Decomposing Spillover Effects in Shopping Malls

Manuel Weber
WHU - Otto Beisheim School of Management
Christian Schlereth
WHU - Otto Beisheim School of Management

Cite as:
Weber Manuel, Schlereth Christian (2024), Decomposing Spillover Effects in Shopping Malls. *Proceedings of the European Marketing Academy*, 52nd, (119163)

Paper from the 53rd Annual EMAC Conference, Bucharest, Romania, May 28-31, 2024

Decomposing Spillover Effects in Shopping Malls

Abstract:

With the rise of indoor customer tracking, many shopping mall operators are installing sensor technologies to gain insights into customer behavior and movement patterns. However, limited research exists on cross-store spillovers and their economic impact. This study employs network analysis techniques to explore the link between store performance and spillover effects. We decompose spillover into customer inflow from the mall entrance or another store and customer outflow to the mall exit or another store and derive four spillover metrics. Using customer tracking and store sales data from a German mall, we find that first and last stops in a customer's shopping trip are more valuable than intermediate stops. Stores gaining more first-stop and last-stop shoppers can enhance performance. This unexplored link between foot traffic and store performance provides practical guidance for mall operators and retailers to optimize individual stores within a mall.

Keywords: Indoor Customer Tracking, Spillover Effects, Network Analysis

Track: Retailing & Omni-Channel Management

1. Introduction

Shopping malls, hereinafter referred to as malls, have long been at the intersection of commerce and community, serving as vibrant hubs for retail activity. Yet, the foot traffic dynamics within these ecosystems have largely remained a black box. The retail stores within the mall form a network. While some stores attract a disproportionately high number of customers to the mall, others benefit from cross-store customer spillovers. Rent payments of a store are usually based on a pre-negotiated share of sales, with large stores receiving rent discounts (see Pashigian & Gould, 1998). However, rent payments are not based on actual foot traffic to the store and, thereby, do not precisely reflect the importance of individual stores for the mall as a whole. Consequently, a mere sales perspective hinders mall operators in optimizing tenant mixes and enhancing the overall shopping experience for customers.

At the same time, mall operators are increasingly investing in sensor technologies that track offline customer behavior (The Economist, 2023). With these technologies, mall operators aim to catch up with online retailers' numerous web-tracking possibilities. Retailers can also benefit from tracking technologies to better understand customer characteristics and habits, introduce new real-time advertising solutions, identify peak times, and find ideal locations for store promoters inside the mall. Furthermore, mall operators can use sensor technologies to generate insights on spillovers inside the mall. However, the relationship between spillovers and individual store performances is largely unknown. Especially movement patterns, such as if the store was the first, the last, or an intermediate stop on a customer's shopping trip, are unexplored.

We aim to (1) decompose spillover effects and (2) measure the economic value of spillovers in terms of store performance. For that purpose, we define spillovers as all movements from and to a store, decompose them into customer inflow and outflow using network analysis techniques, and identify suitable spillover metrics (see Chung, Ahn, & Ahn, 2022). For the customer inflow, we distinguish between customers who enter the store as a first stop on their shopping trip ("first-stop shoppers") and those who have visited another store before. For the customer outflow, we distinguish between customers who leave the store as a last stop on their shopping trip ("last-stop shoppers") and those who continue shopping in other stores. In our empirical study, we draw insights from two unique datasets collected in a regional mall in Germany over 15 months: a 3D sensor customer tracking dataset and the monthly sales dataset for each store.

Our study carries profound implications for academia and industry alike. Researchers gain a novel lens for examining spillover effects in a mall as we integrate cutting-edge technology with established consumer behavior theory, addressing a critical gap in the literature. Practitioners gain actionable insights for optimizing store locations, influencing customer movement paths, and maximizing sales. We are the first to combine store sales data in a mall with (GDPR-compliant) customer tracking data and to measure the relationship between foot traffic and store performance. Finally, we transfer two methods primarily used in online marketing to stationary retail: network analysis and customer tracking.

