Integrating Location Intelligence within Shopping Centre Reconfiguration: A Monte Carlo Simulation

Manil Wagle
Department of Geography and Environmental Studies
Wilfrid Laurier University
MWagle@wlu.com

Joseph Aversa
Ted Rogers School of Management,
Toronto Metropolitan University
javersa@ryerson.ca

Tony Hernandez
Ted Rogers School of Management,
Toronto Metropolitan University
thernand@ryerson.ca

Sean Doherty
Department of Geography and Environmental Studies
Wilfrid Laurier University
sdoherty@wlu.ca

Abstract

Technological advancements and evolving consumer behaviors have significantly transformed the retail landscape. Traditional shopping centers, now under pressure to innovate, are leveraging location intelligence—insights from geospatial data—to stay relevant. This study explores how spatial big data can enhance leasing decisions for store expansions using Monte Carlo simulations. Focusing on a fast-fashion retailer considering expanding from 14,000 sqft to 30,000 sqft within a shopping center, it examines the impacts on sales performance. Data from Wi-Fi beacons, capturing customer traffic and sales trends from January 2022 to December 2023, provides a robust basis for analysis. The study aims to offer a quantifiable method for shopping center landlords and retailers to make informed leasing decisions under uncertainty, with two primary research objectives: leveraging spatial big data to enhance store expansion decisions and understanding how increased retail square footage impacts sales performance.

1. Introduction

Over the past decade, the retail landscape has undergone significant transformations, primarily driven by technological advancements and evolving consumer behaviours and preferences. Traditional shopping centres, once thriving hubs of commerce and social interaction, now face significant pressure to innovate and adapt to maintain relevance (Ameen et al., 2021; Rice et al., 2022). Among the many strategies employed to rejuvenate these retail spaces, the integration of location intelligence has emerged as a pivotal tool in reconfiguring shopping centres to meet contemporary demands. Location intelligence, that is, deriving meaningful insights from geospatial data, offers a unique perspective to understand and predict consumer patterns and optimize space, ultimately enhancing the overall shopping experience (Aversa et al., 2018; Gupta and Ramachandran, 2021). By leveraging data from various sources such as GPS, mobile devices, social media, and transactional records, retailers and shopping centre managers can gain granular insights into foot traffic, dwell times, and customer preferences (Azmy et al., 2024; Aversa et al., 2024). This data-driven approach enables a more responsive and dynamic management of shopping centres, allowing owners and managers to understand their consumers better (Zhu et al., 2021).

Decision-making in a business context is inherently complex due to the countless factors influencing the process and the consequential impacts of these decisions on various business aspects (Kilestik et al., 2022). This complexity is further magnified when business leaders face higher-risk decisions with significant uncertainty and limited information. The challenge intensifies when no past examples guide decisions, rendering predictive models based on historical data ineffective. This research addresses such a scenario by focusing on leasing decisions related to store expansions within shopping centres. This study uses Monte Carlo simulations to investigate how businesses can make informed decisions under these constraints. A common dilemma of shopping centre landlords is deciding whether to expand a retail store - this type of decision is often made in a time-sensitive manner with limited information. Therefore, this study aims to provide a quantifiable method to assist shopping centre landlords in making such leasing decisions. This research study has two interconnected research objectives:

1) How can spatial big data be leveraged to enhance store expansion decisions within shopping centres using Monte Carlo simulations?

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2) Understand how expanding retail square footage impacts sales performance.

2. Research context

2.1 Shopping centres

Modern shopping centres have evolved into multi-faceted, experiential, and technology-integrated spaces that go beyond traditional retailing. Shopping centres have transformed into comprehensive destinations for shopping, entertainment, dining, and socializing (Youssef, 2021). Beyond traditional services, they offer personalized experiences like loyalty programs, concierge services, and personalized shopping assistance, all designed to make shopping more seamless and enjoyable. These centres have evolved into multifunctional urban spaces, integrating residential, office, and entertainment facilities, and have grown to embody the modern civic square, facilitating not only economic transactions but also serving as cultural and social hubs that significantly influence urban quality of life (Lowe, 2000; Marans & Stimson, 2011). Shopping centres have evolved from traditional local markets to complex retail environments, highlighting their role in facilitating and transforming urban consumption patterns (Corniani, 2011). Shopping centres are no longer just physical marketplaces but have become significant urban phenomena influencing consumer behaviour and urban social structures. This evolution is marked by an increasing focus on the intangible aspects of consumption, such as the atmosphere, branding, and experience offered by these centres, which are pivotal in defining consumer choices and preferences (Lin et al., 2020). Shopping centres are increasingly designed to serve as retail spaces and public venues that promote social interaction and cultural activities. By incorporating sustainable design principles and cultural elements, these spaces aim to improve the urban environment and contribute to the community's social fabric. This shift highlights the evolving role of shopping centres in urban development, reflecting broader societal trends toward sustainability and cultural richness in urban planning.

