ARTICLE IN PRESS

Journal of Retailing xxx (xxxx) xxx

Contents lists available at ScienceDirect

Journal of Retailing

journal homepage: www.elsevier.com/locate/retail

Keeping the mall alive? Identifying drivers of shopping mall satisfaction and survival from customer reviews

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ARTICLE INFO

Editor: Dr Katrijn Gielens

Keywords:
Perceived mall retail environment attributes
Mall survival
Multi-attribute theory
Aspect-based sentiment analysis
Customer reviews

ABSTRACT

As digital commerce expands, shopping malls with similar observable characteristics experience sharply different trajectories, raising the question of why some sustain customer satisfaction and survive while others close. We develop an aspect-based sentiment analysis to extract sentence-level sentiment toward five perceived mall retail environment (PMRE) attributes, mall access, mall atmosphere, cross-store assortment, within-store assortment and price and promotion from more than 250,000 online customer reviews and examine their associations with mall satisfaction and mall survival across two large-scale studies in the United States and the United Kingdom. Review-level analyses show that sentiment toward mall-controlled PMRE attributes, especially cross-store assortment and mall atmosphere, is more strongly associated with mall satisfaction than sentiment toward tenant-controlled PMRE attributes. These associations vary systematically with mall size, population density, and population income. Mall-year survival models show that higher mall satisfaction is associated with higher chance of survival and that satisfaction statistically accounts for the association between PMRE attribute sentiment and survival. This pattern is consistent with satisfaction serving as the central evaluative conduit linking cumulative customer perceptions to long-term mall viability. Together, the findings clarify which controllable PMRE attributes relate most strongly to customer satisfaction, when these associations are strongest, and how aggregated customer evaluations correspond to mall survival.

As digital commerce expands, shopping malls exhibit markedly divergent trajectories: Nearly 72 percent of malls in the United States have closed since the 1980s, and many of those that remain face record-high vacancies and declining profits (Levin, 2022; Wells, 2022). Yet, others remain resilient and continue to satisfy customer expectations, even when they appear to share similar observable characteristics. For instance, both the Northlake Mall in Atlanta, Georgia, and the Neshaminy Mall in Bensalem, Pennsylvania, share

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https://doi.org/10.1016/j.jretai.2026.02.003

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similar characteristics, since both are mature malls (54 vs. 56 years old) with a modest mall size (29 vs. 40 stores) and the same number of mall anchors (4 each). Their mall floor area is comparable (962,000 sq ft vs. 1025,297 sq ft) and they are both located in areas with a comparable population age, income, and density. Yet while the Neshaminy Mall closed in 2023, the Northlake Mall continues to thrive today. Similar patterns appear elsewhere: Grand Traverse Mall in Traverse City, Michigan, closed despite similar characteristics in mall size, mall anchors, and mall floor area to the still-thriving Wilton Mall in New York, and the Pembroke Mall in Virginia closed while the similar Dartmouth Mall remains operational.

This divergence prompts a central question: why do malls with seemingly similar characteristics, such as mall age, mall size, and population density, exhibit such different outcomes in mall satisfaction and mall survival? Ailawadi and Keller's (2004, p. 332) summary of the typical "retailer attributes" (e.g., store atmosphere), adapted by Chebat et al. (2010) to the mall context (e.g., mall atmosphere), might answer this question. Understanding the relative impact of these attributes on mall performance is essential for guiding resource allocation decisions in an increasingly competitive retail industry (Gielens et al., 2021).

Mall managers seeking to understand the performance implications of these attributes often face measurement limitations. Unlike standalone retailers, malls typically have to rely on broad performance indicators such as foot traffic or infrequent and expensive customer satisfaction surveys. These, more traditional ways of measuring mall performance, offer limited granularity and fail to capture shifting customer perceptions in real time. Accordingly, there have been calls for approaches that offer more timely and granular insights, ideally even at the individual customer level (Bradlow et al., 2017; Gielens & Lamey, 2024; Grewal et al., 2021). In response, we develop an aspect-based sentiment analysis approach (Liu et al., 2020), which enables mall managers to leverage the text-based feedback provided in online customer reviews (e.g., from Yelp, TripAdvisor, or Google) to identify and quantify customer sentiment toward perceived mall retail environment (PMRE) attributes, capturing what customers talk about and their sentiment.

Customer evaluations of shopping malls often conflate mall-controlled and tenant-controlled

PMRE attributes, which obscures which levers mall managers can actually act upon to improve mall satisfaction and mall survival. Following Chebat et al. (2010), we distinguish mall-controlled PMRE attributes, namely mall access, mall atmosphere, and cross-store assortment, from tenant-controlled PMRE attributes, namely within-store assortment and price and promotion. This distinction aligns with multi-attribute theory, which posits that customers evaluate complex offerings by assigning weight and responsibility to distinct attributes under the control of identifiable decision makers. Thus, the relative importance of PMRE attributes for customers' mall satisfaction may vary. Moreover, prior research suggests that customers evaluate retail agglomerations differently depending on contextual factors (Teller & Reutterer, 2008), implying that mall characteristics such as mall age and mall size, as well as location characteristics such as population density and population income, may condition how customers weight specific PMRE attributes when forming satisfaction judgments. Identifying these boundary conditions will help mall managers invest in the right levers for their specific context. In addition, it remains unclear how sentiment toward specific PMRE attributes relates to longer-term performance, and whether mall satisfaction serves as the central evaluative conduit linking PMRE attribute sentiment to mall survival. Accordingly, we examine three research questions:

RQ1. How does customer sentiment toward mall-controlled versus tenant-controlled PMRE attributes relate to mall satisfaction?

RQ2. Do mall- and location-specific characteristics moderate the relationship between customer sentiment toward PMRE attributes and mall satisfaction?

RQ3. Does mall satisfaction statistically account for the association between PMRE attribute sentiment and mall survival?

To empirically examine the relationships between customers' sentiments toward PMRE attributes, mall satisfaction, and mall survival, we apply a large-scale text-mining and sentiment-based approach using over 250,000 customer reviews from TripAdvisor, Yelp, and Google, drawing on observational review and panel data. Following an aspect-based sentiment analysis approach, we develop dictionaries for each PMRE attribute and mine customers' sentence-level sentiments toward each of the five PMRE attributes using the SiEBERT model (D'Aniello, Gaeta & La Rocca, 2022; Hartmann et al., 2023). We assess mall performance implications of the PMRE attributes' sentiments across two studies. Study 1 draws on 81,615 TripAdvisor and Yelp reviews from 79 shopping malls across the United States and the United Kingdom to assess how customer sentiment toward PMRE attributes relates to mall satisfaction, and how this relationship varies by mall characteristics such as size, population density, and local income levels. Study 2 leverages 169,458 Google reviews for a matched panel dataset of 62 closed and 62 surviving malls to investigate how PMRE attribute sentiments and mall satisfaction are associated with mall survival.

Our study makes three substantive contributions. First, using aspect-based sentiment analysis, we establish a novel methodological lens that disaggregates customer sentiment at the attribute level. Unlike traditional surveys, this approach enables fine-grained and dynamic insights into PMRE attributes (Bradlow et al., 2017). We show that mall-controlled PMRE attributes, such as mall atmosphere and cross-store assortment, exhibit stronger associations with mall satisfaction than tenant-controlled PMRE attributes, such as within-store assortment and price and promotion, while mall access plays a comparatively limited role. Second, we contribute to the literature on retailer survival and closure (Kupfer et al., 2024) and the relevance of customer sentiment (Zhang & Luo, 2023) by demonstrating that the association between PMRE sentiment and survival is statistically accounted for by mall satisfaction. This positioning aligns with prior work that identifies satisfaction as a key link to behavioral outcomes (Rust & Zahorik, 1993). Third, we enrich the retail satisfaction literature by showing that the associations between PMRE attributes and mall satisfaction vary with mall- and location-specific characteristics, such as mall age, population density, and local population income levels. Mall managers can use these findings to better align investments with customer sentiment patterns associated with higher satisfaction and survival.

1. Conceptual background and development

1.1. Conceptual model

We examine how PMRE attributes are associated with (1) mall satisfaction and (2) mall survival, considering also mall heterogeneity, as outlined in Fig. 1. Specifically, we explore whether perceptions of mall-controlled PMRE attributes have a stronger relationship with satisfaction than perceptions of tenant-controlled PMRE attributes. Further, we investigate the role of mall- and location-specific characteristics in moderating these relationships, building on prior retailing literature that focuses on shopping malls in Table 1 and the limited research on store/mall closure in Table 2. Notably, while previous mall studies rely on survey data, we adopt a secondary data approach using observational data from customer reviews and aspect-based sentiment analysis.

1.2. Perceived mall retail environment attributes

Multi-attribute theory (Wallenius et al., 2008) explains how decision-makers assign an overall evaluation of an object or experience based on a combination of attributes, each contributing to the overall utility perception (Iacobucci et al., 1995). Indeed, in line with the multi-attribute perspective on retailing (Mittal et al., 1998; Vaughn & Hansotia, 1977), Blut et al. (2018) show that customer satisfaction and store performance are influenced by a range of individual store attributes. However, both the attributes and their effects may vary across retail formats. Thus, while overall customer evaluations are still likely to depend on multiple attributes, insights on store-based attributes may not be directly transferable when explaining customer satisfaction with malls and mall survival (Ganesh et al., 2007; Jindal et al., 2020).

Five key perceived mall retail environment (PMRE) attributes have been suggested to influence customers' evaluation of malls (Chebat et al., 2010): mall access, mall atmosphere, cross-store assortment, within-store assortment, and price and promotion.

Mall access relates to the overall convenience and comfort of the shopper (Wagner, 2007; Ahmed et al., 2007). For example, it involves the availability of parking space and intra-mall navigation. Unlike a standalone store whose success might hinge on neighbourhood proximity, malls often serve as regional hubs, requiring them to accommodate a diverse and dispersed customer base (Oppewal & Holyoake, 2004). Ample parking spaces, ease of access by public transport, and seamless navigation between stores are critical elements of a mall, as they collectively influence customers' evaluation of mall access.

Mall atmosphere encompasses elements like design, ambiance, and shared spaces. As noted by Babin and Attaway (2000) and Michon et al. (2005), a pleasant and moderately arousing mall atmosphere significantly enhances mall satisfaction. A single store's atmosphere is confined to its immediate environment, but the atmosphere of a mall is collectively shaped by its corridors, food courts, and public areas. As a result, for example, a customer drawn to the aesthetic cohesion of a mall may overlook a less appealing individual store, while poorly maintained malls risk alienating customers despite appealing stores.

Assortment encompasses cross-store and within-store attributes. *Cross-store assortment* refers to the breadth of products and services offered across stores. Unlike a standalone store, where variety is limited to a single product category, malls provide one-stop shopping through a mix of, e.g., fashion, electronics, dining, and entertainment stores. This diversity is key, especially for time-constrained customers, as noted by Messinger and Narasimhan (1997). *Within-store assortment*, by contrast, involves the depth of options within specific stores, such as electronics or fashion stores offering multiple, competing brands and styles. While no research studies the implications of assortment on customers' satisfaction with malls, Broniarczyk et al. (1998) suggest that the perception of a wide within-store assortment can drive mall satisfaction and store choice. Notably, the within-store assortment depends heavily on each tenant's decisions, limiting the direct control of the mall management over this attribute, whereas mall management has direct control over the cross-store assortment by attracting a certain set of tenants.