2. Literature Review

Research on mall dynamics and tenant mixes was prominent in the 1990s and early 2000s (e.g., Bloch, Ridgway, & Dawson, 1994; Ganesh, Reynolds, & Luckett, 2007). It has recently gained a revival with the rise of traffic tracking technologies (e.g., Liu et al., 2019).

Eppli and Benjamin (1994) divided the research on malls into four areas: central place theory, i.e., "the relationship between retail trade area size and distance traveled to the retail area" (p. 6), retail agglomeration economics, i.e., the clustering of heterogeneous and homogeneous retailers in a mall (p. 11), mall lease valuation (e.g., Benjamin, Boyle, & Sirmans, 1990), and spillover effects, which they called "retail demand externalities" arguing that larger stores generate customer traffic for smaller stores exhibiting an externality effect. Spillover effects have mainly been studied in cross-sectional studies, i.e., by comparing mall characteristics such as the number of large chain stores in a mall and resulting store performances (e.g., Gould, Pashigian, & Prendergast, 2005). More recently, Chung et al. (2022) have investigated spillover effects as foot traffic between a mall and retail stores in the surrounding area but not within a mall and not linked to store sales. Other studies focused on shopper typologies in malls (e.g., Bloch et al., 1994; Ganesh et al., 2007), space allocation (e.g., Yuo & Lizieri, 2013), and new store entries into existing retail clusters (e.g., Ailawadi, Zhang, Krishna, & Kruger, 2010).

In recent years, a new research stream on customer tracking technologies for in-store (e.g., Hui, Huang, Suher, & Inman, 2013; Kakatkar & Spann, 2019) and out-of-store (e.g., Vallapuram, Kwon, Lee, Xu, & Hui, 2022) stationary retail settings, such as malls, has emerged. We show a selection of studies focusing on spillover effects in malls from both research streams in Table 1. In this study, we combine the research streams on malls by analyzing spillover effects using out-of-store customer tracking data as well as store performance data.

Author(s) (Year)	Dependent Variable(s)	Study Type	Store Performance	Cross-Store Movements	Size of Dataset
Eppli (1991)	Store sales density	Cross-sectional study	yes	no	approx. 4,500 stores in 54 malls
Gould et al. (2005)	Store rent density and sales density	Cross-sectional study	yes	no	approx. 2,500 stores in 35 malls (one year)
Simona Damian, Dias Curto, and Castro Pinto (2011)	Total mall customer traffic	Cross-sectional study	no	no	approx. 4,000 stores in 35 malls (three years)
Pei et al. (2020)	Customer traffic density	Foot traffic study	no	yes	approx. 600,000 customers in two shopping malls, approx. 600 stores (one week)
Vallapuram et al. (2022)	Customer traffic (app registrations)	Foot traffic study	no	yes	272,079 stores in 625 London neighborhoods (three years)
This study	**Store sales density**	**Foot traffic study**	**yes**	**yes**	**approx. 22 million movements and sales of 31 stores over 15 months**

Notes. Density is measured per square meter.

Table 1. Literature Table

3. Spillover Measurement

3.1 Network analysis of foot traffic

We applied network analysis techniques to measure spillovers in a mall in terms of foot traffic. In marketing, network analysis has primarily been used to analyze social networks (e.g., Ansari, Koenigsberg, & Stahl, 2011), but it has also been applied to physical networks such as retail clusters (e.g., Vallapuram et al., 2022). We conceptualized the mall as a network. Nodes within this network represent stores interconnected by directed edges denoting movements between stores. Additionally, we introduced mall entrances or exits as separate nodes. Given that we did not know end-to-end paths of shopping trips, we interpreted the network as a set of ego networks that only contained first-degree, directed connections from the ego perspective of each individual store (see Stolz & Schlereth, 2021). The distinction between the full and ego networks is shown in Figure 1. Note that we incorporated a temporal dimension in the ego network, resembling a customer shopping trip in a mall.