The pandemic underscored the significant role of shopping centres beyond conventional shopping, highlighting their importance in the urban social fabric and quality of life (Vilnai-Yavetz et al., 2022). During lockdowns, the government-sanctioned closures of shopping centres revealed their role as not merely commercial centres but as crucial social spaces deeply integrated into consumers' daily lives. This period of absence illuminated how centres serve multiple dimensions of urban life, offering a mix of functional, recreational, and social experiences that are challenging to replicate through other retail formats such as online shopping (Kumar, 2021).

The academic literature emphasizes the community benefits stemming from shopping centres, which drive economic growth by providing direct and indirect employment and capital investment (Cloete, 2020; Eduful, 2021). The economic effect of shopping centres, including eliminating undesirable land uses, stabilizing communities, and increasing tax revenues, has been well documented (Cloete, 2020). Shopping centres shape community dynamics and consumer interactions (Musil, 2011; Bailey, 2020). The vibrancy of a community often mirrors its commercial heart, with retail development being a key factor in urban renewal efforts aimed at boosting community vitality and sustainability (Guimarães, 2017). Research in this field often focuses on the interplay between economic and social impacts, given that shopping centres serve both socio-cultural and economic functions. They foster cultural identity within the communities they serve, enhance community sustainability, create a unique sense of place, and offer diverse goods and services.

2.2 Role of forecasting in shopping centre planning

Shopping centres are planned and managed entities. The decision-making process in shopping centres predominantly focuses on developing leasing strategies that maintain and enhance the commercial mix. Existing studies have explored various methodologies for determining lease rates within these commercial spaces (Benjamin et al., 1990; Brueckner, 1993, & Guveen et al., 2022). For several reasons, understanding the close link between store expansion and sales performance is essential. Firstly, the primary goal of expanding a store's retail space is to increase sales. A larger store can accommodate more inventory, attract more customers, and provide a better shopping experience, leading to higher sales. By closely linking expansion decisions to sales performance, landlords and retailers can ensure that the investment in additional space will generate sufficient revenue to justify the costs.

Additionally, leasing strategies in shopping centres are often based on sales performance. Establishing the potential sales uplift from the store expansion is crucial for setting realistic lease rate expectations. Post-expansion, landlords typically aim to increase rents proportionally to sales increments. Additionally, landlords employ various clauses that generate additional revenue when sales exceed predefined thresholds. The concept of a percentage rent rate, which supplements the base rent, has been identified as a key element in setting rent levels (Wheaton, 2000). However, most decision-making models in shopping centre literature heavily rely on historical data and traditional retail metrics. This approach notably overlooks the complexities introduced by modern retail dynamics, such as the dramatic increase in online shopping, changing consumer preferences, and the evolving expectation for centres to provide comprehensive experiential environments.

Furthermore, the lack of integration of real-time data, such as foot traffic, social media engagement, and sales figures, into retail rent models is a significant oversight. This gap highlights a missed opportunity for developing responsive models that can dynamically adjust to fluctuations in retail conditions. A particularly evident deficiency is the minimal attention paid to the impact of e-commerce, which has significantly altered the retail landscape. Despite its profound influence, only a recent study by Liu et al. (2022) has directly addressed how digital commerce reshapes the dynamics of physical retail spaces, pointing to a substantial gap in the literature.

