Review of Applied Science and Technology
Volume 04, Issue 02 (2025)
Page No: 616 – 638
Doi: 10.63125/d2d96554

DATA-DRIVEN BUSINESS ANALYSIS: A COMPREHENSIVE ANALYSIS OF PREDICTIVE ANALYTICS IN PRICING STRATEGIES, MARKETING DECISIONS AND OPERATIONAL EFFICIENCY

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Citation:
Imran, H. M., Islam, M., Shahraum, S. S., Ahmed, M. R., & Hossain, A. O. (2025). Data-driven business analysis: A comprehensive analysis of predictive analytics in pricing strategies, marketing decisions and operational efficiency. *Review of Applied Science and Technology*, *4*(2), 616–638. https://doi.org/10.63125/d2d96554

Received:
September 04, 2025

Revised:
September 09, 2025

Accepted:
September 11, 2025

Published:
September 14, 2025

Abstract
In today's dynamic and competitive business environment, organizations face increasing pressure to make marketing decisions that are both timely and effective. Traditional intuition-based approaches are no longer sufficient to understand complex consumer behavior and market trends. This research paper explores how business analytics, through predictive and descriptive statistical models, can optimize marketing decisions. Using a real-world-inspired case study of 1,000 taco delivery orders across multiple U.S. cities, the study applies descriptive statistics, correlation analysis, and regression modeling to uncover insights into customer behavior, pricing strategies, and operational efficiency. Findings reveal that toppings and taco size significantly influence pricing, while weekend orders lead to higher customer tips. Delivery inefficiencies were also identified as critical areas for optimization. Beyond the food delivery industry, the implications of this study extend to marketing professionals and managers across sectors such as retail, corporate services, healthcare, energy, and finance. For example, retailers can leverage analytics to refine product assortments and promotional campaigns, healthcare organizations can optimize patient engagement strategies, energy firms can forecast demand more accurately, and financial institutions can enhance customer segmentation and risk assessment. Business analytics tools such as Tableau, Power BI, R, Python, SAS, and advanced Excel modeling can further support these applications, enabling professionals to translate raw data into actionable insights. Future research could expand the scope of this study by incorporating larger and more diverse datasets, integrating real-time data streams, or applying advanced techniques such as machine learning, sentiment analysis, or predictive demand modeling. This would provide deeper insights into consumer behavior and allow for more adaptive decision-making. Ultimately, the findings highlight that adopting analytics can significantly enhance decision quality by improving forecasting accuracy, optimizing resource allocation, and reducing inefficiencies. In marketing contexts, efficiency improvements may translate into shorter campaign cycles, increased ROI, and better alignment of products or services with customer preferences.

Keywords
Business Analytics; Predictive Modeling; Prescriptive Analytics; Marketing Strategy; Customer Segmentation;

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INTRODUCTION

In the era of digital transformation, businesses operated in an environment characterized by intense competition, rapidly shifting customer preferences, and unprecedented volumes of data. Traditional marketing strategies that rely heavily on intuition and experience are increasingly inadequate for navigating such complexity (Chen, 2012). Instead, organizations are turning to data-driven approaches that leverage business analytics to support evidence-based decision-making (Delen & Demirkan, 2013). Business analytics, encompassing descriptive and predictive methodologies, enables firms to extract meaningful insights from large datasets, identify patterns, and forecast future outcomes with greater precision. (Shmueli & Koppius, 2011). Marketing decisions—such as customer segmentation, campaign design, pricing, and distribution—are particularly well-suited to benefit from analytics-driven approaches. Descriptive analytics helps organizations understand past performance and market trends (Chen, 2012), while predictive analytics provides foresight into customer behavior and demand fluctuations (Provost & Fawcett, 2013). By integrating these tools into marketing processes, businesses can optimize pricing strategies, enhance customer engagement, allocate resources more effectively, and ultimately achieve sustainable growth (Wamba et al., 2017)).

This research paper aims to demonstrate the practical application of business analytics in optimizing marketing decisions through a real-world-inspired case study of 1,000 taco delivery orders across multiple U.S. cities. Using descriptive statistics, correlation analysis, and regression modeling, the study investigates how factors such as taco size, toppings, order timing, and delivery performance influence pricing, tipping, and operational efficiency. These variables provide a micro-level perspective of customer behavior and operational dynamics, which can be extrapolated to other industries. For instance, product size and add-ons (taco size and toppings) mirror product bundling and customization in retail; order timing relates to peak-demand forecasting in energy and healthcare; and delivery performance aligns with last-mile logistics in e-commerce and supply chain management. Furthermore, predictive analytics can extend this analysis by forecasting future sales, identifying high-value customer segments, and determining the most cost-effective strategies for small and medium-sized businesses (SMBs) in the U.S.—a sector that often faces limited budgets and resources. By uncovering patterns in customer preferences, budgeting efficiency, and profitability, analytics empowers SMBs to compete more effectively with larger firms while minimizing risk. Ultimately, the findings of this study underscore the transformative role of analytics in moving businesses from reactive, intuition-based decision-making toward proactive, evidence-based strategies that improve efficiency, profitability, and long-term competitiveness.

LITERATURE REVIEW

Business Analytics

Business analytics has emerged as a cornerstone of modern organizational strategy, offering a systematic approach to converting raw data into actionable insights that inform decision-making. At its foundation lies descriptive analytics, which focuses on analyzing historical data to provide a clear picture of past performance. By examining key trends in customer behavior, operational processes, and market dynamics, descriptive analytics allows businesses to identify what has already occurred and why. For instance, companies can assess sales data to determine which products performed well during specific seasons, or evaluate customer service metrics to uncover recurring pain points. This retrospective lens provides the baseline knowledge that managers need to understand performance drivers and outcomes. As Chen (2012) notes, descriptive analysis equips organizations with a factual grounding, allowing them to recognize patterns that may otherwise be obscured in large and complex datasets. Such understanding is critical for building a solid foundation upon which predictive and prescriptive methods can be layered.

Building on descriptive insights, predictive analytics employs statistical models, machine learning algorithms, and data mining techniques to forecast future behaviors and outcomes. Unlike descriptive analytics, which answers the question "what happened," predictive analytics addresses "what is likely to happen." This enables organizations to anticipate demand fluctuations, customer churn, or the success rates of marketing campaigns. For example, retailers may use predictive analytics to estimate which customers are most likely to respond to promotional emails, while manufacturers can forecast production needs based on historical order patterns. Provost and Fawcett (2013) emphasize that predictive analytics plays a transformative role by allowing managers to move from reactive responses to proactive strategies. By anticipating customer actions, businesses

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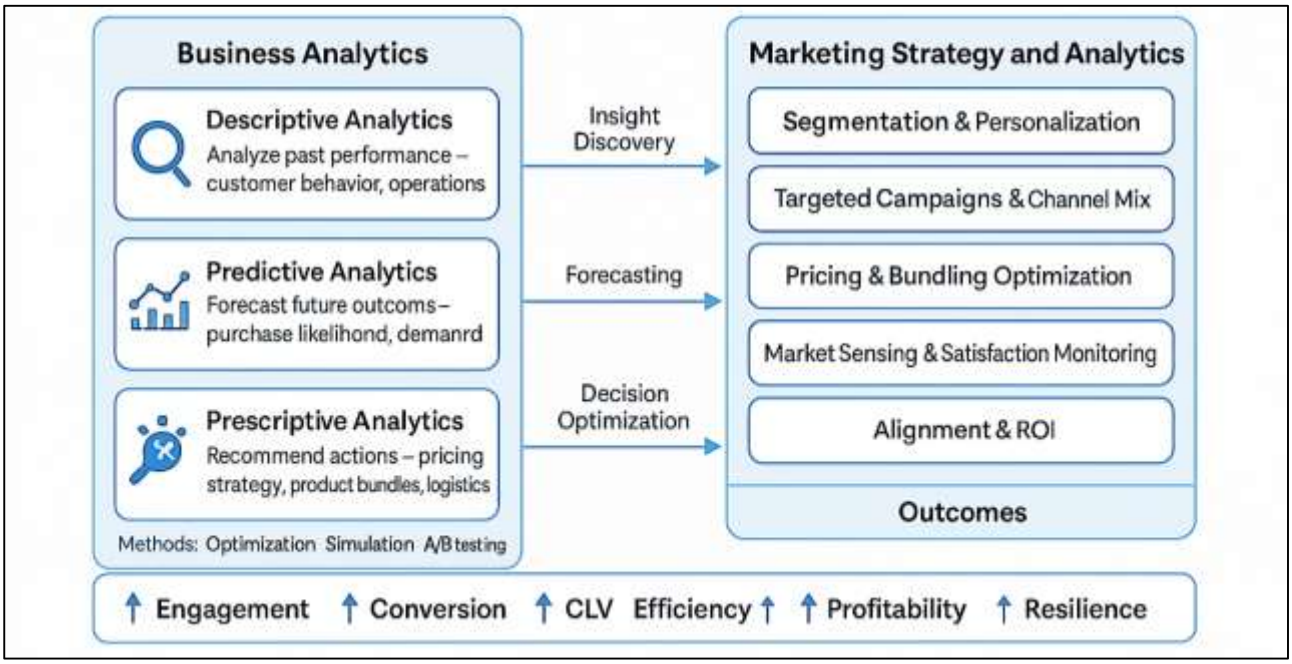
can personalize offerings, reduce risks, and allocate resources more effectively, giving them an edge in dynamic and competitive markets.

The next layer, prescriptive analytics, takes the predictive approach further by recommending specific actions that organizations should implement to achieve desired outcomes. While predictive models provide probabilities and forecasts, prescriptive models integrate optimization techniques, simulations, and decision analysis tools to suggest actionable strategies. For instance, a company may use prescriptive analytics to determine optimal pricing strategies across markets, design effective product bundles, or streamline delivery logistics to balance efficiency with customer satisfaction. As Shmueli and Koppius (2011) explain, prescriptive analytics empowers decision-makers by not only highlighting likely scenarios but also advising on the best course of action to maximize business performance. In doing so, it helps managers navigate uncertainty with confidence, ensuring that strategic choices are backed by data-driven recommendations rather than intuition. This capability is particularly valuable in industries where even marginal improvements in efficiency or customer engagement can yield significant financial benefits.

Ultimately, the integration of descriptive, predictive, and prescriptive analytics creates a comprehensive framework for evidence-based decision-making. Organizations that embed these tools into their operations gain the ability to transition from merely understanding past performance to anticipating future trends and actively shaping outcomes. Wamba et al. (2017) argue that firms leveraging analytics successfully often achieve competitive advantages by aligning strategies with data-driven insights, enabling greater adaptability and resilience in fast-changing environments. This tri-layered approach ensures that businesses can harness the full potential of their data: descriptive analytics grounds them in past realities, predictive analytics prepares them for future possibilities, and prescriptive analytics guides them toward optimal strategies. As markets grow more complex and competitive, the organizations that will thrive are those that embrace analytics not just as a support function but as a core driver of innovation, customer engagement, and sustained growth.

