people to sit around and experience the ambience. In contrast, Starbucks creates a luxurious ambience as a “third-place” (Oldenburg and Brissett 1982) that provides both a respite and an escape from the daily routines of home and work. It is thus expected that physical space attributes will more strongly influence competitor visit-related outcomes for Starbucks than Dunkin Donuts customers. Overall, we expect that Starbucks, which acts as a third-space and venue for escape for an affluent, younger tech-savvy audience will demonstrate dominance of virtual engagement on its effect on competitive spillovers. Also, we expect that greater effects of cannibalization, or opposing effects of physical and virtual engagement will be experienced in store formats which are in the proximity of more competitors. In regions where competition does not exist, convergence will occur.

**Onboarding customer data**

To collect the above variables specified in the framework, we combined several sources. Increased pressure to acquire customers in digital environments, backed by availability of customer data, has increased manager’s need for response speed. This has led managers to rethink traditional analytical methods. Time-consuming surveys, in-depth interviews, and a reduction in response quality have pushed marketers toward increasing reliance on tools that can be observed continuously and analyzed as real-time dashboards to generate warning signals. Simultaneously, there has been a rise in “Alt Data,” which are indirect metrics generated from Big Data, such as social media and geolocation, representing human centric consumer knowledge (Datascrum 2019). In line with these trends, we designed this study by connecting datasets from Twitter, Yelp, GPS movement data, the US Census, US business database from the Restaurant Industry, and Brand Websites based on identifiable store locations over a time period of 6 months. Location data were used as the anchor, which cross-matched with additional data platforms, provided us with the variables we needed. For example, store address mapped on brand websites yielded store format data. Similarly, store address from Safegraph coordinates when combined with Safegraph GPS Metrics provided data on co-visits which when combined with competitors identified via Yelp, yielded competitive spillovers data (Fig. 2).
Data collection and filtering

Tweets from a set of 10,000 store locations from the Safegraph GPS movement database were extracted to observe prevalence of tweets over a 6-month period, from May 1 to October 31, 2019, correlating with warmer weather and outdoor movement. Five layers of filtering were applied based on the content and context of the tweets. First, only Tweets that originated from within 48 m of an identifiable store location were considered for further filtering. To ascertain we were examining store visitor (customer) tweets, multi-tweeters who were making announcements for local community boards, traffic and commuting-related announcements, store promotions, and hiring announcements were eliminated. To avoid content such as tourist selfies and the like, we eliminated stores that tend to receive visitors from foreign countries as identified by the GPS movement database. After applying the above filters, stores that generated fewer than 6 tweets were removed.

Of the remaining stores, two coffee retailers, Starbucks and Dunkin Donuts, were selected since they had sufficient store locations (773), split between both Dine-In and Drive-Thru formats. Finally, using polygon estimates, we computed store square-feet areas, estimated store boundaries, and the relationship between emanating tweets and those store boundaries to ascertain that the tweets were posted while customers were inside store boundaries.

The above 773 stores, Dunkin Donuts and Starbucks, were located in 217 US Cities and generated 30,848 tweets from store premises from a period of May 1 to October 31, 2019. Historical tweets were extracted from these addresses and integrated with a separate database of customer movement from these stores which had 2,052,825 tracked visitors in this period. Store visitors’ future visit destinations were matched with a Yelp database of restaurants that were (i) less than 5 miles away from the origin store locations and (ii) served primary menu items of the origin stores. The analysis was performed on store-level data (Table 1).

Table 1 Sources

| Type of data | Name of source |
|--------------|----------------|
| 1 | Social media data generated from retail store addresses of Limited-Service Restaurant Brands | Limited-Service Restaurant Brands |
| 2 | GPS movement data within and from those stores to other stores | Safegraph |
| 3 | Review website data to identify destination stores within proximity that are competitors of the origin store | Yelp |
| 4 | Brands store locators indicating retail format | Starbucks, Dunkin Donuts |
| 5 | Demographic profiles of local zip codes | Census |
| 6 | Restaurant Industry competitor density in the region | US Business Database |
Model and measures

Competitor Spillover Index

The dependent variable, Competitor Spillover Index (CSI), indicates visits to competitor brands that the customers to a given store visited on the same month as the origin store, where customer overlap differs by at least 5% from the data provider’s national average. We extend literature on competitor spillovers (Sahni 2016) which measured users’ visits from a restaurant’s webpage to its competitors, by retrieving customer movements from origin store locations to competitors via anonymized GPS location data.

The Competitive spillover Index was measured in the following steps.

1. **Identifying spillovers**: Safegraph provided information about “Co-visits,” i.e., brands that the visitors to the origin store visited in the same month as the visit to the origin store where customer overlap differs by at least 5% from the database’s national average.

