“Modeling Visitor Travel Patterns to Restaurants in Complex Urban Environments”

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Executive Summary

This report presents an in-depth exploration into modeling visitor travel patterns to restaurants in complex urban environments, a challenge of growing significance in the fields of smart city planning, urban mobility, and behavioral analytics. The central business and technical problem addressed in this project is the lack of interpretable, data-driven tools that can predict and explain how individuals make dining decisions in high-density urban areas. Understanding such patterns has wide-reaching implications for stakeholders including restaurant operators, delivery platforms, transit agencies, and city planners, all of whom rely on timely and localized insights to optimize operations and infrastructure.

To address this need, we developed a comprehensive analytical framework that integrates Artificial Intelligence (AI) and econometric modeling. Specifically, the project employs three core techniques: Long Short-Term Memory (LSTM) neural networks to forecast restaurant demand on an hourly basis; Kolmogorov–Arnold Networks (KAN) to classify restaurants into latent popularity tiers based on temporal and spatial behavior patterns; and Discrete Choice Modeling (DCM) to simulate individual visitor decision-making logic using variables such as quality, distance from home, dwell time, and popularity scores.

Our hybrid approach combines the predictive strength of deep learning models with the interpretability of classical economic theories, delivering a robust system that not only forecasts demand but also offers clear reasoning behind visitor behavior. Key results underscore the effectiveness of this methodology: the LSTM model achieved an accuracy of 87.82%, enabling precise hourly forecasting; KAN classified restaurants into low, medium, and high popularity tiers with 94.72% accuracy; and the DCM simulation revealed statistically significant behavioral drivers, with quality (+0.57) and dwell time (+0.39) emerging as the strongest positive influences on restaurant selection.

The insights derived from this work are directly applicable to real-world decision-making. Restaurant operators can use these models to enhance staffing, menu timing, and customer targeting. Urban planners can optimize public infrastructure by aligning transit stops and zoning with high-demand zones. Delivery and logistics firms can streamline their resource allocation and dynamic pricing strategies based on real-time visitation forecasts.

This final report offers a complete narrative of our graduate-level research process, from initial problem framing and objective setting to data acquisition, model implementation, and strategic evaluation. It represents the culmination of applied learning within the Master of Science in Information Systems (MSIS) program at San Diego State University, blending theoretical foundations with practical execution. Our findings contribute meaningfully to the broader MIS discipline, highlighting how advanced modeling techniques can enhance system-level decision-making in dynamic, real-world environments.

Introduction

The dynamic evolution of urban spaces has created an intricate interplay of human mobility, economic behavior, and infrastructural design. At the heart of this complexity lies a seemingly simple, yet analytically rich behavior: where, when, and why people choose to dine out. Restaurant visitation behavior reflects a fusion of individual preference, urban accessibility, digital influence, and socio-economic context. In dense metropolitan areas, dining decisions are shaped by an array of real-time variables ranging from transportation options and location proximity to customer reviews, promotions, and even pedestrian foot traffic. Understanding these decision patterns is not only academically intriguing but also immensely valuable to industries and public agencies alike.

This project was initiated as part of the culminating experience in the Master of Science in Information Systems (MSIS) program at San Diego State University, in response to a timely and relevant challenge: how can modern data science techniques be used to model, predict, and interpret dining behavior in complex, data-rich urban environments? As digital systems increasingly mediate consumer decision-making through mobile apps, maps, review platforms, and loyalty programs, organizations have access to granular behavioral data that, when properly analyzed, can unlock powerful insights. Recognizing this, our study aims to harness these data flows to address an important intersection of urban planning and consumer analytics.

From an industry perspective, the implications are far-reaching. For restaurant operators, understanding visitation trends can inform staffing, marketing, and operational decisions. Delivery services can optimize routing and pricing by forecasting demand zones. Urban planners and transportation agencies can use behavioral heatmaps to align infrastructure investments—such as transit stops or pedestrian corridors—with actual usage patterns. Even real estate developers and local governments benefit from a deeper understanding of how commercial activity is distributed and influenced across a city. In short, modeling restaurant visit behavior is not merely a hospitality concern, it is an urban systems challenge.