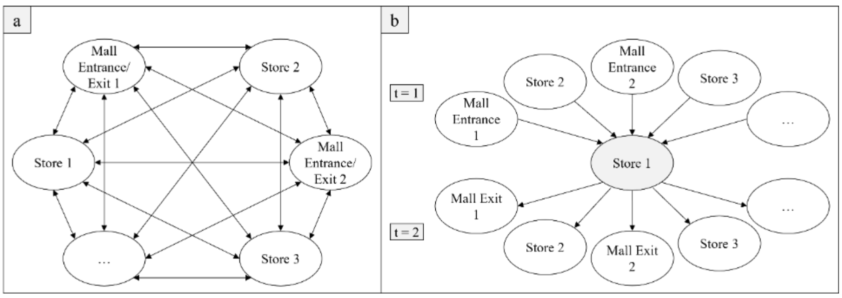


Figure 1. (a) Full Network and (b) Ego Network of Store 1

Then, we simplified each ego network by summarizing all other stores in the network into a single node, “Other Store.” For each store’s ego network, we discerned four distinct movement paths. Customers entering the store (at t = 1) can either come from the “Mall

Entrance" (path A) or the "Other Store" (path B). Customers leaving the store (at t = 2) can either go to the "Mall Exit" (path C) or the "Other Store" (path D). For customers who move on paths (A) and (C), the visit to the store is either the first or the last stop on their shopping trip. We call these customers first-stop and last-stop shoppers. For customers on paths (B) and (D), visiting the store is an intermediate stop on their shopping trip. We aggregated the frequency of customer movements for each path and constructed four spillover metrics using the path frequencies. Each metric lies between zero and one, where 0.5 serves as a threshold indicating which side is more prevalent. The conceptualized ego network with the resulting spillover metrics is shown in Figure 2. Note that the entrance and exit are usually the same in a real-world mall.

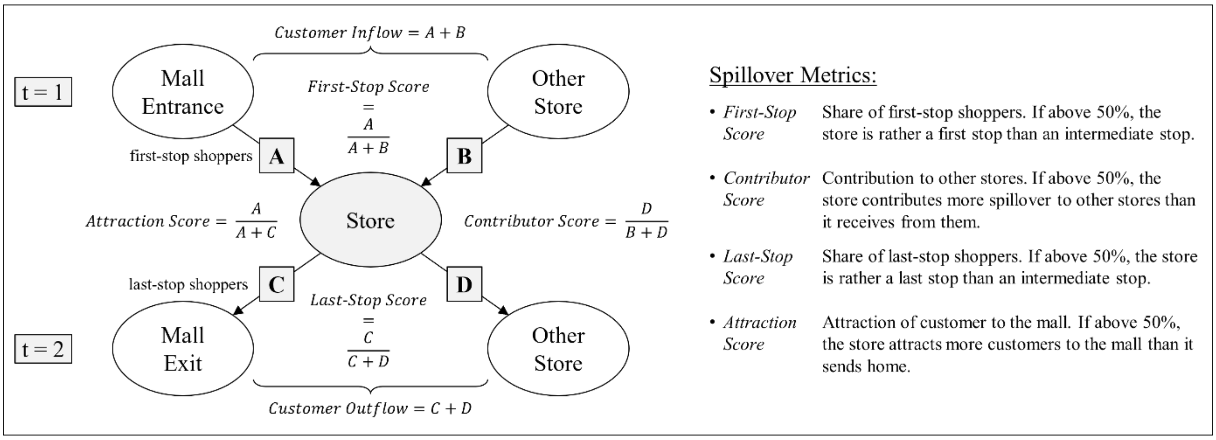


Figure 2. Conceptualized Ego Network with Spillover Metrics

3.2 *Linkage to store performance and expected effects*

As we aimed to measure the economic value of spillovers, we statistically examined how the constructed metrics relate to store performance. We expected that higher numbers of customer inflows and outflows correspond with better store performance, as a temporal relationship exists between customers entering or leaving a store and buying a product.