Forecasting emerges as a pivotal tool in shopping centre planning, blending quantitative methodologies with qualitative insights to enhance decision-making accuracy. While sophisticated data models like Geographic Information Systems (GIS) and spatial interaction models provide a robust framework for analyzing retail locations, they must be complemented by site-specific qualitative data gathered through site visits (Wood and Tasker 2008). These visits allow for the assessment of nuanced factors such as local competition, site visibility, and consumer traffic patterns, which are often underrepresented in quantitative data. Echoing the same sentiment, Reynolds and Wood (2010) detail the evolution of forecasting in retail location decision-making, highlighting the shift from intuition-based to more sophisticated, data-driven approaches. Retail firms extensively employ advanced quantitative models yet emphasize the importance of qualitative insights such as site visits. These complementary methods are essential for calibrating and refining forecasts integrating tacit knowledge and empirical data (Aversa et al., 2018; Aversa et al., 2021).

The utilization of big data and predictive analytics in enhancing forecasting for shopping centres is still nascent but showing promise, particularly in mall design and understanding customer behaviours. Dennis et al. (2001) highlighted the potential of data mining within shopping centres to bolster customer knowledge management, thereby boosting satisfaction and centre performance. Similarly, Patel et al. (2022) demonstrated how K-Means clustering, an unsupervised machine learning technique, can optimize mall layout and refine customer segmentation based on spending behaviours and demographic data. This approach facilitates a deeper understanding of customer patterns, enabling tailored services that improve consumer experiences and operational efficiency. Bradlow et al. (2017) further support this by illustrating how new technologies and data sources allow retailers to predict better and understand customer behaviours, enhancing engagement and efficiency. They note the importance of advanced statistical methods like Bayesian analysis and data mining in supporting real-time decisions and personalized marketing strategies. Aversa et al. (2021) discussed integrating big data within retail organizations, emphasizing its crucial role in making informed retail location decisions. They identified that a robust data environment and clear corporate strategies are essential for leveraging big data effectively. However, this comes with challenges, such as the need for specialized skills and overcoming data silos within organizations. Collectively, these studies affirm the transformative impact of big data on decision-making processes in the context of shopping centres, underscoring its value in enhancing market dynamics comprehension and customer insight.

The existing literature primarily discusses forecasting in the context of retail location determination, focusing on site selection, new store placement, and understanding customer behaviour (Saha et al., 2023; Robinson and Caradima, 2023; Cheah et al., 2022). However, there appears to be a gap in the literature regarding retail store expansion within the same shopping mall. This oversight suggests a need for further research into the strategies and forecasting models specific to expanding existing retail spaces within established shopping centres.

2.3 Use case of Monte Carlo simulations

Monte Carlo simulation is a mathematical technique to model and analyze complex systems. This process involves generating multiple scenarios to estimate the probability distribution of specific outcomes or events. In this research, we apply a Monte Carlo simulation to assess the potential benefits of expanding retail space in incremental sales. According to Bonate (2012), Monte Carlo simulation's fundamental principle lies in its ability to produce a sequence of independent random numbers following a specified distribution with defined mean and variance. He also notes that Monte Carlo simulation aids in determining the standard error and the sampling distribution of statistics, providing solutions in scenarios where the parametric theory falls short and no analytical resolution exists. The Monte Carlo simulation is a probabilistic method that addresses complex deterministic problems. Running numerous experimental trials with random outcomes leverages modern computers' computational power to estimate uncertainties. In uncertainty estimation, Monte Carlo simulations use random numbers to sample the uncertainty space of parameters rather than relying on point estimates typical of conventional methods. This approach aligns more closely with the probabilistic nature of actual measurement processes. Monte Carlo simulation provides a more realistic method for uncertainty estimation by considering this probabilistic perspective (Papadopoulos et al., 2001).

While there has been extensive research on the application of Monte Carlo simulations across various industries and domains (Table 1), there remains a noticeable gap in studies focusing on their use within the context of shopping centres, particularly in decisions related to store expansion. This paper aims to contribute to the academic discourse by exploring the application of Monte Carlo simulations, specifically in shopping mall environments. Table 1 highlights a selection of academic papers that have discussed the use of Monte Carlo simulations in various domains. It is important to note that this list is not exhaustive but illustrates the breadth of Monte Carlo simulations' applicability in managing uncertainties across different fields.