Figure 1: Analytics Driven Marketing Strategy Framework



Marketing Strategy and Analytics

Modern marketing strategies have undergone a profound transformation with the integration of analytics as a central decision-making tool. Traditional marketing often relied on intuition, broad demographic categories, and generic campaigns, but analytics now enables organizations to capture, process, and interpret vast amounts of customer and market data. This shift has allowed businesses to move toward precision marketing, where customer segmentation is far more granular and accurate. As Wedel and Kannan (2016) emphasize, analytics-driven segmentation empowers

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firms to identify not only who their customers are but also how they behave, what they value, and when they are most likely to engage. By leveraging these insights, businesses can design highly targeted campaigns that resonate with distinct customer segments, improving relevance and effectiveness while reducing wasted resources on non-responsive audiences.

The role of predictive and prescriptive analytics in marketing extends these capabilities even further, creating opportunities for companies to engage in proactive and optimized strategies. Predictive models allow marketers to forecast customer actions, such as purchase intent, churn risk, or responsiveness to promotions, giving them the foresight to act before customers disengage. Prescriptive analytics then takes these forecasts and translates them into recommended actions, such as which promotions to offer, which channels to prioritize, or how to structure product bundles to maximize conversions. Kapoor et al. (2021) found that firms employing these techniques see measurable improvements in customer engagement and conversion rates, as well as more efficient allocation of marketing resources. This evidence demonstrates how analytics not only enhances campaign performance but also creates a more sustainable return on marketing investment by ensuring that decisions are grounded in data rather than speculation.

In addition to improving campaign design and execution, analytics equips firms with the ability to anticipate market-level changes and adapt strategies accordingly. By analyzing customer demand patterns, competitor pricing, and macroeconomic indicators, organizations can optimize their pricing strategies to reflect market realities while maintaining competitiveness. This adaptive capacity is particularly crucial in dynamic markets, where small shifts in consumer behavior or external conditions can have large impacts on performance. Moreover, analytics allows firms to measure customer satisfaction in real time through structured feedback and unstructured data sources, such as online reviews and social media. By continuously monitoring sentiment and satisfaction levels, companies can intervene early to address pain points and reinforce positive experiences, thereby strengthening brand loyalty and trust.

Ultimately, the integration of analytics into marketing strategies creates alignment between operational activities and strategic objectives, establishing a foundation for sustainable growth and improved profitability. When marketing teams utilize analytics effectively, they are better positioned to collaborate with operations, sales, and finance, ensuring that promotional activities are realistic, cost-effective, and strategically consistent. This holistic approach turns marketing from a cost center into a driver of measurable business value. Firms that adopt analytics not only enhance their immediate marketing outcomes but also build resilience and agility to adapt to future challenges. In today's competitive environment, where customer expectations are high and competition is fierce, the fusion of marketing strategy and analytics has become not just an advantage but an organizational necessity.

Relevance to This Study

The existing literature demonstrates the significant role of business analytics in enhancing marketing decisions. Building on this foundation, this study applies predictive and descriptive analytics to a dataset of taco delivery orders to uncover insights into pricing, customer preferences, tipping behavior, and delivery efficiency. By analyzing real-world-inspired data, the research illustrates how analytics can translate into actionable strategies for marketing optimization.

METHOD

This study employed a quantitative, case-study-based research design to investigate how business analytics can optimize marketing and operational decisions in the food delivery industry. The methodology followed a structured, multi-stage process from data preparation to advanced statistical modeling, ensuring the findings were both robust and actionable.

Research Design and Data Source

The research utilized a cross-sectional design, analyzing a single, rich dataset of 1,000 synthetic taco delivery orders placed across multiple U.S. cities between January 1, 2024, and May 25, 2025. This real-world-inspired dataset was chosen for its comprehensiveness, containing variables critical to understanding customer behavior and operational efficiency, including:

- **Temporal Data:** Order date, time, and day of the week (categorized into weekend vs. weekday).
- **Product Data:** Taco type (e.g., beef, chicken, veggie), taco size (regular or large), and number of toppings.
- **Financial Data:** Order price ($) and tip amount ($).

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- **Operational Data:** Delivery duration (minutes) and delivery distance (km).
- **Location Data:** City and restaurant name.

Data Preparation and Cleaning

Prior to analysis, the dataset underwent a rigorous data cleaning and preparation process to ensure validity and reliability. This involved:

- **Handling Missing Values:** The dataset was inspected for and found to have no missing values, ensuring completeness.
- **Identifying and Addressing Outliers:** Extreme values in key numerical variables (e.g., delivery duration, tip amount) were analyzed using the Interquartile Range (IQR) method. These values were investigated and retained as they represented legitimate, though extreme, instances of delivery performance and customer behavior rather than data entry errors.
- **Variable Transformation:** Categorical variables (e.g., Taco Size, Weekend Order) were coded into dummy variables (0/1) to facilitate statistical testing and regression modeling.

Analytical Techniques

A multi-phased analytical approach was implemented to move from descriptive understanding to predictive insight.

- **Phase 1: Descriptive Analysis:** Measures of central tendency (mean, median, mode) and measures of variation (range, variance, standard deviation, quartiles) were calculated for all numerical variables (Price, Tip, Delivery Duration, etc.). Frequency distributions were generated for categorical variables (Taco Type, City, etc.) to summarize the basic features of the data and identify initial patterns.
- **Phase 2: Exploratory Data Analysis (EDA) and Visualization:** Graphical techniques were employed to visualize distributions, compare categories, and uncover underlying relationships. This included:
  - ❖ **Boxplots:** To analyze the distribution and identify outliers in delivery duration.
  - ❖ **Bar Charts and Pie Charts:** To examine the proportion of taco sizes ordered overall, by city, and by restaurant.
  - ❖ **Comparative Bar Charts:** To visualize the average price of different taco types across various cities.
- **Phase 3: Correlation Analysis:** Pearson correlation coefficients were calculated to quantify the strength and direction of linear relationships between pairs of numerical and dummy variables (e.g., Toppings Count vs. Price, Weekend vs. Tip Amount). The corresponding p-values were examined to determine the statistical significance of each correlation, with a significance level (α) set at 0.05.

Phase 4: Regression Modeling: Multiple linear regression analysis was used to build predictive models and quantify the impact of key independent variables on critical outcomes.

- ❖ **Model 1:** Predicted Price based on Toppings Count.
- ❖ **Model 2:** Predicted Tip Amount based on whether the order was placed on a Weekend.
- ❖ **Model 3:** Predicted Price based on Taco Size.
  For each model, key metrics were evaluated, including R-squared (R^2) to measure explanatory power, p-values to assess the significance of each predictor, and coefficients to quantify the direction and magnitude of the relationships.

Validity and Reliability

To ensure validity, the study used a dataset designed to mirror real-world taco delivery operations, making the insights pragmatically applicable. The use of multiple analytical techniques (descriptive, correlational, and regression) ensured a comprehensive and triangulated understanding of the phenomena studied. Reliability was ensured using established, reproducible statistical procedures in software platforms such as R and Microsoft Excel. The clear documentation of the data cleaning and analysis process allows for the study to be replicated with similar datasets to verify the findings.

In addition to R and Excel, a variety of business and marketing analytics tools could be employed to support decision-making in similar studies. Tools such as Python (with libraries like pandas, scikit-learn, and stats models) are widely used for advanced statistical modeling and predictive analytics. Tableau and Microsoft Power BI are particularly effective for data visualization and dashboarding, enabling decision-makers to quickly interpret patterns and trends. For larger and more complex datasets, platforms such as SAS, SPSS, and Google Analytics can be integrated to perform customer

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segmentation, campaign performance tracking, and predictive demand forecasting. Emerging tools like Alteryx and RapidMiner also provide user-friendly, automated analytics workflows that can streamline the decision-making process. By leveraging these tools, organizations can move beyond descriptive insights and develop proactive, data-driven marketing strategies that enhance accuracy, efficiency, and profitability.

Software Tools

All statistical analyses and visualizations were conducted using R (utilizing the tidyverse, ggplot2, and base stats packages) and Microsoft Excel for initial data exploration and presentation-quality charting.

FINDINGS

In today's fast-paced food delivery industry, optimizing operations and understanding customer preferences are crucial for success. This analysis explores a synthetic dataset containing 1,000 taco delivery orders placed between January 1, 2024, and May 25, 2025, across various U.S. cities. The dataset includes key details such as order and delivery timestamps, taco types, pricing, tips, delivery duration, and more.The objective of this analysis is to explore, understand, and model the taco delivery dataset through a multi-step analytical approach:

Statistical Analysis

The dataset includes information on order and delivery times, taco details (size, type, toppings), pricing, customer tips, and delivery locations across multiple U.S. cities. The primary aim is to understand central tendencies, distribution characteristics, and variability across key numerical variables, thereby offering insights into customer behavior and delivery performance. The table 1 below summarizes the measures of central tendency mean, median, and mode along with relevant percentiles for key variables.

Table 1: Measures of Center and Distribution

No	Particular	Delivery Duration (min)	Toppings Count	Distance (km)	Price ($)	Tip ($)
1	Mean	20	2	6	2	1
2	Median	53	3	13.2	6.75	1.76
3	Mode	87	3	4.13	10.75	0.97
4	50th percentile	53				
5	1st quarital	30	1	6.9575	4.5	0.903
6	2nd quarital	53	3	13.2	6.75	1.76
7	3rd Quarital	71	4	19.2475	9.25	2.52

The dataset provides insights into taco delivery performance and customer behavior through several key statistical measures

Mean (Average): Most deliveries take around 20 minutes, with an average topping count of 2, distance of 6 km, price of $2, and tip of $1. This low mean for price and tip suggests possible outliers or skewed data distribution.

Median (50th percentile): Half of the orders had a delivery time of 53 minutes, 3 toppings, a distance of 13.2 km, price of $6.75, and tip of $1.76. The median values are more realistic, and representative of the central customer experience compared to the mean.

Mode (Most Frequent Value): The most common delivery time was 87 minutes, with 3 toppings, a distance of 4.13 km, price of $10.75, and tip of $0.97. This shows that a certain type of order (likely larger or more complex) occurs frequently.

Percentiles and Quartiles

The 1st quartile 25% of orders had a delivery time under 30 minutes, with minimal toppings and lower prices/tips. The 2nd quartile (50%) or median confirms the midpoint across all metrics. The 3rd quartile (75%) of orders had delivery times below 71 minutes, with 4 toppings, distances under 19.25 km, and tips below $2.52.