In addition, we drew inspiration from consumer behavior theory, anticipating that high first-stop and last-stop scores correspond with superior store performance. First stops benefit from customers' goal-directed behavior (Bagozzi & Dholakia, 1999; Lee & Ariely, 2006) and prioritization (Fernbach, Kan, & Lynch, 2015). Customers often have specific goals in mind when entering a mall, increasing the likelihood of purchasing desired items at the first stop. Prioritization is important for time-conscious customers who aim to fulfill their shopping goals quickly. Last stops benefit from decision fatigue (Massara, Melara, & Liu, 2014) and the scarcity principle (Wu, Xin, Li, Yu, & Guo, 2021). Towards the end of a shopping trip, decision fatigue may prompt quicker purchases without extensive deliberation, and the scarcity principle increases the perceived value and urgency to buy as an item becomes less available. Finally, we explored the relationships between the two remaining metrics *Attraction Score* and *Contributor Score* and store performance without a definite expectation.

4. Empirical Study

4.1 Research setting and data

We conducted an empirical study in cooperation with an operator of a regional mall in Germany to demonstrate the measurement of spillover metrics and their economic value. In April 2022, the mall installed 3D sensors to track customer movements between all retail stores' entrances and central locations, such as elevators, escalators, or mall entrances (however, not inside stores). This approach is compliant with GDPR as end-to-end tracking of personally identifiable shopping trips is not allowed. The retail stores must report monthly sales figures to the mall operator, which were kindly provided for the purpose of this study.

We obtained two datasets: (1) a 3D sensor tracking dataset with roughly 24 million customer movements and (2) a store sales panel dataset covering all 38 stores over 15 months (April 2022 to June 2023). The first dataset included all sensor-to-sensor customer movements. For each movement, starting sensor, ending sensor, starting time, and duration were tracked. We excluded all movements that took place outside business hours, with at least one non-store sensor, such as restrooms, and with the same starting and ending sensors. The cleaned 3D sensor tracking dataset comprised roughly 22 million customer movements. We aggregated the customer movements by calculating the path frequencies and the spillover metrics per store and month, as described in Figure 2. From the second dataset, we excluded seven stores, of which five had incomplete sales figures due to tenant changes, and two had separate entrances from outside the mall not equipped with a sensor. The cleaned store sales panel dataset comprised 465 sales observations of 31 stores in 15 months. Finally, we combined the store sales dataset with the calculated spillover metrics of each store and month.

4.2 Modeling

We constructed two fixed effects regression models to investigate the relationship between customer spillovers and store performance. We incorporated month-fixed and store-fixed effects into both models to control for omitted variables that are constant over time and across stores. *Sales Density*, i.e., sales per square meter, served as the dependent variable in both models, measuring store performance and controlling for store size. We logarithmized the absolute variables *Sales Density*, *Customer Inflow*, and *Customer Outflow* to approximate a normal distribution, reducing biases caused by outliers and enabling a percentage interpretation similar to the spillover metrics.

We separated two fixed effects regression models to avoid issues of multicollinearity. While the first model concentrates on the relationship between store performance and the number as well as direction of customers entering a store, the second resembles the relationship between store performance and the number of customers as well as the direction of customers leaving a store. The regression models are shown in Table 2.

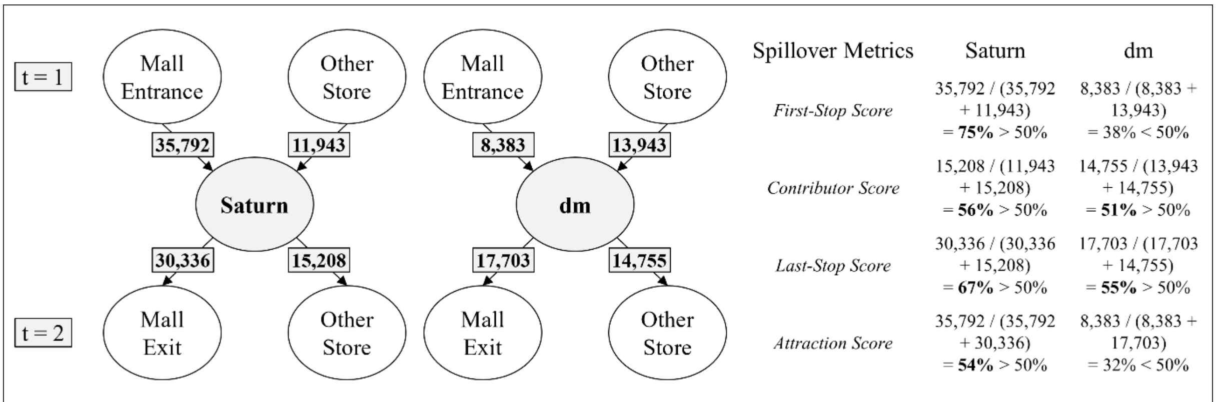
Model	
(1)	$\ln(Sales\ density_{it}) = \beta_0 + \beta_1 * \ln\,(Customer\ Inflow_{it}) + \beta_2 * First\text{-}Stop\ Score_{it} + \beta_3 * Attraction\ Score_{it} + StoreFE_i + MonthFE_t + \varepsilon_{it}$
(2)	$\ln(Sales\ density_{it}) = \beta_0 + \beta_1 * \ln\,(Customer\ Outflow_{it}) + \beta_2 * Last\text{-}Stop\ Score_{it} + \beta_3 * Contributor\ Score_{it} + StoreFE_i + MonthFE_t + \varepsilon_{it}$