2. **Identifying competitors**: Stores containing common menu items as the origin store were identified as “competitor brands” from Yelp’s restaurant database within a 5-mile radius, common menu items, and store names matched with the Safegraph database. Hence, even McDonald’s, a fast-food chain, could be a competitor brand to the coffee store Starbucks, as their coffee competed with Starbucks. Origin store locations from which visitor movements are tracked (e.g., a Starbucks at 1532 E Algonquin Rd Fl 1, Algonquin IL 60102) are known as Point Of Interest (POI).

3. **The competitor spillover (CS) score for each competitor of the POI (referred to as the “competitor brand”) is a percentage representing the median of the following calculation:** (same-month visitors to both the competitor brand and the POI / total monthly visitors to the POI) — (monthly visitors to the competitor brand / total monthly visitors in Data panel). As an example, Dunkin Donuts (competitor brand) was found via Yelp nearby Starbucks (POI) carrying similar menu item (coffee), and since the Safegraph data showed visitors to Starbucks also visited Dunkin Donuts within 30 days, the above metric for Dunkin Donuts (21) from the Safegraph database was included in the CS score for Starbucks visitors. In essence, the CS score for each brand represents the extent to which visitors to the POI co-visit other specific brands over and above the average stores in the data panel.

4. Further, the CSI for a POI is computed as a sum of the CS values of all competitor brands co-visited over a period of 30 days.

Overall, the competitive spillover measure for point of origin store p, to competitor brand c, is given as below,

\[
CS_{pc} = \frac{V_{pc}}{V_p} - \frac{V_c}{V_{..}} \times 100
\]

with \(V_{..}\) representing the total number of monthly visitors in the panel data set, \(V_c\) being the monthly visitors to competitor c, \(V_p\) being the monthly visitors to point of origin p, and finally \(V_{pc}\) is the same-month visitors to both point of origin store p and competitor store c.

\[
CSI_p = \sum_{c=1}^{n} CS_{pc}
\]

Hence, \(CSI_p\), the Competitor Spillover Index is a sum of Competitor Spillover values for origin store p, to n competitor brands. For example, in Fig. 3, the origin store is Starbucks at 1532 E Algonquin Rd Fl 1, Algonquin IL 60102, the competitor brands are \{McDonalds, Dunkin Donuts\} as both these outlets shared coffee on the menu and were within 5 miles of the POI; the CS values are \{42; 21\} and the CSI is 63.

Physical engagement with the store

a. **Dwell time**: This was measured as the median time (in minutes) customers spent inside stores provided by the Safegraph Panel.

b. **Crowding**: Total number of visitors on each store premise over 6 months was divided by square footage of the

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**Fig. 3** CSI data format

| POI       | Street Address | Co-Visits (From Safegraph) | CS of Competitor Brands (Matched with Yelp’s menu and proximity) | CSI |
|-----------|----------------|---------------------------|---------------------------------------------------------------|-----|
| Starbucks | 1532 E Algonquin Rd Fl 1, Algonquin IL 60102 | \{'McDonald's";42,"Walmart";35,"Walgreens";33,"Jewel-Osco";32,"Thorntons";30,"Target";28,"BP";28,"Shell Oil";24,"Dollar Tree";21,"Dunkin";21,"Panera Bread";20,"Mobil";19,"Portillo's Restaurants";19,"Subway";19,"Kohls";18,"Meijer";15,"ALDI";15,"Taco Bell";15,"Culver's";15,"T.J. Maxx";14\} | McDonald's:42; Dunkin":21 | 63 |
store. Both variables, number of visitors and square footage, were from Safegraph.

**Virtual engagement with the store**

iii. **Situated Engagement Index:** Of the 30,848 tweets collected from store premises, SEI was computed from tweets generated from store premises containing brand mentions. The measure developed is inspired by the three dimensions of perceived engagement from Dwivedi (2015). In effect, it includes, from each store, enthusiasm, calculated from store-generated tweets using ANEW scale (Bradley and Lang 1999), vigor, indicated as prevalence (%) of location-based tweets containing brand mentions, and absorption, indicated by number of words used in the tweets with brand mentions. An average of the standardized values of these three indicators for each store helped compute the Situated Engagement Index.

iv. **Situated Virality Index:** An index was adapted from Arora et al. (2019); including likes, retweets, and replies to messages posted on social media. We retrieved likes, retweets, and replies of the above tweets for each store location and computed an average of the standardized values to generate an index for each store.

v. **Network Reach:** This variable measures how many social media users are exposed to in-store tweets containing brand mentions. It is a weighted sum of the product of frequency of a user’s tweets and his follower count. For example, if a Starbucks store has two users tweet containing their brand mentions, the first one has 100 followers and tweets twice; the second has 200 followers and tweets thrice; the Network Reach of the Starbucks store is \((100 \times 2) + (200 \times 3) = 800\).

