# Use of Pricing and Revenue Analytics to Support Menu Strategy in Global Fast Food Organizations

**Usman Javed**[1] **and Noman Siddiqi**[2]
[1] Mehran University of Engineering and Technology, Department of Telecommunication Engineering, Jamshoro–Hyderabad Road, Jamshoro, Sindh, Pakistan
[2] Balochistan University of Information Technology, Engineering and Management Sciences, Faculty of Telecommunication and Networking, Airport Road, Quetta, Balochistan, Pakistan

**ABSTRACT**
Global fast food organizations operate in markets characterized by intense price competition, high operating leverage, and rapidly evolving customer expectations. Menu strategy, encompassing price levels, price structures, and product configurations, has become a central managerial lever for balancing traffic growth and unit economics across heterogeneous markets. At the same time, transactional data from digital channels and in-store systems have expanded the opportunities to embed pricing and revenue analytics into day-to-day decision making. This paper examines how pricing and revenue analytics can support menu strategy in global fast food chains, with particular attention to the integration of demand modeling, menu architecture, and operational constraints. The discussion covers the construction of data assets, the selection of econometric and machine learning methods for estimating price response, and the formulation of optimization problems that align menu design with revenue and margin objectives. The paper also considers the role of experimentation and simulation in evaluating menu changes before large scale deployment, and outlines organizational and governance factors that influence the adoption of analytics driven menu processes. While the focus is on fast food organizations with international footprints, the conceptual framework is relevant for multi unit food service networks that face similar constraints in capacity, service time, and brand positioning. The aim is to provide a technically oriented treatment that connects modeling choices to practical menu decisions without assuming a single universally optimal approach.

**KEYWORDS**

## 1. Introduction

Global fast food organizations serve large volumes of customers across markets that differ in income levels, cultural preferences, regulatory environments, and competitive intensity [1]. Menu strategy in this context must address multiple objectives at once: sustaining traffic in a price sensitive customer base, protecting brand positioning, managing food and labor cost inflation, and ensuring that kitchen and front of house operations remain stable under varying demand. Pricing decisions are visible to customers and competitors, and even small changes in menu prices or product configurations can shift demand volumes in ways that propagate through capacity utilization, queue lengths, and labor scheduling. As digital ordering, delivery aggregators, and personalized promotions spread across markets, decision makers increasingly look to pricing and revenue analytics to support a more systematic approach to menu design.

Traditional menu decisions in fast food chains have often relied on rule of thumb approaches such as target food cost percentages, gross margin thresholds, and periodic benchmarking against competitors. While these approaches remain widely used, they do not fully exploit the granularity of modern transactional data. Point of sale systems, kiosk logs, mobile app events, and delivery platform feeds provide detailed records of item selections, discounts, order compositions, timestamps, and store

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identifiers. When combined with external data on competition, weather, income, and mobility, these sources make it possible to estimate demand models that capture price response, substitution patterns, and temporal effects [2]. However, transforming these data into actionable guidance for menu strategy requires careful modeling choices, robust validation, and alignment with operational constraints.

Pricing and revenue analytics in fast food chains differ from revenue management in industries such as airlines and hotels because the product set is highly granular, transactions are relatively low in value, and capacity constraints occur at multiple stages of the service process. For example, a restaurant may be constrained by grill capacity during lunchtime, by fryer capacity when promoting certain items, or by delivery kitchen resources in peak digital periods. Menu strategy must therefore consider not only the direct revenue impact of price changes but also the mix of items that are promoted or discounted, the average preparation time of the resulting orders, and the implications for service time and customer experience. Analytics initiatives that focus solely on revenue or margin outcomes without representing these operational constraints risk generating recommendations that are not feasible or that erode service quality.

This paper considers how a technically oriented pricing and revenue analytics program can support menu strategy in global fast food organizations. It focuses on the link between demand modeling, optimization, and implementation rather than prescribing a single model class or algorithm [3]. Demand models can range from relatively simple log linear specifications to discrete choice formulations and flexible machine learning approaches. Optimization problems can be structured to reflect revenue maximization, margin targets, capacity constraints, and policy rules such as price ladders between item sizes. Implementation involves embedding model outputs into menu change processes that are subject to governance, brand standards, and franchise relationships.

