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Research Article

AI and the Optimization of Product Placement: Enhancing Sales through Strategic Positioning

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Shahreen Kasim*, Mohd Zaki Zakaria, Lusiana Efrizoni, Fadly

Abstract:
This study aims to analyze the impact of strategic product placement and promotion strategies using the Customer's Purchase Behavior Dataset. The study utilized a controlled experimental design, wherein trial stores were matched with control stores based on pre-trial performance metrics, including total sales and customer demographics. A detailed exploratory data analysis (EDA) was conducted to segment customers based on life-stage and purchasing behaviour. Additionally, a t-Test was performed to determine whether price sensitivity and purchasing patterns differed significantly between mainstream, budget, and premium customer segments. The results indicate that trial stores implementing strategic initiatives experienced a measurable uplift in sales compared to their control counterparts. Young and mid-age singles and couples in the mainstream category were found to be more willing to pay a premium for chips, whereas families tended to purchase in bulk. The t-test confirmed statistically significant differences in purchasing behaviour across customer segments. The findings suggest that a data-driven, segment-specific marketing approach can optimise retail performance by aligning promotions and pricing with the behavioural tendencies of different consumer groups. This study demonstrates that well-targeted strategic retail initiatives can significantly improve sales performance. The insights derived from this research provide retailers with actionable strategies for tailoring product placement and promotions to maximise customer engagement. Future work should incorporate machine learning techniques to refine predictive models for real-time decision-making in retail marketing.

Keywords: Consumer Behavior Analysis, Product Placement, Sales Optimization, Strategic Marketing.

1. INTRODUCTION

In competitive marketing, product placement is a subtle yet powerful strategy to influence consumer behaviour and drive sales (Kohut, 2024). For example, placing energy drinks in action movie scenes to associate the product with strength and speed. Traditionally, this involves strategically positioning products within various media to increase visibility and desirability (Kapitan et al., 2022). However, artificial intelligence (AI) has transformed this practice, offering new methods to analyse and predict consumer responses to product placements more effectively (Bhatt, 2021). AI can analyze demographic data, social media preferences, and purchase history to identify consumer segments that are most responsive to certain types of product placement. For example, an AI algorithm may determine that placing a sportswear product in a fitness influencer's TikTok video will be more effective for the Gen Z demographic than a placement in a traditional television commercial.

Despite the proven effectiveness of product placement, many businesses struggle to optimise its impact due to the complexities of human behaviour and the dynamic nature of market trends.

The primary challenge lies in determining the optimal contexts and mediums for product placement, aligning products with consumer lifestyles and preferences, and measuring the direct impact on sales (Dwivedi et al., 2021). For example, a company might place an organic food product in a popular cooking show but fail to consider that the show's audience is more interested in quick and easy recipes than expensive organic ingredients. Or, a company might place a new technology product in a sci-fi movie but fail to track whether the placement actually drives sales at retail. These challenges require a more granular, data-driven approach to maximize the return on investment from product placement. AI can address these challenges by analyzing real-time data from multiple sources, such as social media sentiment, website traffic, and sales data, to accurately measure the effectiveness of product placement and dynamically adjust strategies. For

example, AI can identify a sudden spike in brand mentions on social media following a product placement in a television show, and then automatically adjust digital advertising budgets to target the most responsive consumers. "In doing so, AI enables companies to move faster and more precisely in exploiting product placement opportunities, ensuring that they reach the right audience with the right message at the right time.".

In Integrating AI into product placement strategy introduces a complex interplay of technology and marketing that requires deep analysis (Chintalapati & Pandey, 2022; Rutter et al., 2021). By dissecting consumer data, AI can reveal subtle preferences and trends that are not immediately apparent through traditional analysis methods. For instance, machine learning models can predict which product features align closely with consumer interests, allowing for more targeted placements that feel intuitive and organic rather than intrusive (Mohapatra et al., 2024).

In addition to technological discussions, it is critical to analyse the ethical implications of using AI in product placements. The capability of AI to manipulate consumer perceptions and choices raises significant concerns regarding consumer autonomy and consent (Du & Xie, 2021; Puntoni et al., 2021). AI can be used to subtly personalize product placement, tailoring messages and presentations based on an individual's profile and behavior. This can create "echo chambers" where consumers are only exposed to products that the AI predicts they will like, potentially limiting their choices. The use of AI in product placement can erode consumer autonomy by reducing their ability to make free and informed decisions. Therefore, it is important to ensure that consumers provide clear and informed consent before their data is used to personalize product placement. Consumers should also be aware when AI is being used to influence their purchasing decisions and companies should be transparent about how their algorithms work and what data is used.