**Control variables**

f. **Competitors per square mile:** Number of coffee shops in the zip code was retrieved from the US Business Database and then divided by area of zip codes in square miles.

g. **Race (%White):** Percentage of population in the zip code that is White, retrieved from Census data.

h. **Median Age:** Median age of residents of the zip code, retrieved from Census Data.

i. **Household Income:** Median household income in the zip code, retrieved from Census Data

**Scenarios**

We observe two brands across two types of retail format, Dine-In and Drive-Thru. The two brands are Starbucks and Dunkin Donuts.

**Analysis and findings**

**External validation of metrics**

(1) **Higher** the density of the population in the zip code, more time people are willing to spend inside stores in the area. In other words, people prefer not to hangout in isolated or sparsely populated areas.

(2) The **more crowded** the stores are, **higher** are the number of store reviews on Yelp.

(3) The **higher** are the store’s ratings on Yelp, **higher is** the Spillover Index, i.e., engagement measured from In-Store tweets (Table 2).

**Data distribution and model specification**

The methodology needs to suit the characteristics of our data. CSI is count data that are likely to display overdispersion as demonstrated by a long tail distribution. Hence, we observe the CSI distribution and run tests to find that (i) the long tail pattern exists, and (ii) the distribution of the dependent variable demonstrated, by the Kolmogorov–Smirnov and the Shapiro–Wilk tests, that the CSI fits neither the normal nor the Poisson distributions (Fig. 4; Table 3).

| Dependent variable | Predictor                  | Unstandardized Beta | SE         | Standardized Beta | t        | Sig     |
|--------------------|---------------------------|---------------------|------------|-------------------|----------|---------|
| Dwell time         | Population density        | 0.00                | 0.00       | 0.11              | 3.18     | 0.0015  |
| Crowding           | Number of reviews on yelp  | 0.0030              | 0.0015     | 0.0684            | 2.0189   | 0.0440  |
| (Situated Engagement from Tweets) | Store rating on yelp | 0.0121              | 0.0034     | 0.1177            | 3.5608   | 0.0004  |
To examine which model fits best, we consider Negative Binomial and the Poisson, which is a simpler special case of the Negative Binomial models (Schmittlein et al. 1987, p. 5). We use a likelihood ratio (LR) test to determine whether a Poisson or Negative Binomial model fits best. The null hypothesis of the LR-test posits that the equidispersion assumption, i.e., \( \mu = \sigma^2 \); implicit in the Poisson model; is true (Cameron and Trivedi 2013). The Negative Binomial model estimates an additional parameter, theta (\( \theta \)), relaxing that assumption. Results in Table 4 show that the null hypothesis of the Poisson restriction is rejected in favor of a Negative Binomial regression for all four scenarios (Dunkin Donuts and Starbucks, Dine-Ins and Drive-Thrus) since all four \( \chi^2 \) values, 35,844.994, 3761.253, 50,910.914, 45,983.388 for CSI exceed 2.705, and yield \( p \)-values < 0.001. Based on the likelihood tests and fit criteria similar to Rietveld, van Dolen et al. (2020), we find that a Negative Binomial specification is more appropriate to model CSI due to overdispersion in the data. As a result, we adopt a count data model with a Negative Binomial distribution to allow for overdispersion. The model is often used for overdispersed count data such as CSI, here called \( y_i \). We observe \( y_i \) follow-up visits to a competing store with probability
\[ p(y_i) = \frac{\Gamma(y_i + \alpha)}{\Gamma(\alpha)\Gamma(y_i + 1)} \left( \frac{\alpha}{\alpha + \mu_i} \right)^\alpha \left( \frac{\mu_i}{\alpha + \mu_i} \right)^{y_i}, \]

where \( E(y_i) = \mu_i = \exp(x_i^T\beta) \) is the vector of independent variable values for the \( i \)th retail outlet, and \( \beta \) contains the unknown parameters of interest. The above parameterization is called NB2 (Hilbe 2011). In our case, the values \( \mu_i \) are interpreted as the predicted rate of CSI for consumers who had visited the \( i \)th retail outlet. The additional parameter \( \alpha \) handles the relative surplus of zero visits.

### Results

In this section in Table 5, we discuss the results from our models across the four scenarios and conclude with a comparison of the elasticities and effects of physical and virtual engagement. The Negative Binomial models for Dunkin Donuts Dine-Ins \((\chi^2(11) = 67.44, p = 0.000)\), Dunkin Donuts Drive-Thrus \((\chi^2(11) = 47.32, p = 0.000)\), Starbucks Dine-Ins \((\chi^2(11) = 52.40, p = 0.000)\), and Starbucks Drive-Thrus \((\chi^2(11) = 90.61, p = 0.000)\) show that all 4 scenario models are significant as a whole. The model explains the variance in the CSI in all 4 scenarios with a Pseudo \( R^2 \) of 0.32% for Dunkin Donuts Dine-Ins, 2.33% for Dunkin Donuts Drive-Thrus, 0.18% for Starbucks Dine-Ins, and 0.68% for Starbucks Drive-Thrus. Table 6 provides tests of all 4 models as whole (Omnibus Test). The likelihood ratio chi-square provides a test of the overall model comparing these models to models without any predictors (a “null” model). We can see that our models are all significant improvements over null models by looking at the \( p \)-value of this test.