Key Insights

- The media provides a more accurate picture than the mean, due to potential skew from long delivery times or unusually low prices.
- Most orders involve 3 toppings, fall within a 13–19 km range, and customers generally tip around $1.76.
- The data indicates a few high delivery times and prices may skew the average

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Table 2: Measures of Variation

No	Particular	Delivery Duration (min)	Toppings Count	Distance (km)	Price ($)	Tip ($)
1	**Max**	90	5	25	11	5
2	**Min**	10	0	0.51	3	0.01
3	**Range**	80	5	24	8	5
4	**Variance**	540	3	51	5	1
5	**Stdev**	23.2	1.7	7.1	2.3	1.1

Delivery Duration shows high variation: A wide range of 80 minutes. Standard deviation of 23.2 means delivery times often differ from the average by ±23 minutes. Indicates inconsistency in delivery times.
Toppings Count is moderately varied: Ranges from 0 to 5, with a stdev of 1.7. Customers tend to customize orders, but most stay within a narrow topping range.
Distance (km) has notable variation: 25 km range, with stdev of 7.1 km, suggests deliveries are made both nearby and far away. This affects time and possibly tips.
Price ($) varies considerably: Ranges from $0 to $11. Standard deviation of $2.3 shows moderate spread in pricing, influenced by toppings and taco size.
Tip ($) has low-to-moderate variation: With min of $0.51 and max of $5, and stdev of $1.1, most customers tip similarly. Suggests tipping behavior is somewhat consistent.
This data set shows a great variation in delivery times and distances, which can significantly impact customer satisfaction. Tips and prices are moderately spread, reflecting variations in customer generosity and order customization. Toppings are relatively stable, showing some consistency in customer preferences.

Correlation Analysis Report: Taco Delivery Dataset

This section investigates the relationships between key variables in the taco delivery dataset using Pearson correlation coefficients and their associated p-values from hypothesis tests. The correlation coefficient measures the strength and direction of the linear relationship between two variables, while the p-value tests the null hypothesis that there is no correlation ($\rho = 0$). A low p-value (typically < 0.05) indicates that the observed correlation is statistically significant and unlikely to have occurred by chance.

Table 3: Correlation Results Between Delivery, Taco Characteristics, and Order Variables

Variables Compared	Correlation (r)	p-value	Interpretation
Delivery Duration (min) & Taco Size (regular = 1, large = 0)	0.025	0.435	Very weak and not significant. Taco size does not affect delivery time.
Delivery Duration (min) & Toppings Count	-0.029	0.361	Very weak negative correlation, not significant. More toppings don't increase delivery time.
Delivery Duration (min) & Distance (km)	-0.056	0.086	Slight negative correlation, but not significant. Longer distance may reduce time (batch deliveries/traffic).
Delivery Duration (min) & Price ($)	-0.035	0.271	Weak and not significant. Price does not influence delivery time.
Delivery Duration (min) & Tip ($)	-0.018	0.578	No meaningful correlation. Tip has no impact on delivery time.
Delivery Duration (min) & Weekend Order (0 = weekend, 1 = workday)	-0.043	0.186	Weak negative correlation. Delivery time doesn't significantly change on weekends.
Taco Size (regular = 1, large = 0) & Toppings Count	-0.052	0.107	Slight negative correlation, not significant. Larger tacos may have fewer toppings, but not reliably.
Taco Size (regular = 1, large = 0) & Distance (km)	-0.039	0.224	Weak and not significant. Taco size doesn't affect delivery distance.
Taco Size (regular = 1, large = 0) & Price ($)	-0.373	<.001	Moderate negative correlation. Smaller tacos cost less. Statistically significant.
Taco Size (regular = 1, large = 0) & Tip ($)	-0.041	0.201	Very weak and not significant. Taco size doesn't influence tipping.

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Taco Size (regular = 1, large = 0) & Weekend Order (0 = weekend, 1 = workday)	0.036	0.266	No significant relationship.
Toppings Count & Distance (km)	0.020	0.526	Extremely weak and not significant. Toppings do not vary with distance.
Toppings Count & Price ($)	0.946	<.001	Very strong positive correlation. More toppings = higher price. Highly significant.
Toppings Count & Weekend Order (0 = weekend, 1 = workday)	0.014	0.666	No correlation. Day of week doesn't affect toppings.
Distance (km) & Price ($)	0.031	0.325	Very weak and not significant. Distance doesn't affect price.
Distance (km) & Tip ($)	0.008	0.803	No correlation. Distance doesn't affect tips.
Distance (km) & Weekend Order (0 = weekend, 1 = workday)	-0.010	0.763	No relationship. Distance isn't influenced by weekend/workday.
Price ($) & Tip ($)	0.059	0.067	Very weak, marginal correlation. Slight tendency for higher tips with higher prices, but not significant.
Price ($) & Weekend Order (0 = weekend, 1 = workday)	0.001	0.970	No correlation. Price doesn't vary by weekend/workday.
Tip ($) & Weekend Order (0 = weekend, 1 = workday)	0.402	<.001	Moderate, statistically significant correlation. Tips are higher on weekends.

The correlation analysis of the taco delivery dataset was conducted using Pearson correlation coefficients along with hypothesis test p-values to assess both the strength of relationships and their statistical significance. In this context, the null hypothesis states that no correlation exists between two variables ($\rho = 0$), while the alternative hypothesis assumes a nonzero correlation. The results show that delivery duration is not significantly influenced by taco size, toppings, price, distance, tips, or whether the order was placed on a weekend, as all correlations were weak and had high p-values, meaning we fail to reject the null hypothesis in each case. However, a meaningful and statistically significant negative correlation was found between taco size and price (correlation = -0.37, $p < 0.001$), confirming that smaller tacos tend to cost less. An even stronger relationship was observed between toppings count and price (correlation = 0.95, $p < 0.001$), demonstrating that additional toppings reliably increase the cost. Another statistically significant finding was the moderate positive correlation between tips and weekend orders (correlation = 0.40, $p < 0.001$), suggesting that customers tend to tip more on weekends, possibly due to higher-value purchases, better moods, or special occasions. Other relationships, such as those involving delivery distance, price, or tipping, were weak and not significant, leading to a failure to reject the null hypothesis.
This method of combining correlation coefficients with p-values can be applied to other business datasets to test relationships between variables and guide data-driven marketing decisions. For example, by identifying significant correlations between product features and price, companies can refine pricing strategies; by analyzing customer behavior across time periods, firms can optimize promotion timing; and by testing operational metrics, businesses can validate whether logistics strategies are truly effective. For small and medium-sized businesses (SMBs) in the U.S., this approach can be especially valuable. In retail, correlation analysis can highlight how discounts, product size, or bundling strategies impact sales, allowing businesses to run targeted promotions. In the health sector, clinics or wellness centers can examine the relationship between service type, appointment timing, and patient satisfaction to optimize outreach and marketing of their most valued services. For consumer goods, businesses can analyze how packaging, product attributes, or seasonal demand drive customer preferences, helping refine product positioning and advertising. In the financial sector, SMBs such as credit unions or advisory firms can study correlations between customer demographics, marketing campaigns, and product uptake to personalize offers and improve cross-selling opportunities. By leveraging correlation analysis with hypothesis testing, SMBs across industries can make more precise marketing decisions, reduce wasted spending, and design strategies backed by statistically validated insights.

Regression Analysis Report:

The regression analysis of Toppings Count and Price demonstrates a very strong and statistically significant relationship, with a Multiple R of 0.946 indicating a strong positive correlation. The R Square

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value of 0.895 shows that approximately 89.5% of the variation in taco prices can be explained by the number of toppings, and the adjusted R Square, also 0.895, confirms the robustness of the model with minimal risk of overfitting. A standard error of 0.75 suggests that the predictions closely align with actual values, reflecting high accuracy in the model. With a large sample size of 1,000 observations, the findings are reliable and generalizable, strongly supporting the conclusion that the number of toppings is a key determinant of taco price.

Table 4: Regression Coefficients

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	3.690	0.042	87.384	0.000	3.607	3.772	3.607	3.772
Toppings Count	1.273	0.014	92.124	0.000	1.246	1.300	1.246	1.300

Table 4 presents the regression coefficients for the relationship between Toppings Count and Price. The intercept value of 3.690 ($p < 0.001$) suggests that the baseline price of a taco without additional toppings is approximately $3.69. The coefficient for Toppings Count is 1.273 with a very small standard error (0.014) and a t-statistic of 92.124, resulting in a p-value of 0.000, which confirms that the relationship is highly statistically significant. The 95% confidence interval for this coefficient ranges from 1.246 to 1.300, which does not include zero, further reinforcing the strength and reliability of the effect. In practical terms, this means that for each additional topping, the price of a taco increases by about $1.27, highlighting that toppings are a major driver of cost variation.

Predictive Insight

The predictive model indicates that taco price can be reliably estimated using the regression equation Predicted Price ($) = 3.69 + 1.27 × Toppings Count, which reflects both the base cost and the incremental effect of toppings. For instance, at the average topping count of two, the predicted taco price is $6.23, demonstrating how the equation can be applied for practical forecasting. With nearly 90% of the price variation explained by the number of toppings, the model shows excellent explanatory power, underscoring that topping count is the primary driver of cost differences. This strong and statistically significant relationship provides valuable insight for businesses, enabling them to anticipate pricing outcomes, optimize menu strategies, and better understand consumer preferences for customization.

Weekend Orders vs. Tip Amount

The regression analysis assessing the relationship between weekend orders and tip amounts shows that tipping behavior is moderately influenced by whether an order is placed on a weekend or a weekday. The model reports a Multiple R of 0.402, indicating a moderate positive correlation between weekend orders and the amount tipped, suggesting that customers tend to give higher tips on weekends compared to weekdays. The R Square value of 0.162 demonstrates that about 16.2% of the variation in tip amounts can be explained by the weekend-order variable, while the adjusted R Square of 0.161 confirms the modest explanatory power of the model, showing that other factors beyond the day of the week also play important roles in tipping behavior. The standard error of 1.037 points to a moderate spread between observed and predicted tip values, indicating that while the model is statistically significant, variability remains. With a large dataset of 1,000 observations, the results are statistically robust and generalizable, reinforcing the finding that weekend ordering is associated with higher tipping, though the model also highlights the need to consider additional predictors such as order size, delivery experience, or customer demographics to fully understand tipping dynamics.