The analysis is organized around the progression from data assets to models and then to decision support. The first step is to define the relevant data structures for menu analysis, including transaction level datasets, store day and store interval aggregates, and store level attributes. The second step is to construct demand and price response models that are sufficiently rich to capture key behavioral patterns while remaining estimable at scale across a wide network of restaurants. The third step is to formulate menu optimization problems that translate price response estimates into recommendations for list prices, bundles, and promotions under specified constraints. The final step is to consider how experimentation, performance tracking, and governance can be used to maintain and adjust the analytics over time as menus, technologies, and competitive conditions change.

In keeping with the complexity of global operations, the discussion does not assume homogeneous behavior across markets, nor does it treat price optimization as a one time exercise. Instead, pricing and revenue analytics are treated as a set of tools that can be configured differently for value oriented markets, premium urban formats, and emerging channels such as delivery only kitchens. The objective is to describe how analytical models and optimization formulations can be linked to the practical questions that arise when designing and maintaining menus in large fast food organizations.

## 2. Pricing and Revenue Analytics in Global Fast Food Context

Pricing and revenue analytics in global fast food chains rest on the observation that revenue at the restaurant level is a function of both traffic and average check. Traffic depends on factors such as location, brand awareness, service quality, and competitive density. Average check reflects menu composition, prices, and promotional intensity. A basic decomposition of restaurant revenue separates total revenue into the product of guest count and average spend, but menu decisions often require more granular insight: which items drive visits, which items contribute most to gross profit, and how sensitive different customer segments are to changes in price [4] [5]. Revenue analytics uses historical data to provide a structured view of these components.

One starting point is to express restaurant revenue as the sum of item level revenues. If the set of items is indexed by $i$ and the restaurant by $j$, revenue over a period can be written as

$$R_j = \sum_i p_{ij} q_{ij} \tag{1}$$

where $p_{ij}$ is the effective price of item $i$ at restaurant $j$ and $q_{ij}$ is the quantity sold over the period. In fast food chains, effective price incorporates promotions, coupons, and digital discounts that may differ by channel or by daypart. Revenue analytics examines how changes in listed prices, discount structures, and promotional mechanics alter the quantities $q_{ij}$ and thus revenue $R_j$. Because the chain operates across many restaurants and markets, the same logical items may have different price levels and promotional calendars.

A common concept in menu strategy is the distinction between traffic driving items and margin driving items. Traffic driving items, often referred to as key value items, are typically high visibility products that customers use to form price perceptions. Margin driving items may be add ons, sides, or premium variants with relatively higher contribution margins [6]. Pricing analytics seeks to quantify the elasticities of both types of items, recognizing that mispricing traffic drivers can lead to loss of visits, while mispricing margin drivers may leave contribution margin unrealized. In practice, elasticity estimates are often heterogeneous across stores, regions, and channels, which introduces a need for modeling structures that can share information while allowing for local variation.

Global fast food organizations also face exchange rate movements, tax changes, and cost shocks that feed into menu decisions. For example, per unit food costs may change due to commodity price movements, local procurement conditions, or shifts in supplier contracts. Labor cost structures may differ depending on local regulations and wage norms. Revenue analytics integrates these cost components into the analysis by constructing contribution measures at the item level, such as

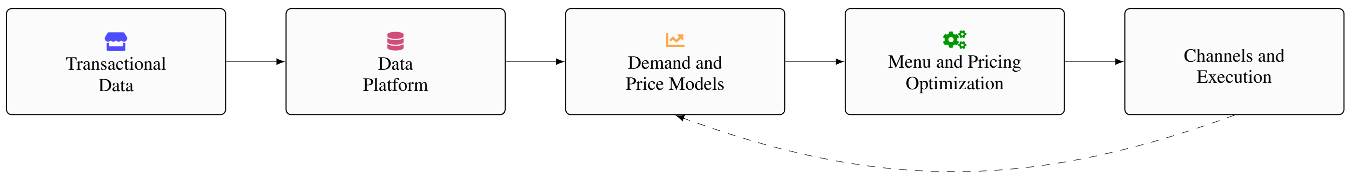


**Figure 1** High level flow of data and analytics for menu strategy in global fast food organizations, from transactional data collection through platform integration, demand and price modeling, optimization of menu prices and structures, and deployment across customer facing channels, with a feedback loop from realized outcomes back into model refinement.