### Physical engagement

Our results suggest that for Dunkin Donuts Dine-In \((\beta = -0.03, p < 0.01)\), Starbucks Dine-In \((\beta = -0.013, p < 0.01)\), and Starbucks Drive-Thru \((\beta = -0.018, p < 0.05)\), increases in dwell time lower future competitor visits. However, for Dunkin Donuts Drive-Thru \((\beta = -0.13, p > 0.65)\), dwell time has no significant effect on future competitor visits. Crowding displays a negative effect on competitor visits for Dunkin Donuts Dine-In \((\beta = -0.23, p < 0.01)\), but no significant effects on Dunkin Donuts Drive-Thru \((\beta = 1.13, p > 0.65)\), Starbucks Dine-In \((\beta = 0.03, p > 0.30)\), and Starbucks Drive-Thru \((\beta = -0.092, p > 0.26)\). Dwell time and crowding interaction have a positive effect on competitor visits for Dunkin Donuts Dine-In \((\beta = 0.01, p < 0.01)\), but display no significant effects on Dunkin Donuts Drive-Thru \((\beta = 0.12, p > 0.70)\), Starbucks Dine-In \((\beta = 0.001, p > 0.50)\), and Starbucks Drive-Thru \((\beta = -0.11, p > 0.11)\). Longer people hang out at a store, and more crowded or popular it is, higher is the likelihood of being engaged physically with the store, so it makes sense that these stores show fewer competitor visits. However, as more and more people start hanging out longer at these locations, it may lead customers to compete for products and services, thus inducing irritation and triggering increased spillover competitor visits in future. In essence, Dunkin Donuts Dine-In stores show that physical engagement affects future competitor visits in unexpected directions, but not Starbucks (Table 7).

### Virtual engagement

Our results suggest that Situated Engagement has no significant effects for Dunkin Donuts Dine-In \((\beta = -0.25, p > 0.80)\), Starbucks Dine-In \((\beta = 0.356, p > 0.54)\), Dunkin Donuts Drive-Thru \((\beta = -2.08, p > 0.86)\) but it does on Starbucks Drive-Thru \((\beta = -2.628, p < 0.03)\). However, social media’s responses to Situated Engagement significantly affects CSI for both Starbucks Dine-In \((\beta = 4.68, p < 0.04)\) and Starbucks Drive-Thru \((\beta = -83.6, p < 0.01)\), but not Dunkin Donuts Dine-In \((\beta = 1.13, p > 0.30)\), or Dunkin Donuts Drive-Thru \((\beta = 3765, p > 0.40)\). The Network Reach made effective by the store’s Situated Engagement negatively affected CSI for Dunkin Donuts Drive-Thru \((\beta = -0.0003, p < 0.02)\), Starbucks Dine-In \((\beta = -0.00001, p < 0.01)\), as well as Starbucks Drive-Thru \((\beta = -0.00005, p < 0.01)\). The effect of social media responses on CSI is positive for Starbucks Dine-In restaurants, but negative for Starbucks Drive-Thrus. This is expected because for coffee shops Dine-In restaurants are located in regions very densely packed with competitors, thus social buzz inspires more excitement in the coffee category and inspires higher CSI, whereas Drive-Thrus are located in areas with very few competitors, and social buzz inspires greater loyalty.

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**Table 4** Model specification

| Model specification          | BIC difference (PRM-NBRM) | AIC difference (PRM-NBRM) | Likelihood ratio \( (\chi^2) \) | Sig. \( (p) \) |
|------------------------------|---------------------------|---------------------------|-----------------------------------|----------------|
| Dunkin Donuts Dine-In        | 35,839.551                | 155.164                   | 35,844.994                        | 0.00           |
| Dunkin Donuts Drive-Thru     | 3758.034                  | 150.37                    | 3761.253                          | 0.00           |
| Starbucks Dine-In            | 50,905.155                | 160.596                   | 50,910.914                        | 0.00           |
| Starbucks Drive-Thru         | 45,978.411                | 317.113                   | 45,983.388                        | 0.00           |
Interactions

The Dwell time × Situated Engagement interaction between physical and virtual engagement displays a positive effect on CSI for Dunkin Donuts Dine-In stores ($\beta = 0.062$, $p < 0.005$), implying that though increase in physical engagement lowers CSI, such a rise coupled with an increase in Situated Engagement can increase CSI. This is expected because Dine-In formats of coffee stores are situated around dense competition, and excitement experienced in one store can spillover in the form of visits to other stores in the same category. However, the effect of the interaction on CSI for Dunkin Donuts Drive-Thru was marginally significant ($\beta = 0.884$, $p < 0.08$), whereas those for Starbucks Dine-In ($\beta = −0.022$, $p > 0.50$), and Starbucks Drive-Thru ($\beta = 0.1$, $p > 0.11$) were not significant.