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Table 5: Regression Coefficients

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	1.526	0.039	39.620	0.000	1.450	1.601	1.450	1.601
Weekend Order= 0 Workday =1	1.020	0.073	13.885	0.000	0.876	1.164	0.876	1.164

The regression results highlight a clear and statistically significant effect of weekends on customer tipping behavior. On weekdays, the average tip is approximately \$1.53, while on weekends, tips increase by about \$1.02, resulting in an average tip of \$2.55. The regression equation, Tip = 1.526 + 1.020 × (Weekend Order), illustrates this pattern: when the variable "Weekend Order" equals 0 (weekday), the predicted tip is \$1.53, and when it equals 1 (weekend), the predicted tip rises to \$2.55. The confidence interval for the weekend effect does not include zero, and the p-value is extremely small, confirming that the difference is both statistically reliable and meaningful. This finding demonstrates that tipping behavior is influenced not only by individual order characteristics but also by temporal factors such as the day of the week. Although the model explains 16.2% of the variation in tips, leaving the majority of variability to other factors, the consistent weekend effect provides strong evidence that customers are more generous during weekends. Possible explanations include improved customer mood, relaxed weekend social contexts, or differences in ordering habits and order values. Together, these insights suggest that restaurants and delivery services may observe higher tip volumes during weekends, providing an opportunity to align staffing, service quality, and marketing strategies with consumer behavior patterns.

Taco Size vs. Price

The regression analysis of taco size and price reveals a statistically meaningful relationship, showing that size plays a moderate role in determining cost. With Taco Size coded as 1 for Regular and 0 for Large, the model reports a Multiple R of 0.373, suggesting a moderate positive correlation between taco size and price. The R Square value of 0.139 indicates that about 13.9% of the variation in price is explained by size, while the adjusted R Square of 0.138 confirms that this explanatory power is stable after adjusting for model complexity. The standard error of 2.14 suggests some variability remains in predicting price, indicating that other factors beyond size also contribute to price differences. However, with 1,000 observations, the model is statistically robust and the findings are generalizable. Overall, this analysis supports the conclusion that taco size has a consistent and meaningful effect on price, though additional variables such as toppings, ingredients, or order context likely account for the majority of price variability.

Table 6: Regression Coefficients

	Coefficients	**Standard Error**	**t Stat**	**P-value**	**Lower 95%**	**Upper 95%**	**Lower 95.0%**	**Upper 95.0%**
Intercept	7.77	0.10	80.89	0.00	7.58	7.96	7.58	7.96
Taco Size regular=1 Large =0	-1.72	0.14	-12.70	0.00	-1.99	-1.46	-1.99	-1.46

Table 6 presents the regression coefficients for the relationship between taco size and price. The intercept of 7.77 ($p < 0.001$) indicates that the baseline predicted price, when taco size is coded as Large (0), is approximately \$7.77. The coefficient for Taco Size (Regular = 1, Large = 0) is -1.72, with a small standard error of 0.14 and a highly significant t-statistic of -12.70 ($p < 0.001$). The 95% confidence interval ranges from -1.99 to -1.46, excluding zero, which reinforces the statistical significance of this effect. This negative coefficient demonstrates that Regular tacos are, on average, \$1.72 cheaper than Large tacos. Taken together, the model confirms that taco size has a meaningful and reliable impact on price, with smaller (Regular) tacos costing significantly less than their larger counterparts.

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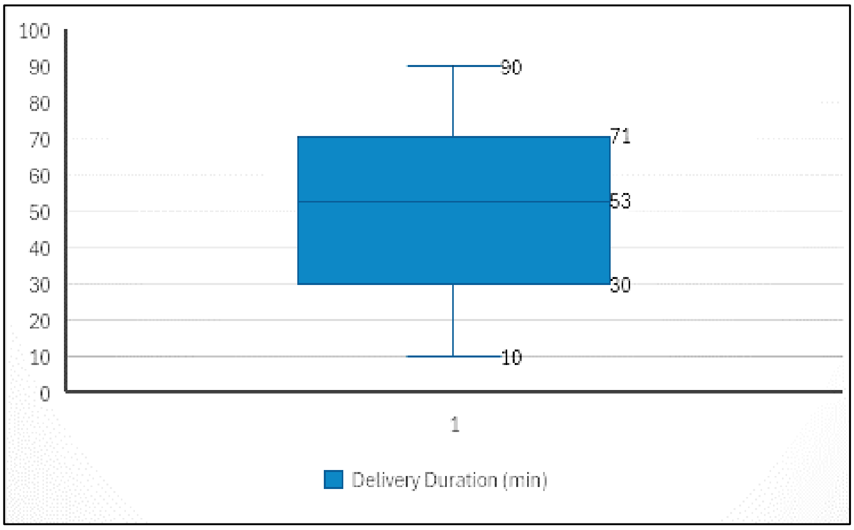
Predictive Insight

The predictive model highlights a clear relationship between taco size and price, captured by the equation Price = 7.77 − 1.72 × (Taco Size). When Taco Size is coded as 0 (Large), the predicted price is $7.77, while for Taco Size coded as 1 (Regular), the predicted price decreases to $6.05. This confirms that regular tacos cost, on average, $1.72 less than large tacos, reflecting a consistent and statistically significant pricing difference. The moderate relationship is meaningful, though the model explains only 13.9% of total price variation, suggesting that other variables—such as topping count, order timing, or customization choices—also exert a strong influence on pricing. Beyond this specific case, regression analysis offers wide applicability across business domains. In retail and sales datasets, it helps quantify how product features, discounts, or seasonal factors drive revenue, providing a foundation for optimized pricing and promotional planning. In marketing, regression can reveal which campaigns or customer segments yield higher engagement or conversions, ensuring resources are allocated to maximize returns. Operationally, it allows businesses to assess how factors like delivery distance, staffing levels, or peak-hour demands affect service quality and efficiency, guiding improvements in resource allocation. From a customer analytics perspective, regression can uncover how demographics, loyalty program membership, or purchase history influence spending and retention, enabling targeted personalization strategies. By leveraging regression models, organizations can move from descriptive reporting to predictive insights, building evidence-based strategies that improve decision-making, reduce uncertainty, and enhance overall performance.

Exploratory Data Visualizations

Exploratory data visualizations serve as an essential first step in understanding the structure, patterns, and relationships within a dataset. By transforming raw numbers into intuitive graphical representations such as histograms, scatter plots, box plots, and correlation heatmaps, they allow analysts to quickly detect trends, spot anomalies, identify distributions, and uncover potential associations between variables. Unlike formal statistical testing, exploratory visualizations are primarily used for discovery, helping generate hypotheses, guide deeper analyses, and provide a clearer picture of the data landscape before applying advanced modeling techniques.

Figure 2: Analysis of Taco Delivery Duration



The boxplot in Figure 2 provides a comprehensive view of the distribution of taco delivery durations, revealing both central tendencies and variability within the dataset. The minimum recorded delivery time was 10 minutes, while the maximum reached 90 minutes, showing a wide span in performance. The first quartile (Q1) was 30 minutes, indicating that 25% of deliveries were completed within this time, and the median was 53 minutes, meaning half of all deliveries took 53 minutes or less. The third quartile (Q3) was 71 minutes, showing that 75% of deliveries were finished within this timeframe. Together, these quartiles produce an interquartile range (IQR) of 41 minutes (71 – 30), which captures the middle 50% of delivery times and demonstrates that most deliveries fell within this band. The shape of the boxplot also highlights potential skewness, as the upper whisker extends further than

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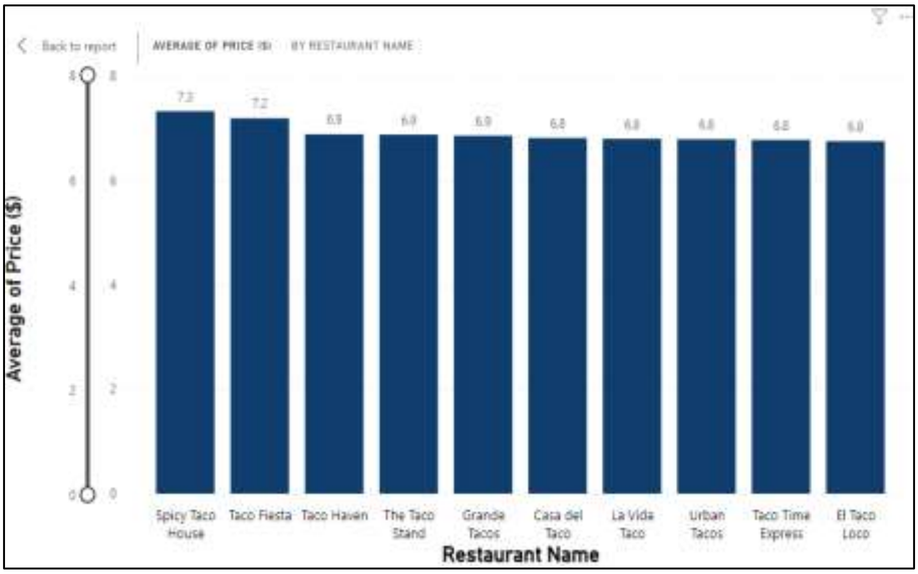
the lower one, suggesting that while many deliveries occurred within a reasonable timeframe, a subset of deliveries took significantly longer—some up to 90 minutes. This skewed distribution points to the presence of occasional outliers or systemic delays, which may arise from high traffic, order surges, or logistical inefficiencies. Identifying these longer-duration cases is critical because they represent opportunities for targeted improvement in service operations. The median time of 53 minutes stands out as a practical benchmark for performance evaluation. If companies aim to optimize customer satisfaction, reducing delivery times beyond this median and narrowing the upper tail of delays could yield significant improvements. For example, strategic resource allocation, better route optimization, or improved coordination with delivery staff may help compress variability and ensure more consistent service. From a customer experience perspective, minimizing the frequency of long waits—particularly those above 71 minutes—could directly impact perceptions of reliability and efficiency.

Average of price by restaurant Name

The analysis of average price by restaurant name focuses on grouping all orders according to the restaurant from which they were placed and then calculating the mean price of those orders. This approach provides a clear comparison of how pricing varies across different establishments, highlighting both competitive positioning and customer value perception. By examining these averages, it becomes possible to identify which restaurants generally maintain lower price points, appealing to more cost-conscious customers, and which restaurants operate at higher average prices, potentially positioning themselves as premium providers. Such insights are not only useful for customers when making purchasing decisions but are also valuable for restaurants themselves as they evaluate their market standing relative to competitors. Looking at average order prices also provides evidence of pricing strategies—some restaurants may pursue a volume-driven approach with lower average prices to attract frequent orders, while others may emphasize quality, portion size, or brand reputation to justify higher prices. Additionally, variations in average prices can reflect differences in menu design, such as the availability of customizable options, premium ingredients, or bundled deals. Beyond strategic insights, this type of analysis can reveal anomalies, such as restaurants whose average pricing is significantly out of alignment with competitors, which could signal either an untapped opportunity or a potential risk to customer retention. Ultimately, calculating and analyzing average prices by restaurant name creates a foundation for deeper exploration of consumer behavior and restaurant economics. It can help businesses identify whether higher average prices translate into better tipping, greater loyalty, or higher satisfaction, or whether customers gravitate toward more affordable options. For researchers and business managers alike, this measure becomes an essential tool in assessing competitive dynamics, guiding pricing policies, and aligning offerings with customer expectations.