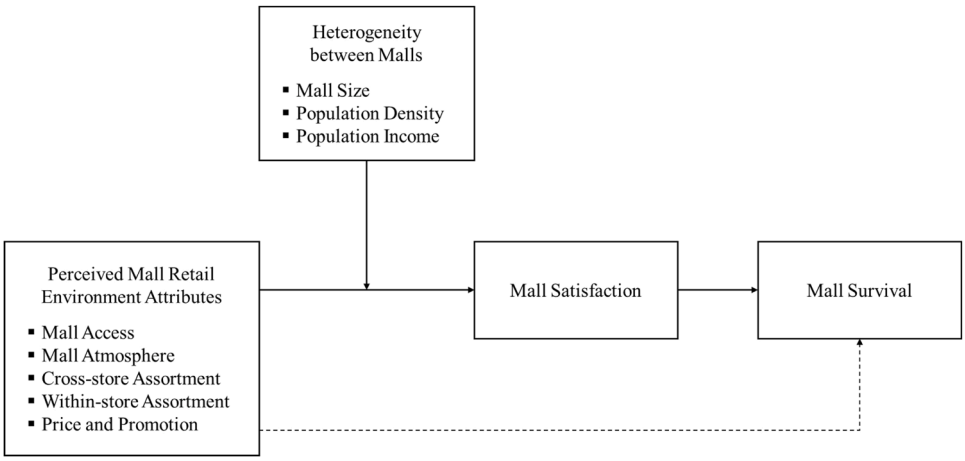

Fig. 1. Conceptual model.

Table 1
Illustrative overview of research on perceived mall retail environment attributes.

		Sample			PMRE Attributes					
Article	Focus	Customers	Malls	Countries	MA	MT	WS	CS	PP	Main Findings
Bloch et al. (1994)	Customer activities within shopping malls	600	3	USA				✓		Identification of mall habitat activities and mall-related shopping orientations.
Beatty and Ferrell (1998)	Investigation of impulse buying in malls	533	1	USA	✓	✓	✓		✓	The mall situation and individual differences in shopping enjoyment influence impulse purchases.
Wakefield and Baker (1998)	Impact of the retail mix on customers' excitement at the mall	438	1	USA	✓	✓	✓	✓		Tenant variety, mall environment, and shopping involvement affect mall excitement and patronage intentions.
Severin et al. (2001)	Stability of retail-shopping choice preferences	1840	3	Canada, Norway, USA	✓	✓	✓	✓	✓	Existence of spatial consistency and stability over time for shopping center choice.
Teller and Reutterer (2008)	Agglomeration attributes and attractiveness	1082	1	Austria	✓	✓	✓	✓		Tenants and atmosphere are the main drivers of agglomeration attractiveness.
Mohan et al. (2013)	Shopping mall environment and impulse buying	733	1	India		✓		✓		Mall environment and personality variables affect impulse buying.
Chebat et al. (2014)	The effects of mall renovation on customer spending	545	1	Canada		✓				Mall atmosphere affects shopping values and spending.
Teller et al. (2016)	Competition between urban agglomerations and shopping malls	2161	3	Europe	✓	✓		✓		Significant differences arise in why respondents patronize the two types of shopping agglomerations.
Diallo et al. (2018)	Mall service quality and loyalty in different cultural contexts	750	3	Morocco, Senegal, Tunisia	✓	✓	✓	✓		Overall satisfaction with the mall mediates the effect of service quality on customer loyalty.
Katrodia et al. (2018)	Gender differences in buying behavior in shopping malls.	700	1	South Africa	✓	✓		✓	✓	Gender differences and shopping mall attractiveness related to the retail mix affect shopping behavior.

Note: MA = Mall access, MT = Mall atmosphere, CA = Cross-store assortment, WA = Within-store assortment, PP = Price and promotion.

Price and promotion in malls are particularly complex attributes. In standalone stores, pricing is straightforwardly decided upon by the store, and customers form their corresponding value perceptions for this specific store (Ailawadi & Keller, 2004). In malls, however, pricing reflects the collective perception of all offers and stores. Moreover, seasonal sales or individual promotions by stores can influence overall perceptions of price and promotion, while being outside the mall management's direct control.

1.3. Mall-controlled vs. tenant-controlled perceived mall retail environment attributes

Importantly, mall managers do not have direct control over all of these PMRE attributes. Mall-controlled attributes are seen as the responsibility of mall management, while tenant-controlled ones are viewed as store-specific (Jackson et al., 2011; Arnold et al., 2009). Thus, their influence on mall satisfaction and mall survival will likely differ. Mall-controlled PMRE attributes include mall access, mall atmosphere, and cross-store assortment, elements broadly curated by the mall management (Chebat et al., 2010). Mall access directly shapes convenience, and deficiencies are typically blamed on the mall (Teller & Elms, 2010). Mall atmosphere contributes significantly to overall impressions of malls (Anselmsson, 2016), with prior work showing that negative atmospheric cues reduce loyalty to malls (Babin & Attaway, 2000; Michon et al., 2005). The diversity of stores and categories, cross-store assortment, is managed by the mall and signals its market positioning (Wakefield & Baker, 1998).

In contrast, tenant-controlled PMRE attributes, within-store assortment as well as price and promotion, are generally seen as the responsibility of individual retailers (Chebat et al., 2005; Chebat et al., 2010). For example, limited size selection at a fashion store, perceived pricing unfairness at a specific store, or an individual promotional activity are rather attributed to the individual store, not the mall. As a result, while all attributes should influence customers' evaluation of a mall, their satisfaction with tenant-controlled PMRE attributes may have weaker effects on overall mall satisfaction. Accordingly, we explore how customer sentiment toward mall- versus tenant-controlled PMRE attributes influences mall satisfaction.

1.4. Heterogeneity of the perceived mall retail environment attributes–mall satisfaction link

The implications of the PMRE attributes are unlikely to be uniform across all malls. Prior research suggests that mall- and location-specific characteristics, especially mall size, population density, and population income, may influence this relationship (Teller & Reutterer, 2008).

A *larger mall size* attracts a broader customer base with diverse shopping preferences and budgets (Wakefield & Baker, 1998). This

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Table 2
Research on store/mall closure and survival.

Study	Domain	Focus	Sample	Data Structure	Matching	Method	Main Findings
A) Studies that investigate store closure and survival on an aggregated level							
Carree and Thurik (1996)	Industrial Organization	Stores	8 time points for 23 store types	Panel data	—	Seemingly unrelated regression	Store closure is more likely for store types where (a) profitability is low, (b) demand growth is low, and (c) unemployment growth is high.
Mayadunne et al. (2018)	Production Economics	Stores	Hypothetical example	Time series data	—	Mixed integer programming	Store closure is more likely for the firm with lower revenue, considering the equilibrium store closing decisions of two competing firms.
Warren and Gordon-Larsen (2018)	Statistics in Society	Stores	27 time points for 4 cities	Panel data	—	Survival model	Store closure is more likely for (a) stores with a lower sales volume and (b) stores located in high-poverty, non-white areas.
B) Studies that investigate individual store closure and survival							
Star and Massel (1981)	Retailing	Stores	Archival data of 17,252 retail firms	Cross-sectional data	—	Descriptives	Store closure is more likely for retail firms that are (a) smaller, (b) located in urban counties, (c) have a lower ticket size, and (d) are owned by partnerships.
Shields and Kures (2007)	Retailing	Stores	Archival data of 2076 Kmart stores	Cross-sectional data	—	Logistic regression	Store closure is more likely for stores that are in areas with (a) higher poverty rates and (b) fewer moderate-income families, as well as located (c) closer to competitors and (d) further from distributors.
Kupfer et al. (2024)	Retailing	Stores	3557 key informant surveys for 2548 retail stores	Cross-sectional data	—	Logistic regression	Store closure is more likely for stores that have (a) an exclusive assortment, (b) less diversified offerings, (c) a focus on media products, (d) lower accessibility, (e) a lower store size, (f) a city-center location, (g) a smaller population size, (h) a less aesthetic shopping experience, (i) shorter opening hours, and (j) no retail chain association.
C) Studies that investigate individual mall closure and survival							
Our research	Retailing	Malls	169,458 customer reviews for 124 shopping malls	Panel data	Propensity score matching	Survival model	Mall closure is more likely for malls with lower mall satisfaction, which is driven by perceptions of (a) mall access, (b) mall atmosphere, (c) cross-store assortment, (d) within-store assortment, and (e) price and promotion.

increases the importance of, for example, the cross-store assortment, as customers expect a variety of specialized boutiques, mid-range retailers, and entertainment options (Yim You & Xu, 2012). Hence, a well-curated mix of stores may be especially important for larger malls to reinforce the mall's role as a one-stop shopping destination (Weiler et al., 2003). In contrast, smaller malls, constrained in their store selection, must satisfy customers in other ways. These malls may, for example, rely more on a pleasantly designed atmosphere to satisfy customers (Baker et al., 1994). In large malls with high foot traffic, atmosphere may play a lesser role in customers' satisfaction (Bitner, 1992).

Malls in *densely populated areas* serve customers with many retail choices in close vicinity. In such areas, customers often have easy access to multiple outlets from the same retailer (Reimers & Clulow, 2004). To satisfy customers in such areas, malls' within-store assortment (e.g., a diverse product selection) may be especially important (Arentze et al., 2005). With many competing malls and stores nearby, customers likely expect variety within stores. If a store lacks within-store assortment, customers may choose alternative stores outside the mall. In contrast, in sparsely populated areas, where customers travel longer distances and have fewer alternatives, mall access might become a more critical determinant of satisfaction (Sethuraman et al., 2022). If a mall in a low-density area fails to provide convenient access, customers may opt for alternative shopping methods, such as online retail.

The *population income levels* of customers around the mall's location likely determine the importance of specific PMRE attributes (Gauri et al., 2008). Higher-income customers tend to prioritize mall atmosphere, associating a premium shopping experience with prestige and exclusivity (Grewal et al., 2003). Mall atmosphere may become more important for customers in such areas. Conversely, lower-income customers are more price-sensitive and actively seek discounts and promotional offers (Wakefield & Inman, 2003; Lal & Rao, 1997). Customers' sentiments towards the price and promotions in a mall should become more important for their satisfaction.

Accordingly, we explore whether these mall- and location-specific characteristics moderate the relationship between customer sentiment toward PMRE attributes and mall satisfaction?

1.5. Perceived mall retail environment attributes, mall satisfaction, and mall survival

Beyond their likely influence on customers' satisfaction with a mall, customers' evaluations of the PMRE attributes may also be associated with mall survival. Research on individual stores shows that store attributes are associated with satisfaction, which is associated with long-term outcomes such as loyalty, share of wallet, and whether a store prospers (Sirohi et al., 1998; Hunneman et al., 2015; Hunneman et al., 2021). By extension, sentiments toward PMRE attributes may similarly indicate mall survival through their impact on mall satisfaction.