Scenarios

Overall, the Dunkin Donuts retail formats demonstrated greater effects of physical engagement and physical-virtual interaction on CSI, whereas Starbucks stores displayed stronger effects of virtual engagement on CSI. The Dwell Time x Situated Engagement interaction led to more CSI for Dunkin Donuts (Dine-In and Drive-Thru) but not for Starbucks. Observing the pseudo-$R^2$, we notice that Dunkin Donut stores also explain more variance in CSI than Starbucks stores. Also, within brands, the virtual and the physical engagement explain more CSI from the Drive-Thru format than from Dine-In stores. This could be because the Dine-In stores are located in high competitor density areas with greater variety of marketing stimuli and alternate influencers that can trigger CSI, whereas in regions with Drive-Thrus, there are fewer competitors and alternate influencers.

Control variables

To find effects of virtual and physical engagement on CSI, we included a set of control variables regarding neighborhood characteristics, i.e., competitor density, race, household income, and median age of the zip codes in which stores were located. All control variables significantly predicted CSI for Dunkin Donuts Drive-Thrus; race, income,
Discovering synergies and conflicts in online and offline in-store engagement and age were significant for Starbucks Dine-Ins, race and competition were significant for Starbucks Drive-Thrus, whereas race and income were significant for Dunkin Donuts Dine-Ins.

**Elasticities**

To illustrate the relative importance of physical and virtual engagement-related metrics, we calculated the elasticities using the average values of the variables. The elasticities indicate that an increase of 1% of a predictor will lead to a corresponding % increase in CSI. For Dunkin Donuts, the Dine-In stores display stronger influences of physical engagement such that a 1% increase in Dwell Time and Crowding reduce CSI by (0.86%, 0.37%) whereas a 1% increase in Dwell Time × Crowding, increases CSI by 0.28%. A 1% increase in Dwell Time × Situated Engagement increases CSI by 0.18%. Overall, for Dunkin Donuts Dine-In stores, physical engagement is the most dominant predictor, led by Dwell Time. For Dunkin Donuts Drive-Thru, a 1% increase in Network Reach reduces CSI by 0.6%. In other words, for Dunkin Donuts Drive-Thrus, virtual engagement plays a stronger role than physical engagement compared to Dine-In stores. In Starbucks Dine-In stores, a 1% increase in Situated Virality increases CSI by 0.028% whereas a 1% increase in Dwell Time and Network Reach reduces CSI by 0.36% and 0.08%, respectively. In Starbucks Drive-Thru stores, a 1% increase in Dwell Time, Situated Engagement, Situated Virality and Network Reach lower CSI by 0.32%, 0.30%, 0.26%, and 0.5%, respectively. Overall, for both retail formats of Starbucks, Network Reach displays stronger influence than Situated Virality, and Dunkin Donuts displays stronger effects of physical engagement than virtual.

**Multicollinearity**

We examined the Variance Inflation Factors (VIFs) to rule out multicollinearity. For Dunkin Donuts Dine-Ins, Starbucks Dine-Ins and Starbucks Drive-Thrus, the VIF scores were below the critical cut-off value of 5, with the highest VIF being 3. For these scenarios, we conclude that multicollinearity is not a concern. However, for Dunkin Donuts Drive-Thrus, the lowest sample scenario (N=25), several variables including Dwell Time, Crowding, and Situated Engagement displayed VIFs over 5.00. While most of these variables were not significant, the interaction term Dwell Time × Situated Engagement, though marginally significant, should not be used to draw inferences for reasons of collinearity. However, Network Reach, which is the only significant factor, can be interpreted as illustrated in the previous section, as its VIF (1.8), is below the critical threshold (Table 8).

A further comparison with OLS models on the same data revealed NBRM is a better choice (Table 9).

**Discussion**

Our study explores whether engagement indicators from physical and virtual platforms have convergent effects on competitor store visits. Using a Negative Binomial model, we find that CSI of store visitors is contingent upon indicators of both physical and virtual engagement. However, the extent to which the dominant platform is physical or virtual depends on the brand’s audience and the retail format. So we discuss the answers to several questions. Is one medium more favorable to a specific brand? What evidence exists for Cannibalization or Convergence? Does Context play a role in their cannibalization or convergence?