Table 1. Overview of Monte Carlo simulation applications across various domains

Domain	Study	Key Application	Findings
Power Systems	Billinton and Karki, 1999	Assessing system reliability and operational health	Provides additional well-being indices, aiding capacity reserve evaluation.
Reliability Engineering	Alexander, 2003	Estimating the reliability of pump systems	Aids in more accurate decision-making for system reliability improvements.
Project Management	Kwak and Ingall, 2007	Risk analysis in project schedules and budgets	Helps justify reserves and set realistic expectations by quantifying risk.
Finance	Dagpunar, 2007	Pricing of financial derivatives	Enhances accuracy and efficiency in financial computations for exotic derivatives.
Finance	Suhobokov, 2007	Financial risk quantification using Value at Risk (VaR)	Improves VaR calculation accuracy, particularly in Forex exposure.
Finance	Dagpunar, 2008	Risk management in financial systems	Assesses risk and pricing of complex financial instruments, aiding decision-making.
Hydrology	Charalambous et al., 2013	Design flood estimation	Provides more realistic design flood estimates, showing potential to replace traditional methods.
Insurance	Casarano et al., 2017	Solvency assessment under Solvency II Directive	Offers market-consistent valuation of technical provisions and solvency capital requirements.
Energy Modeling	Dhaundiyal et al., 2019	Thermal decomposition of biomass	Enhances understanding of biomass pyrolysis through precise kinetic parameters.
Finance	Silva et al., 2019	Analysis of economic risks and cost estimation	Enhances risk management by creating contingency plans and providing more reliable financial forecasts.

3. Data and Methodology

3.1 Overview of the Data

This study focuses on a fast-fashion retailer within a shopping centre contemplating an expansion from its current 14,000 sqft space to 30,000 sqft. Neither the retailer nor the landlords possess sufficient data on the impacts of similar expansions in comparable markets to proceed with the expansion confidently. Understanding the outcomes of such an expansion is crucial for the retailer, as it involves significant additional costs. The retailer's financial health could quickly deteriorate if the expansion does not yield the expected results. Similarly, accurate estimation is essential from the landlord's perspective as they typically invest capital in such expansions, with arrangements such as percentage rents—where the landlord receives a portion of the retailer's sales once a pre-agreed sales threshold is surpassed. Additionally, landlords allocate expansion space to specific retailers that could otherwise be rented out to new tenants. Therefore, both parties must achieve precise estimations.

The spatial data used for this study is derived from Wi-Fi beacons installed throughout the shopping centre. Wi-Fi beacons are small, wireless devices placed strategically around the mall that interact with mobile devices via Wi-Fi signals. As customers with smartphones move through the mall, their devices continuously send and receive signals to and from these beacons. Each interaction is logged by the beacons, allowing for precise tracking of the number and movement of visitors within the mall. This technology captures the entry and exit of each mobile device into specific stores and general areas, effectively mapping out customer foot traffic and dwell times. This data is crucial for analyzing traffic patterns, assessing the popularity of specific locations within the mall, and understanding customer behavior in real time. The dataset utilized in this study comprises historical monthly data from January 2022 to December 2023, spanning a two-year period. This dataset captures a variety of metrics pertinent to a retail environment within a shopping mall. It provides critical insights into sales trends, customer traffic, and other key performance indicators necessary for evaluating the feasibility and potential impacts of expanding the store from 14,197sqft to 30,000sqftt. The primary reason for selecting data from 2022-2023 is due to the significant impact of the COVID-19 pandemic on shopping mall operations. Initially, data from 2020 were considered, but due to mall closures during the pandemic, the historical sales figures did not accurately reflect the financial performance of retailers. To ensure the analysis used data reflecting the store's potential operating conditions, only post-pandemic data were included, excluding any data from periods when the store was affected by pandemic-related closures.

Additionally, the selected data period accounts for seasonality, capturing variations in consumer behavior throughout the year. This consideration of seasonality is crucial as it includes peak shopping periods such as holidays and sales events, as well as slower periods. By using a comprehensive dataset that spans two full years, the analysis can better account for these seasonal fluctuations, providing a more accurate and robust assessment of the store's performance and the potential impacts of its expansion. This approach ensures that the data used for analysis accurately represents the store's performance in a stable, post-pandemic market environment, and accounts for seasonal variations, providing a reliable basis for assessing the impacts of the proposed expansion.