The importance of some attributes may be directly associated with mall survival, irrespective of overall mall satisfaction. Recent findings on restaurant survival, for example, suggest that customer sentiment toward restaurants' attributes, such as the sentiment to food, service, environment and price-quality, are indicative of their survival (Zhang & Luo, 2023). Moreover, customer attitudes and satisfaction are known not to always translate into actual behaviors (Mittal et al., 1998). Thus, even if a customer's satisfaction with a mall is high (low), the mall may still close (survive) if customers' sentiment toward a critical attribute (e.g., mall access) is negative (positive). Therefore, we examine whether mall satisfaction statistically accounts for the association between PMRE attribute sentiment and mall survival.

2. Empirical approach

2.1. Using customer reviews to analyze experiences with PMRE attributes

Customer reviews offer a unique lens through which customers' PMRE attribute sentiments can be assessed, as they capture direct, verbatim reflections of their mall experiences (Gielens & Lamey, 2024). Web Appendix A contains examples of customer reviews for shopping malls. Both TripAdvisor and Yelp allow customers to provide overall satisfaction ratings (e.g., star ratings), which capture their general mall satisfaction and detailed explanations in their written reviews, which are ideal for aspect-based sentiment analysis. The popularity of these platforms attracts a large and diverse pool of reviewing customers (van Laer et al., 2019). Finally, both platforms provide review-level metadata, such as review length and reviewer history, which we use as controls to address systematic differences in review behaviour and documented self-selection patterns in online review data (Schoenmueller et al., 2020).

In Study 1, we test the relative importance of mall-controlled and tenant-controlled attributes for mall satisfaction and explore the heterogeneity between malls in a large-scale sample of customer reviews from TripAdvisor and Yelp. In Study 2, we test the relationship between PMRE attributes, mall satisfaction, and mall survival, using a large-scale sample of customer reviews from Google Reviews. Unlike TripAdvisor and Yelp, used in Study 1, Google retains review profiles of malls labelled as "permanently closed" or "temporarily closed" after closure. So, with this second dataset, we are in a unique position to compare the ratings and written reviews between malls that survived and those that closed down.

2.2. An aspect-based sentiment analysis of PMRE attributes in customer reviews

To examine how mall- and tenant-controlled PMRE attributes affect mall satisfaction, we employ aspect-based sentiment analysis (Liu et al., 2020) to extract sentiments and the PMRE attributes to which they relate from customer reviews. For example, mentioning "easy parking" or "clean and spacious design" in a customer review reflects both a positive sentiment and the reason for such positive sentiment (e.g., mall access and mall atmosphere). Similarly, a customer review criticizing "a lack of variety of stores" indicates a negative sentiment and cross-store assortment as the reason for this negativity. Importantly, the same review may contain both positive

and negative sentiments. For instance, consider the following customer review: "Great store variety. Also, easy parking. Only downside was the lack of promotions. Still a great spot overall!" While the overall sentiment of the review is positive, it contains specific positive (i.e., cross-store assortment and mall access) and negative (i.e., price and promotion) sentiments. General (aspect-independent) sentiment analysis approaches used in marketing research so far would classify such a review text holistically as either positive or negative without distinguishing the specific attribute-dependent sentiments (Pan & Zhang, 2011). Uncovering PMRE attribute-specific sentiments from customer reviews offers two critical benefits. First, it enables the empirical assessment of the conceptualizations outlined by multi-attribute theory, such that multiple customer sentiments can be identified and assessed for each individual PMRE attribute. Second, it enables a granular exploration of the relative influence of each PMRE attribute sentiment on mall satisfaction, informing resource allocation decisions by mall managers.

To enable a PMRE aspect-based sentiment analysis in customer review texts, we followed the steps outlined in Fig. 2. We removed all non-textual reviews from the respective Yelp and TripAdvisor datasets, so that only reviews remain that contain a written review and a review satisfaction rating. We then split each customer review text into its individual sentences using an automated sentence parser. Since there were no pre-existing text mining dictionaries for the PMRE attributes, we developed new dictionaries, one for each PMRE attribute (see details in Table 3 and Web Appendix B). In Step 1, we generated a list of candidate words and terms from an open-ended survey where U.K. shoppers ($N = 2554$) described their shopping experiences. Each open-ended response was coded by two research assistants to contain (or not contain) each PMRE attribute, with intercoder agreement >0.80 and reconciliation. In Step 2, we expanded the list of terms with common variants, synonyms/antonyms, and frequently mentioned brand names (via named-entity recognition), then stemmed terms. In Step 3, we refined the lists by manually removing ambiguous words based on sentence-level checks in random Yelp/TripAdvisor subsamples. In Step 4, we applied seeded topic modeling (LDA) using the curated word lists to discover additional attribute-related words, followed again by manual inspection. The final dictionaries contain 1157 unique words/stems/terms across the five PMRE attributes. In Step 5, we validated the new dictionaries with human coding and found high agreement for each term belonging to its respective PMRE attribute (0.88–0.98 across attributes; no class-imbalance issues). For each sentence, we then measured whether each of the PMRE attributes was mentioned in a sentence using the newly developed dictionaries.

We then applied the SiEBERT model (D'Aniello, Gaeta & La Rocca, 2022), a fine-tuned version of RoBERTa (Hartmann et al., 2023), to identify the sentiment of each sentence in each review. Compared to other models, SiEBERT emerged as the most accurate in capturing sentiment, likely due to its extensive training on customer reviews (see Web Appendix C for detailed benchmark results). Thus, for every sentence across all reviews, the model returned a final score that is either 1 (for positive sentiment) or −1 (for negative sentiment).

We next created the sentence-level PMRE attribute sentiment. The example review: "Great store variety. Also, easy parking. Only downside was the lack of promotions. Still a great spot overall!", would be split into four sentences: "Great store variety.", "Also, easy parking", "Only downside was the lack of promotions.", "Still a great spot overall!". The first sentence contains a mention of the cross-store assortment PMRE attribute and a SiEBERT-based positive (1) score. Thus, this sentence-level aspect-based sentiment score for cross-store assortment is 1 (1 mention of cross-store assortment × 1 SiEBERT positive sentiment score). The third sentence: "Only downside was the lack of promotions," would score a −1 for the price and promotion PMRE (i.e. 1 for price and promotion × −1 SiEBERT based sentiment score). The last sentence: Still a great spot overall!" scores 0 (i.e. 0 for all PMRE attributes × 1 SiEBERT-based sentiment score).

We then summed all sentence-level aspect-based sentiment scores for each PMRE attribute for each customer review. For example, if a review contained two negative mentions of the PMRE attribute mall access, then summing the attribute-based scores across the review would result in a −2 score for mall access at the review-level. Using the measurement of this sentiment-based approach, we test the relative influence of the different PMRE attributes-based sentiments for overall mall satisfaction (Study 1) and shopping mall survival (Study 2) next.

3. Study 1: PMRE attributes and mall satisfaction

3.1. Sampling and data collection

We collected customer review data from TripAdvisor and Yelp, focusing on shopping malls in the largest cities of the United States and the United Kingdom. We chose TripAdvisor and Yelp for three reasons. First, both platforms allow customers to provide overall satisfaction ratings (e.g., star ratings) and detailed written reviews, which are ideal for aspect-based sentiment analysis. Second, the popularity of these platforms attracts a large and diverse pool of reviewers who typically describe their mall experiences in detail (van Laer et al., 2019). Finally, both platforms offer review-level metadata, such as review length and reviewer history, which serve as important controls in our analysis.

The mall selection followed a systematic, multi-stage procedure designed to ensure both conceptual relevance to our research and a reproducible sampling logic. First, we identified the largest 26 U.S. and 10 U.K. cities based on 2020–2021 population rankings,[1] ensuring the inclusion of major metropolitan areas with significant retail infrastructures and consumer activity (King, 2023). Within each metropolitan area, we compiled an exhaustive list of identifiable shopping malls using multiple online review platforms (i.e.,

[1] While this method has limitations, such as the exclusion of some high-profile malls, it provides a practical and robust foundation for exploring the drivers of mall satisfaction in competitive market contexts. Future research could expand on this by considering alternative sampling approaches (e.g., number of stores or total square footage) or investigate very small or large malls with exceptionally low or high review counts.

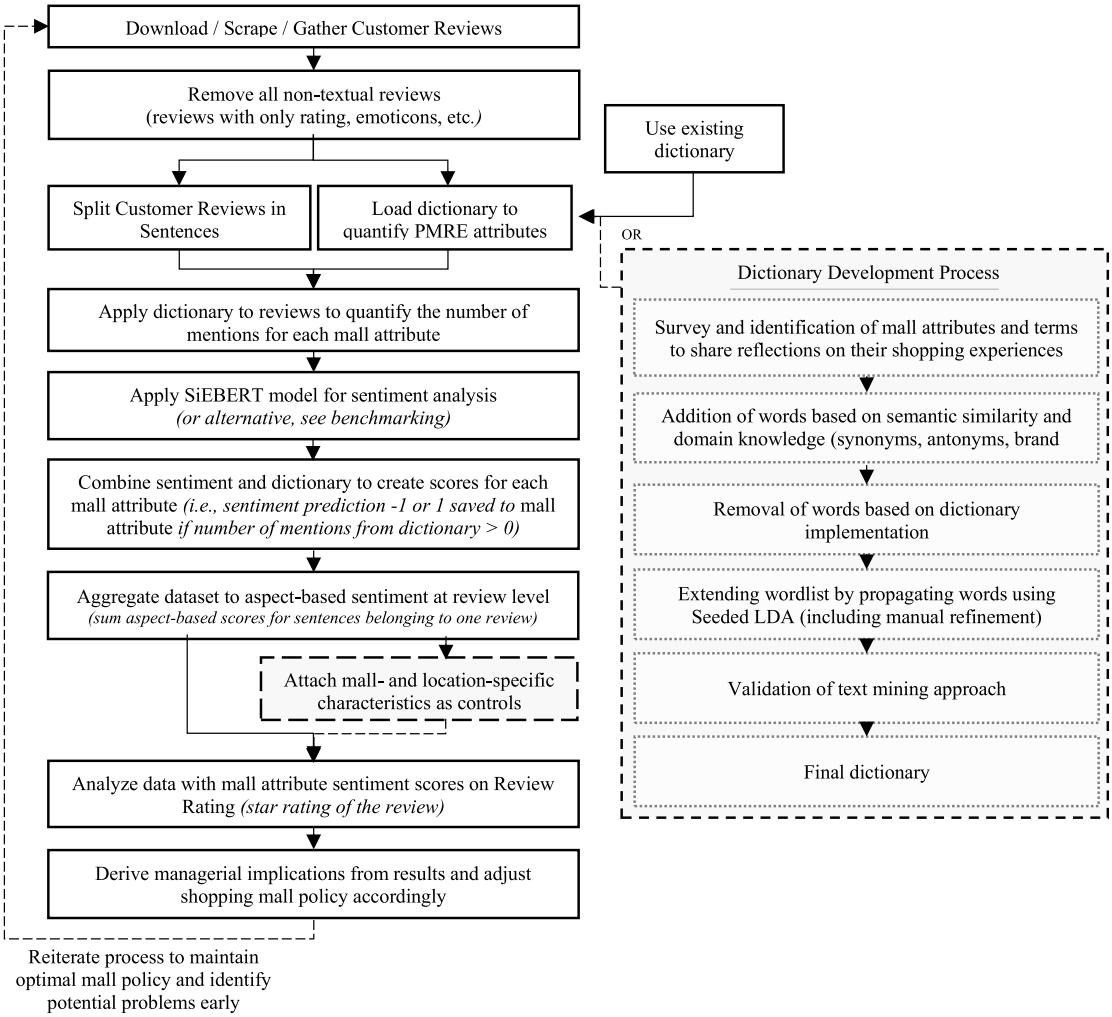

Fig. 2. Using customer reviews to identify and optimize PMRE attributes. Note. The dictionary development process is an optional step to replace the current dictionaries. This step is advised for applying the proposed approach to a context other than shopping malls.