First, Dunkin Donuts customers CSI are significantly explained by their physical engagement metrics, but not by virtual. In contrast, Starbucks stores weigh heavily on virtual engagement metrics, while one metric of physical engagement, Dwell Time, is also significant. This demonstrates, the dominant influence of one platform, varies by brand and the audience they serve.
### Table 8 Parameter values by brand and retail format

| Parameter                        | Dunkin Donuts Dine-In | Dunkin Donuts Drive-Thru | Starbucks Dine-In | Starbucks Drive-Thru |
|----------------------------------|-----------------------|--------------------------|-------------------|----------------------|
| (Intercept)                      | $\beta$ 4.01          | Sig. ($p <$) 0.00        | $\beta$ 6.89      | Sig. ($p <$) 0.1     | $\beta$ 2.457        | Sig. ($p <$) 0.000    | $\beta$ 5.211        | Sig. ($p <$) 0.0     |
| Physical engagement metrics     |                       |                          |                   |                      |                       |                          |                   |                      |
| Dwell Time                       | $\beta$ -0.03         | Sig. ($p <$) 0.00        | $\beta$ -0.13     | Sig. ($p <$) 0.68    | $\beta$ -0.013       | Sig. ($p <$) 0.000    | $\beta$ -0.02        | Sig. ($p <$) 0.048  |
| Crowding                         | $\beta$ -0.23         | Sig. ($p <$) 0.00        | $\beta$ 1.13      | Sig. ($p <$) 0.68    | $\beta$ 0.028        | Sig. ($p <$) 0.331    | $\beta$ -0.09        | Sig. ($p <$) 0.27   |
| Dwell Time x Crowding            | $\beta$ 0.01          | Sig. ($p <$) 0.00        | $\beta$ 0.12      | Sig. ($p <$) 0.72    | $\beta$ 0.001        | Sig. ($p <$) 0.506    | $\beta$ -0.01        | Sig. ($p <$) 0.11   |
| Virtual engagement metrics      |                       |                          |                   |                      |                       |                          |                   |                      |
| Situated Engagement Index (SEI)  | $\beta$ -0.25         | Sig. ($p <$) 0.81        | $\beta$ -2.08     | Sig. ($p <$) 0.87    | $\beta$ 0.356        | Sig. ($p <$) 0.546    | $\beta$ -2.63        | Sig. ($p <$) 0.029  |
| Situated Virality Index          | $\beta$ 1.13          | Sig. ($p <$) 0.31        | $\beta$ 3765.01   | Sig. ($p <$) 0.42    | $\beta$ 4.678        | Sig. ($p <$) 0.030    | $\beta$ -83.6        | Sig. ($p <$) 0.009  |
| Network Reach                    | $\beta$ 0             | Sig. ($p <$) 0.99        | $\beta$ -0.0003   | Sig. ($p <$) 0.02    | $\beta$ -0.00001     | Sig. ($p <$) 0.000    | $\beta$ -0           | Sig. ($p <$) 0      |
| Interaction                      |                       |                          |                   |                      |                       |                          |                   |                      |
| Dwell Time x SEI                 | $\beta$ 0.06          | Sig. ($p <$) 0.88        | $\beta$ 0.08      | Sig. ($p <$) 0.08    | $\beta$ -0.02        | Sig. ($p <$) 0.512    | $\beta$ 0.1          | Sig. ($p <$) 0.119  |
| Control variables                |                       |                          |                   |                      |                       |                          |                   |                      |
| Competitors per square mile      | $\beta$ 0             | Sig. ($p <$) 0.53        | $\beta$ 1.96      | Sig. ($p <$) 0       | $\beta$ 0            | Sig. ($p <$) 0.020    | $\beta$ 1.002        | Sig. ($p <$) 0.045  |
| Race (White %)                   | $\beta$ 1.87          | Sig. ($p <$) 0           | $\beta$ -7.17     | Sig. ($p <$) 0.01    | $\beta$ 0.368        | Sig. ($p <$) 0.306    | $\beta$ -0.03        | Sig. ($p <$) 0.206  |
| Median age                       | $\beta$ 0.02          | Sig. ($p <$) 0.11        | $\beta$ 0.33      | Sig. ($p <$) 0.01    | $\beta$ 0.036        | Sig. ($p <$) 0.005    | $\beta$ 0            | Sig. ($p <$) 0.127  |
| HHI                              | $\beta$ 0             | Sig. ($p <$) 0.01        | $\beta$ 0         | Sig. ($p <$) 0       | $\beta$ 0            | Sig. ($p <$) 0.058    | $\beta$ -0.54        | Sig. ($p <$) 0      |