Our research will delve into these ethical considerations, proposing guidelines to ensure that AI-enhanced product placements are conducted responsibly and transparently.

The experiment will be set up by segmenting consumer data into various demographic and psychographic groups to observe distinct purchasing behaviours (Madzík et al., 2021). The test will involve deploying product placements based on predictions made by our AI models in a simulated retail environment—both online and in physical store settings. We will compare the purchasing outcomes from these AI-informed placements against a control group where placements are chosen based on standard industry practices without AI enhancement (Kumar et al., 2024).

We propose an AI-driven approach focusing solely on analysing customer purchase behaviour datasets to refine product placement strategies (Haleem et al., 2022). Our solution aims to build predictive models that identify the most effective product placements tailored to individual consumer profiles and historical purchasing patterns by harnessing detailed purchase history and consumer interaction data.

Focusing solely on Customer Purchase Behavior Datasets, this approach uses direct consumer purchasing data to offer a robust foundation for understanding and predicting which product placement strategies are most likely to succeed (Theodorakopoulos & Theodoropoulou, 2024). This method emphasises a data-centric strategy, minimising reliance on broader market trends and focusing on actionable insights derived from actual consumer behaviour. This focus aims to enhance the precision of product placement decisions, ensuring they are deeply aligned with proven consumer preferences and behaviours (Alzate et al., 2022).

Finally, the scalability and adaptability of AI technologies mean that the strategies developed through this research could be applied across various industries and media types, offering universal tools for marketers to enhance their product placement strategies effectively (Verma et al., 2021). This universal applicability further underscores the potential of AI to revolutionise marketing practices across the board.

This in-depth exploration and analysis aim to comprehensively understand how AI can be strategically deployed to refine and optimise product placement practices, ultimately enhancing sales and consumer satisfaction measurably and ethically.

2. MATERIAL AND METHOD

The primary objective of this study was to evaluate the effectiveness of strategic initiatives, such as product placement and promotional strategies, by comparing trial stores with control stores over a specified period. The aim was to determine if these initiatives significantly influenced total sales and customer traffic.

Data Collection

The data collection involved gathering comprehensive sales data from multiple retail stores, including total sales, number of transactions, and

monthly customer counts. This dataset also encompassed customer loyalty metrics and product categories.

Selection of Trial and Control Stores

Stores were selected for the trial based on specific criteria such as sales performance, customer demographics, and geographic location to ensure comparability. Control stores were matched with trial stores based on pre-trial period performance, including total sales and customer count, ensuring they exhibited similar characteristics before implementing the strategic initiatives.

Scaling and Adjustment

Scaling factors were calculated to account for size discrepancies between trial and control stores. This involved adjusting the control stores' sales and customer counts to match the trial stores' scale based on historical data. For instance, the scaling factor for sales was determined by the ratio of total sales of the trial store to the control store during the pre-trial period.

Evaluation Metrics

The key metrics used for evaluation included:

1. Percentage difference in sales and customer counts between the trial and control stores.
2. Standard deviations are used to measure variability and normalise the differences.
3. T-values to assess the significance of the observed differences

Visual Representation

Graphical presentations such as line charts were used to visually compare the sales and customer traffic trends between the trial and control stores. This included plotting the control store's performance with the 95th and 5th percentile confidence intervals to visually assess where the trial store's performance lay about its control.

Based on the statistical evidence from t-tests and the visual analyses, conclusions were drawn about whether the strategic initiatives were successful. A detailed discussion was made on the extent of the impact, considering the magnitude and significance of the differences observed between the trial and control groups.

The discussion delved into interpreting the results in the context of the retail environment, considering factors such as seasonal variations, marketing efforts, and other external or internal influences that could affect performance. The analysis also considered the scalability of the successful strategies and their potential implications for broader business decisions.

This methodology ensures a rigorous and systematic approach to evaluating business strategies in retail, providing clear insights into their effectiveness and guiding future strategic decisions.