TripAdvisor, Yelp). Second, inclusion of a mall in the final sample was then determined by review-based data availability. Specifically, a mall was retained only if it had at least 50 English-language written reviews on both TripAdvisor and Yelp. This selection criterion reflects our conceptual focus on consumer sentiment towards PRME attributes and functioned as an objective and replicable filter. Importantly, this procedure also meant that not all malls within each city were included, only those meeting the data sufficiency criterion. Third, while our focus on large metropolitan areas provided a systematic basis for identifying eligible malls, the review-based inclusion criterion inherently mitigated potential selection bias among malls within these areas. The approach excluded sparsely reviewed or inactive malls that would otherwise lack review data. Thus, the final sample reflects a balanced and data-driven representation of active, consumer-visible malls in major metropolitan areas across the US and the UK.

A full list of malls and their exact location is provided in Web Appendix E1, ensuring transparency and replicability. Across the 36 metropolitan areas, the final dataset comprises 79 shopping malls and 81,615 customer reviews (58,645 from TripAdvisor and 22,970 from Yelp; 59,758 from the United States and 21,857 from the United Kingdom), spanning a ten-year period from 2010 to 2019. On average, each mall attracted 1033 reviews (range: 123–13,895), with an average review length of 82 words (SD = 73.12). The average star rating across all reviews was 4.05 (SD = 1.07). The observed distribution of polarity and imbalance aligns with prior work in online review research as displayed in Web Appendix D (Schoenmueller et al., 2020).

3.2. Measurement

Dependent variable. The star rating from each review (1 = "very negative", 5 = "very positive") serves as a proxy for the customer's overall satisfaction with the mall.

Independent variables. Customer sentiment toward the five PMRE attributes was constructed at the review level using aspect-based

Table 3
Overview of the dictionary development process.

Step	Initial Terms	Terms Added / Removed	Details of Addition / Removal
Step 1: Survey and identification of mall attributes and terms	0 terms	653 terms added	Surveyed 2554 U.K. customers, asking them to reflect on a recent visit to a specific retail location with an open-ended survey. This data was used for the dictionary creation.
Step 2: Addition of words based on semantic similarity and domain knowledge	653 terms	623 variations in expressions, synonyms and antonyms added; 389 brand names added (e.g., Gucci)	Two research assistants identified synonyms and antonyms for the initial word list. Bigrams were selected according to their frequency in the survey responses. Brand names were automatically identified by OpenNLP.
Step 3: Removal of words based on dictionary implementation	1665 terms	793 terms removed	Two independent coders removed all expressions that could include multiple interpretations or overlap across categories. All remaining words were stemmed. The dictionary was applied to a subset of data, and further words were removed in cases of false positives.
Step 4: Extending wordlists by propagating words using Seeded LDA (including manual refinement)	872 terms	285 terms added	Implemented a seeded latent Dirichlet analysis for semi-supervised topic modeling. Using the refined term list from Step 4 as an initial dictionary of keywords, we define the desired topics and identify related topic words. We extracted the 1000 most frequent terms per topic and refined the final terms to add by manual inspection, keeping only those deemed likely by all coders (in Steps 2 and 3).
Step 5: Validation of text mining approach			We compare dictionary-based classifications with those of a human coder. For each mall attribute, we used a subset of 50 reviews from Study 1. Human classification converged with the automated text analysis: Precision ranges from 0.84 to 1.00, recall ranges from 0.89 to 1.00 and the F-measure ranges from 0.88 to 0.98.
Final Dictionary	1157 terms: 125 for "mall access," 293 for "mall atmosphere," 197 for "cross-store assortment", 471 for "within-store assortment", and 71 for "price and promotion".		

Note: The initial number of words represents the starting number for that step, not necessarily the overall number of words obtained prior to that step.

sentiment analysis, as detailed in Fig. 2.

Moderator variables. Data on mall size (number of stores) and mall age were manually collected from archival sources such as mall websites, local directories, and floor maps. Population density was measured as the number of inhabitants within a 5-mile radius using the Global Human Settlement Layer from the European Union. Average household income and median population age were obtained on the ZIP code level from the US and UK census bureaus.

Control variables: We controlled for several review- and reviewer-level factors. Review length was included because longer reviews typically convey more information and may relate to greater satisfaction (Villarroel Ordenes et al., 2017); local reviewer (i.e., a reviewer with a local address), as local visitors may represent repeat customers, whereas nonlocal reviewers are more likely first-time visitors; the reviewer's total number of reviews since authors with few reviews often show polarity or positivity imbalance (Schoenmueller et al., 2020). Finally, we controlled for the review platform (TripAdvisor or Yelp) to account for potential platform-specific rating differences. Details are in Table 4, descriptive statistics and correlations are in Web Appendix E2.

3.3. Model-free evidence

Fig. 3 shows that customer reviews most frequently mention mall-controlled attributes, while tenant-controlled attributes, such as price and promotion, appear less often. Average sentiment follows the same pattern, suggesting that mall-controlled attributes may have a greater impact on mall satisfaction.

3.4. Method

We use an ordinal logit model to fit the nature of the review star rating. The unit of observation in Study 1 is the individual customer review. Each review provides a star rating (overall mall satisfaction) and review-level PMRE sentiment measures. Mall characteristics (e.g., size, population density) are measured at the mall level and merged with review-level data. Fixed effects are specified at the mall level, and time fixed effects are based on the review posting date. We include fixed effects for the shopping mall to control for unobserved time-invariant characteristics of the malls, such as the floor plan, and fixed effects for year, month, and day of the week to control for unobserved time-variant characteristics that affect all malls simultaneously, such as the general consumption climate or nationwide events (e.g., "Black Friday"). Formally:

$$logit[P(MS_{ik} \leq j)] = \beta_0 + \beta_1 MA_{ik} + \beta_2 MT_{ik} + \beta_3 CA_{ik} + \beta_4 WA_{ik} + \beta_5 PP_{ik} + \sum_{p=6}^{9} \beta_p CV_{pik} + \sum_{q=1}^{79} \gamma_k + \sum_{l=1}^{9} \delta_{lik} + \sum_{m=1}^{11} \mu_{mik} + \sum_{n=1}^{6} \tau_{nik} + \varepsilon_{ik} \quad (1)$$

Table 4
Measurement of variables.

Variable	Reason for Inclusion	Operationalization	Source
Mall satisfaction	Dependent variable	Star rating from the review (1 = "very negative", 5 = "very positive").	Review rating
Mall closure	Dependent variable	Dummy indicating whether a mall was closed (1) or still operating (0).	Desk research
Mall access	Independent variable	Total number of positive minus negative mentions of mall access in the review.	Review text
Mall atmosphere	Independent variable	Total number of positive minus negative mentions of mall atmosphere in the review.	Review text
Cross-store assortment	Independent variable	Total number of positive minus negative mentions of cross-store assortment in the review.	Review text
Within-store assortment	Independent variable	Total number of positive minus negative mentions of within-store assortment in the review.	Review text
Price and promotion	Independent variable	Total number of positive minus negative mentions of price and promotion in the review.	Review text
Review length	Longer reviews likely provide more information that may relate to a more satisfactory experience.	Total number of words in each review (in words).	Review text
Local reviewer	Local reviewers may represent repeat visitors, while foreign reviewers are more likely to be first-time visitors.	Dummy indicating whether a reviewer has a local address.	Review platform
Number of reviews	Reviews from authors with small amounts of total reviews tend to be selective and provide polarity and positivity imbalance.	Total number of reviews given by the author of the focal review in the dataset.	Review platform
Review platform	There may be platform-specific differences that lead to differences in satisfaction ratings.	Dummy indicating whether a review was published on TripAdvisor or Yelp.	Review platform
Mall size	A higher number of stores in the shopping mall may increase the cross-store assortment.	Total number of stores within the mall (in 10 stores).	Mall websites
Population density	A larger nearby population may ease mall accessibility and increase the number of competitors.	Number of people in a 5-mile radius of the shopping mall ZIP code (in 1000,000 people).	Global Human Settlement Layer dataset
Population income	Higher average income may indicate a higher willingness to spend money.	Average income of the population in the shopping mall's ZIP code (in $100,000 income).	US and UK census bureaus
Mall age	Older shopping malls may have a more established reputation.	Number of years since the official opening of the shopping mall (in 10 years).	Mall websites
Population age	An older population may have different tastes than a younger population.	The median age of the population in the ZIP code of the shopping mall (in 10 years).	US and UK census bureaus

Notes. Information on local reviewer status is not available in Google Reviews and, therefore, not included in Study 2.

where MS_i is the star rating $j = 1,2,3,4,5$ in customer review i for mall k; MA_{ik} is the sentiment for mall access, MT_{ik} is the sentiment for mall atmosphere, CA_{ik} is the sentiment for cross-store assortment, WA_{ik} is the sentiment for within-store assortment, and PP_{ik} is the sentiment for price and promotion; CV_{pik} denote the group of p control variables for review i for mall k. γ_k are the mall fixed effects, δ_{lik} denote the year fixed effect for every year l across the ten-year timespan 2010–2019 of the study. μ_{mik} is the month fixed effect for every month m, τ_{nik} is the fixed effect for each day of the week n and ε_{ik} is the error term for every review i for mall k By clustering standard errors at the mall level, we account for dependencies among reviews related to the same mall k.

To capture the moderation effects, we introduce interactions between each of the PMRE attributes and mall size, population density, and population income. Because moderator variables are measured at the mall level, interaction terms capture cross-level effects between review-level sentiment measures and mall-level contextual characteristics. We further explore potential interaction effects with mall age and population age. We do not include main effects for the moderators as these are already captured by the mall-fixed effects $\sum MALL_k$, thus we specify:

$$\begin{aligned} logit[P(MS_{ik} \leq j)] &= \beta_0 + \beta_1 MA_{ik} + \beta_2 MT_{ik} + \beta_3 CA_{ik} + \beta_4 WA_{ik} + \beta_5 PP_{ik} + \sum_{p=6}^{9} \beta_p CV_{pik} + \sum_{q=1}^{79} \gamma_k + \sum_{l=1}^{9} \delta_{lik} + \sum_{m=1}^{11} \mu_{mik} + \sum_{n=1}^{6} \tau_{nik} \\ &+ \Psi_1(\mathbf{S}_{ik} \times ML_k) + \Psi_2(\mathbf{S}_{ik} \times PD_k) + \Psi_3(\mathbf{S}_{ik} \times PI_k) + \Psi_4(\mathbf{S}_{ik} \times AG_k) + \Psi_5(\mathbf{S}_{ik} \times PA_k) + \varepsilon_{ik} \end{aligned} \tag{2}$$

where $\mathbf{S}_{ik} = \{MA_{ik},\ MT_{ik},\ CA_{ik}, WA_{ik}, PP_{ik}\}$ denotes the vector of PMRE sentiment measures for review i for mall k. The terms $\mathbf{S}_{ik} \times ML_k$, $\mathbf{S}_{ik} \times PD_k$, $\mathbf{S}_{ik} \times PI_k$, $\mathbf{S}_{ik} \times AG_k$ and $\mathbf{S}_{ik} \times PA_k$ represent vectors of interaction terms between the PMRE sentiment measures and, respectively, mall size, population density, population income, mall age, and population age (all measured at the mall level k). These interactions capture how the associations between PMRE attributes and review ratings vary across mall- and location-specific characteristics. Multicollinearity was not a concern, with the highest VIF of 2.32.