Table 2. Description of dataset variables used in empirical analysis

Column Name	Description
Sales Date	Indicates the month and year for each data entry, providing a temporal context for the dataset.
GLA (Gross Leasable Area)	Represents the total area currently occupied by the retailer, held constant at 14k square feet, which is crucial for comparing performance metrics before and after the proposed expansion.
Sales	Monthly sales figures for the retailer, offering insights into financial performance over the selected period, essential for evaluating revenue trends and profitability.
Retailer Traffic	Quantifies the number of mobile devices entering the store, serving as a direct measure of customer engagement and foot traffic specific to the retailer. This metric is derived from over 475 strategically placed Wi-Fi beacon sensors throughout the mall.
Mall Traffic	Represents the total foot traffic within the entire mall, derived from interactions between customer smartphones and a network of Wi-Fi beacons. This measure provides insights into overall visitor interest and mall attractiveness, enabling analysis of visitor movement patterns and dwell time.

This study allows us to understand the direct consequences of expansion on sales and customer behavior for this retailer. We acknowledge the potential benefits of including additional spatial variables such as proximity to other stores, the layout of the shopping center, and external factors like public transportation links. However, the scope of this initial study was constrained to available data, primarily derived from smartphone and Wi-Fi interactions. Future research can expand this model by integrating these additional spatial variables to enhance the predictive power and accuracy of the Monte Carlo simulations. While this study focuses on a single store, the methodology can be scaled to include multiple retailers and more complex spatial datasets, providing a more comprehensive view of shopping center dynamics.

3.2 Methodology

The methodology employed in this study involves a comprehensive Monte Carlo simulation to assess the effects of increasing a retail store's size from 14k to 30k square feet. Historical data from 2022 to 2023 is initially imported and cleaned to ensure data accuracy. This involved converting the 'date' column to DateTime format and setting it as the index for time series analysis, which helps organize and manage the data chronologically. Any commas in the 'GLA' (Gross Leasable Area) column were removed, and the column was converted to an integer type to ensure numerical accuracy. Subsequently, the dataset was examined for any missing values or anomalies. This step is crucial as missing or incorrect data points can significantly affect the simulation results. Identifying and rectifying these issues involved checking for and addressing any gaps or outliers in the data. By ensuring that all data points were accurate and complete, the integrity of the dataset was maintained. It is crucial to define the parameters for the simulation, such as the number of iterations—set at 10 million in this case—and the projected growth rates for both traffic and sales post-expansion. Defining these parameters is crucial for several reasons. Firstly, setting a high number of iterations ensures that the simulation accurately captures the variability and distribution of potential outcomes. Many iterations allow the simulation to explore a wide range of possible scenarios, leading to more robust and reliable estimates of the mean and confidence intervals. This helps reduce the standard error of the mean and provides a precise estimate of the potential impact of the expansion. Secondly, defining the projected growth rates for traffic and sales post-expansion is essential because these parameters directly influence the simulation's results. Accurate growth rate projections ensure that the simulation reflects realistic changes in traffic and sales, providing a credible evaluation of the expansion's impact. In this analysis, estimating growth rates for traffic and sales involves a series of systematic steps designed to provide a comprehensive understanding of the potential impacts of store expansion. Historical distributions of sales, retailer, and mall traffic are initially sampled. This sampling is crucial as it ensures that the growth rates reflect real-world variability and historical trends, providing a robust basis for further analysis. Sales are subsequently adjusted proportionally to the relative changes observed in the sampled traffic data. This step is essential because it simulates how variations in customer traffic directly influence sales, thereby offering valuable insights into the relationship between traffic and sales. By adjusting sales in response to changes in traffic, we can better predict the financial outcomes of the store expansion under different traffic scenarios. The next phase calculates the average sales impact derived from retailer-specific and overall mall traffic. Averaging the effects of traffic changes from these two sources helps integrate their combined influence on sales. This dual-source approach acknowledges that the number of visitors entering the specific store and the overall foot traffic within the mall contribute to sales performance. By clearly defining and implementing these parameters, the analysis ensures a thorough evaluation of the store expansion's potential impacts. This detailed approach not only enhances the accuracy of the predictions but also provides a nuanced understanding of the various factors influencing sales growth, thereby supporting more informed decision-making. The execution phase of this analysis consists of conducting the predefined simulations, where each iteration forecasts potential sales and customer traffic increases. The results from each simulation run are systematically recorded for further statistical examination. During this phase, Python's statistical libraries are used to analyze the simulations' outputs. This analysis involves calculating mean values, confidence intervals, and standard deviation to assess the likely impacts of the store expansion. Additionally, histograms provide a visual representation of the data, which aids in interpreting and understanding the simulation results.