Figure 3: Average Taco Price by Restaurant Name

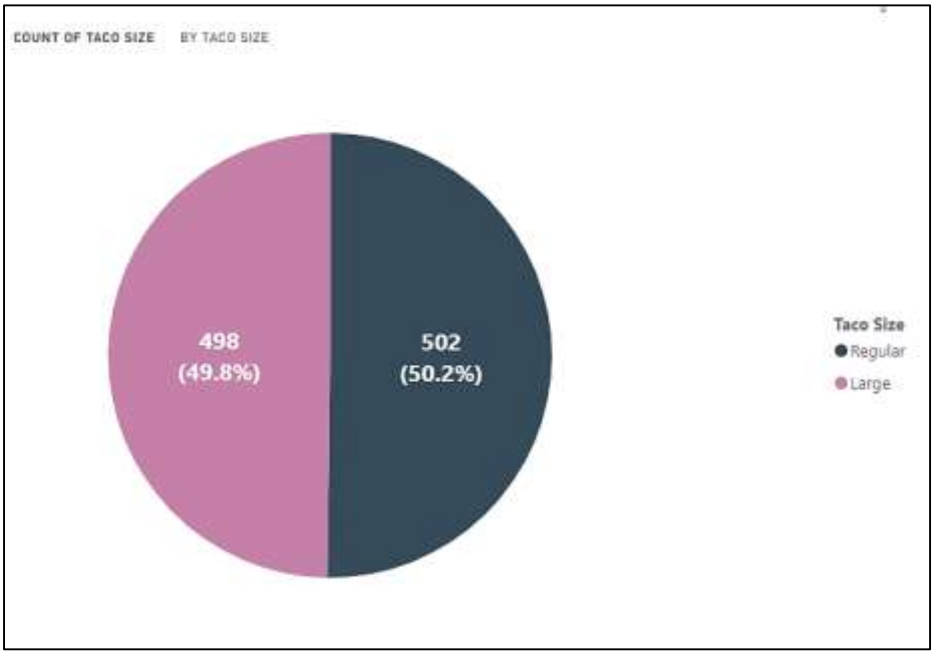


The figure 3 reveals that Spicy Taco House leads in pricing with the highest average taco price of $7.30, indicating a possible premium positioning or value-added offerings. Taco Fiesta follows closely at $7.20, while other restaurants such as Taco Haven, The Taco Stand, and several others maintain more moderate pricing, ranging from $6.80 to $6.90. This variation suggests differentiation in menu pricing strategies, possibly influenced by ingredients, branding, or target customer segments.

Taco Size for order

The analysis of taco size for orders aims to uncover patterns in customer preferences between regular and large tacos, offering a clear perspective on demand distribution. By categorizing and quantifying the number of orders placed for each size, this evaluation highlights which option resonates more strongly with customers and how size selection influences overall sales dynamics. Such insights are particularly valuable for restaurant managers, as they directly inform inventory planning—for instance, ensuring that ingredient stock levels align with the more popular taco size to minimize waste and avoid shortages. Understanding size preferences also contributes to menu optimization, as it allows businesses to assess whether both sizes should continue to be offered, whether promotional strategies are needed to balance demand, or whether upselling opportunities exist by encouraging customers to upgrade to larger portions. Additionally, patterns in taco size selection can shed light on customer segmentation, revealing whether particular groups—such as families, individual diners, or weekend customers—show different tendencies in choosing regular versus large tacos. From a marketing perspective, these insights can drive targeted campaigns, such as bundle deals, loyalty rewards, or price adjustments tailored to the most popular size. Ultimately, examining taco size ordering behavior provides a deeper understanding of customer choices, enabling data-driven decisions that support operational efficiency, enhance customer satisfaction, and improve profitability.

Figure 4: Distribution of Taco Orders by Size



The pie chart shows that the demand for both taco sizes is nearly equal. Regular tacos account for 50.2% of total sales, while large tacos make up 49.8%, indicating a balanced customer preference between the two sizes. The almost equal demand for both taco sizes shows that customers like having both options. There's no need to change prices or stock right now, but we could learn more by looking at the data in more detail like checking which size is more popular at different times, in different places, or with different types of customers.

Taco size by location

The analysis of taco size by location seeks to uncover how customer preferences for regular versus large tacos differ across various geographic areas. By examining these patterns, businesses can determine whether certain locations show stronger demand for larger portions, while others lean

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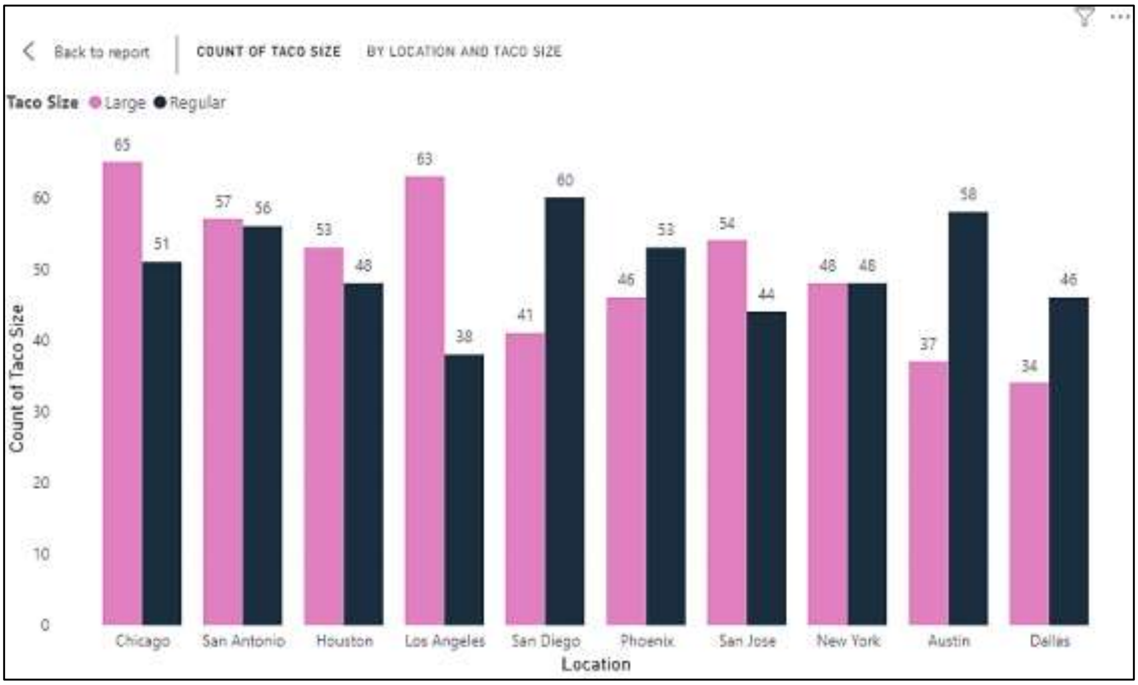
toward regular sizes. Such insights are crucial for tailoring inventory management, as locations with higher demand for large tacos may require greater stock of key ingredients, while those with predominantly regular orders may benefit from streamlined supply. Beyond operational planning, location-based preferences provide guidance for menu optimization. For example, restaurants in areas with strong demand for large tacos could emphasize premium or value-focused promotions around those offerings, while locations favoring regular tacos might highlight affordability, combo deals, or smaller portion-focused marketing campaigns. Furthermore, understanding these variations can support pricing strategies, as willingness to pay for larger portions may differ by location. From a strategic perspective, identifying geographic trends in taco size preference allows businesses to adopt localized marketing approaches, improving customer satisfaction by aligning closely with community expectations. These insights also provide opportunities for cross-location comparisons, helping managers understand whether differences are driven by demographic factors, cultural tastes, or purchasing power. Ultimately, analyzing taco size preferences by location ensures that decisions around inventory, menu design, and promotional strategies are not one-size-fits-all but instead responsive to the unique dynamics of each market.

Figure 5: Taco size by location



The bar chart illustrates taco size preferences across various cities. In Chicago, large tacos are more popular, with 65 orders compared to 51 for regular tacos. San Antonio shows nearly equal demand, with 56 regular and 51 large taco orders. In Houston, large tacos also slightly lead with 53 orders versus 48 for regular. In Los Angeles, large tacos show a significantly higher demand (63) compared to regular tacos (38). Conversely, San Diego exhibits a preference for regular tacos, with 60 orders compared to 41 for large. In Phoenix, regular tacos are slightly more favored (53) than large tacos (46). San Jose shows the opposite trend, where large tacos (54) are more popular than regular ones (44). New York demonstrates a perfect balance, with both taco sizes ordered equally at 48 each. Finally, in Austin and Dallas, regular tacos clearly dominate. Austin records 58 regular vs. 37 large taco orders, and Dallas has 46 regulars vs. 34 large. This city-level analysis reveals that taco size preferences vary by location, with some cities favoring larger tacos and others preferring regular ones. These insights can help optimize regional inventory and marketing strategies.