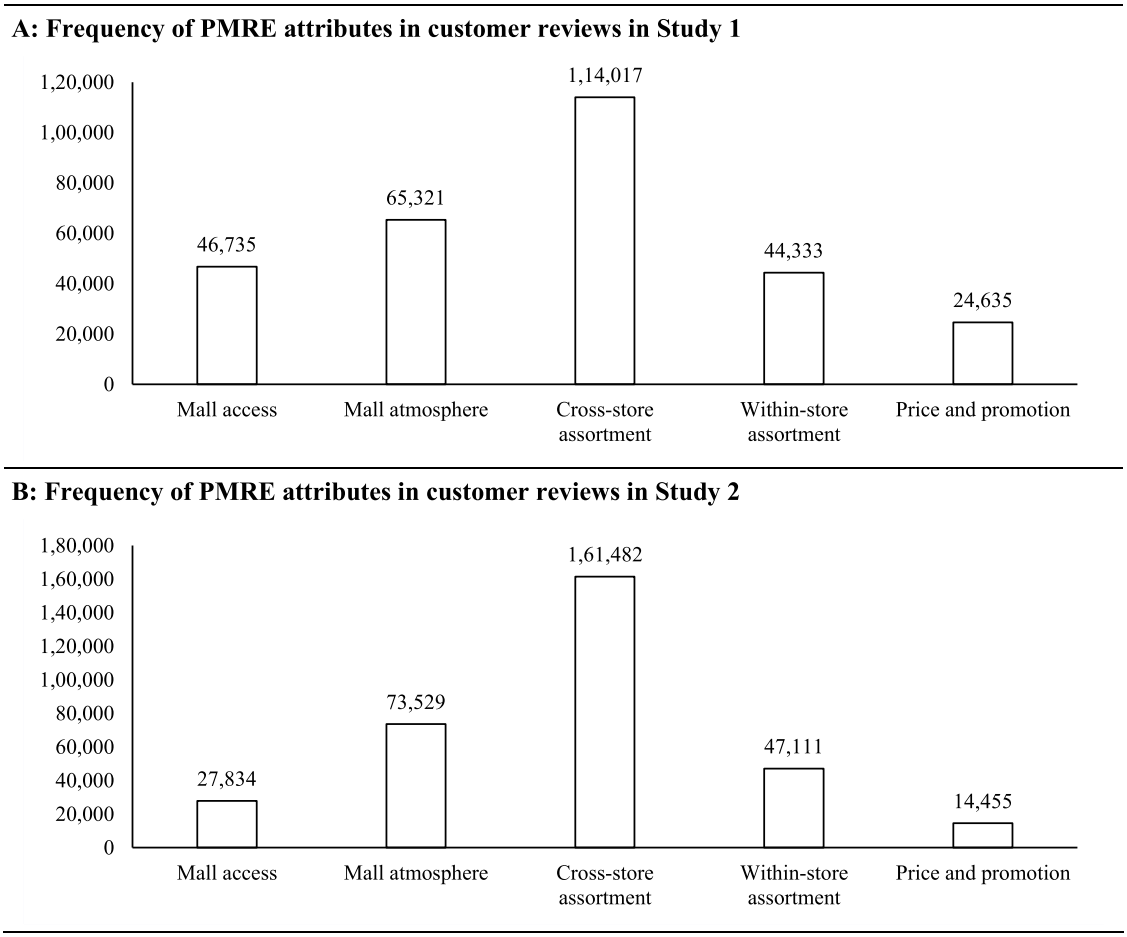

Fig. 3. Model-free evidence.

3.5. Results for mall-controlled vs. tenant-controlled PMRE attributes

Model 1 in Table 5 examines the relationship between PMRE attributes and mall satisfaction. The odds ratios indicate the change in the likelihood of a one-star increase in satisfaction for a one-unit increase in sentiment toward each attribute.[2] All five PMRE attributes show positive and significant effects. Cross-store assortment has the strongest relationship ($\beta = 0.261$, $p < .001$, OR = 1.298), indicating that when customers perceive a one-unit more positive cross-store assortment, the odds of a higher star rating increase by 30 %. Mall atmosphere also plays an important role in mall satisfaction ($\beta = 0.228$, $p < .001$, OR = 1.257) while price and promotion ($\beta = 0.170$, $p < .001$, OR = 1.185), mall access ($\beta = 0.157$, $p < .001$, OR = 1.170) and within-store assortment ($\beta = 0.144$, $p < .001$, OR = 1.155) appear less relevant. Using the lincom command in STATA, we computed point estimates, standard errors, z statistics, p-values, and confidence intervals for linear combinations of parameters. We compared the average effect of mall-controlled attributes (mall access, atmosphere, and cross-store assortment) with that of tenant-controlled attributes (within-store assortment and price and promotion) using the formula:

$$var(A_{MC} - A_{TC}) = var(A_{MC}) + var(A_{TC}) - 2cov(A_{MC}, A_{TC}) \tag{3}$$

where A_{MC} is the average effect of the mall-controlled attributes and A_{TC} is the average effect of the tenant-controlled attributes and derived 95 % confidence intervals for the statistical difference. Mall-controlled attributes ($A_{MC} = 0.215$, $p < .001$) have a stronger relationship with mall satisfaction than tenant-controlled attributes ($A_{TC} = 0.157$, $p < .001$; $\Delta = 0.059$, $p = .001$).

Pairwise tests further show that mall atmosphere and cross-store assortment are more strongly associated with satisfaction than within-store assortment and price and promotion (all $\Delta \geq 0.058$, $p < .010$), while mall access does not differ significantly from either tenant-controlled attribute (both $\Delta \leq 0.014$, $p > .703$).

[2] A one-unit increase means that there is one more positive (or one less negative) mention of a PMRE attribute within a review.

Table 5
Results for mall-controlled vs. tenant-controlled attributes.

	Model 1: Full Sample				Model 2: TripAdvisor				Model 3: Yelp			
	Coefficient		SE	OR	Coefficient		SE	OR	Coefficient		SE	OR
PMRE Attributes												
Mall access	0.157	**	0.027	1.170	0.175	**	0.036	1.191	0.151	**	0.018	1.163
Mall atmosphere	0.228	**	0.013	1.257	0.246	**	0.017	1.278	0.212	**	0.010	1.237
Cross-store assortment	0.261	**	0.007	1.298	0.275	**	0.009	1.316	0.242	**	0.008	1.274
Within-store assortment	0.144	**	0.015	1.155	0.173	**	0.021	1.189	0.114	**	0.011	1.121
Price and promotion	0.170	**	0.013	1.185	0.194	**	0.018	1.214	0.130	**	0.016	1.139
Control Variables												
Review length	−0.006	**	0.001	0.994	−0.009	**	0.001	0.991	−0.004	**	0.000	0.996
Local reviewer	0.039		0.035	1.039	0.065		0.036	1.067	0.113		0.069	1.120
Number of reviews	−0.022	**	0.003	0.979	−0.039	**	0.004	0.962	−0.009	**	0.002	0.992
Review platform (TripAdvisor vs. Yelp)	0.447	**	0.068	1.563								
Fixed Effects												
Mall	Included				Included				Included			
Year	Included				Included				Included			
Month	Included				Included				Included			
Weekday	Included				Included				Included			
Akaike Information Criterion	178,118.60				120,198.80				56,840.10			
Number of Shopping Malls	79				78				79			
Number of Customer Reviews	81,615				58,645				22,970			
Linear Combinations of Parameters												
Mall-controlled PMRE attributes	0.215, SE = 0.010, $p < .001$				0.232, SE = 0.013, $p < .001$				0.202, SE = 0.007, $p < .001$			
Tenant-controlled PMRE attributes	0.157, SE = 0.011, $p < .001$				0.184, SE = 0.015, $p < .001$				0.123, SE = 0.009, $p < .001$			
$\Delta_{\text{Mall- and tenant-controlled PMRE attributes}}$	0.059, SE = 0.018, $p = .001$				0.048, SE = 0.025, $p = .052$				0.080, SE = 0.013, $p < .001$			

$^{**}p < .01$, $^{*}p < .05$. Note: We omit the cut points to increase table readability. SE = clustered standard errors, OR = odds ratios.

3.6. Robustness checks and additional analyses

Our findings remain robust across multiple analyses.[3] Specifically, weighted results based on the frequency of mentions of the PMRE attributes are fully in line with the main analysis. Interestingly, the frequency of mentions and the average sentiment score already point to the importance of mall-controlled attributes, as reported in Web Appendix E4.

Separate estimations for TripAdvisor and Yelp reviews (Models 2 and 3 of Table 5) confirm positive and significant effects for all PMRE attributes (all $p < .001$). In both subsamples, mall-controlled attributes show stronger relationships with mall satisfaction ($A_{MC} \geq 0.202$, $p < .001$) than tenant-controlled attributes ($A_{TC} \geq 0.122$, $p < .001$; $\Delta \geq 0.048$, $p \leq .052$).

We also tested random 50 % data splits, separate samples for local and non-local reviewers, and country-specific models. The random splits remain consistent ($A_{MC} \geq 0.214$, $p < .001$; $A_{TC} \geq 0.154$; $p < .001$; $\Delta \geq 0.058$, $p \leq .012$). Results are similar for local reviewers ($A_{MC} = 0.213$, $p < .001$; $A_{TC} = 0.136$; $p < .001$; $\Delta = 0.077$, $p < .001$) and for the US sample ($A_{MC} = 0.219$, $p < .001$; $A_{TC} = 0.1463$ $p < .001$; $\Delta = 0.073$, $p < .001$). No differences emerge for non-local reviewers ($A_{MC} = 0.225$, $p < .001$; $A_{TC} = 0.198$; $p < .001$; $\Delta = 0.028$, $p = .188$) or the UK sample ($A_{MC} = 0.209$, $p < .001$; $A_{TC} = 0.209$; $p < .001$; $\Delta = 0.001$, $p = .979$). Pairwise tests reveal that for non-local reviewers and the UK sample, the relationships of mall access, mall atmosphere, and cross-store assortment do not differ significantly from price and promotion (all $\Delta \leq 0.039$, $p > .095$).

We also distinguish between positive and negative sentiment for each PMRE attribute. Both positive ($A_{MC} = 0.088$, $p < .001$; $A_{TC} = 0.045$; $p = .020$, $\Delta = 0.043$, $p = .005$) and negative sentiment ($A_{MC} = -0.428$, $p < .001$; $A_{TC} = -0.241$; $p < .001$, $\Delta = 0.186$, $p < .001$) of mall-controlled attributes show stronger relationships with satisfaction than tenant-controlled ones. Negative effects of both mall-controlled ($\Delta = 0.516$, $p < .001$) and tenant-controlled ($\Delta = 0.286$, $p < .001$) attributes are more pronounced than positive ones. This pattern holds across all five PMRE attributes (all $\Delta \geq 0.219$, $p < .001$) except within-store assortment ($\Delta = 0.044$, $p = .218$). Details in Web Appendix E5 to E7.