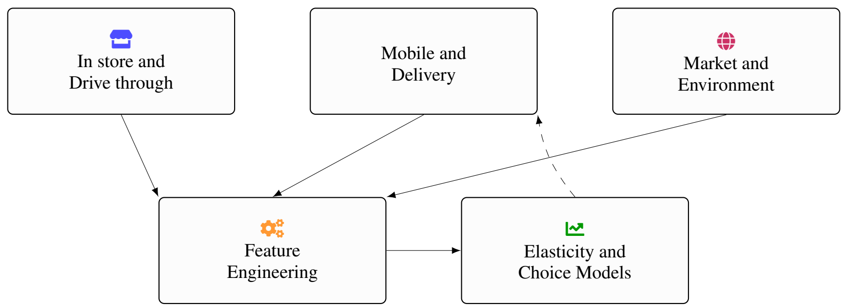


**Figure 2** Schematic view of data sources and modeling components for pricing and revenue analytics in menu design, showing in store and drive through data, digital and delivery channels, and external market information converging into feature engineering and model construction, with selected model outputs providing targeted feedback into digital channel configuration.

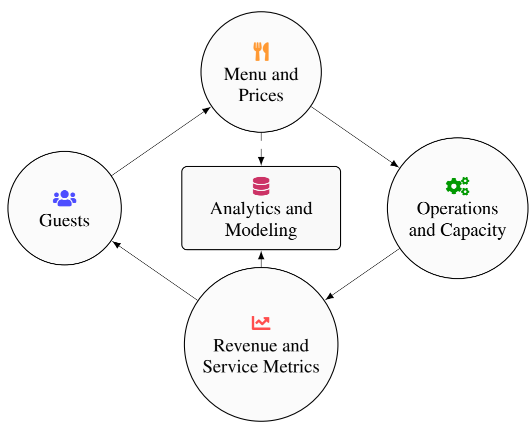


**Figure 3** Feedback loop connecting guests, menu and price configuration, operational capacity, and realized revenue and service metrics, with an analytics and modeling layer that ingests menu and performance data and supports iterative refinement of pricing and menu strategy in fast food networks.

revenue minus variable food cost and, where appropriate, approximations of labor cost associated with item preparation. These contribution measures are then linked to demand models to evaluate the impact of price changes on both revenue and contribution [7].

Competitive dynamics are another element of the context. In many markets, fast food chains monitor advertised prices of competitors for comparable items and adjust menus accordingly. Some chains define band policies that restrict prices of key items to be within a certain range of a benchmark competitor. Pricing analytics in this setting may focus on quantifying willingness to pay and perceived value relative to competing offers. However, the presence of constraints based on competitor prices means that the optimization problem is not one of unconstrained profit maximization but rather one of selecting prices within allowable intervals that best meet revenue and margin objectives while respecting brand guidelines and local regulations such as price transparency requirements.

Operational constraints, including kitchen capacity and service time targets, interact with revenue outcomes in ways that are particularly salient in fast food operations. Promotions that emphasize resource intensive items can create bottlenecks that lengthen queues and reduce throughput, even if the promoted items generate high gross margins. Revenue analytics therefore cannot be separated from capacity considerations [8]. An increase in revenue from a menu change may be offset by a reduction in customer satisfaction due to longer waiting times or order inaccuracies under stress. As a result, menu strategy must be evaluated not only on revenue and contribution metrics but also in terms of throughput and service performance indicators such as average service time and order completion times across channels.

| Channel | Example records | Typical granularity | Notes |
|---|---|---|---|
| In store point of sale | Item lines, tender codes | Transaction level | High volume, core check data |
| Drive through | Order timestamps, lane id | Transaction level | Strong time of day patterns |
| Kiosk ordering | Screen flows, add on events | Event and basket | Rich sequence information |
| Mobile app | Session logs, coupons | User and session | Enables customer histories |
| Delivery platforms | Partner ids, fees | Transaction and store day | Varies by aggregator |
| External data | Weather, events | Store day or hourly | Shared across channels |

**Table 1** Main channels and data granularity relevant for pricing and revenue analytics in fast food menu strategy.

| Item class | Price visibility | Typical elasticity band | Role in menu |
|---|---|---|---|
| Key value items | Very high | Moderate to high | Anchor price perception |
| Core sandwiches | High | Moderate | Structure main choice set |
| Sides and add ons | Medium | Low to moderate | Drive contribution margin |
| Beverages | Medium | Low | Support check size and bundles |
| Limited time offers | High during campaign | Variable | Support novelty and traffic |
| Premium tiers | Medium | Low | Enable upsell and trade up |

**Table 2** Stylized view of item classes, perceived price visibility, and indicative elasticity bands used in menu analytics.