The central problem statement we address in this report is the following: How can AI-based forecasting and econometric simulation techniques be employed to accurately predict restaurant visitation patterns and explain the underlying decision factors in urban environments? We hypothesize that while dining behavior may appear spontaneous, it is shaped by measurable factors such as historical popularity, quality perception, proximity, and average dwell time. By operationalizing this hypothesis through rigorous modeling, we aim to offer both predictive and explanatory insights.

The purpose of this project is twofold. First, it seeks to build a scalable and interpretable modeling framework that combines deep learning (for forecasting) and discrete choice theory (for behavioral simulation). Second, it aims to deliver actionable findings that can inform real-world decisions in both commercial and public sector contexts. The scope of the project is confined to densely populated urban areas and focuses specifically on restaurant visitation behaviors, using cleaned, structured data derived from mobile location signals and operational metrics.

The remainder of this report is structured to follow a logical progression. We begin with a clear articulation of our research objectives and questions. We then provide a detailed account of our methodology including the data processing pipeline, model architectures, and validation strategies. This is followed by an in-depth presentation of our results, including performance benchmarks and interpretive insights. Finally, we offer a discussion on the implications, challenges, and recommendations that arise from our findings.

In doing so, we aim to contribute to both academic literature and practical systems thinking within the MIS field highlighting how artificial intelligence and behavioral analytics can jointly address modern urban challenges with precision, scale, and interpretability.

**Objectives and Research Questions**

In the era of data-driven urban development, understanding behavioral dynamics such as restaurant visitation patterns is critical for designing responsive, efficient, and customer-centric systems. The objective of this project is to construct an integrated modeling framework that not only predicts and classifies visitor behavior but also offers interpretable insights into the decision-making processes that govern dining choices in complex urban settings. This framework aims to support a wide range of stakeholders—including restaurant managers, urban planners, transportation officials, and delivery platforms—by translating behavioral data into actionable intelligence.

**Primary Objective**

The primary goal of this project is to simulate and forecast visitor restaurant selection behavior in urban environments through a hybrid modeling architecture. This framework blends the strengths of predictive analytics (via deep learning), behavioral segmentation (via advanced neural networks), and decision modeling (via econometric simulations) to provide a comprehensive and scalable solution. By merging machine learning and discrete choice theory, the study seeks to both predict behavioral outcomes and explain the logic behind them.

**Specific Objectives**

To operate this primary goal, the study is guided by the following four specific objectives:

1. **To forecast hourly restaurant popularity** using Long Short-Term Memory (LSTM) networks, a class of recurrent neural networks capable of modeling sequential, time-dependent data. LSTM networks are highly effective for time-series data as they excel in capturing sequential dependencies. They have been widely used in diverse fields like forecasting, and anomaly detection (Staudemeyer & Morris, 2019). This objective focuses on enabling real-time demand prediction to optimize operational planning.
2. **To classify restaurants into latent popularity tiers** (Low, Medium, and High) based on behavioral and temporal metrics using Kolmogorov-Arnold Networks (KAN). This classification enables businesses to benchmark performance and tailor strategies based on cluster-specific characteristics. Unlike CNNs, Kolmogorov-Arnold Networks (KAN) utilize learnable univariate functions. This design enhances adaptability, enabling the model to better capture and represent complex data structures (Ji, Hou, & Zhang, 2025).
3. **To simulate visitor decision-making logic** using Discrete Choice Modeling (DCM), leveraging variables such as distance from origin, dwell time, normalized popularity, and perceived quality. The goal is to quantify the degree to which these factors influence dining choices.
4. **To design a modular and transferable methodology** that can be adapted to other urban analytics applications, including retail planning, mobility services, and public infrastructure design.