Notes. Both models include store-fixed and month-fixed effects, $StoreFE_i$ and $MonthFE_t$.

Table 2. Fixed Effects Regression Models

4.3 Results

We demonstrate the computation and interpretation of the spillover metrics in one month for the two largest stores in the dataset in terms of sales: Saturn, a large consumer electronics retail chain, and dm, a drugstore chain. Saturn fulfills multiple functions in the mall as measured by the spillover metrics: it attracts more customers to the mall than it sends home (54%) and contributes more to other stores than it receives from them (56%), as both metrics are larger than 50%. At the same time, it attracts many one-stop shoppers who visit the mall solely to shop at Saturn (*First-Stop Score* = 75%; *Last-Stop Score* = 67%). In contrast, dm rather serves as a last stop (55%) and does rather not attract customers to the mall (32%). The exemplary calculations of the four spillover metrics are shown in Figure 3.



Notes. Based on the data cleansing, inflows and outflows differ in some months due to excluded movements to restrooms etc. On average, the differences between inflows and outflows are negligible for the two presented stores. Scores above the 50% threshold are printed in bold.

Figure 3. Calculated Spillover Metrics for Saturn and dm in June 2023

The results of the fixed effects regression models meet our expectations. All coefficients, except for *Contributor Score*, indicate a highly significant relationship with the dependent variable. Except for *Attraction Score*, all coefficients are positive. We report the estimated regression results for both models in Table 3.

Model	Variable	ln(Sales Density)						
		Coefficient	*SE*	95% CI		*p*	*VIF*	R^2
				LL	*UL*			
(1)	Constant	3.5493***	0.3442	2.8728	4.2259	0.0000	-	0.2044
	ln(Customer Inflow)	0.1988***	0.0279	0.1439	0.2537	0.0000	1.028271	
	First-Stop Score	2.6530***	0.4003	1.8663	3.4398	0.0000	1.355569	
	Attraction Score	-1.6575***	0.4124	-2.4682	-0.8468	0.0001	1.346802	
(2)	Constant	2.6031***	0.3642	1.8872	3.3189	0.0000	-	0.1972
	ln(Customer Outflow)	0.2100***	0.0297	0.1517	0.2683	0.0000	1.008457	
	Last-Stop Score	2.6462***	0.4173	1.8259	3.4665	0.0000	1.011209	
	Contributor Score	0.1769 n.s.	0.5551	-0.9142	1.2680	0.7501	1.016484	

Notes. Number of stores = 31, number of months = 15, total N = 465. SE = standard error; CI = confidence interval; LL = lower limit; UL = upper limit; VIF = variance inflation factor. The estimated coefficients shall not be interpreted as causal effects but as correlations. All coefficients, except for the constant, can be interpreted in percentages. Both models include store-fixed and month-fixed effects. The asterisks *, **, and *** denote a significant difference at the 5%, 1%, and 0.1% levels, respectively. The abbreviation "n.s." indicates no significance.