### Table 9 Comparison between OLS and NBRM

| Parameter                        | Dunkin Donuts Dine-In | Dunkin Donuts Drive-Thru | Starbucks Dine-In | Starbucks Drive-Thru |
|----------------------------------|-----------------------|--------------------------|-------------------|----------------------|
|                                 | OLS Beta (SE)         | NBRM Beta (SE)           | OLS Beta (SE)     | NBRM Beta (SE)       |
| Dwell Time                       | NS (0.004)            | NS                       | NS (0.0037)       | NS                   |
| Crowding                         | NS (0.061)            | NS                       | NS                | NS                   |
| Dwell Time x Crowding            | NS (0.002)            | NS                       | NS                | NS                   |
| Situated Engagement Index (SEI)  | NS                    | NS                       | NS                | NS                   |
| Situated Virality Index          | NS                    | NS                       | NS                | NS                   |
| Network Reach                    | NS                    | NS                       | NS                | NS                   |
| Dwell Time X SEI                 | NS (0.02)             | NS                       | NS                | NS                   |
| Competitors per square mile      | NS (0.468)            | NS                       | NS                | NS                   |
| Race (White %)                   | 181.156 (64.54)       | NS                       | NS                | 1.002 (0.499)        |
| Median Age                       | NS                    | NS                       | NS                | NS                   |
| HHI                              | NS (0.00008)          | NS                       | NS                | NS                   |
Second, we notice that while both retail formats of Starbucks show significance of both physical and virtual engagement indicators, the Dine-In retail format demonstrates effects of cannibalization, whereas the Drive-Thru retail format shows all effects of indicators are convergent. In other words, for Dine-In formats, different indicators affect outcomes in opposite directions, some positive and some negative, thus deterring from each other’s effects. However, for Drive-Thru format, all engagement indicators lower CSI. It is thus reasonable to assume that physical and virtual engagement converge toward the outcome in retail contexts as Drive-Thrus for Coffee Stores, where competitor density is low, and alternatives are limited. However, in contexts where retail competition is high, effects of physical and virtual engagement may be in opposite directions (cannibalization) on competitor spillovers.

Third, a caveat in the above logic: in the Starbucks Dine-In format, two indicators of virtual engagement have opposite significant effects on CSI. Increased virality demonstrates a positive effect on (an increase in) CSI, likely due to high competitor density in the surroundings and consequent WOM Spillover effects consistent with the findings of Sanchez et al. (2020). However, Network Reach has a negative effect on CSI, which indicators that multiple indicators of engagement even within the same platform can cannibalize each other in terms of effects toward competitor spillovers.

Fourth, the Dunkin Donuts Dine-In also demonstrates a significant interaction between physical and virtual engagement, though virtual engagement indicators are not significant. This is consistent to “catalytic effects” of media synergy, which accounts for a medium that by itself may not contribute to outcomes but has an effect in interaction with other media (Raman and Naik 2004). Hence, for Dunkin Donuts Dine-In formats, virtual engagement can be an effective accomplice, but not the primary driver for engagement.

The findings in this paper about effects of physical and virtual engagement indicators on a common outcome provide an interesting extension to the literature on advertising spillover effects (Sanchez et al. 2020). Overall, we conclude that both physical and virtual engagement indicators can explain future CSI, where the cannibalization-convergence effects depend on brand and retail format. As store locations (and hence formats) change from sparsely populated to high-density areas, with more competing outlets and sources of information, virtual and physical engagement have more incongruent effects on competitive spillovers.

**Managerial insights**

Broadly, managers can use the findings of this study to set their expectations of customers future behaviors. Managers of Starbucks Drive-Thrus know increases in physical and virtual engagement are likely to reduce CSI, but for Dine-Ins they know situated virality can increase CSI. In such circumstances, managers need to monitor social media feeds of store visitors such that sensational updates can be cautioned against and balanced with incentives for retention. Based on such monitoring, Starbucks managers can track engagement metrics by regions, or cities to detect danger zones where customers are likely to visit competitors. For example, view below the application of situated virality scores, which are sensitive to context (Dine-In or Drive-Thru) (Table 10).

For Dine-In stores, higher situated virality implies higher risk for CSI, so cities Dublin, Edgewater, and Forest Hills which have higher situated virality scores seem to be at higher risk. In contrast, for Drive-Thrus, lower situated virality implies higher risk for CSI, so cities below the average score, i.e., Irving, Mesquite, and Naperville are at greater risk. Such monitoring frames for indicators of engagement can be deployed to determine future courses of action. Network Reach is a metric that can be monitored to assess if the physical stores are populated by virtually active social media celebrities. So even if a store does not have a lot of visitors, having a few visitors who post frequently from inside the store to large social media followings can become engagement assets for the store. In the case of Dunkin Donuts Dine-Ins, managers know that increases in both Dwell Time and crowdedness are likely to increase CSI. Hence, stores which detect increases in both can provide incentives and promotions to customers in the store to spillover to Dunkin Donuts stores in the vicinity that are not as crowded. The above is an example of how the output of the analysis can be used as a decision-aid for monitoring stores by managers, and one would need to account for biases in neighborhood size and other attributes to draw more generalizable conclusions from the above scores.