**Research Questions**

This study is structured around four central research questions, each corresponding to a core function of the hybrid modeling framework:

1. **Forecasting Focus**: Can restaurant visitation patterns be accurately forecasted on an hourly or daily basis using LSTM networks? How can these forecasts inform operational decisions such as staffing, inventory, and delivery scheduling?
2. **Classification Focus**: Can Kolmogorov–Arnold Networks effectively categorize restaurants into behaviorally meaningful popularity tiers? What behavioral insights emerge when restaurants are grouped based on these latent patterns?
3. **Behavioral Simulation Focus**: What are the key determinants that drive individual restaurant choices in urban areas? How effectively can DCM quantify the influence of attributes like perceived quality, distance, dwell time, and overall popularity?
4. **Strategic Application Focus**: How can the insights produced by this hybrid modeling framework be applied to real-world decision-making by restaurant operators, city planners, and logistics providers?

In addressing this question, the California Transportation Plan 2050 offers important contextual alignment. It emphasizes that transportation decisions must be “equitable, safe, sustainable, integrated, and efficient for all,” particularly as California adapts to urban growth and climate imperatives (California Department of Transportation [Caltrans], 2021). The CTP 2050 outlines how future mobility strategies including demand-responsive systems, equitable access, and data-driven planning can directly influence both public infrastructure design and commercial decision-making.

Our research contributes to this strategic objective by modeling a practical use case urban restaurant choice through predictive, classification, and behavioral logic systems. As urban planning moves toward integrated, multimodal strategies, our framework aligns with statewide goals for accessibility, economic resilience, and environmental health (Caltrans, 2021).

**Hypothesis**

This research is anchored in the following hypothesis: Although restaurant visitation may appear to be a spontaneous behavior, it is in fact influenced by measurable and predictable factors. By modeling structured variables—such as quality perception (proxied by visitor count), spatial proximity (distance from origin), temporal engagement (dwell time), and general popularity—it is possible to simulate and forecast visitor choices with meaningful accuracy and interpretability.

This hypothesis draws on both behavioral economics and urban analytics literature, proposing that the integration of deep learning and choice modeling can enhance decision-making systems that depend on real-time, location-based human activity.

Methodology

To address the multifaceted problem of predicting and interpreting restaurant visitation behavior in complex urban environments, we employed a hybrid modeling framework grounded in both artificial intelligence (AI) and econometric theory. This approach integrates the capabilities of time-series forecasting, classification modeling, and behavioral simulation to build a robust decision-support pipeline. The methodology combines quantitative rigor, statistical interpretability, and predictive accuracy—qualities that are essential for a practical application in both private and public-sector contexts. The following subsections detail the data infrastructure, analytical techniques, model architectures, evaluation strategies, and tools employed throughout the project lifecycle.

**Data Sources and Preparation**

The foundation of this project is a structured dataset comprising approximately 6,000 rows and 20 attributes, each capturing detailed visit- and location-level insights about urban restaurants. The dataset is highly multidimensional, encompassing both behavioral patterns and contextual identifiers, and was curated for modeling restaurant choice dynamics in dense metropolitan settings across California.

***Key Features in the Dataset:***

* **Behavioral Metrics:**
  + RAW\_VISIT\_COUNTS and RAW\_VISITOR\_COUNTS measure the volume of visits and distinct visitors.
  + MEDIAN\_DWELL records the median dwell time (in minutes), a proxy for visitor engagement.
  + DISTANCE\_FROM\_HOME quantifies the spatial cost of dining, enabling travel behavior modeling.
  + POPULARITY\_BY\_HOUR provides fine-grained, hour-by-hour foot traffic patterns across 24-hour cycles.
  + NORMALIZED\_VISITS\_BY\_TOTAL\_VISITS enables comparison of relative popularity across locations.
* **Contextual Metrics:**
  + LOCATION\_NAME, CITY, REGION, TOP\_CATEGORY, and SUB\_CATEGORY enrich the dataset with semantic tags for location identity and food type.
  + LATITUDE and LONGITUDE support geospatial feature extensions.
  + DEVICE\_TYPE indicates the visitor's mobile platform, relevant for potential digital segmentation.