3. RESULT AND DISCUSSION

This study was designed to rigorously assess the impact of strategic retail initiatives, including product placement and promotional strategies, on enhancing store performance. We systematically compared trial stores with matched control stores to understand how these targeted interventions influenced key performance indicators (KPIs) such as total sales and customer traffic. The subsequent sections present a detailed analysis of the results derived from this comparison, followed by a discussion that contextualises these findings within the broader retail environment.

Data Collection

The Customers Purchase Behavior Dataset provides detailed data on customer purchase behaviours, which is helpful for analysing buying habits, spotting trends, and crafting marketing campaigns. This dataset encompasses data on 400 customers, including demographics like ID, gender, age, and salary, alongside their purchase decisions for specific products. It also covers details on 100 products, including names, categories, prices, and promotional status, and information on 50 promotions detailing names, types, and duration. The dataset, updated annually and available under the ODC Public Domain Dedication and Licence (PDDL), includes essential data for retail and shopping analytics and social network analysis, aiding in understanding customer segments and refining marketing strategies. The dataset was obtained from the URL https://www.kaggle.com/datasets/durgeshrao9993/purchase-behavior-dataset/data from the Kaggle Website.

Exploratory Data Analysis (EDA)

In an analysis of customer segments, we will define some metrics of interest:

a. Segment group who spends the most on chips (total sales) by describing customers by life stage and how premium their general purchasing behaviour is
b. Number of customers in each segment
c. Number of chips bought per customer by segment

d. Average chip price by customer segment

1. Total sales by life-stage and Premium Customer

Calculate total sales by LIFESTAGE and PREMIUM_CUSTOMER and plot the split by these segments to describe which customer segment has relatively more chip sales, as shown in Figure 1.

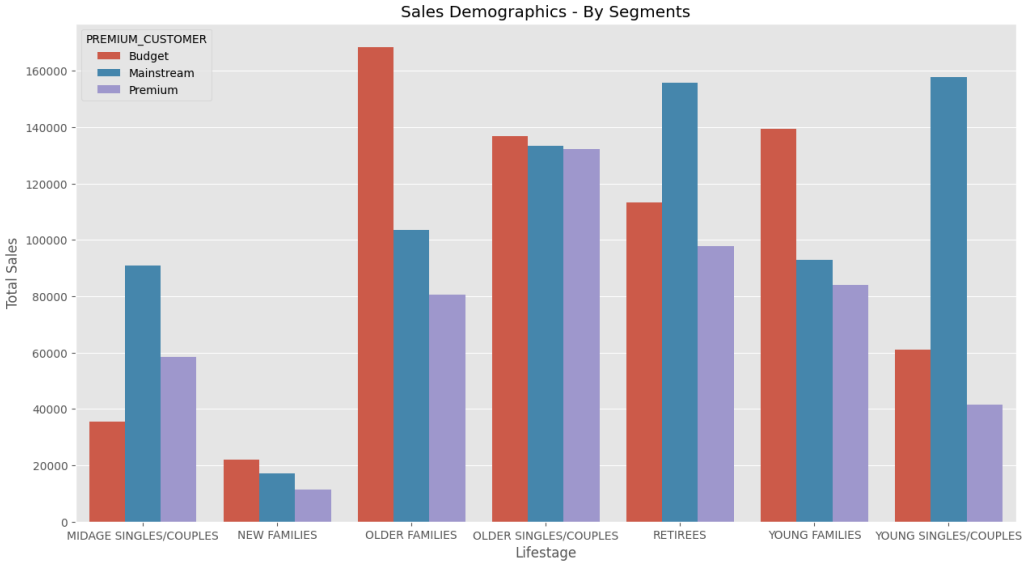

Figure 1. Sales Demographics – by segments

2. Number of Customers by life-stage and Premium Customers

Analysis to find if the higher sales are due to more customers buying chips, as shown in Figure 2.