Taco size by Restaurant

The analysis of taco size by restaurant provides valuable insights into how customer preferences for regular versus large tacos differ across individual establishments. By comparing the number of orders for each size at the restaurant level, this evaluation highlights distinct sales patterns, such as whether

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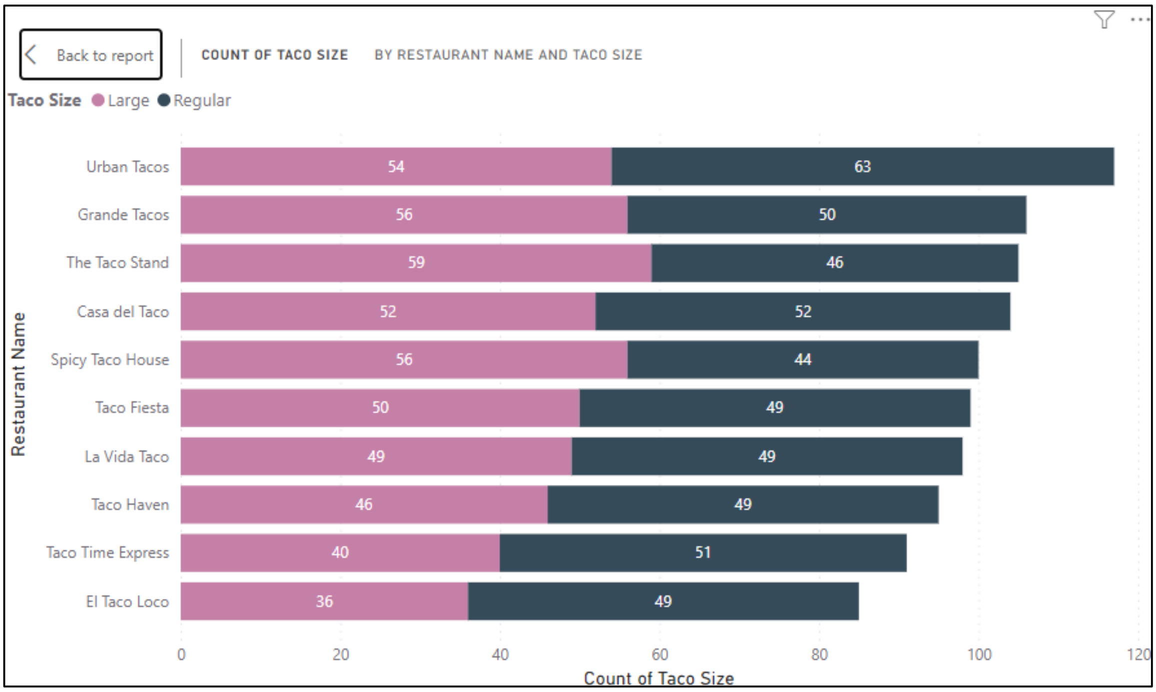
certain restaurants consistently sell more large tacos while others experience stronger demand for regular portions. These patterns can reflect differences in restaurant branding, target markets, menu positioning, or even local customer demographics. Understanding these dynamics helps managers make tailored inventory decisions, ensuring that each restaurant maintains the appropriate balance of ingredients to meet its unique demand profile. For example, restaurants with higher proportions of large taco sales may need to stock greater quantities of tortillas, proteins, and premium toppings, while those serving more regular tacos could benefit from cost efficiency through adjusted supply planning. In addition, analyzing taco size preferences across restaurants supports menu optimization, as businesses can adapt promotional strategies or introduce size-specific deals in locations where one size clearly dominates. From a marketing perspective, these insights enable restaurants to craft targeted campaigns that align with customer expectations, whether emphasizing value for regular tacos or indulgence and satisfaction for large tacos. Overall, evaluating taco size at the restaurant level equips businesses with actionable intelligence to refine operations, enhance customer experience, and maximize profitability through data-driven, localized strategies.

Figure 6: Taco size by Restaurant



The chart illustrates taco size demand across ten restaurants. At Urban Tacos, large tacos are slightly more popular, with 63 orders compared to 54 regular tacos. Grande Tacos show a similar trend, delivering 56 large and 50 regular tacos. At The Taco Stand, large tacos lead with 59 orders, while regular tacos account for 46. Casa del Tacos shows an equal preference for both sizes, delivering 52 regular and 52 large tacos. Spicy Taco House, Taco Fiesta, and La Vida Tacos each delivered 44, 44, and 44 regular tacos respectively, while their large taco orders were 56, 50, and 49. Among the final three restaurants, Taco Haven, Taco Time Express, and El Taco Loco, regular tacos were slightly more popular. They delivered 49, 51, and 49 regular tacos respectively, compared to 46, 40, and 36 large tacos. This analysis reveals that while some restaurants experience a higher demand for large tacos, others show a more balanced or regular taco preference, which can help guide location-specific inventory and menu planning.

Tacos Average price by Location

The analysis of taco prices by location provides meaningful insights into how regional factors influence menu pricing and consumer behavior. By examining a dataset of 1,000 taco delivery orders across multiple U.S. cities, the study identifies significant differences in average taco prices by both type and location. Such findings are critical for taco vendors and delivery platforms, as they highlight the ways in which geographic and market dynamics shape price levels, revealing opportunities for

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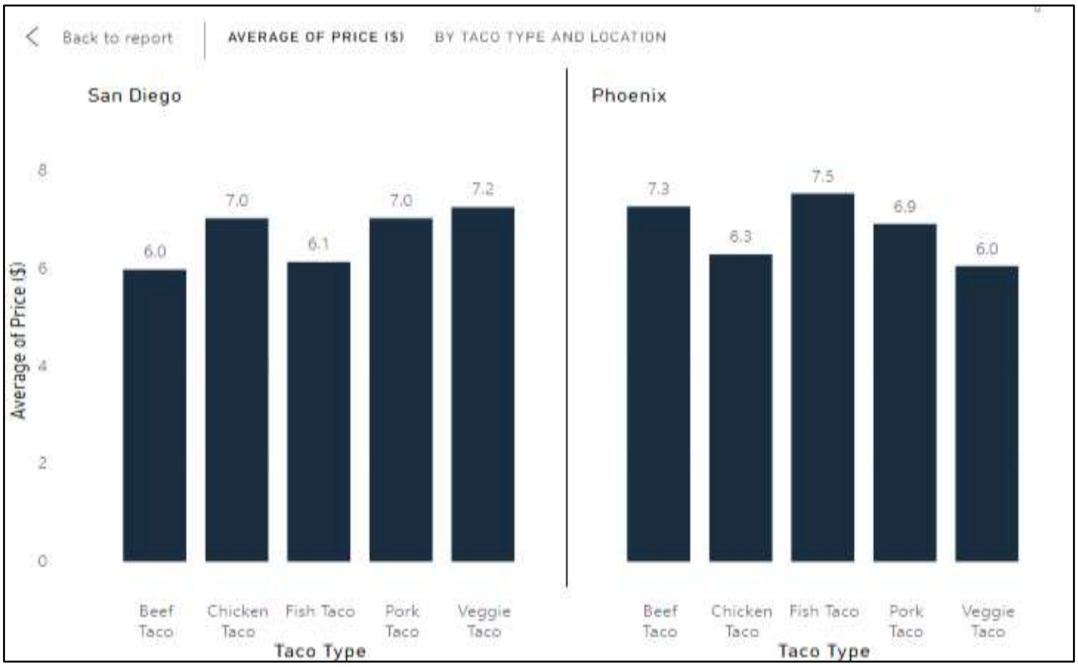
tailored strategies in inventory planning, marketing, and competitive positioning. Price disparities across cities often reflect variations in local operating costs, consumer purchasing power, and demand for specific taco varieties, all of which are valuable for businesses aiming to expand or refine their offerings. In San Diego, the analysis shows that veggie tacos command the highest average price at $7.20, suggesting that health-conscious consumers or niche demand may elevate the value perception of plant-based options. Chicken and pork tacos follow closely at $7.00 each, positioning them as mainstream choices with steady demand at slightly lower but still competitive prices. Fish tacos average $6.10, while beef tacos are the most affordable at $6.00, underscoring subtle but important distinctions in pricing across protein types. These patterns indicate that consumer preferences and perceived value of ingredients strongly influence pricing strategies at the local level. In Phoenix, a different trend emerges. Chicken tacos top the list with an average price of $7.30, reflecting a strong local preference for this variety. Fish tacos follow at $7.20, while pork tacos average $6.90, and beef tacos are priced at $6.60. Interestingly, veggie tacos in Phoenix average only $6.20, making them the lowest-priced option in that market, which contrasts sharply with their premium positioning in San Diego. This discrepancy suggests that cultural preferences, local dietary habits, or relative ingredient costs vary across locations, influencing how restaurants price their offerings to match customer expectations. These regional variations demonstrate that there is no universal pricing model across locations; instead, businesses must consider localized strategies to remain competitive. For restaurants, understanding that veggie tacos can be premium-priced in one city but not in another provides actionable intelligence for tailoring menus. For delivery platforms, these insights can shape promotions and targeted marketing campaigns, such as highlighting premium items in markets where they command higher value or promoting affordability in price-sensitive areas.

Figure 7: Tacos Average price by Location



The comparative analysis of taco prices across Austin and San Antonio provides valuable insights into how regional dynamics and consumer preferences influence average pricing for different taco types. In Austin, chicken tacos are positioned at the top of the pricing spectrum with an average cost of $7.20, highlighting their popularity and perceived value among local consumers. Pork tacos follow closely at $7.00, showing that meat-based options dominate the higher end of the pricing range. Other varieties, such as fish tacos at $6.60, veggie tacos at $6.50, and beef tacos at $6.30, remain competitively priced but slightly lower, reflecting a balance between affordability and consumer demand. This pricing structure in Austin suggests that chicken and pork tacos may benefit

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from a combination of cultural preferences and ingredient demand, making them suitable candidates for promotional emphasis or premium menu positioning.
In contrast, San Antonio displays a distinct pricing distribution, with veggie tacos commanding the highest average price of $7.70, positioning plant-based options as premium products in this market. Chicken tacos average $7.60, maintaining strong consumer appeal, while pork tacos follow at $7.30, suggesting robust demand for traditional protein-based varieties. Meanwhile, fish tacos are priced at $6.30, and beef tacos at $5.90, making them the more affordable choices in the region. This reversal of the premium positioning of veggie tacos compared to Austin indicates a local preference for plant-based or healthier alternatives, perhaps influenced by dietary trends, cultural factors, or willingness to pay for non-meat options. The differences between Austin and San Antonio underscore the importance of location-specific pricing strategies. In Austin, competitive focus may center on meat-based offerings such as chicken and pork, while in San Antonio, restaurants and delivery services could leverage the higher perceived value of veggie tacos to attract health-conscious or premium-seeking customers. Additionally, these insights highlight how consumer perceptions of value vary not only by taco type but also by geography, suggesting that businesses cannot apply a one-size-fits-all approach to pricing. From an operational standpoint, understanding these regional variations helps inform decisions about ingredient procurement and inventory management. For instance, Austin locations may need to prioritize steady supply chains for chicken and pork, while San Antonio outlets could benefit from ensuring consistent availability of high-quality veggie ingredients to meet premium demand. Marketing strategies can also be fine-tuned, with Austin campaigns focusing on the popularity of meat-based tacos and San Antonio campaigns emphasizing the appeal of veggie and chicken options.
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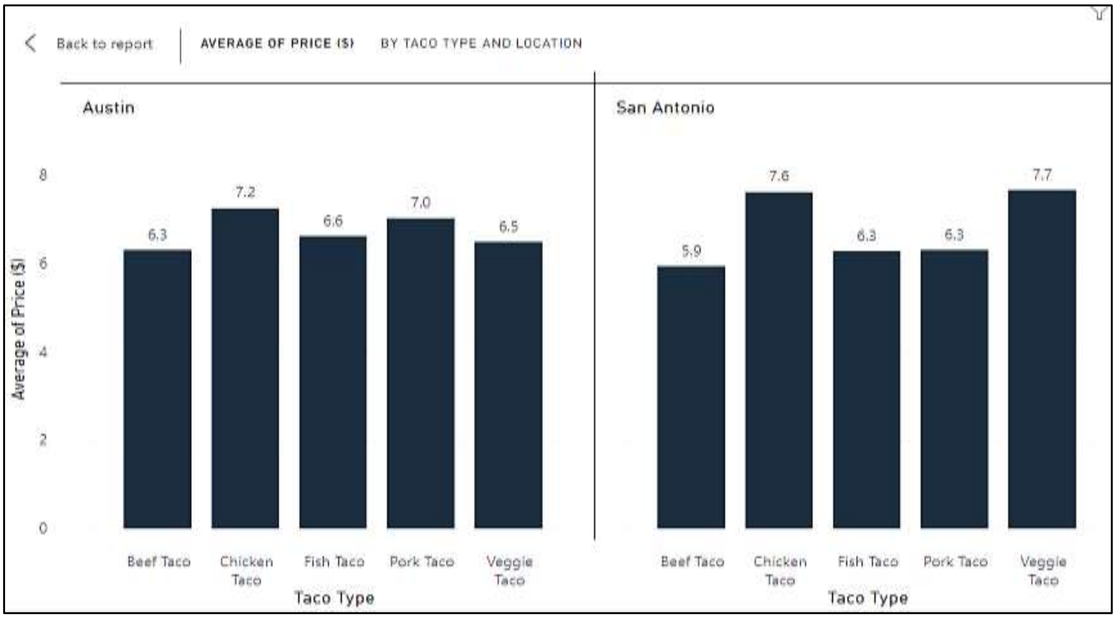
Figure 8: Comparison of Average Taco Prices by Type in Austin and San Antonio