## 3. Data Infrastructure and Feature Engineering for Menu Strategy

Effective use of pricing and revenue analytics requires a data infrastructure that captures transaction level details at sufficient granularity while remaining manageable at scale. Fast food organizations process large numbers of transactions each day, and historical archives may span multiple years across thousands of restaurants. A basic transaction level record typically contains a transaction identifier, timestamp, store identifier, ordered items with quantities and prices, applied discounts or coupons, payment method, and channel indicator, such as in store, kiosk, drive through, or delivery. For menu analysis, it is often necessary to reconstruct item level observations from these transaction level records, which involves exploding the order line items into separate records with associated quantities and effective prices.

In addition to core transaction data, menu strategy benefits from the inclusion of contextual variables [9]. These can include day of week, calendar events, school holidays, and weather conditions for each store location. When available, customer level attributes from loyalty programs or mobile apps provide further segmentation variables such as visit frequency, typical spend, and historical responsiveness to promotions. Store level attributes such as location type, trade area classification, proximity to transportation nodes, and competitive density are also important. These features allow the modeling of heterogeneous effects and can support clustering of restaurants into groups with similar demand patterns.

An important feature engineering step for pricing analytics is the construction of effective price measures. While list prices are usually available from menu databases or configuration files, the prices that enter demand models should reflect realized revenue per unit net of discounts. For each item record, an effective price can be computed by dividing realized revenue for that item by the quantity sold in the transaction. When multi item discounts or basket level coupons are present, allocation rules are needed to distribute the discount across items [10]. Allocation can be proportional to list revenue, contribution margins, or specified policy rules. The resulting item level effective prices can then be aggregated to store day or store interval levels as needed.

Demand modeling often relies on aggregation of item level data into store day or store time interval panels. For example, a store day item level panel might record for each item and store the total quantity sold, average effective price, and measures of promotional support, such as whether the item was part of a featured bundle or displayed on digital boards. Aggregation reduces data volume and can smooth idiosyncratic transaction level noise. However, aggregation also obscures within day dynamics and customer level heterogeneity. An alternative is to aggregate at finer time intervals, such as fifteen minutes or one hour, which retains more temporal structure at the cost of higher dimensionality [11].

Item level demand across stores and days can be summarized by simple statistical relationships that form the starting point for more advanced modeling. For instance, a log linear relationship between quantity and price can be written at the store day level as

$$\log q_{ij} = a_i + b_i \log p_{ij} + u_{ij} \tag{2}$$

where $q_{ij}$ is the quantity of item $i$ sold in store $j$, $p_{ij}$ is the effective price, $a_i$ is an item specific intercept capturing baseline demand, $b_i$ is a price response parameter, and $u_{ij}$ is an error

| Model family | Target level | Main strengths | Main limitations |
|---|---|---|---|
| Log linear regression | Item by store day | Simple, interpretable | Limited substitution structure |
| Pooled panel model | Clustered stores | Shares information | Sensitive to pooling assumptions |
| Discrete choice model | Basket or item share | Structured cross effects | Higher estimation complexity |
| Gradient boosting | Item by store day | Captures nonlinearities | Indirect elasticity extraction |
| Hierarchical model | Item and store levels | Encodes heterogeneity | Requires careful priors |

**Table 3** Common modeling families employed to estimate price response and demand in global fast food networks.

| Feature group | Example features | Source layer | Purpose |
|---|---|---|---|
| Price and promotion | Effective price, discount flags | Transaction and menu | Capture direct incentives |
| Temporal structure | Day of week, season index | Calendar | Represent seasonality patterns |
| Store context | Format, trade area type | Master data | Encode structural differences |
| Customer profile | Visit frequency proxy | Loyalty or device | Approximate segment mix |
| Operational load | Queue length proxy | Operations logs | Connect to capacity effects |
| Market signals | Competitor price index | External feeds | Reflect relative positioning |

**Table 4** Illustrative feature groups engineered for pricing and revenue analytics in menu strategy.

term that may include unobserved demand shocks. While this simple specification ignores many relevant factors, it motivates feature engineering around log prices, seasonality controls, and store specific shifts.