Three different scaling factors of 0.8, 1.0 and 1.2 are used to systematically vary key parameters and examine their impact on the outcomes with confidence intervals for each scenario. This approach tests the robustness of the model under different hypothetical scenarios that reflect variations beyond anyone's control. By integrating these scaling factors, the analysis ensures that the conclusions are robust and well-supported by empirical evidence, thereby providing a solid foundation for decision-making regarding store expansions. This methodological framework forecasts potential financial outcomes and effectively mitigates risks associated with store expansion decisions.

A scaling factor of 0.8 represents a conservative scenario, assuming the potential sales and customer traffic will be lower than initially expected. This scenario helps understand the impacts if the store expansion performs below market predictions, providing insights into worst-case conditions. Conversely, a scaling factor of 1.0 assumes that sales and traffic will likely follow market predictions, serving as the baseline. This reflects the expected outcome if the expansion aligns perfectly with current market forecasts. Finally, a scaling factor of 1.2 represents an optimistic scenario where potential sales and customer traffic exceed initial assumptions, allowing us to evaluate best-case conditions and the potential for higher-than-expected performance. By integrating these scaling factors into the simulations, we can determine confidence intervals for each scenario, providing a spectrum of possible outcomes. This method ensures that the conclusions drawn from our analysis are both robust and empirically validated, effectively accounting for various market conditions and uncertainties. This comprehensive approach prepares us for various market conditions, offering a thorough and practical basis for decision-making. Consequently, our methodology is adaptable and grounded in real-world applicability, ensuring the analysis is reliable and actionable.

4.0 Results

The results are stratified into three distinct parts, each corresponding to one of the scaling factors applied during the simulations to understand the impact of store expansion under varying market conditions. To provide a comprehensive analysis, we also include a base level of performance to compare the scenarios of store expansion with the current sales per square foot. Before discussing the simulated scenarios, it is essential to establish the baseline performance of the retailer. Currently, the store operates at 14,197 square feet with a sales performance of $1,735 per square foot. This base level will help in understanding the percentage increase in sales achieved through the proposed expansion.

Across all examined scenarios, the projected mean incremental sales and percentage increase in total sales demonstrate robustness, providing a compelling justification for the expansion from a revenue standpoint. The observed standard deviations and confidence intervals highlight such sales projections' inherent risks and uncertainties, underscoring the necessity of careful risk management practices. Furthermore, the additional revenue per square foot emerges as a crucial metric, affirming the efficiency and effectiveness of the space expansion in generating sales. This positive indicator across all cases reassures stakeholders of the potential financial viability of the expansion, suggesting that the increased floor area is likely to lead to proportionate or greater increases in sales revenue.

The simulation employs 10 million iterations, resulting in a huge sample size that significantly reduces the standard error of the mean (SEM), leading to a narrower confidence interval. Despite having only 24 data points, a consistent variability within the dataset can still yield a narrow confidence interval. Through repeated random sampling, the Monte Carlo method generates a distribution of incremental sales that converges to the true mean with a high number of iterations, providing a precise estimate with a narrow confidence interval. While the high standard deviation indicates variability in individual sales data, the precise mean estimate achieved through extensive sampling ensures robust and reliable results, offering a clear understanding of the potential impact of scaling factors on incremental sales.

Despite the substantial increase in total sales across all scenarios, there is a notable decline in sales per square foot following the expansion. When a store expands its physical space, the increase in total sales might not proportionately match the increase in square footage. Although total sales rise, the larger area leads to a lower sales density, resulting in decreased sales per square foot. Expanding the store size might attract more customers, but there is a limit to the number of customers that can be drawn to a single store, leading to diminishing returns in sales density. When increasing a store's size, not all added space is used for direct sales. Additional space may be allocated for experiential purposes, customer service, or supporting online sales. This non-transactional space does not contribute to sales productivity in the same way as traditional retail space, leading to a lower overall sales per square foot metric.