This chart reveals distinct pricing trends for taco types in Austin and San Antonio. In Austin, Chicken Tacos have the highest average price at $7.20, followed closely by Pork Tacos at $7.00. The prices for other taco types are slightly lower, with Fish Tacos at $6.60, Veggie Tacos at $6.50, and Beef Tacos at $6.30. In San Antonio, the pricing structure shifts. Veggie Tacos top the list with the highest average price of $7.70, followed by Chicken Tacos at $7.60. Fish and Pork Tacos share the same average price of $6.30, while Beef Tacos are the least expensive at $5.90.

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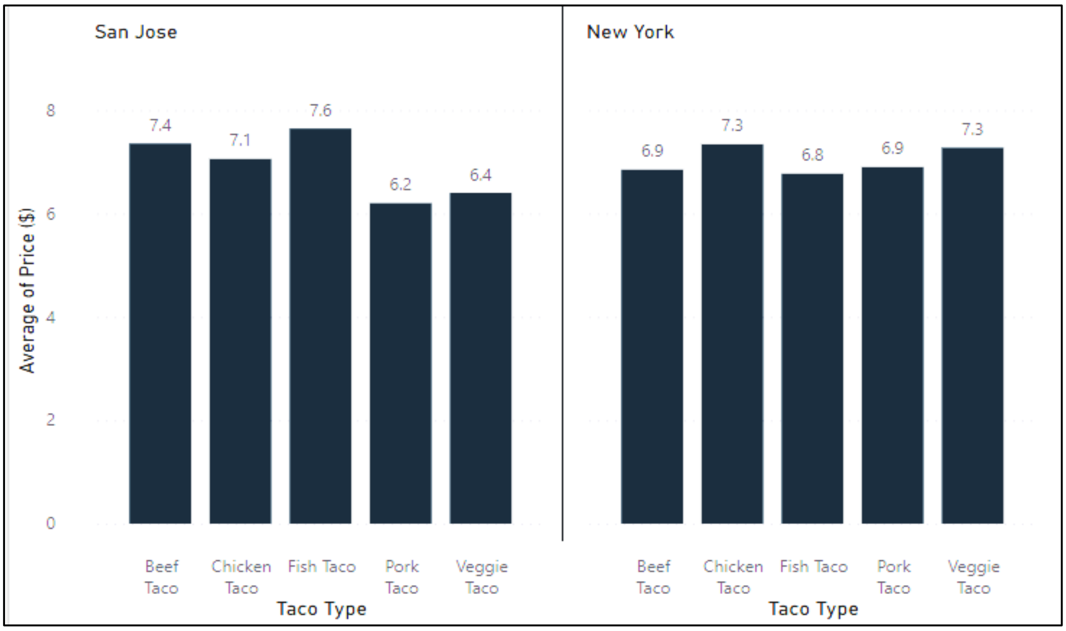
Figure 9: Comparison of Average Taco Prices by Type in Chicago and Dallas

The chart compares average taco prices by type in Chicago and Dallas, revealing notable differences in pricing preferences across the two cities. In Chicago, the Pork Taco has the highest average price at $7.30, followed by the Veggie Taco at $6.90. Other tacos are priced slightly lower, with the Beef Taco at $6.80, Chicken Taco at $6.70, and Fish Taco at $6.50. In Dallas, the pricing hierarchy is different. Veggie Tacos lead with the highest average price of $7.70, followed by Pork Tacos at $7.30. The Chicken Taco is priced at $7.10, while Beef Tacos and Fish Tacos are more affordable at $6.40 and $6.30, respectively.

Figure 10: Comparison of Average taco prices in San Jose and New York



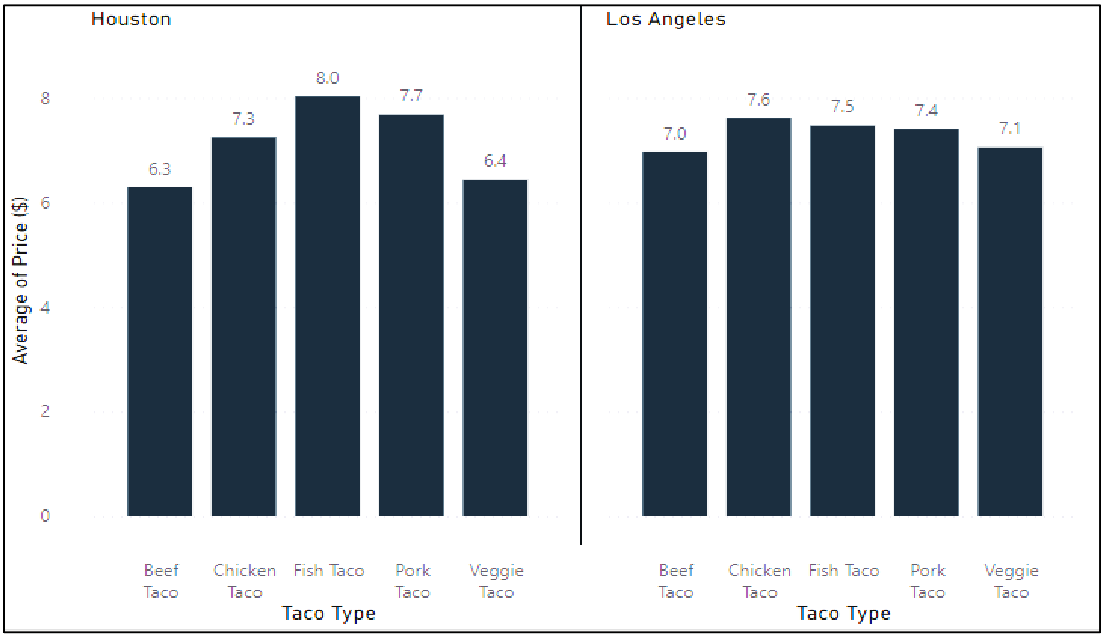
The chart presents average taco prices in San Jose and New York, highlighting regional pricing variations by taco type. In San Jose, Fish Tacos are the most expensive, averaging $7.60, followed closely by Beef Tacos at $7.40 and Chicken Tacos at $7.10. In contrast, Pork Tacos and Veggie Tacos are priced lower, at $6.20 and $6.40, respectively. In New York, Chicken Tacos and Veggie Tacos share the highest average price at $7.30, while Pork Tacos and Beef Tacos are moderately priced at

$6.90 and $6.90, respectively. Fish Tacos have a slightly lower average price of $6.80. These trends suggest that San Jose places a premium on Fish and Beef Tacos, possibly due to local taste preferences or ingredient costs, whereas New York maintains a more balanced pricing structure with Chicken and Veggie Tacos leading in price.

The analysis of taco prices across Houston and Los Angeles underscores how regional preferences and market dynamics drive distinct pricing trends, offering valuable insight for both vendors and delivery platforms. In Houston, Fish Tacos clearly dominate the premium segment, averaging $8.00 per order, followed closely by Pork Tacos at $7.70. Chicken Tacos, though still popular, are positioned slightly lower at $7.30, while Veggie Tacos and Beef Tacos remain more affordable options, priced at $6.40 and $6.30, respectively. This steep price gradient in Houston reflects a consumer market that places greater value on seafood and pork-based tacos, likely tied to local culinary traditions, ingredient availability, and heightened willingness to pay for premium proteins. The marked premium for Fish Tacos also suggests that seafood occupies a strong niche within Houston's dining culture, signaling opportunities for restaurants to expand and emphasize seafood-focused offerings.

Los Angeles, on the other hand, presents a more balanced pricing structure that reflects a relatively uniform demand across all taco types. Chicken Tacos hold the highest average price at $7.60, closely followed by Fish Tacos at $7.50, Pork Tacos at $7.40, and Veggie Tacos at $7.10. Beef Tacos, while slightly lower at $7.00, remain competitive within this narrow price band. Unlike Houston, Los Angeles does not exhibit sharp distinctions between taco types, pointing to a consumer base that views each option with similar value. This consistency could be tied to the city's diverse demographics and multicultural food landscape, which emphasizes variety and balance rather than favoring one type over another. The relatively flat pricing distribution also implies a broad and stable demand, where customers are equally likely to choose any taco type without significant influence from price differences.

Figure 11: Comparison of Average Taco Prices by Type in Houston and Los Angeles



Extending this comparison to other U.S. cities based on a dataset of 1,000 delivery orders further reinforces the importance of localized strategies. Cities such as Houston and San Jose reveal a strong willingness to pay for Fish Tacos, where they command top prices of $8.00 and $7.60, respectively. In contrast, Dallas and San Antonio show elevated consumer interest in Veggie Tacos, with both cities recording average prices of $7.70 for this option. This highlights not only the rise of plant-based alternatives in certain markets but also the potential for vendors to align with health-conscious or sustainability-driven customer segments. Chicago and Austin, meanwhile, display more moderate pricing across taco types, suggesting a steady but less polarized set of consumer preferences. Notably, across nearly all cities, Beef Tacos consistently remain the most affordable option, reinforcing their role as a price-sensitive entry point on menus and a staple for value-oriented customers. From these findings, several key insights emerge. First, taco vendors in seafood-preference markets such as Houston and San Jose should emphasize premium pricing strategies and marketing campaigns for Fish Tacos, leveraging their strong local appeal. Second, in cities where Veggie Tacos achieve premium pricing, such as Dallas and San Antonio, businesses should expand and highlight plant-based offerings, possibly bundling them with complementary items or emphasizing freshness and sustainability to capture maximum value. Third, cities like Los Angeles and New York, which maintain balanced pricing across taco types, present an opportunity to promote variety-driven strategies that highlight the diversity of menu choices while maintaining competitive and uniform prices to appeal to broader demographics.