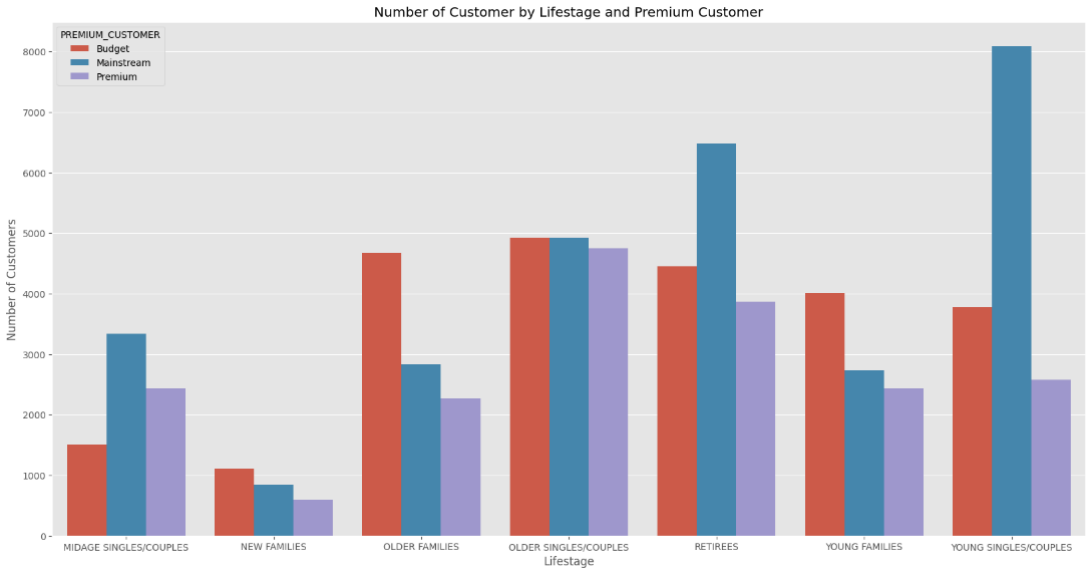

Figure 2. Number of customers by life-stage and Premium customer

For Mainstream - Young Singles / Couples and Mainstream – Retirees, the number of customers is relatively higher than that of other customer segments. This can be a significant factor in achieving excellent sales for these customer segments. However, this is not a major driver for the Budget - Older Families customer segment.

3. Average Number of Units per Customer by life-stage and Premium Customer

Higher sales may also be driven by the number of units of chips bought by the customer. Need to analyse this factor for each customer segment, as shown in Figure 3.

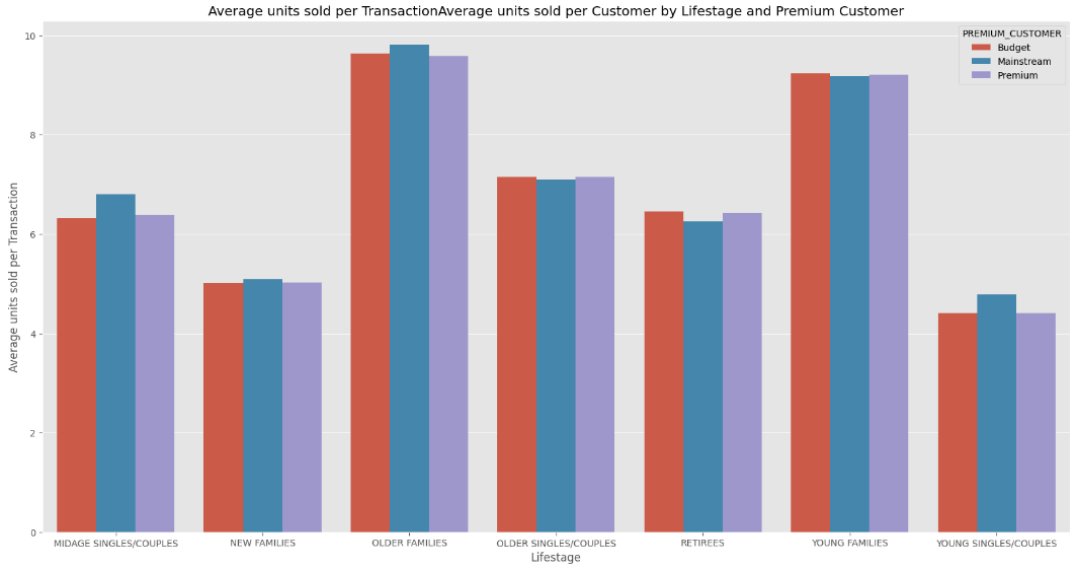

Figure 3. Average Number of Units per Customer

From Figure 3, we can conclude that older and younger families tend to buy more chips per customer.