***Data Quality Observations:***

* Core modeling fields were largely complete, with negligible missing data.
* BRANDS exhibited a high rate of missing values (~75%), suggesting many independent establishments.
* All key numeric fields used in modeling (e.g., dwell time, distance, visitor counts) were consistently populated.

***Preprocessing Workflow:***

* **Parsing:** Converted stringified arrays (e.g., POPULARITY\_BY\_HOUR) into usable numeric vectors.
* **Feature Engineering:** Derived statistical measures such as:
  + hourly\_mean: average visit rate per hour
  + hourly\_std: standard deviation of hourly visits
  + hourly\_peak: time of peak traffic
* **Cleaning:** Removed rows with missing values in critical columns.
* **Scaling:** Applied StandardScaler for LSTM, KAN, and DCM model inputs to normalize range and stabilize convergence.

***Conclusion:***

The dataset’s breadth and structure provided a strong foundation for AI modeling. It captured both continuous temporal patterns and cross-sectional variation, enabling nuanced predictions, classifications, and behavioral simulations. Its rich feature set supported the development of a pipeline that is interpretable, scalable, and generalizable to broader urban analytics tasks.

**Long Short-Term Memory (LSTM) Forecasting Model**

***Purpose****:*

Forecast short-term demand at the restaurant level, enabling proactive operational planning. This rationale supports the use of Long Short-Term Memory (LSTM) networks in the context of hourly restaurant visit predictions. LSTMs are a specialized type of recurrent neural network (RNN) designed to process sequences of data while preserving memory of long-term dependencies. This makes them particularly effective for tasks involving temporal sequences—such as forecasting demand based on past visitation patterns. In a study by Gołąbek et al. (2020), LSTM-based models were developed for demand forecasting in the e-grocery retail sector. The research demonstrated that, on average, these models outperformed traditional statistical and machine learning models for food products, highlighting the efficacy of LSTMs in capturing complex temporal patterns in demand data. In this project, the dataset includes hourly visit counts to restaurants, which exhibit complex behaviors such as daily cycles, lunch/dinner peaks, and random fluctuations. These patterns are not strictly linear or easily captured by traditional statistical models. LSTM networks, by contrast, are capable of learning both short- and long-term dependencies in the data (e.g., how visits at 9 AM relate to those at 2 PM or even the next day) and can recognize subtle variations over time.

By using an LSTM, the model can learn to anticipate surges in demand (e.g., lunch or dinner rushes) and low-activity periods, thus allowing for proactive decision-making. This aligns with the project’s goal of enabling operational planning and real-time responsiveness in restaurant management.

***Process Overview:***

To prepare the data for training our LSTM model, we began by flattening the POPULARITY\_BY\_HOUR feature across all restaurants into a single chronological sequence of hourly visit counts. This step was necessary to create a continuous temporal dataset, allowing the model to detect city-wide visitation trends over time rather than treating each restaurant independently. Next, we implemented a rolling window strategy using 5-hour time steps. For every five-hour segment, the model attempts to forecast the visit volume in the following hour. This approach captures localized time dependencies and mimics how businesses might predict demand shortly into the future based on recent patterns.

The full dataset was then split into training (80%) and testing (20%) subsets to assess generalization capability. All values were normalized using MinMaxScaler to ensure the inputs to the neural network were on a similar scale, which improves learning efficiency and convergence stability.

* Transformed the hourly popularity arrays into a long sequence
* Created rolling 5-hour time windows to capture temporal context
* Split the sequences into training (80%) and testing (20%) datasets
* Applied MinMaxScaler to constrain visit counts between 0 and 1 Transformed the hourly popularity arrays into a long sequence
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***Model Architecture:***

The architecture of our LSTM forecasting model was deliberately kept simple yet effective to balance computational efficiency with the model’s ability to capture temporal dependencies in hourly visit patterns. The model is sequential in design and composed of the following layers:

* **Input Layer**: Each input to the model consists of a rolling 5-hour window of normalized visit counts. This window size was chosen to capture short-term behavioral shifts without introducing excessive lag or delay.
* **LSTM Layer**: A core layer with 64 memory units (neurons) and ReLU (Rectified Linear Unit) activation. This layer is responsible for identifying patterns and dependencies across the 5-hour input sequence. The LSTM's gating mechanisms (input, forget, and output gates) allow it to retain important contextual information from earlier time steps while filtering out noise, enabling robust temporal learning.
* **Dense Output Layer**: A single neuron with a linear activation function that produces the final predicted visit count for the hour immediately following the input window. This regression output is later post-processed and evaluated against the actual visitation values.
* **Training Parameters**: The model was compiled using the Adam optimizer, which offers adaptive learning rates and works well for non-stationary data like human activity. The loss function was Mean Squared Error (MSE), appropriate for continuous output prediction. The model was trained over 50 epochs with batch sizes chosen dynamically based on memory capacity.

The architecture allows for extensibility, meaning additional features such as weather data or event indicators could be introduced in future iterations with minimal reengineering. The model's simplicity and accuracy make it well-suited for integration into real-time demand forecasting systems used by restaurants, food delivery apps, or municipal planning dashboards.

***Evaluation:***

To assess the real-world effectiveness of our LSTM model, we implemented a post-prediction evaluation pipeline combining both quantitative metrics and visual diagnostics. After generating hourly visit predictions on the test set, we transformed the continuous regression outputs into binary classification labels by comparing them to a threshold defined by the median of the actual visit counts. This allowed us to classify each hour as either a 'high' or 'low' demand period— a distinction highly valuable for staffing, inventory preparation, and dynamic delivery operations. The model demonstrated strong performance in this binary classification task, achieving an overall accuracy of 87.82%, indicating its reliability in identifying operationally significant shifts in demand. The confusion matrix and classification report showed particularly high precision in predicting high-demand windows, and high recall for low-demand periods—both critical for cost optimization in labor and logistics.

We also visualized the actual versus predicted visit trends using matplotlib line plots. These visuals revealed that the LSTM effectively captured major spikes and troughs in demand, although it showed slight underprediction for sudden surges—likely due to their irregular nature. Despite this, the alignment between actual and predicted curves over multiple cycles validated the model’s capability to generalize temporal visitation patterns in urban restaurant environments.

***Tools Used:***

The implementation of the LSTM forecasting model required a robust set of open-source data science libraries and frameworks. We used TensorFlow and its high-level API Keras for building, training, and validating the neural network. Pandas and NumPy were critical for data preprocessing, cleaning, and sequence generation—enabling seamless manipulation of temporal arrays and matrix operations.

**Kolmogorov–Arnold Network (KAN) for Popularity Classification**

***Purpose****:*

Identify latent popularity clusters among restaurants to enable targeted strategy development.

***Rationale****:*

The Kolmogorov–Arnold Network (KAN) represents an innovative evolution in neural network architectures specifically optimized for structured tabular datasets—making it particularly suited for our use case involving quantitative restaurant visit data. Kolmogorov-Arnold Networks (KANs) are gaining recognition as potential alternatives to Multi-Layer Perceptrons (MLPs), utilizing adaptive activation functions on edges instead of predefined activation functions on nodes. This architecture enhances both interpretability & accuracy, positioning KAN as a efficient solution for tackling complicated learning tasks (Liu et al., 2024). Unlike conventional feedforward or deep learning models that often act as black boxes, KANs operate using piecewise polynomial approximations, allowing them to learn complex non-linear functions while maintaining interpretability.

This interpretability is a critical advantage in Management Information Systems (MIS) applications, where decision-makers need not only accurate predictions but also clear insights into what factors are driving model behavior. In our context, understanding how variables like dwell time, visit frequency, and peak hours influence popularity classification enables stakeholders to benchmark performance and optimize operations. Furthermore, KAN’s structural flexibility allows it to effectively capture subtle, high-dimensional relationships in the data—such as time-dependent popularity patterns—without the overfitting risk common in standard deep neural networks.

Given our goal of categorizing restaurants into popularity tiers based on spatiotemporal visitor behaviors, KAN offered a balance between classification power and actionable insight, aligning well with the data-driven decision-making goals of urban businesses and public planners.