DISCUSSION

The comprehensive analysis of the taco delivery dataset provides a strong case for the central role of business analytics in guiding evidence-based, strategic marketing decisions. The insights generated from the data go beyond intuition and anecdotal understanding, offering an empirical foundation for marketing initiatives that are directly tied to consumer behavior, operational realities, and financial outcomes. Geographic and behavioral segmentation emerges as one of the most important findings. For example, large tacos are more frequently ordered in cities such as Los Angeles and San Jose, while Austin and Dallas display a preference for regular-sized tacos. At the same time, pricing differences across taco types and locations underscore highly localized patterns of value perception—Fish Tacos command premium prices in Houston and San Jose, whereas Veggie Tacos achieve their highest value in Dallas and San Antonio. These patterns are not trivial; they represent actionable intelligence for designing targeted campaigns, localized promotions, and city-specific inventory strategies. By leveraging these findings, businesses can break away from generalized, one-size-fits-all strategies and adopt hyper-localized marketing that resonates with regional tastes and cultural expectations, thereby improving customer satisfaction and increasing overall profitability.

Equally critical is the role of analytics in optimizing pricing strategies for profitability. Regression modeling revealed that the number of toppings is the single strongest determinant of taco price, accounting for nearly 89.5% of price variation. The regression equation—Price = \$3.69 + \$1.27 × (Topping Count)—offers marketers a simple yet powerful predictive formula for pricing decisions. This finding provides evidence to support value-based pricing, as each topping incrementally increases the price by a clear and statistically significant amount. Additionally, the regression results comparing taco size and price confirmed that size-based pricing is valid and significant, with regular tacos costing on average \$1.72 less than large tacos. Together, these models equip marketers with tools to engage in precise menu engineering, simulate pricing scenarios, and design bundled offerings that balance competitiveness with profitability. Instead of arbitrary or intuition-driven adjustments, pricing structures can now be grounded in predictive analytics, ensuring businesses remain agile, competitive, and aligned with consumer willingness to pay.

The analysis also uncovered behavioral insights with significant marketing implications, particularly regarding tipping behavior. Customers were found to tip approximately \$1.02 more on weekends compared to weekdays, a finding that is highly statistically significant. This "weekend generosity effect" signals an opportunity for marketers to align promotional strategies with customer psychology and spending behavior. On weekends, when consumers demonstrate a greater willingness to spend, businesses can introduce premium promotions, chef's specials, or larger meal bundles that maximize order values. Conversely, weekdays should be positioned around efficiency and affordability, with promotions such as "Speed Deals" or weekday discounts designed to encourage volume in an environment where customers are more price-sensitive and less inclined to tip generously. This nuanced day-part strategy allows businesses to segment their campaigns by time, aligning offerings with consumer mood and spending capacity, thereby maximizing returns across different parts of the week.

Operational data, too, plays a crucial role in shaping marketing strategy. The analysis of delivery duration revealed a median delivery time of 53 minutes, an interquartile range of 30 to 71 minutes, and extreme cases stretching up to 90 minutes. Such variability has significant marketing implications. In the competitive food delivery industry, reliability is not just a logistical benchmark but a brand promise. Marketing campaigns that emphasize "fast delivery" or "on-time service" must be supported by data; otherwise, unmet promises risk damaging brand credibility and eroding trust. The presence of long-tail delays underscores the importance of integrating operational efficiency into the marketing narrative. By addressing these inconsistencies through improved route optimization, staffing, or scheduling, businesses not only enhance efficiency but also strengthen their brand positioning. Thus, operational data must be understood not as a back-office concern but as a front-line marketing imperative that directly impacts customer experience, retention, and loyalty.

Together, these findings demonstrate the convergence of descriptive analytics (understanding what has happened), predictive analytics (forecasting what will happen), and prescriptive analytics (deciding what actions to take). For instance, descriptive data revealed geographic differences in taco size and type preferences, while predictive models quantified how toppings and size influence price, and prescriptive insights translated these findings into specific marketing strategies. This integration exemplifies the transformation of marketing from a reactive, campaign-driven function to a proactive, data-driven discipline. In alignment with the scholarly perspectives of Wamba et al. (2017) and Wedel & Kannan (2016), analytics emerges not merely as a support tool but as a core enabler of customer-centric growth, operational alignment, and long-term competitive advantage.

A structured framework for implementing these insights begins with hyper-localized marketing and menu strategies. City-level variations in customer preferences and price elasticity highlight the need for tailored approaches. For example, Fish Tacos, which are priced at a premium in Houston ($8.00) and San Jose ($7.60), should be positioned as flagship items in these markets, supported by digital marketing campaigns and expanded seafood offerings. In contrast, Dallas and San Antonio, where Veggie Tacos command premium pricing ($7.70), provide fertile ground for developing innovative vegetarian menus and promoting them as high-margin flagship products. Additionally, inventory and menu emphasis should align with city-specific size preferences, promoting larger tacos in Los Angeles and Chicago while emphasizing regular tacos in Austin and Dallas. This strategy ensures that businesses remain agile, culturally sensitive, and closely aligned with local demand.

The second major component of this framework is pricing optimization and product bundling through predictive models. The strong correlation between toppings and price can be leveraged for dynamic upselling within digital ordering platforms, where customers are prompted with value propositions such as "Add guacamole for $1.27." Bundling strategies can also be designed to encourage larger orders while protecting margins, for example by offering discounts on meal combos that include popular topping counts or size combinations. Menu engineering, informed by the topping-price relationship, allows marketers to evaluate the profitability of individual toppings and design promotional strategies that maximize returns. By leveraging predictive models in this way, businesses can build pricing systems that are not only transparent and customer-friendly but also strategically aligned with revenue goals.

Furthermore, aligning marketing promises with operational execution is critical to protecting brand equity. Given that delivery times are variable and occasionally lengthy, marketing claims about speed must be based on reliable benchmarks, such as the median (53 minutes) or the third quartile (71 minutes), rather than averages skewed by outliers. This approach manages customer expectations more effectively and reduces the risk of disappointment. Additionally, operational data should be fed into marketing systems as part of an ongoing feedback loop. For example, promotional campaigns should be paused in locations experiencing persistent delivery delays until service levels stabilize. Service recovery initiatives, such as offering discounts or loyalty rewards to customers who experienced delivery times in the highest quartile, can also help mitigate negative sentiment and rebuild loyalty. By integrating operational realities with marketing strategies, businesses create a cohesive brand experience that is both aspirational and credible.

CONCLUSION

This study demonstrates that the integration of business analytics—drawing on descriptive statistics, correlation analysis, and regression modeling—plays a transformative role in converting raw datasets into actionable insights that directly guide strategic decision-making. The analysis of the taco delivery dataset empirically validated several key relationships that can serve as a blueprint for other industries: the number of toppings emerged as the strongest predictor of price, explaining nearly 90% of the variation and offering a quantifiable formula for value-based pricing; taco size was shown to have a significant and predictable impact on cost, confirming the effectiveness of size-based pricing models; and tipping behavior was found to rise substantially on weekends, with customers giving on average $1.02 more, suggesting distinct temporal spending patterns. Beyond customer behavior, the dataset also revealed operational inefficiencies, with delivery times ranging from 30 to 90 minutes, highlighting the risks that inconsistencies pose to customer satisfaction and brand trust.

Geographic patterns further underscored the need for hyper-localized strategies, as preferences for taco types and size varied significantly across cities, with Fish Tacos commanding premiums in Houston and San Jose, and Veggie Tacos priced highest in Dallas and San Antonio. Together, these findings illustrate how analytics bridges descriptive (what has happened), predictive (what is likely to happen), and prescriptive (what should be done) approaches, enabling businesses to ground their strategies in data rather than intuition.

The broader significance of this approach lies in its transferability across industries, making analytics a universal framework for evidence-based management. Companies in retail, SaaS, healthcare, and manufacturing can replicate the same methodology to validate assumptions, confirm the true drivers of performance, and prevent resource misallocation on ineffective strategies. By modeling the relationship between features and value, businesses can design profitable pricing schemes, create strategic product bundles, and identify upselling opportunities, while segmentation analysis empowers hyper-targeted campaigns that improve engagement and conversion. Operational analytics ensures that marketing promises are supported by reliable service delivery, protecting brand equity and customer loyalty. Finally, predictive models extend the impact of analytics by enabling organizations to forecast demand, allocate resources more effectively, and align strategies with consumer behavior—such as leveraging weekend spending surges or adjusting inventory to match geographic preferences. In conclusion, the fusion of analytics with strategic planning transforms decision-making from reactive guesswork to proactive, data-driven management. This not only strengthens profitability and operational efficiency but also builds sustainable competitive advantage in markets where agility, personalization, and reliability are critical to long-term success.

RECOMMENDATIONS

The findings of this study, while insightful, are based on a synthetic but realistic dataset restricted to a single product category, which naturally places limitations on scope and generalizability. To strengthen and expand the utility of these insights, future research should adopt a more longitudinal perspective by employing time-series data that captures seasonal shifts, holiday effects, and cyclical demand fluctuations. Such analysis would provide businesses with predictive foresight into high-demand periods and enable them to plan pricing, inventory, and staffing strategies more effectively. Moreover, advanced predictive models leveraging machine learning could be developed to address complex challenges such as churn prediction, customer lifetime value estimation, and dynamic pricing optimization. These techniques would allow firms to move beyond static insights toward adaptive, real-time strategies that respond fluidly to evolving market conditions. Expanding the data sources used in analysis also represents a critical direction for future research. Incorporating unstructured data—such as customer reviews, social media feedback, and even service interaction logs—would provide a more holistic understanding of customer sentiment, brand perception, and hidden drivers of loyalty or dissatisfaction. Furthermore, advancing from correlation-based insights to causal inference would significantly enhance strategic decision-making. Controlled experiments, such as A/B testing weekend promotions or varying topping-based pricing strategies, could validate whether observed relationships truly reflect causality rather than coincidence. By combining longitudinal data, machine learning models, unstructured data analysis, and causal inference, businesses can refine their strategies with greater precision and reliability. This multidimensional approach ensures not only the continuous improvement of operational and marketing practices but also the intelligent shaping of future growth trajectories in increasingly competitive markets.

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