3.7. Results for the heterogeneity of malls

Table 6 presents the moderating effects of mall- and location-specific characteristics. Model 4 includes all interactions between the five PMRE attributes and the five contextual factors. Non-significant effects were iteratively removed, leaving only significant interactions in Model 5. Larger malls increase the importance of cross-store assortment ($\beta = 0.003$, $p = .001$, OR = 1.003) but reduce the importance of mall atmosphere ($\beta = -0.002$, $p < .001$, OR =0.998). Higher population density raises the relevance of within-store assortment ($\beta = 0.032$, $p = .001$, OR = 1.032), price and promotion ($\beta = 0.058$, $p = .014$, OR = 1.060), while reducing that of mall access ($\beta = -0.036$, $p = .037$, OR = 0.965). Greater population income decreases the effect of within-store assortment ($\beta =$

[3] A stereotype logistic regression, a cumulative link model relaxing the proportional odds assumption (Fernández et al. 2021), and a panel model with mall-fixed effects all yield consistent results (all $\Delta \geq .036$, $p \leq .001$).

Table 6
Results for the heterogeneity of malls.

	Model 4: All Moderators				Model 5: Reduced Set			
	Coefficient		SE	OR	Coefficient		SE	OR
PMRE Attributes								
Mall access	0.153	**	0.015	1.166	0.157	**	0.025	1.170
Mall atmosphere	0.222	**	0.008	1.248	0.223	**	0.008	1.250
Cross-store assortment	0.261	**	0.006	1.299	0.261	**	0.007	1.299
Within-store assortment	0.148	**	0.011	1.159	0.145	**	0.012	1.156
Price and promotion	0.176	**	0.010	1.193	0.168		0.013	1.182
Control Variables								
Review length	−0.006	**	0.001	0.994	−0.006	**	0.001	0.994
Local reviewer	0.041		0.035	1.042	0.040		0.035	1.040
Number of reviews	0.000	**	0.000	1.000	0.000	**	0.000	1.000
Review platform (TripAdvisor vs. Yelp)	0.447	**	0.069	1.564	0.448	**	0.069	1.566
Interaction Effects								
Mall size × Mall access	0.000		0.002	1.000				
Mall size × Mall atmosphere	−0.002	**	0.001	0.998	−0.002	**	0.001	0.998
Mall size × Cross-store assortment	0.003	**	0.001	1.003	0.003	**	0.001	1.003
Mall size × Within-store assortment	0.000		0.001	1.000				
Mall size × Price and promotion	0.002	*	0.001	1.002	0.002	*	0.001	1.002
Population density × Mall access	−0.040	*	0.018	0.961	−0.036	*	0.017	0.965
Population density × Mall atmosphere	−0.010		0.009	0.990				
Population density × Cross-store assortment	−0.008		0.006	0.992				
Population density × Within-store assortment	0.044	**	0.007	1.045	0.032	**	0.009	1.032
Population density × Price and promotion	0.035	*	0.014	1.036	0.058	*	0.024	1.060
Population income × Mall access	0.074		0.042	1.077				
Population income × Mall atmosphere	0.032		0.023	1.033				
Population income × Cross-store assortment	−0.001		0.015	0.999				
Population income × Within-store assortment	−0.054	*	0.021	0.948	−0.045	*	0.023	0.956
Population income × Price and promotion	−0.005		0.025	0.995	0.002		0.021	1.002
Mall age × Mall access	0.001		0.003	1.001				
Mall age × Mall atmosphere	−0.003		0.001	0.997				
Mall age × Cross-store assortment	0.001		0.002	1.001				
Mall age × Within-store assortment	0.002		0.001	1.002				
Mall age × Price and promotion	0.004		0.002	1.004				
Population age × Mall access	−0.054		0.028	0.947				
Population age × Mall atmosphere	0.009		0.011	1.009				
Population age × Cross-store assortment	0.009		0.008	1.009				
Population age × Within-store assortment	0.049	**	0.014	1.050	0.046	*	0.018	1.047
Population age × Price and promotion	0.000		0.016	1.000				
Fixed Effects								
Mall	Included				Included			
Year	Included				Included			
Month	Included				Included			
Weekday	Included				Included			
Akaike Information Criterion	177,991.00				178,009.00			
Number of Shopping Malls	79				79			
Number of Customer Reviews	81,615				81,615			
Linear Combinations of Parameters								
Mall-controlled PMRE attributes	0.212, SE = 0.006, $p < .001$				0.214, SE = 0.009, $p < .001$			
Tenant-controlled PMRE attributes	0.162, SE = 0.006, $p < .001$				0.156, SE = 0.009, $p < .001$			
$\Delta_{\text{Mall- and tenant-controlled PMRE attributes}}$	0.050, SE = 0.010, $p < .001$				0.057, SE = 0.014, $p < .001$			

$^{**}p < .01$, $^{*}p < .05$. Notes: We omit the cut points to increase table readability. SE = clustered standard errors, OR = odds ratios.

−0.045, $p = .048$, OR = 0.956), but does not affect price and promotion (β = 0.002, $p = .932$, OR = 1.002). Additionally, mall size increases the importance of price and promotion (β = 0.002, $p = .026$, OR = 1.002), population income decreases the effect of within-store assortment (β = −0.045, $p = .048$, OR = 0.956), and population age increases it (β = 0.046, $p = .012$, OR = 1.047). All significant moderations are in Fig. 4.

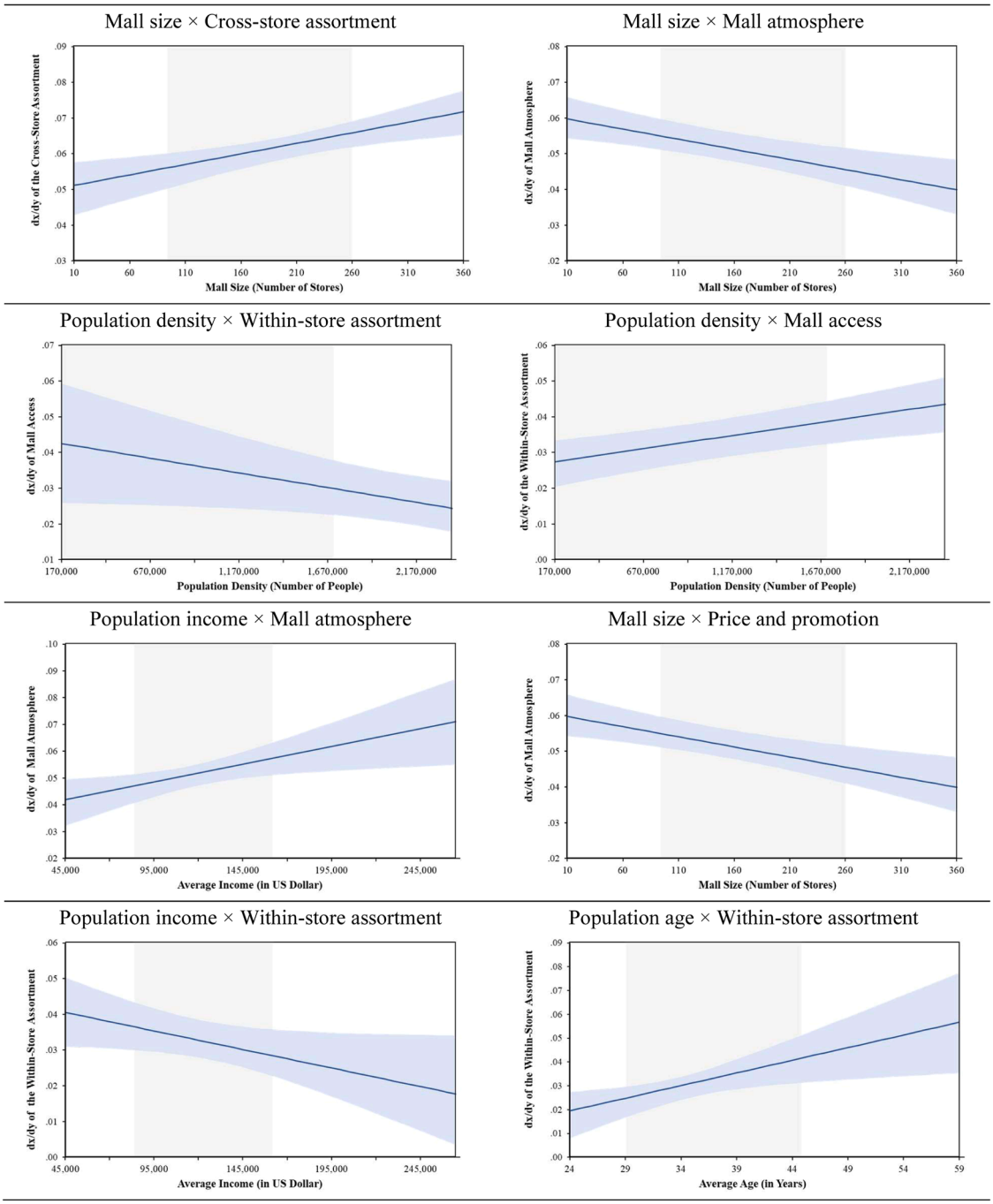

Fig. 4. Moderating effects of mall- and location-specific characteristics.

4. Study 2: PMRE attributes, mall satisfaction, and mall survival

4.1. Sampling and data collection

Identifying closed malls is challenging due to complex ownership structures and the absence of reliable closure records.[4] Many

[4] Many shopping malls get repurposed in an alternative format, using a different name or parent company just before bankruptcy. No public records about individual malls include detailed closure or bankruptcy information.

malls close quietly, rebrand, relocate, or undergo redevelopment without formal announcements. To overcome this, we constructed the dataset in three stages to identify and match closed and surviving malls.

First, we manually compiled a list of closed malls using multiple sources, including Google searches (e.g., "abandoned mall", "dead mall"), retail association reports, local news outlets, and archived directories. Closure status was verified through Google Maps, where malls were required to be labeled as "permanently closed" or "temporarily closed" as of 2024.[5] Consistent with Study 1, we included only malls with at least 50 written reviews to ensure data quality. This process identified 64 closed shopping malls across the United States and the United Kingdom.

Second, we matched these closed malls to surviving malls. While prior research highlights the importance of geographical location in explaining store closures (Kupfer et al., 2024; Shields & Kures, 2007; Warren & Gordon-Larsen, 2018; Star & Massel, 1981), purely location-based matching could introduce endogeneity, as the closure of one mall may affect nearby competitors. To avoid this, we compiled a comprehensive list of surviving malls in the United States ($N = 929$) and the United Kingdom ($N = 447$) using national Wikipedia directories,[6] unusual retail formats and malls labeled "permanently closed" on Google were excluded. For all malls, we manually collected mall- and location-specific characteristics data through web searches, directories, floor plans, and mall websites, including mall size, population density, average income, mall age, and population age. This procedure yielded a dataset of 1312 malls across both countries.