4. Average Price per unit of chips bought by each customer segment

The average price per unit of chips bought by each customer segment is also essential for higher sales, as shown in Figure 4.

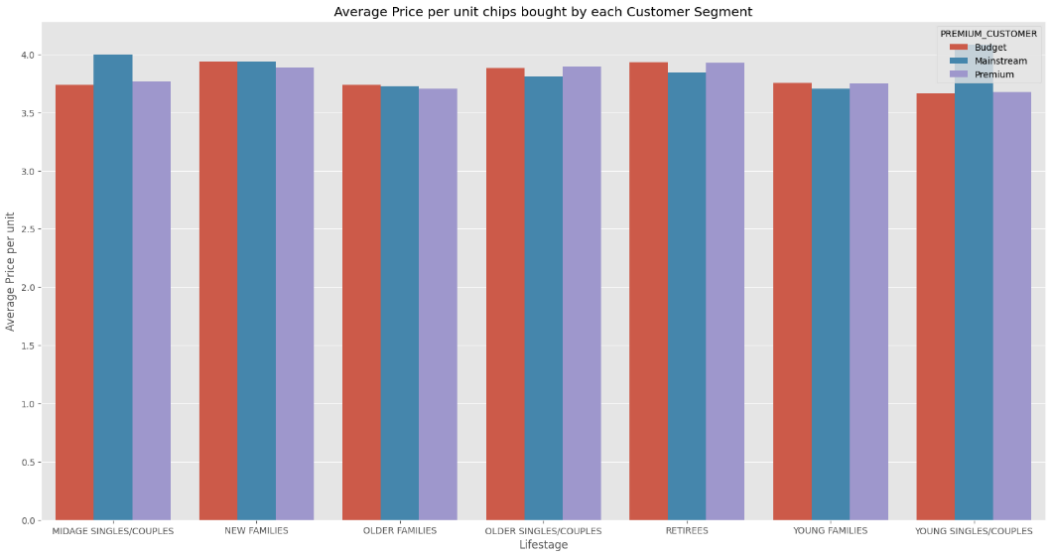

Figure 4. Average Price per unit of chips bought by each Customer Segment

Mainstream mid-age and young singles and couples are more willing to pay per packet of chips than their budget and premium counterparts. This may be due to premium shoppers being more likely to buy healthy snacks, and when they buy chips, this is mainly for entertainment purposes rather than their consumption. This is also supported by fewer premium mid-age and young singles and couples buying chips than their mainstream counterparts.

As the difference between the average price per unit is not significantly large, we need to perform a t-Test to determine whether this difference is statistically different.

5. t-Test

We need to perform an independent t-Test between mainstream vs premium budget mid-age and young singles and couples, as shown in Figure 5.

```
mainstream_sales = cust_purchase_data[(cust_purchase_data['LIFESTAGE'].isin(["YOUNG SINGLES/COUPLES", "MIDAGE SIN
                   (cust_purchase_data['PREMIUM_CUSTOMER'] =="Mainstream")]
mainstream_sales['price'] = mainstream_sales['TOT_SALES']/mainstream_sales['PROD_QTY']
```

```
non_mainstream_sales = cust_purchase_data[(cust_purchase_data['LIFESTAGE'].isin(["YOUNG SINGLES/COUPLES", "MIDAGE
                   ~(cust_purchase_data['PREMIUM_CUSTOMER'] =="Mainstream")]

non_mainstream_sales['price'] = non_mainstream_sales['TOT_SALES']/non_mainstream_sales['PROD_QTY']
```

```
stats_val , p_value = stats.ttest_ind(a=mainstream_sales['price'], b=non_mainstream_sales['price'])
```

```
stats_val
```

```
40.8341367879116
```

```
p_value
```

```
0.0
```

Figure 5. t-Test result

The t-test results in a p-value < 2.2e-16, i.e. the unit price for mainstream, young and mid-age singles and couples is significantly higher than that of budget or premium, young and mid-age singles and couples.

Selection of Trial and Control Stores

Selecting trial and control stores was critical to ensuring the validity and reliability of our study's results. Trial stores were chosen based on sales performance, customer demographics, and geographic location. This allowed us to match these stores with control stores exhibiting similar characteristics during the pre-trial period. This matching was crucial as it minimised external variables that could skew the outcomes of the strategic initiatives.