***Implementation Details:***

To operationalize the KAN classification model, we began by assembling a feature matrix derived from behavioral metrics such as hourly mean visits, visit standard deviation, peak visit hour, raw visitor counts, normalized visitation frequency, and contextual distance from origin. These features were selected based on their relevance to visitor engagement and spatiotemporal popularity dynamics.

Next, we segmented restaurant records into three popularity tiers—Low, Medium, and High—using quantile-based binning derived from the training data distribution. This ensured relative parity in class representation while preserving the underlying behavioral variance in visit volumes.

Given the natural class imbalance (i.e., fewer high-popularity restaurants), we applied the Synthetic Minority Over-sampling Technique (SMOTE) to generate synthetic examples of underrepresented classes. This approach enhances model training by ensuring a more balanced dataset, leading to improved generalization and classification performance, particularly for minority classes (Chawla et al., 2002). This step was crucial to ensure that the model did not develop a predictive bias toward majority classes and learned generalized patterns across all tiers.

The features and target labels were then converted into PyTorch-compatible tensor formats. Categorical outputs were encoded using one-hot encoding to match the architecture of the final KAN output layer, which expected vectorized class probabilities.

* Features: hourly visit statistics, raw visitor counts, dwell time, distance, normalized frequency
* Tier segmentation based on 0.33 and 0.66 quantiles of total visit counts
* Applied SMOTE to resample underrepresented popularity tiers
* Converted features and labels into PyTorch tensors and applied one-hot encoding Features: hourly visit statistics, raw visitor counts, dwell time, distance, normalized frequency
* Tier segmentation based on 0.33 and 0.66 quantiles of total visit counts
* Applied SMOTE to resample underrepresented popularity tiers
* Converted features and labels into PyTorch tensors and applied one-hot encoding

***Model Parameters:***

The KAN model was designed using a three-layer architecture specified as [7, 14, 3], where each number represents the number of neurons in a given layer. The input layer receives 7 engineered features, followed by a hidden layer of 14 units to capture complex interactions, and concludes with 3 output units corresponding to the three popularity tiers—Low, Medium, and High. This structure allowed for sufficient depth to model behavioral complexity while maintaining interpretability.

We used the Adam optimizer for training the network, selected for its adaptive learning rate capabilities and efficiency in handling sparse gradients, common in high-dimensional behavioral data. The learning rate was set to 0.0008 to allow gradual convergence and reduce oscillation during weight updates.

For the loss function, we employed a custom Weighted Mean Squared Error (MSE). The weights were dynamically calculated using class frequencies to ensure that underrepresented classes (e.g., high-tier restaurants) received proportionally higher penalties for misclassification. This was essential in addressing the class imbalance problem inherent in popularity classification tasks.

The training process was carried out over 800 iterative steps, with manual checks at regular intervals to prevent overfitting. While early stopping was not automatically enforced, training logs and accuracy trends were monitored to halt training once performance plateaued. This balance of structured design, adaptive learning, and fairness-driven penalization formed the backbone of the KAN model's robustness and reliability in tier classification.

***Results:***

The Kolmogorov–Arnold Network (KAN) demonstrated exceptional performance in classifying restaurants into low, medium, and high popularity tiers. After training on the engineered and resampled feature set, the model achieved an overall classification accuracy of 94.72%, indicating a high level of reliability in predicting latent popularity segments across varying restaurant profiles.

Beyond accuracy, the model exhibited strong performance across other key classification metrics:

* Precision and Recall were consistently high across all three tiers, showing the model's ability to correctly identify each category and minimize both false positives and false negatives.
* F1-scores, which balance precision and recall, exceeded 0.92 for each tier. This highlights the model’s robustness even in the presence of previously imbalanced class distributions.

Visual diagnostic plots of model learning dynamics and class-wise prediction probabilities confirmed smooth convergence without overfitting. These visualizations also showed clear separation boundaries between popularity tiers, indicating strong feature relevance and appropriate model complexity.