Feature engineering also encompasses the construction of indicators for menu events. These may include flags for new product introductions, discontinuations, recipe changes, or changes in product placement on menu boards. For promotion analysis, indicators can capture whether an item is part of a limited time offer, whether it is promoted as part of a bundle, and whether the promotion is limited to certain channels. When analyzing global menus, harmonization of item definitions across markets is required, because similar items may have different names or slight recipe variations. A mapping from local product codes to global item families can be maintained to support cross market modeling [12].

Handling missing data and data quality issues is an important aspect of the infrastructure. Transaction data may contain gaps due to system outages, store renovations, or incomplete integration of delivery platforms. Price data may show discontinuities when stores change menu boards or when tax configurations are updated. Careful filtering and imputation are needed to avoid spurious inferences about price response. For example, days with abnormal transaction counts due to system malfunctions may be excluded, and effective prices that reflect obvious data entry errors can be corrected or removed. Outlier detection methods can help identify unusual price quantity combinations that may indicate recording problems rather than true demand behavior.

## 4. Demand Modeling and Price Response Estimation

Building on the data infrastructure, pricing and revenue analytics for menu strategy rely on demand models that quantify how item level quantities respond to changes in prices and other drivers [13]. A basic approach is to estimate log linear models for each item separately, using regressions that relate log quantity sold to log price and control variables. While this approach is tractable and interpretable, it does not capture substitution patterns between items and may be unstable for items with sparse data. To address these limitations, multi item models and discrete choice formulations can be employed.

A multi item demand system can be represented in linear form as

$$q = A + Bp + \varepsilon \tag{3}$$

where $q$ is a vector of item quantities, $p$ is a vector of prices, $A$ is a vector of intercepts, $B$ is a matrix of price response coefficients, and $\varepsilon$ is a vector of error terms. The diagonal elements of $B$ correspond to own price effects, and the off diagonal elements represent cross price effects that capture substitution or complementarity between items. Elasticities can be derived by scaling these coefficients with observed prices and quantities [14]. If $D_p$ is a diagonal matrix with prices on the diagonal and $D_q$ is a diagonal matrix with quantities, a matrix of price elasticities can be approximated by

$$E = D_p^{-1} B D_q \tag{4}$$

where each element of $E$ represents the percentage change in quantity of one item associated with a small percentage change in the price of another item, under the linear approximation.

| Objective or constraint | Mathematical role | Typical scope | Example use |
|---|---|---|---|
| Revenue | Primary objective | Store or cluster | Maximize expected sales |
| Contribution margin | Objective or side metric | Store or system | Protect profit under cost shifts |
| Capacity ceiling | Inequality constraint | Daypart or station | Limit peak load from promotions |
| Price ladder | Linear constraint | Item families | Maintain size gaps and tiers |
| Competitor band | Interval constraint | Key value items | Keep prices within local band |
| Exposure limit | Constraint on variants | Experiment cells | Control risk in testing |

**Table 5** Typical objectives and constraints that appear in menu pricing optimization formulations.

| Element | Example choice | Reasoning | Notes |
|---|---|---|---|
| Unit of analysis | Store day | Balance noise and volume | Used in many pilots |
| Test horizon | 4 to 8 weeks | Cover multiple cycles | Longer for strong seasonality |
| Store selection | Matched pairs | Reduce structural bias | Match on pre period metrics |
| Primary metric | Revenue per store day | Direct impact measure | Sometimes normalized by traffic |
| Guardrail metric | Service time index | Protect guest experience | Often monitored daily |
| Update cadence | Weekly readout | Combine stability and speed | Supports staged decisions |

**Table 6** Example design choices for controlled experiments evaluating menu and price changes.

In practice, estimation of $B$ must contend with collinearity of prices, limited and discrete price movements, and unobserved demand shocks that may be correlated across items.

Discrete choice models offer an alternative representation of demand that directly models the probability that a customer chooses each item from the menu. In a multinomial logit specification, the utility that a customer derives from item $i$ can be written as

$$U_i = x_i' \beta + \varepsilon_i \tag{5}$$

where $x_i$ is a vector of item attributes such as price, size, and nutritional content, $\beta$ is a vector of coefficients to be estimated, and $\varepsilon_i$ is a random term that captures idiosyncratic preferences. The choice probability for item $i$ in a menu with alternatives indexed by $k$ is

$$s_i = \frac{\exp(U_i)}{\sum_k \exp(U_k)} \tag{6}$$

Demand for item $i$ can then be modeled as the product of the number of customers and the choice probability $s_i$. Incorporating price into $x_i$ allows the estimation of price sensitivities and cross elasticities that respect the adding up constraints of probabilities. Extensions such as nested logit or mixed logit can account for correlation in unobserved utilities and heterogeneity in price response [15].