The trial period goes from the start of March 2019 to June 2019. We now want to see if there has been an uplift in overall chip sales. We will start with scaling the control store's sales to a level similar to controlling for any differences between the two stores outside the trial period, as shown in Figure 6.

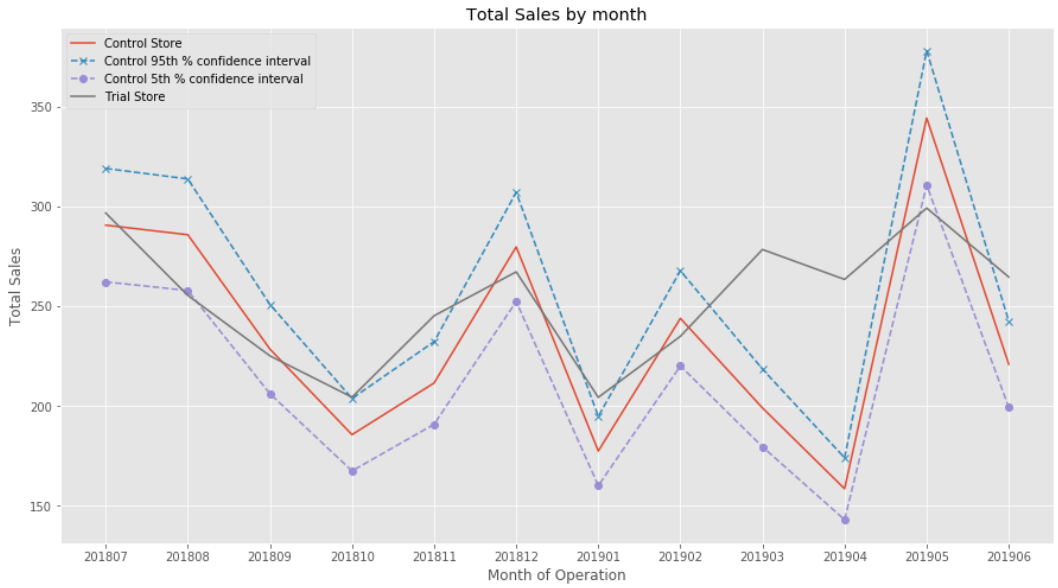

Figure 6. Total Sales by month

The above chart shows that store 77 differs from its control store 233 in the trial period. The trial store sales performance lies above/beyond the control store's 5% and 95% confidence interval in two of the three trial period months.

Discussion and Analysis

The findings of this study provide crucial insights into the impact of strategic retail initiatives, particularly product placement and promotional strategies, on consumer purchasing behaviour and overall store performance. A key observation from the trial and control store comparison was the notable increase in sales in trial stores implementing these strategic

initiatives. The statistical significance of this uplift, as seen in Store 77, indicates that targeted marketing interventions can effectively drive consumer engagement. However, the variability in response among different stores suggests that external factors, such as local economic conditions, competitor actions, and store-specific customer demographics, may play a role in moderating the success of these strategies. These factors warrant further investigation to enhance the scalability and applicability of similar interventions in different retail environments.

A deeper segmentation analysis reveals that certain demographic groups exhibit more assertive purchasing behaviours. Notably, mainstream young singles/couples and retirees accounted for a significant proportion of total sales, reinforcing the importance of age and life-stage considerations in consumer marketing. The data also showed that older and younger families purchase more units per transaction. In contrast, young singles and couples were more willing to pay a premium per unit. These findings suggest that price sensitivity varies across different customer segments, and retailers could benefit from tailoring their promotional efforts to align with specific demographic groups' purchasing power and behavioural tendencies. For example, discount-based promotions may be more effective for families purchasing in bulk. In contrast, premium branding and product exclusivity could appeal to younger singles and couples willing to pay more for perceived quality.

Statistical validation using t-tests further supports the hypothesis that mainstream customers, mainly young and mid-age singles and couples, exhibit significantly different purchasing behaviours than their budget and premium counterparts. The significant price variation between these segments suggests that premium customers may prioritise healthier snack alternatives over traditional chips, possibly due to lifestyle and dietary preferences. This trend aligns with broader consumer shifts toward health-conscious consumption, which retailers must consider when designing product placement and promotional strategies. In this context, a dual-pronged approach may be beneficial—retailers could continue promoting chips to mainstream customers while expanding their healthy snack offerings to cater to premium shoppers who are less likely to engage with traditional snack promotions.