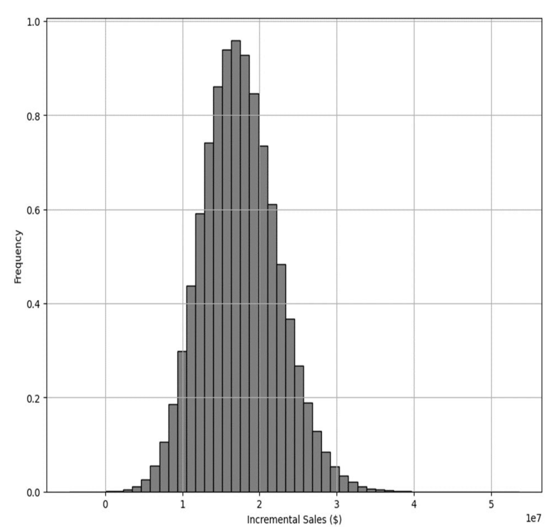

Figure 1. Histogram of incremental sales for scaling factor 0.8

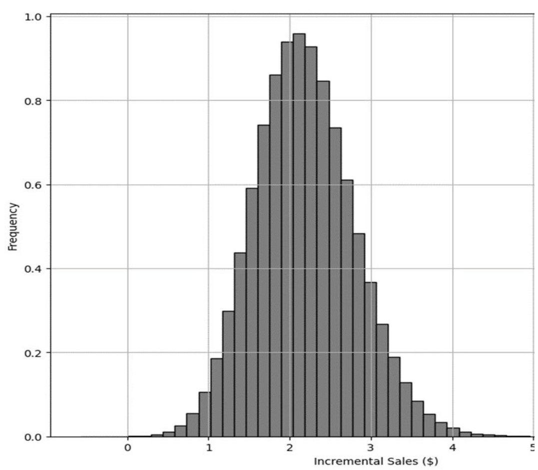

Figure 2. Histogram of incremental sales for scaling factor 1.0

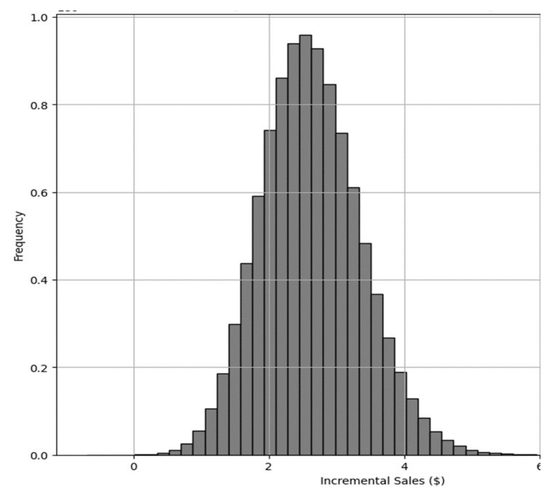

Figure 3. Histogram of incremental sales for scaling factor 1.2

Table 3. Summary of key metrics across different scaling scenarios for store expansion

Scenario	Mean incremental sales (in million $)	Standard deviation (in million $)	95% confidence interval (in million $)	Revenue per square foot ($)	Change in revenue per square foot ($)	Percentage increase in total sales (in million $)
Conservative (0.8)	$17.46	$4.89	$17.45 - $17.46	$1,104.96	-$630.04	70.9%
Expected Baseline (1.0)	$21.82	$6.11	$21.82 - $21.83	$1,381.20	-$353.80	88.6%
Optimistic (1.2)	$26.19	$7.33	$26.18 - $26.19	$1,657.44	-$77.56	106.3%

5. Discussions and Conclusions

The paper establishes a data-driven framework using Monte Carlo simulations to make informed store expansion decisions, even with limited historical data. The methodology involves using a small dataset of 24 monthly data points and applying Monte Carlo simulations with 10,000,000 iterations to estimate the potential impact of store expansion on sales. This large number of iterations reduces the standard error of the mean and results in narrow confidence intervals, providing precise estimates despite the limited data. By sampling from the historical distributions of sales and traffic, the framework adjusts sales based on relative changes in traffic, reflecting the relationship between these variables. Different scaling factors (0.8, 1.0, and 1.2) are used to test the model's robustness under various scenarios, providing a range of possible outcomes. This framework highlights the importance of integrating both quantitative and qualitative insights and real-time data to adjust to fluctuations in retail conditions dynamically. The use of Monte Carlo simulations in this context offers a robust approach to decision-making, providing shopping centre managers and landlords with a reliable tool to assess the financial viability of store expansions.