In large scale fast food applications, the number of items, stores, and time periods often leads to high dimensional parameter spaces. Regularization methods and hierarchical modeling are therefore used to stabilize estimates and enable information sharing across items and stores. For example, if $\theta$ denotes a vector of model parameters, one can estimate them by solving a penalized optimization problem of the form

$$\min_{\theta} \; \ell(\theta) + \lambda \|\theta\|_1 \tag{7}$$

where $\ell(\theta)$ is a loss function such as the negative log likelihood and $\lambda$ is a non negative regularization parameter. The $\ell_1$ norm encourages sparsity in the parameter estimates, which can be beneficial when many potential predictors are included, such as interactions between item and store attributes. Alternative penalties, such as ridge or elastic net, can also be employed [16].

Machine learning methods, including gradient boosted trees and neural networks, are increasingly applied to demand modeling for fast food menus. These methods can capture nonlinear relationships and complex interactions between features. For example, a gradient boosting model can learn different price response patterns across dayparts, channels, and store clusters without explicitly specifying these interactions. However, translating such models into interpretable elasticity measures suitable for optimization can be challenging. Approaches such as local derivative approximations and partial dependence analysis can be used to approximate price sensitivities from nonlinear models, although care must be taken to ensure stability and robustness.

Model validation in this context involves assessing both predictive performance and stability of price response estimates. Predictive performance can be evaluated through out of sample metrics such as mean absolute percentage error at the store day item level. Stability can be examined by testing whether estimated elasticities are consistent across different time periods

| Role | Main focus | Key decisions | Analytics interface |
|---|---|---|---|
| Central analytics | Modeling and tools | Specifications, recalibration | Owns models and pipelines |
| Global menu team | Architecture and guardrails | Price ladders, ranges | Reviews recommendations |
| Market lead | Local adaptation | Final price points | Provides local constraints |
| Operations lead | Capacity and service | Feasibility checks | Interprets load implications |
| Franchise council | Alignment and adoption | Implementation timing | Gives feedback on pilots |

**Table 7** Illustrative governance roles involved in analytics informed menu and pricing decisions.

| Menu lever | Revenue impact channel | Operational impact | Typical use case |
|---|---|---|---|
| List price change | Average check shift | Limited direct effect | Periodic menu board updates |
| Bundle configuration | Mix and attachment | Preparation complexity | Drive add on incidence |
| Limited time offer | Incremental traffic | Station specific load | Seasonal campaigns |
| Channel specific deal | Channel mix | Order assembly pattern | Encourage digital adoption |
| Size tier structure | Trade up behavior | Packaging and storage | Simplify or expand tiers |
| Placement and visuals | Choice shares | Minimal mechanical change | Reinforce value messaging |

**Table 8** Overview of menu levers, their primary revenue channels, and associated operational impacts in fast food chains.

or subsets of stores [17]. In addition, plausibility checks based on domain knowledge are important. For instance, own price elasticities for core items are typically expected to be negative and of magnitudes that align with observed customer behavior. Cross elasticities should reflect known substitution patterns, such as substitution between small and large sizes or between similar sandwiches, while extreme complementarity estimates may indicate model misspecification or data issues.

## 5. Revenue and Menu Optimization

Once demand and price response models are available, pricing and revenue analytics can be used to formulate optimization problems that support menu strategy. A basic objective is to select item prices that maximize expected revenue or contribution subject to constraints arising from operations, brand guidelines, and regulatory requirements. Let $p$ denote a vector of decision prices for a given restaurant or store cluster and let $q(p)$ denote the corresponding vector of predicted item quantities from the demand model. An expected revenue objective can be represented as [18]

$$\max_{p} \sum_{i} p_i q_i(p) \tag{8}$$

where the sum is taken over the set of items on the menu. If variable food costs $c_i$ are available, the objective can be formulated in terms of contribution margin by replacing $p_i$ with $p_i - c_i$. In practice, the optimization is typically carried out not for a single restaurant but for groups of restaurants with similar characteristics, subject to price policies that may constrain prices to lie within market specific bands.