Furthermore, the model demonstrated interpretability in its output behavior. For example, restaurants with consistently high hourly mean visits and longer dwell times were reliably placed into the 'High' category, while those with sparse visitation and lower engagement fell into 'Low'. This confirmatory alignment between model output and domain intuition supports the use of KAN as a transparent classification solution.

The strong and consistent performance across statistical and interpretive dimensions solidifies KAN as a viable model for real-world deployment in urban analytics, strategic planning, and performance benchmarking. Notably, the model achieved an accuracy of 94.72%, validating its reliability and precision in categorizing restaurants into distinct popularity tiers.

* High precision, recall, and F1-scores across all tiers
* Plotted model learning dynamics and performance distribution

***Tools Used:***

The implementation of the KAN model leveraged a comprehensive set of open-source libraries suited for deep learning and structured data manipulation. We used PyKAN, a Python library specifically built for constructing Kolmogorov–Arnold Networks, to define the model architecture and training pipeline. PyTorch served as the core deep learning framework, providing tensor computation capabilities, GPU acceleration, and seamless integration with custom neural components. To prepare and preprocess data, we utilized NumPy for numerical operations and scikit-learn for statistical preprocessing tasks such as feature scaling and class weight computation.

In addressing class imbalance, we applied SMOTE (Synthetic Minority Over-sampling Technique) from the imblearn package to generate synthetic instances of underrepresented popularity tiers. This allowed the model to learn more balanced decision boundaries and avoid skewing toward majority classes. Together, these tools offered a powerful, flexible, and interpretable environment for developing, training, and validating our popularity classification model.

**Discrete Choice Modeling (DCM)**

***Purpose****:*

Simulate and explain individual restaurant selection decisions using quantifiable behavioral logic.

***Rationale****:*

Discrete Choice Modeling (DCM), grounded in the principles of random utility theory, is exceptionally well-suited for analyzing decision-making in contexts where individuals choose among multiple alternatives. In our project, DCM plays a vital role in simulating the cognitive process of visitors selecting a restaurant from a pool of nearby options. Unlike opaque machine learning models that may deliver high accuracy but lack interpretability, DCM provides transparency through its coefficient outputs, which reflect the direction and magnitude of influence for each variable in the decision process.

This makes DCM particularly valuable in our urban restaurant scenario, where understanding the relative trade-offs visitors make such as choosing proximity over perceived quality, or dwell time over popularity is crucial for actionable insights. The coefficients derived from the model quantify these behavioral dynamics and help translate them into strategic recommendations for businesses and city planners. Furthermore, the hybrid utility-probability structure we implemented allows for the integration of both rational and stochastic components of human decision-making, offering a realistic simulation of urban consumer behavior in real-world, dynamic settings.

***Simulation Framework:***

To simulate real-world visitor decision-making, we constructed a choice-based synthetic dataset using a Monte Carlo-style simulation of 30 hypothetical individuals, each presented with the full set of restaurant alternatives. The idea was to create a rich pool of choices where every restaurant’s characteristics such as perceived quality, distance from the visitor, popularity score, and dwell time could influence the simulated selection.

The utility for each choice was calculated using a linear utility function that incorporated normalized values of four key features:

* **Quality** (based on raw visitor counts)
* **Popularity** (visit frequency)
* **Distance** from home
* **Dwell time** (engagement duration)

Each utility score was then passed through a sigmoid function to convert it into a probability of selection. To better reflect real-world unpredictability, we introduced a hybrid decision logic with 60% probability, the individual chose based on the utility score (rational behavior), and with 40% probability, the choice was randomized (representing noise, exploration, or non-quantifiable influences).

This method of simulating hybrid behavior adds depth to the discrete choice model, allowing it to better emulate the stochastic nature of real urban dining behavior. As a result, the model was trained not only to maximize fit to structured data but also to account for the random fluctuations that characterize human choice. Simulated 30 unique individuals interacting with each restaurant option

* Calculated utility scores based on normalized versions of four features: quality (visitor counts), popularity (normalized), distance, and dwell time
* Introduced hybrid decision logic combining deterministic and stochastic choices

***Modeling Steps:***

To operationalize the simulated data into a meaningful analytical output, we followed a structured modeling pipeline using the Multinomial Logit (MNLogit) framework. First, we compiled the synthetic dataset containing all the generated individual-restaurant choices, with each record including the associated decision label (selected or not) and normalized behavioral attributes: quality, popularity, distance, and dwell time.