Third, we applied propensity score matching (PSM) to match each closed mall with a surviving mall that had comparable mall- and location-specific characteristics, using 1:1 nearest-neighbor matching based on Mahalanobis distance.[7] Before matching, closed and surviving malls differed substantially: surviving malls were generally larger, located in higher-population markets, and in areas with lower average income, yielding an average standardized mean difference (SMD) of 0.33, indicating considerable imbalance (Stuart, 2010). After PSM, the balance improved substantially. The average SMD was reduced by 0.25 points (76 %), with most characteristics showing reductions between 76–87 %. The majority of covariates had SMDs < 0.10, indicating stringent balance; the exception was mall age, which slightly increased but remained below the conventional threshold of 0.25 (Rubin, 2001). Table 7 provides an overview of the PSM results and balance statistics. A visualization is presented in Fig. 5.

A total of 64 matched mall pairs (128 malls: 64 closed and 64 surviving) were retained for analysis. No closed malls were dropped during matching, ensuring complete representation. For each mall, we collected all available Google Reviews, including star ratings, review texts, and mall- and location-specific characteristics listed in Table 7. Reviews were processed following the same procedure as in Study 1: Only reviews containing written content were included, and malls required at least 50 reviews for meaningful analysis. Four pairs were excluded because one mall in each pair failed to meet this threshold, resulting in a final sample of 62 matched pairs.

Review texts were split into sentences and analyzed using the same aspect-based sentiment approach as in Study 1 to identify and classify positive and negative mentions of PMRE attributes, which were then aggregated to the review level. Reviews posted after the closure year were removed for closed malls,[8] while all available reviews for surviving malls were retained. The final dataset includes 169,458 Google reviews (68,239 for closed malls and 101,219 for surviving malls), averaging 1746 reviews per mall (range: 100 to 3075) with an average star rating of 3.77 ($SD = 1.32$). Web Appendix F1 provides the complete list of all mall locations.

4.2. Measurement

Dependent variables. Shopping mall survival served as the binary dependent variable, coded 0 for closed and 1 for surviving malls (Kupfer et al., 2024; Zhang & Luo, 2023). The star rating of each review was used as a proxy for the customer's mall satisfaction.

Independent variables. Aspect-based sentiment scores for the PMRE attributes were measured using the same procedure as in Study 1.

Control variables. Control variables are in line with Study 1, except that the "local reviewer" variable was excluded because Google's "local guide" designation reflects user activity rather than geographic proximity. Mall- and location-specific controls were included, as mall-fixed effects would interfere with the binary survival outcome. Descriptive statistics and correlations are provided in Web Appendix F2.

4.3. Method

While sentiment is initially measured at the individual review level, these measures are aggregated to the mall–year level to align with the time-varying structure of the survival model. The review-level data were transformed into a mall-year panel, by computing the yearly mean sentiment score for each PMRE attribute within each mall. Specifically, for each mall and calendar year, we averaged

[5] Google Review profiles can be reactivated by the owner or by reports of visitors after the profile has been marked as permanently closed. When a profile is marked as permanently closed, Google withdraws it from search results to keep these relevant for their users. Owners of the page are able to delete their profile or start a new profile with a different name on the same address (e.g. after repurposing of the mall).

[6] US malls: https://en.wikipedia.org/wiki/List_of_shopping_malls_in_the_United_States. UK malls: https://en.wikipedia.org/wiki/List_of_shopping_centres_in_the_United_Kingdom. Collected in June 2025.

[7] We benchmarked different matchers, nearest neighbor with and without calipers and with Euclidean distance, optimal matching and full matching. These alternatives left more imbalance resulting in less precise estimates.

[8] We cannot rely on reviews written after the closure, which often feature nostalgic reflections rather than actual experiences, such as "I enjoyed this mall so much when growing up in this area; it will be really missed."

Table 7
Propensity Score Matching Results.

Means Before and After Matching							
Means Before Matching				Means After Matching			% SMD Reduction
Closed Malls ($n = 64$)	Surviving Malls ($n = 1312$)	Standardized Mean Difference		Closed Malls ($n = 64$)	Surviving Malls ($n = 64$)	Standardized Mean Difference	
43.77	44.98	−0.13	Mall age	43.77	45.42	−0.18	-
66.64	88.70	−0.62	Mall size	66.64	69.50	−0.08	87.10
4.14	4.39	−0.13	Mall anchors	4.14	4.09	−0.03	76.92
684,685.67	727,617.64	−0.12	Mall floor area	684,685.67	677,690.53	−0.02	83.33
149,461.44	287,921.43	−0.75	Population density	149,461.44	175,097.58	−0.14	81.33
39.02	38.14	−0.17	Population age	39.02	38.93	−0.02	88.24
80,419.11	66,976.94	−0.37	Population income	80,419.11	77,505.19	−0.08	78.38

Note: Standardized mean differences (SMD) before and after matching are reported for each characteristic. The percentage reduction indicates the extent to which matching improved covariate balance (negative mean reduction in performance).

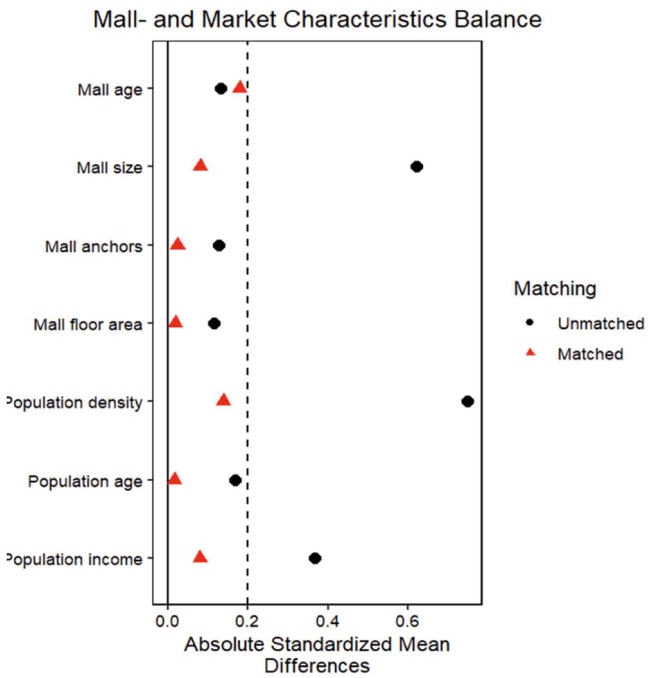

Fig. 5. Covariate Balance Propensity Score Matching.

all review-level attribute sentiment scores to obtain a mall-year attribute sentiment measure and created time-varying controls for review length, number of reviews, and yearly reviews per mall and time-invariant controls for mall size, population density, population income, mall age, and population age. We estimated a hazard survival model:

$$h_k(t) = h_0(t) \bullet \exp(\theta_1 MS_{kt} + \theta_2 MA_{kt} + \theta_3 MT_{kt} + \theta_4 CA_{kt} + \theta_5 WA_{kt} + \theta_6 PP_{kt} + \sum_{p=7}^{9} \theta_p CV_{pkt} + \sum_{q=1}^{5} \alpha_q MC_{qk} \quad (1a)$$

where $h_0(t)$ is the Weibull baseline hazard, MS_{kt} denotes the mall satisfaction for mall k in year t; MA_{kt} is mall access, MT_{kt} is mall atmosphere, CA_{kt} is cross-store assortment, WA_{kt} is within-store assortment, and PP_{kt} is price promotions for mall k in year t, the vector CV_{pkt} contains the p time-varying controls for mall k in year t, and the vector MC_{qk} includes the q the time-invariant controls. We also

Table 8
Results for mall satisfaction and mall survival.

	Model 6				Model 7			Model 8		
	DV: Mall Satisfaction				DV: Mall Survival			DV: Mall Survival		
	Coefficient		SE	OR	Hazard Ratio		SE	Hazard Ratio		SE
Mall satisfaction								0.221	**	0.056
PMRE Attributes										
Mall access	0.177	**	0.019	1.194	1.607		1.093	4.015		3.098
Mall atmosphere	0.346	**	0.015	1.413	0.390	**	0.130	0.946		0.343
Cross-store assortment	0.467	**	0.018	1.596	0.221	**	0.072	0.560		0.224
Within-store assortment	0.207	**	0.014	1.230	0.385		0.312	0.713		0.586
Price and promotion	0.195	**	0.027	1.215	2.046		2.440	6.668		10.307
Control Variables										
Review length	−0.022	**	0.001	0.978	0.966	*	0.017	0.964		0.023
Number of reviews	0.000	**	0.000	1.000	0.989	**	0.004	0.991	*	0.004
Yearly reviews per mall					0.999		0.001	1.000		0.002
Mall size	0.004	**	0.001	1.004	1.004		0.005	1.007		0.004
Population density	0.648	*	0.267	1.912	0.457		0.382	0.814		0.645
Population income	0.255	*	0.116	1.290	2.037		0.925	2.138		0.982
Mall age	0.074		0.043	1.076	0.751		0.125	0.830		0.135
Population age	0.036		0.080	1.037	0.765		0.257	0.769		0.274
Fixed Effects										
Year	Included									
Akaike Information Criterion	461,348.20									
Number of Shopping Malls	124				124			124		
Number of Customer Reviews	169,426				1238			1238		
Linear Combinations of Parameters										
Mall-controlled PMRE attributes	0.330, SE = 0.013, $p < .001$									
Tenant-controlled PMRE attributes	0.201, SE = 0.017, $p < .001$									
$\Delta_{\text{Mall- and tenant-controlled PMRE attributes}}$	0.129, SE = 0.015, $p < .001$									

$^{**}p < .01$, $^{*}p < .05$. Notes: We omit the cut points to increase table readability. SE = clustered standard errors, OR = odds ratios.

estimated an ordered logit model for mall satisfaction.

4.4. Results and robustness checks

Model 6 in Table 8 shows that all PMRE attributes positively relate to mall satisfaction (all $\beta \geq 0.177$, all $p < .001$, all OR ≥ 1.194).[9] Model 7–8 in Table 8 report the survival models; Mall satisfaction is strongly associated with lower closure risk (HR = 0.221, $z = -5.92$, $p < .001$, 95 % CI [0.134, 0.364]); malls with higher satisfaction face substantially lower closure risk. None of the PMRE attributes directly predict closure beyond their effect on mall satisfaction. Thus, mall satisfaction is the strongest observed correlate of mall survival. PMRE attributes are associated with mall satisfaction, which in turn is associated with mall survival, with cross-store assortment and mall atmosphere as most influential, while mall access and price and promotion are less critical. All results hold when excluding all reviews posted during the COVID-19 period (see Web Appendix F3).

5. Discussion

The steep decline in shopping malls since the 1980s (Levin, 2022) underscores the urgent need to understand why some malls succeed while others fail. Drawing on multi-attribute theory and in line with previous research that uncovered multiple store attributes that contribute to individual store performance (Blut et al., 2018), we study the implications of customers' sentiments towards PMRE attributes (Chebat et al., 2010) for mall satisfaction and mall survival. Using an aspect-based sentiment mining approach, we extract sentiment toward PMRE attributes from online customer reviews to offer insights on (1) their relative association with mall satisfaction, (2) mall- and location-specific characteristics that moderate these associations, and (3) the extent to which mall satisfaction statistically accounts for the association between PMRE attribute sentiment and mall survival. Collectively, our results and new methodological approach offer both theoretical as well as practical insights.