Operational constraints can be incorporated into the optimization by adding resource constraints that approximate capacity limits. If each item $i$ requires a certain amount of preparation time or capacity $t_i$ and the restaurant has a capacity limit $T$ over the relevant time window, a simple capacity constraint can be written as

$$\sum_{i} t_i q_i(p) \leq T \tag{9}$$

This constraint captures the idea that item mix and volumes induced by prices should not exceed the effective capacity of the kitchen. In reality, capacity constraints are often more complex, with multiple stations and different bottlenecks across dayparts, but the basic structure illustrates how demand and operations are linked in the optimization.

Menu strategy also involves decisions about the set of items to offer and their roles in the menu architecture. In some formulations, the decision vector includes binary variables indicating whether an item is active on the menu. Let $z_i$ be a binary variable that equals one if item $i$ is on the menu and zero otherwise. The demand for item $i$ under a given price can depend on the set of active items, because the choice set changes [19]. A simplified representation of a menu optimization problem that includes item activation can be expressed conceptually as selecting $p$ and $z$ to approximate the maximization of revenue given the dependence of $q(p,z)$ on both prices and the active set. In practice, this leads to mixed integer nonlinear optimization, which is computationally demanding for large menus, so heuristics and decomposition methods are often used.

Price policies in global fast food chains frequently impose additional constraints such as maintaining fixed price differentials between sizes, enforcing price ladders across good, better, and best offerings, and ensuring that prices end in particular digits for marketing reasons. These constraints can be modeled as linear relationships between prices. For example, if the price of a large size item must exceed the price of the medium size by a fixed gap $g$, one can express this with a constraint of the form $p_L = p_M + g$. While such constraints narrow the feasible set of prices, they also provide structure that can reduce the dimensionality of the decision problem by tying prices for related items together.

Uncertainty in demand model estimates can be incorporated into the optimization through robust or stochastic formulations. In a robust optimization approach, prices are chosen to perform acceptably under a set of plausible demand scenarios rather than optimizing for a single point estimate of price response [20]. This can involve defining uncertainty sets for price elasticity parameters and optimizing prices to maximize the worst case or a risk adjusted revenue measure. Stochastic programming approaches, on the other hand, treat demand as a random variable with a specified distribution and aim to maximize expected revenue or a function that balances expected value and variability.

Dynamic aspects of menu strategy arise when prices and offerings can be adjusted over time in response to observed demand and evolving competitive conditions. A simplified dynamic programming formulation considers a state variable $x$ representing, for example, cumulative learning about demand or a measure of capacity utilization, and an action $a$ representing a price or promotion decision. The value function can be written as

$$V(x) = \max_{a} \left\{ r(x,a) + \beta V(x') \right\} \tag{10}$$

where $r(x,a)$ is the immediate reward, $x'$ is the next state induced by the action and exogenous factors, and $\beta$ is a discount factor between zero and one [21]. While full scale dynamic programming is typically infeasible for large menus and networks, this framework motivates the use of adaptive pricing and experimentation strategies that update decisions based on observed outcomes.

## 6. Experimentation, Governance, and Implementation

The practical impact of pricing and revenue analytics on menu strategy depends not only on model quality and optimization formulations but also on the design of experiments, governance structures, and implementation processes. Experimentation is particularly important because model based predictions of price response and menu performance rely on assumptions that may not hold universally across markets or over time. Controlled experiments, such as A/B tests, provide empirical evidence about the realized effects of menu changes under specified conditions.

In a basic A/B test for a menu change, a set of test restaurants implements a new price or menu configuration and a control set maintains the current configuration. Let $\bar{y}_B$ denote the average outcome metric for the test group, such as revenue per store day, and $\bar{y}_A$ denote the corresponding metric for the control group. A simple estimator of the effect of the change is

$$\Delta[22] = \bar{y}_B - \bar{y}_A \tag{11}$$

This difference can be evaluated with statistical tests that account for variation across days and stores. When test and control stores are matched on pre period performance and characteristics, the resulting estimates provide a more credible assessment of causal impact than observational comparisons alone. However, experiments must be designed to avoid contamination from overlapping promotions, competitor reactions, or spillover effects where customers shift between nearby restaurants.