Table 3. Estimated Coefficients of Fixed Effects Regressions (1) and (2)

For model (1), we can conclude that an increase in *Customer Inflow* and *First-Stop Score* of 1% is associated with an increase in *Sales Density* of 0.1988% and 2.653%, respectively. However, an increase in *Attraction Score* of 1% corresponds with a decrease in *Sales Density* of 1.6575%. While the first two results meet our expectations, *Attraction Score* has a negative relationship with *Sales Density*. For model (2), we can conclude that an increase in *Customer Outflow* and *First-Stop Score* of 1% is associated with an increase in *Sales Density* of 0.21% and 2.6462%, respectively. While these results meet our expectations, we could not find a significant relationship between *Attraction Score* and *Sales Density*.

Finally, we conducted a counterfactual simulation to measure the effect of a 1%-increase in first-stop or last-stop shoppers on sales. We separately simulated the updated spillover metrics for Saturn and dm in June 2023, given 1% additional first-stop shoppers (+358; +84) or 1% additional last-stop shoppers (+303; +177). We then inserted the updated spillover metrics into models 1 and 2, together with the estimated coefficients as well as the store-month-specific intercepts, which were -0.44 (Saturn) and 0.38 (dm) for model 1 and -0.42 (Saturn) and 0.11 (dm) for model 2. We found that an increase in first-stop shoppers of 1% translates into a sales increase of 0.23% for Saturn and 0.33% for dm, as predicted by model (1); an increase in last-stop shoppers of 1% translates into a sales increase of 0.73% for Saturn and 0.77% for dm, as predicted by model (2).

5. Discussion

Our results suggest that, besides the number of customer inflows and outflows, the *First-Stop Score* and the *Last-Stop Score* tend to be meaningful spillover metrics. A store that increases its share of first-stop and last-stop shoppers can improve its performance (e.g., using advertisement campaigns at the mall entrances). Mall operators can use this knowledge to locate certain stores closer to the mall entrances or to place advertisements strategically influencing movement paths. For the *Attraction Score* and the *Contributor Score*, we will need to conduct further studies that measure the economic value of spillovers for other stores.

We contribute to the existing literature by measuring the economic value of foot traffic spillovers in terms of sales. Despite the restriction that tracking end-to-end shopping trips is not allowed, we offer GDPR-compliant insights into customer characteristics when entering and leaving a store. However, we could decompose spillover along different dimensions than mall entrances, mall exits, and other stores. For instance, we could compare spillovers from large to small stores, nearby to distant stores, or stores of the same to stores of different categories, leaving future research potential. We could also control for the distance between stores and include further variables into the models, such as information on prices.

6. Conclusion

In conclusion, we decomposed foot traffic spillovers in a shopping mall into four metrics, demonstrated the measurement of these metrics, and estimated the economic value of spillovers using two fixed effects regression models and counterfactual simulations. Our results show that the previously unexplored link between foot traffic and store performance reveals actionable insights for mall operators and retailers on the roles of individual stores in a mall. We established the metrics *First-Stop Score* and *Last-Stop Score* as meaningful indicators of shopper types entering or leaving a store. Subsequently, we plan to conduct a field experiment in which we want to analyze how customer movements can be influenced using marketing measures, and we plan to combine the tracking data with transactional purchase data or shopping basket data of a single store.

7. References

Ailawadi, K. L., Zhang, J., Krishna, A., & Kruger, M. W. (2010). When Wal-Mart Enters: How Incumbent Retailers React and how this Affects their Sales Outcomes. *Journal of Marketing Research*, *47*(4), 577–593.

Ansari, A., Koenigsberg, O., & Stahl, F. (2011). Modeling Multiple Relationships in Social Networks. *Journal of Marketing Research*, *48*(4), 713–728.

Bagozzi, R. P., & Dholakia, U. (1999). Goal Setting and Goal Striving in Consumer Behavior. *Journal of Marketing*, *63*, 19–32.

Benjamin, J. D., Boyle, G. W., & Sirmans, C. F. (1990). Retail Leasing: The Determinants of Shopping Center Rents. *Real Estate Economics*, *18*(3), 302–312.

Bloch, P. H., Ridgway, N. M., & Dawson, S. A. (1994). The shopping mall as consumer habitat. *Journal of Retailing*, *70*(1), 23–42.