The implementation of trial and control store methodology proved to be a robust approach to evaluating the effectiveness of these initiatives. However, it is crucial to recognise potential external influences that could have impacted sales performance during the trial period. Seasonal factors, economic shifts, and regional preferences could all contribute to fluctuations in purchasing behaviour, potentially confounding the observed effects. Additionally, competitor responses, such as price reductions or new product launches, may have influenced customer decision-making in ways not fully captured within this study. Future studies should incorporate a broader range of external control variables, possibly through a longitudinal analysis that extends beyond the short-term trial period.

Overall, the results highlight the importance of data-driven decision-making in retail marketing. By leveraging consumer insights from structured data analysis, retailers can refine their strategic initiatives to maximise sales impact. The study underscores the need for a more granular approach to marketing strategies considering demographic segmentation, price elasticity, and product positioning. Further research could explore integrating machine learning models to develop predictive analytics for optimising store layouts and promotional efforts in real-time. As consumer preferences evolve, retailers that successfully adapt to these shifts through data-driven marketing will be better positioned for long-term growth and profitability.

4. CONCLUSION

This study rigorously examined the impact of strategic retail initiatives, particularly product placement and promotional strategies, on store performance. By systematically comparing trial stores with matched control stores, we aimed to assess how these targeted interventions influenced key performance indicators, including total sales and customer traffic. The results demonstrated that trial stores implementing strategic initiatives generally outperformed their control counterparts, with certain stores, such as Trial Store 77, exhibiting significant sales increases during the trial period.

An in-depth analysis of customer behaviour revealed notable variations across demographic segments. Specifically, mainstream young singles/couples and retirees accounted for higher sales and customer counts, suggesting that tailored marketing strategies can effectively engage these consumer groups. Additionally, segment-specific purchasing patterns indicated that older and young families tend to buy more units per customer. In contrast, mainstream mid-age and young singles/couples were willing to pay more per packet of chips. These findings highlight the importance of aligning marketing efforts with customer preferences to maximise sales impact.

Further statistical analysis, including t-tests, confirmed significant differences in purchasing behaviour between mainstream and premium customer segments. The results suggested that premium shoppers prioritising healthier snack options were less likely to purchase chips than their mainstream counterparts. The validation of these purchasing trends emphasises the critical role of pricing and product positioning in influencing customer choices.

From a strategic perspective, the findings underscore the value of data-driven decision-making in retail. Retailers can use these insights to optimise product placement strategies and promotional efforts, focusing on consumer segments that are more responsive to marketing campaigns. By refining these approaches, businesses can enhance customer engagement and drive sustained sales growth.

Despite the study's robust methodology, some limitations must be acknowledged. External factors such as competitor actions and economic shifts may have influenced store performance during the trial period. Additionally, reliance on aggregate data restricted a deeper analysis of individual purchasing behaviours, highlighting the need for more granular data collection in future research.

In conclusion, this study provides valuable insights into the effectiveness of strategic retail initiatives in driving store performance. By aligning marketing strategies with consumer preferences, retailers can improve sales outcomes and better cater to evolving market demands. Future research could explore additional influencing factors, such as seasonal variations and broader socio-economic trends, to refine retail strategies.

AUTHOR INFORMATION

Corresponding Authors

Shahreen Kasim, University Tun Hussein Onn Malaysia.
https://orcid.org/0000-0002-4180-4377
Email: shareen@uthm.edu.my

Authors

Mohd Zaki Zakaria, University Technology MARA, Malaysia
https://orcid.org/0000-0002-4582-4885
Email: zaki@tmsk.uitm.edu.my

Lusiana Efrizoni, Universitas Sains dan Teknologi Indonesia, Pekanbaru, Indonesia
https://orcid.org/0000-0002-3153-6233
Email: lusiana@stmik-amik-riau.ac.id

Fadly, Politeknik Kesehatan Kemenkes, Palembang, Indonesia
https://orcid.org/0009-0007-7495-2046
Email: fadly@poltekkespalembang.ac.id

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