Beyond single experiments, global fast food organizations may implement ongoing experimentation programs in which multiple menu variants are tested simultaneously across different regions or channels. Multi arm testing frameworks and adaptive experimentation methods can be used to allocate traffic to different variants in a way that balances learning and performance. For example, bandit algorithms adjust the proportion of stores assigned to each variant based on observed performance, resulting in more exposure for better performing variants while still exploring alternatives. In the context of menu strategy, such methods can be applied to test different price points, bundle structures, or promotional mechanisms.

Governance of pricing and revenue analytics involves defining roles, responsibilities, and decision rights for analytics teams, commercial leaders, franchisees, and local market managers [23]. A central analytics team may develop models and optimization tools, but local teams often have authority over specific menu elements due to local knowledge and regulatory constraints. Clear governance frameworks specify where analytics recommendations are mandatory, where they are advisory, and how exceptions are handled. Documentation of assumptions, model limitations, and data coverage supports transparent review of analytics outputs. In addition, governance processes should include periodic model review and recalibration schedules, particularly in environments where customer behavior or competitive conditions change rapidly.

Implementation of analytics driven menu decisions requires integration with existing systems and workflows. Menu changes must be translated into updates to point of sale configurations, digital menu boards, delivery platform menus, and back office planning tools. These updates may need to be synchronized across markets and channels at specific times to avoid customer confusion and operational disruptions [24]. Therefore, analytics outputs should be delivered in formats that can be directly consumed by menu management systems, with clear mappings from optimization variables to system fields such as price levels, item tags, and promotional flags.

Change management is another aspect of implementation. Restaurant managers, operations leaders, and franchisees may be accustomed to rule based pricing methods and may approach analytics driven recommendations with caution, particularly when recommendations differ from past practices. Providing interpretable explanations of key drivers behind suggested price changes, such as estimated elasticities or observed test results, can support understanding. Training programs and support channels where local stakeholders can ask questions and provide feedback on analytics outputs can also facilitate adoption. In addition, aligning incentive structures so that local decision makers see a direct connection between their performance metrics and the objectives used in the optimization can reduce potential misalignment.

## 7. Conclusion

Global fast food organizations operate in an environment where menu decisions influence not only revenue and margins but also customer experience, operational stability, and brand perception. Pricing and revenue analytics provide a set of tools for structuring these decisions, using historical data and model based predictions to quantify how changes in prices, promotions, and menu architecture are likely to affect demand and contribution under specified conditions [25]. The analysis in this paper has outlined the components of such an approach, starting from data infrastructure and feature engineering, moving through demand modeling and price response estimation, and culminating in optimization, experimentation, and implementation considerations.

Demand modeling for menu strategy can draw on a range of methods, from log linear regressions and multi item systems to discrete choice models and machine learning approaches. Each method offers different trade offs between interpretability, flexibility, and estimation complexity. Representing substitution patterns between items and heterogeneity across stores and customer segments is particularly important in fast food contexts, where menus contain overlapping products and where customer preferences differ across markets and channels. Regularization and hierarchical structures allow models to leverage information across the network while maintaining the capacity to capture local differences. Model outputs such as elasticities and predicted volumes under alternative prices provide inputs to optimization problems that are structured around revenue, contribution, and capacity constraints.

Optimization in this setting is shaped by constraints that arise from operations, policies, and brand considerations [26]. Menu strategy may require respecting price ladders, competitor benchmarks, and resource limits in the kitchen and service areas. Robust and dynamic perspectives can be incorporated to acknowledge uncertainty in demand estimates and to allow adjustments over time as new data arrive. Experimentation, particularly structured A/B tests and ongoing testing programs, plays a role in validating model based predictions and updating beliefs about price response and menu performance. Governance frameworks and implementation processes determine how analytics outputs flow into decision making, interact with local knowledge, and are translated into actual menu configurations across channels and markets.

While the discussion has focused on fast food organizations with global footprints, many of the principles generalize to other multi unit food service formats where menu strategy interacts with capacity, service time, and local market conditions. The treatment here emphasizes that pricing and revenue analytics should be viewed as a set of configurable components rather than as a single prescriptive solution. Organizations can select and adapt demand models, optimization formulations, and experimentation designs that align with their data assets, operational structures, and strategic priorities. Over time, the integration of these components into regular planning and review cycles can support more consistent and evidence based adjustments to menu strategy in response to evolving customer expectations and market conditions [27].


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