| Starbucks Dine-In | Starbucks Drive-Thru |
|-------------------|----------------------|
| Dublin 0.032      | Oak Lawn 0.041       |
| Edgewater 0.026   | Denton 0.029         |
| Glen Ridge 0.025  | Grand Prairie 0.024  |
| Kearny 0.024      | McKinney 0.018       |
| Ridgewood 0.024   | Brentwood 0.017      |
| Forest Hills 0.020| Frisco 0.017         |
| **Average** 0.003 | Fort Worth 0.009      |
| Chicago 0.001     | **Average** 0.002    |
| Emeryville 0.001  | Irving 0.001         |
| Egle 0.001        | Mesquite 0.001       |
| Iselin 0.001      | Mount Kisco 0.001    |
| Long Beach 0.001  | Naperville 0.001     |
| Madison 0.001     | Scarsdale 0.001      |
A broader use is that Customer Service departments of branded stores can utilize such public data sources to monitor effects trigger events and promotions can have at specific locations, and how these events affect physical and virtual engagement and then competitor store visits over next 30 days. Performance differences across locations can be further benchmarked based on demographic composition of localities and their other market characteristics. The model presented in this paper can be used to not only supplement primary research on consumer insights to moderate store operations, but also decide on effectiveness and expansion of variety of store formats. Even before the Covid-Crisis, 80% of Starbucks customer transactions were on-the-go, merging their physical and digital offerings through the Starbucks app (Meisenzahl 2021). The company has accelerated its focus on pickups, curbsides as a part of a nationwide strategy.

The engagement variables in this model raises some deeper questions about the positioning of a corporation’s brand. The pandemic has led retail brands to move increasingly online, developing augmented models to mix online shopping decisions with physical delivery. This has led to more uncertainty about spaces in which brands would like to engage customers. Starbucks has been positioning itself as a “third-space” place outside of home and work where people “connect” for a coffee. At the same time, they have been expanding Drive-Thrus with limited physical engagement. The above model can help us monitor how this “connect” is being accomplished, physically or virtually. If increasing multiple sources of physical engagement, crowdedness and median Dwell Time in Dunkin Donuts Dine-In stores are leading customers away from their stores, and if Starbucks customers in Drive-Thrus are responding favorably to virtual engagement, it is possible that the market is growing toward a model of connecting and engaging virtually rather than physically. Further evidence is provided by the effects of Network Reach, which demonstrates that situated interactions with virtual celebrities reduce CSI across brand and retail format, raising more scrutiny on the perceived benefits of physical congregation. The virtual engagement discussed in this paper is physically situated, which still reinforces the importance of the context of the virtual engagement. But if customers are moving toward more effective virtual interactions, does the company need to pursue retail design so as to make customers spend more time hanging out inside their store environments? The data collected in this study were before the pandemic and thus the effects were not due to external factors. In fact, one would expect some of these effects have been magnified post-pandemic due to evident aversions to physical connection and social distancing.

Limitations and directions for future research

This study is subject to some limitations. First, given that we created an observational study integrating sources of secondary data, design of the metrics we have chosen are limited by data availability. For example, our measures of physical engagement, CSI are defined by measures created by data aggregators. Second, our definition of Situated Engagement, which operationalizes valence as one of the dimensions, is measured using the ANEW algorithm that does not account for negative emotions. Third, there are few retail brands, categories, and formats from which sufficient volumes of social media posts can be captured on premises. Though it makes observing the phenomenon unique and novel, it restricts the generalizability of the study across categories, brands, and formats. Additional generalizability concerns may stem from the big difference in degrees of freedom across the different formats of restaurants. Inferences regarding significance may be affected by the sample size of the restaurant. Overall, one should acknowledge that these limitations are not absolute; in other words, alternative designs to study the same phenomenon using primary data or field experiments would generate different types of limitations. The data analyzed in this study are behavioral data (physical movement and tweets), and the validity conferred by such data can be considered an asset.

The expanding universe of publicly available data is providing marketers new opportunities to explore the realm of Geographical psychology, which focuses on the “spatial distribution of psychological phenomena at the macro-level” (Chen et al. 2020) and their relationship to social and behavioral outcomes. These approaches can be utilized, like in the current manuscript, to observe geographic distributions of consumer responses to marketing actions of brands. Future research needs to take two directions for expanding this line of scholarship: one, is primary data collection investigating mediating variables and psychological effects of virtual environments and interactions on future behaviors; two, is computational statistical research methods and techniques that can identify ways to gather and observe the volumes of location-based data generated across establishments or regions. This would help us know how many tweets are generated by location, brand, for relevant periods of time. The data collection and filtering conducted in the current manuscript were an iterative process used in the absence of established methods for the same. Overall, engagement research needs to grow by drawing from geographical psychology, where engagement is measured cross platforms and more holistically rather than in silos.
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Declarations

Conflict of interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

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