Chung, H., Ahn, D.-Y., & Ahn, S. (2022). Spillover effects of a mega shopping complex on pre-existing, small retail shops over space, over time and across retail types. *Journal of Retailing and Consumer Services*, *65*, 102518.

The Economist (December 24, 2016). A new industry has sprung up selling "indoor-location" services to retailers. Retrieved from https://www.economist.com/business/2016/12/24/a-new-industry-has-sprung-up-selling-indoor-location-services-to-retailers (Last accessed: November 31, 2023).

Eppli, M. (1991). *Retail Leasing Behavior with Anchor Tenant Externalities* (Ph.D. dissertation). University of Wisconsin-Madison.

Eppli, M., & Benjamin, J. (1994). The Evolution of Shopping Center Research: A Review and Analysis. *Journal of Real Estate Research*, *9*(1), 5–32.

Fernbach, P. M., Kan, C., & Lynch, J. G. (2015). Squeezed: Coping with Constraint through Efficiency and Prioritization. *Journal of Consumer Research*, *41*(5), 1204–1227.

Ganesh, J., Reynolds, K. E., & Luckett, M. G. (2007). Retail patronage behavior and shopper typologies: a replication and extension using a multi-format, multi-method approach. *Journal of the Academy of Marketing Science*, *35*(3), 369–381.

Gould, E. D., Pashigian, B. P., & Prendergast, C. J. (2005). Contracts, Externalities, and Incentives in Shopping Malls. *Review of Economics and Statistics*, *87*(3), 411–422.

Hui, S. K., Huang, Y., Suher, J., & Inman, J. J. (2013). Deconstructing the "First Moment of Truth": Understanding Unplanned Consideration and Purchase Conversion Using In-Store Video Tracking. *Journal of Marketing Research*, *50*(4), 445–462.

Kakatkar, C., & Spann, M. (2019). Marketing analytics using anonymized and fragmented tracking data. *International Journal of Research in Marketing*, *36*(1), 117–136.

Lee, L., & Ariely, D. (2006). Shopping Goals, Goal Concreteness, and Conditional Promotions. *Journal of Consumer Research*, *33*(1), 60–70.

Liu, Y., Pei, T., Song, C., Shu, H., Guo, S., & Wang, X. (2019). Indoor Mobility Interaction Model: Insights into the Customer Flow in Shopping Malls. *IEEE Access*, *7*, 138353–138363.

Massara, F., Melara, R. D., & Liu, S. S. (2014). Impulse versus opportunistic purchasing during a grocery shopping experience. *Marketing Letters*, *25*(4), 361–372.

Pashigian, B. P., & Gould, E. D. (1998). Internalizing Externalities: the Pricing of Space in Shopping Malls. *The Journal of Law and Economics*, *41*(1), 115–142.

Pei, T., Liu, Y., Shu, H., Ou, Y., Wang, M., & Xu, L. (2020). What Influences Customer Flows in Shopping Malls: Perspective from Indoor Positioning Data. *ISPRS International Journal of Geo-Information*, *9*(11), 629.

Simona Damian, D., Dias Curto, J., & Castro Pinto, J. (2011). The impact of anchor stores on the performance of shopping centres: the case of Sonae Sierra. *International Journal of Retail & Distribution Management*, *39*(6), 456–475.

Stolz, S., & Schlereth, C. (2021). Predicting Tie Strength with Ego Network Structures. *Journal of Interactive Marketing*, *54*, 40–52.

Vallapuram, A. K., Kwon, Y. D., Lee, L.-H., Xu, F., & Hui, P. (2022). Causal Analysis on the Anchor Store Effect in a Location-based Social Network. *2022 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining*, 202–209.

Wu, Y., Xin, L., Li, D., Yu, J., & Guo, J. (2021). How does scarcity promotion lead to impulse purchase in the online market? A field experiment. *Information & Management*, *58*(1), 103283.

Yuo, T. S.-T., & Lizieri, C. (2013). Tenant Placement Strategies within Multi-Level Large-Scale Shopping Centers. *Journal of Real Estate Research*, *35*(1), 25–52.