5.1. Contributions to research

This research makes three contributions to retail research. First, a key theoretical contribution of this study is the distinction between mall-controlled and tenant-controlled PMRE attributes and their relative influence on mall satisfaction. Applying the retailing

[9] We used model constraint commands to compute point estimates, standard errors and, z statistics, p-values, and confidence intervals for linear combinations of parameters. Mall-controlled attributes (.330, $p < .001$) have a stronger relationship with mall satisfaction than tenant-controlled attributes (.201, $p < .001$; $\Delta = .129$, $p < .001$).

attribute framework established by Ailawadi and Keller (2004) and adapted to malls by Chebat et al. (2010), we find that sentiment towards mall-controlled attributes (mall atmosphere and cross-store assortment) has a stronger relationship with satisfaction than sentiment towards tenant-controlled attributes (within-store assortment and price and promotion). This aligns with multi-attribute theory, which suggests that customers assign greater responsibility to decision-makers with direct control over an experience (Wallenius et al., 2008). Since mall management oversees mall access, atmosphere, and store curation, customers hold the mall accountable for these aspects (Wakefield & Baker, 1998). In contrast, within-store assortment and pricing are retailer decisions, reducing the mall's perceived responsibility for these attributes. Interestingly, mall access, despite being a mall-controlled attribute, played a weaker role in satisfaction than expected. Customers may perceive mall access as a stable, background feature rather than an actively evaluated attribute. According to the expectation-disconfirmation theory (Oliver, 1980), satisfaction judgments arise when experiences deviate from expectations. Since mall access (e.g., parking, infrastructure, and transport) rarely changes, customers may only notice it when it is severely inadequate, making it generally less influential in shaping satisfaction.

Second, this study further extends the multi-attribute conceptualizations in retailing by demonstrating that mall characteristics (i.e., their size, the area's population density, and income levels) shape the relative importance of different PMRE attribute sentiments for mall satisfaction. Larger malls benefit more from cross-store assortment, confirming that variety is a key draw for destination shopping centers (Weiler et al., 2003). However, mall atmosphere played a smaller role in large malls, likely due to crowding effects (Bitner, 1992). Moreover, in high-density areas, within-store assortment was more important for mall satisfaction, reflecting customers' preference for assortment depth in competitive environments (Arentze et al., 2005). Conversely, in low-density areas, mall access played a greater role, as customers face fewer alternatives and travel longer distances to shop (Sethuraman et al., 2022). In addition, in affluent areas, mall atmosphere had a stronger impact, aligning with findings that luxury-oriented customers prioritize shopping ambiance (Grewal et al., 2003). Meanwhile, price and promotion had a weaker effect, indicating that price sensitivity is lower among high-income customers (Lal & Rao, 1997). A one-size-fits-all approach is thus ineffective; instead, managers should tailor strategies based on mall size, location, and customer demographics to optimize satisfaction.

Third, building on research on store closure and survival (Kupfer et al., 2024), we find that Mall satisfaction statistically accounts for the association between PMRE attributes and mall survival. Specifically, sentiments toward all five PMRE attributes are associated with mall satisfaction, and mall satisfaction is associated with mall survival, suggesting that lower customer satisfaction is a primary indicator of closure risk (Naumzik et al., 2022). Thereby, our findings extend prior research on customer satisfaction and business longevity (Sirohi et al., 1998) to the mall context.

Table 9
Simulation results attribute improvements for different malls.

	Simulation 1	**Simulation 2**	**Simulation 3**	**Simulation 4**
Mall Description	Large mall in densely populated, high-income location, younger age	Small mall in densely populated, high-income location, younger age	Large mall in sparsely populated, low-income location, older age	Small mall in medium populated, medium-income location, average age.
Mall Characteristics				
Mall size	260 stores	69 stores	260 stores	69 stores
Population density	1800,000 residents	1800,000 residents	153,000 residents	970,000 residents
Average income	158,000 US dollars	158,000 US dollars	71,000 US dollars	114,000 US dollars
Average population age	29 years	29 years	44 years	37 years
Effects of:				
Mall access	14 %	14 %	20 %	17 %
Mall atmosphere	22 %	**28 %**	22 %	**28 %**
Cross-store assortment	**33 %**	27 %	**33 %**	27 %
Within-store assortment	***12 %***	***12 %***	***19 %***	***16 %***
Price and promotion	21 %	16 %	20 %	***16 %***
Illustrative real-life example from Study 1 Sample	Westfield STRATFORD CITY E20 Located in London, UK, Westfield Stratford City has roughly 350 stores and draws from a densely populated 5-mile area (2082,071 people) with an average income of $86,862 and a median age of 27.	BROOKFIELD PLACE Located in New York City, NY, Brookfield Place has roughly 34 stores and draws from a densely populated area (2038,404 people) with an average income of $120,903 and a median age of 37.	DOLPHIN MALL A SIMON CENTER Located in Miami, FL, Dolphin Mall has roughly 240 stores and draws from a sparsely populated area (344,463 people) with an average income of $62,986 and a median age of 42.	CAMBRIDGESIDE Located in Cambridge, MA, Cambridgeside Galleria has roughly 80 stores and draws from a medium populated area (975,449 people) with an average income of $113,792 and a median age of 32.

Notes: Effects refer to the likelihood of a higher mall satisfaction rating for a one-point increase in customer sentiment towards the mall attribute. The mall characteristics are based on low (−1SD), medium (mean) and high (+1SD) values. The coefficient in bold has the highest and the coefficient in bold and italics has the lowest relationship with mall satisfaction in each simulation.

5.2. Managerial implications

Shopping mall managers operate in an environment where declining foot traffic and rising closure rates make resource allocation decisions increasingly consequential (Levin, 2022; Wells, 2022). A central managerial challenge is determining which perceived mall retail environment (PMRE) attributes warrant prioritization when resources are limited and many drivers of performance appear outside direct managerial control. Our evidence shows that sentiment toward mall-controlled PMRE attributes is more strongly associated with mall satisfaction than sentiment toward tenant-controlled attributes. In particular, cross-store assortment and mall atmosphere exhibit the strongest associations with satisfaction. This recalibrates managerial focus. Investments in tenant mix composition and shared atmospheric quality are more strongly aligned with satisfaction outcomes than efforts targeting within-store assortment or price and promotion, which are largely tenant-controlled.

However, attribute importance is not uniform. The moderating results in Table 6 show that mall size, population density, population income, and population age systematically condition these associations. Larger malls strengthen the association between cross-store assortment and satisfaction but weaken that of mall atmosphere. Higher population density increases the association of within-store assortment and price and promotion, while reducing that of mall access. These findings indicate that average effects are insufficient for decision making. Managers must align improvement efforts with their mall's structural and demographic context rather than apply a uniform investment logic.

The scenario simulations based on Model 5 in Table 6 (see Table 9) translate these conditional effects into interpretable profiles. We computed conditional effects of each PMRE attribute at respective values of the mall characteristics of model 5 in Table 6, so coefficients are the log-odds of observing a higher mall satisfaction. For each mall characteristic we defined three values being low (−1SD), medium (mean) and high (+1SD). We then created four simulations (see Table 9) where we evaluated the marginal effect of a PMRE attribute by using the PMRE attribute coefficient and added the respective interaction coefficient at the low, medium or high value of the mall characteristics. Evaluating marginal effects at low (−1SD), mean, and high (+1SD) levels of mall characteristics shows that the attributes most strongly associated with higher satisfaction differ across mall types. For example, large urban malls (e.g. Westfield Mall in London) derive the strongest relative association from within-store assortment and atmosphere, whereas smaller malls (e.g. Brookfield Place in New York or Cambridgeside Galleria) exhibit relatively stronger associations for atmosphere, within-store assortment, and price and promotion. In lower-density, lower-income areas (e.g. Dolphin Mall in Florida), mall access and within-store assortment become more strongly associated with satisfaction.

Finally, Study 2 shows that mall satisfaction is strongly associated with mall survival. Mall satisfaction statistically accounts for the association between PMRE attribute sentiment and survival. For owners and asset managers, this indicates that attribute-level improvements matter insofar as they correspond to higher aggregate customer satisfaction. Structured aspect-based sentiment analysis of online reviews provides a continuous mechanism to monitor these attribute-level perceptions. Compared with infrequent and costly surveys (Gielens & Lamey, 2024), online review data offer a scalable stream of consumer evaluations (Guyt et al., 2024), enabling earlier identification of weaknesses in mall-controlled attributes most strongly associated with satisfaction and survival.

5.3. Limitations and further research

Expanding data sources beyond TripAdvisor, Yelp, and Google could provide a more comprehensive view of customer sentiment toward PMRE attributes (Bradlow et al., 2017). Incorporating social media discussions, transaction records, and loyalty program data would enable triangulation and a more nuanced understanding of the drivers of mall satisfaction and mall closure. Because online reviews tend to attract consumers with extreme evaluations and generate J shaped distributions, moderate experiences may be underrepresented, introducing selection bias that can influence results (Schoenmueller et al., 2020). Although our data show similar polarity and imbalance scores as prior research and robustness checks mitigate concerns about stability, the non-random nature of review data limits causal interpretation and generalizability. Combining reviews with additional non review data sources would strengthen inference. While aggregating review level sentiment to the mall-year level aligns with the annual hazard specification of mall closure and reduces noise in individual reviews, it abstracts from within year variation. Examining intra year dispersion in sentiment rather than yearly averages could provide a more fine grained understanding of closure dynamics.

Future research should also test boundary conditions. Because our study focuses on malls in the United States and the United Kingdom, where mall culture is well established, the relative importance of PMRE attributes may differ in emerging markets and diverse retail landscapes. Cross country comparisons could reveal distinct patterns in customer preferences, while cross industry analyses could determine whether the findings generalize beyond shopping malls, including malls outside major metropolitan areas. Although we identify the PMRE attributes most influential to satisfaction, the underlying mechanisms remain unexplored. Future research could examine mediating processes such as emotional connection, trust, or habitual shopping behavior to clarify why certain attributes exert stronger effects and to enhance theoretical and managerial insight. Methodologically, advances in large language models create opportunities to compare alternative aspect based sentiment approaches beyond SiEBERT.

Finally, while we incorporate mall- and location-specific characteristics such as mall age, mall size, and population density to build sociodemographic profiles, these data are often irregularly updated by malls online, unavailable through manual web searches, or inconsistently updated by national census bureaus, limiting longitudinal analysis. Integrating longitudinal mall- and location-specific characteristics or operational indicators such as foot traffic, sales performance, and tenant turnover would refine the findings and allow examination of how PMRE attributes interact with broader business performance. Extending the sentiment approach to other retail formats, such as outlet centers that face similar challenges but may prioritize different experience factors, and customizing the methodology to specific retail environments would enable more context specific insights into attribute importance and strategic

resource allocation.

Acknowledgment

The first author handled the measurement and data analysis (guided by the second author) and the first and fifth author managed the data collection for all studies. The third author thanks the Australian Research Council (ARC) for the financial support during this project (ARC Discovery Project: DP230101490). We thank Katrijn Gielens, Francesca Sotgiu, Francesco Balocco, and seminar participants at Vrije Universiteit Amsterdam for valuable feedback on previous versions of this article.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jretai.2026.02.003.

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