The study demonstrates that expanding retail square footage significantly impacts sales performance, as evidenced by the results of the Monte Carlo simulations. Across different scaling scenarios, the mean incremental sales show a substantial increase, justifying the expansion from a revenue standpoint. For instance, in the conservative scenario with a scaling factor of 0.8, the projected mean incremental sales were approximately $17.46 million, with an additional revenue per square foot of $1,104.96. In the baseline scenario with a scaling factor of 1.0, the mean incremental sales were about $21.82 million, yielding $1,381.20 per square foot. The optimistic scenario with a scaling factor of 1.2 showed mean incremental sales of around $26.19 million and $1,657.44 per square foot. The study emphasizes that while the mean incremental sales are robust, the standard deviations indicate significant variability, reflecting the inherent risks and uncertainties. The additional revenue per square foot across all scenarios reassures stakeholders of the potential financial viability of the expansion, suggesting that increased floor area is likely to lead to proportionate or greater increases in sales revenue. The Monte Carlo simulation model employed in this study has proven effective in estimating the potential incremental sales resulting from retail store expansion, even with a limited dataset. The findings suggest that expanding retail square footage can significantly impact sales performance, providing a compelling justification for expansion from a revenue standpoint.

A comprehensive analysis of potential costs and benefits should inform the decision to expand a retail store. Expansion can lead to incremental sales, but it also incurs various costs for the retailer and the landlord. Retailers may face increased rent due to percentage leases, while landlords must account for substantial upfront capital investments and ongoing operational expenses. It is crucial to consider simulation results as indicative rather than definitive, as simulations often omit factors such as market conditions, consumer sentiment, and the purchasing power of customers, which are beyond the control of both the retailer and the landlord.

Despite the robustness of the Monte Carlo simulation in estimating incremental sales, several limitations could impact the results of this study. Firstly, the assumption that sales, retailer traffic, and mall traffic follow a normal distribution may not accurately reflect the real-world distribution of these variables, potentially leading to biased estimates. Additionally, using only 24 monthly data points limits the comprehensiveness of the analysis, as short-term fluctuations and seasonality effects might not be fully captured. Moreover, the high standard deviation observed indicates significant variability in the sales data, which could result in wider confidence intervals if fewer iterations were used. While the large number of iterations (10,000,000) reduces the standard error of the mean and narrows the confidence interval, it does not eliminate the underlying data variability. Furthermore, the model's reliance on historical data assumes that future sales patterns will mirror past trends, which may not hold in dynamic market conditions. Lastly, the equal weighting of retailer and mall traffic in adjusting sales may oversimplify the complex interactions between these factors, potentially overlooking other significant contributors to sales performance. These limitations suggest that while the Monte Carlo simulation provides valuable insights, the results should be interpreted cautiously and supplemented with additional analyses and real-world considerations.

For future research, several avenues could be explored to enhance the robustness and applicability of the findings. Firstly, expanding the dataset to include more historical data points would provide a more comprehensive understanding of sales trends, capturing long-term patterns and seasonal variations more effectively. Incorporating alternative distribution models beyond the normal distribution for sales, retailer traffic, and mall traffic could yield more accurate simulations by better reflecting the true nature of these variables. Additionally, integrating other influential factors, such as marketing efforts, economic conditions, and competitive actions, into the simulation model would offer a more holistic view of the drivers of incremental sales. Further research should incorporate additional spatial data points such as distances to other stores, layout and design of the shopping centre and proximity to public transportation. This could provide a more comprehensive understanding of how spatial relationships influence store performance. This could be developing dynamic models that can adapt to changes in spatial data over time, providing real-time insights for decision-making. Future studies could also employ advanced statistical techniques or machine learning models to dynamically adjust the weighting of retailer and mall traffic, accounting for their varying impacts over time and in different contexts. Conducting sensitivity analyses to assess the impact of key assumptions and parameters on the results would further strengthen the reliability of the conclusions. Lastly, validating the simulation outcomes with real-world post-expansion sales data would provide empirical support for the model's predictions and highlight any discrepancies that need to be addressed.

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