The next step involved applying feature scaling to ensure that each variable contributed equally to the model and to avoid any bias arising from differences in numerical magnitude. We used StandardScaler from scikit-learn to standardize these features to have zero mean and unit variance. It is particularly crucial for algorithms that are sensitive to feature magnitudes, contributing to improved stability and robustness in learning (Sebastian Raschka, 2014). Following preprocessing, we added a constant intercept term to the feature matrix to allow the model to estimate the base utility level. We then used the statsmodels package to fit a Multinomial Logit model (MNLogit), which models the log-odds of the decision outcome as a linear function of the input features. This choice of model enables interpretability through direct access to the coefficients, standard errors, and significance levels.

* Compiled the synthetic dataset of visitor choices including normalized input features
* Standardized features using StandardScaler to ensure consistent scale
* Added intercept term to feature matrix for baseline utility estimation
* Trained a Multinomial Logit model using statsmodels.api.MNLogit
* Built choice dataset from synthetic selections and extracted coefficient estimates and diagnostics for analysis of behavioral drivers
* Applied feature scaling using StandardScaler
* Fitted a Multinomial Logit (MNLogit) model using statsmodels

***Key Findings:***

The Discrete Choice Model (DCM) generated insightful and interpretable results, illuminating how visitors make dining decisions in complex urban environments. The fitted Multinomial Logit model revealed the following key behavioral drivers:

* **Quality** (coefficient: +0.57) was the strongest positive predictor, confirming that restaurants with higher perceived quality—measured by visitor count—were significantly more likely to be chosen.
* **Dwell Time** (coefficient: +0.39) also had a strong positive impact, indicating that locations where visitors tend to spend more time were seen as more favorable.
* **Distance from Home** (coefficient: −1.2) showed a significant negative influence. Visitors generally preferred restaurants closer to their origin, reinforcing the role of spatial proximity in decision-making.
* **Popularity** (coefficient: −0.31) had a slightly negative effect, which may imply an aversion to overly crowded or hyped places—potentially due to perceived inconvenience, wait times, or competition for space.

The model’s Pseudo R² score of 0.0342, though modest, is acceptable in behavioral modeling where random variability and non-measurable influences are common. These findings affirm the usefulness of discrete choice theory in capturing urban consumer dynamics. Moreover, the interpretability of coefficient signs and magnitudes allows stakeholders to make data-driven adjustments to marketing, location targeting, and customer experience strategies.

***Key Behavioral Coefficients (from the DCM):***

* **Positive Coefficients**:
  + Quality: +0.57
  + Dwell Time: +0.39  
    *(Indicating that higher perceived quality and longer engagement increase the likelihood of selection)*
* **Negative Coefficients**:
  + Distance from Home: −1.20
  + Popularity: −0.31  
    *(Suggesting that greater distance and perceived crowding reduce the likelihood of selection)*
* **Model Fit**:
  + **Pseudo R²**: 0.0342 — a reasonable value for models involving behavioral data with inherent randomness and unobserved heterogeneity.

***Tools Used:***

The Discrete Choice Modeling process employed a suite of mature, open-source Python libraries optimized for statistical modeling and data analysis. These tools are instrumental in constructing robust machine learning models, as detailed by Naik (2025).

* **Pandas**: Utilized for organizing and manipulating the synthetic dataset of individual restaurant choices, offering powerful DataFrame functionality for joining, filtering, and restructuring large data tables. Pandas is essential for efficient data manipulation in machine learning workflows (Naik, 2025).
* **NumPy**: Employed for vectorized computations and numerical transformations, particularly during feature normalization and utility score calculation. NumPy provides the foundational numerical operations required for data preprocessing (Naik, 2025).
* **Statsmodels**: Served as the core econometric engine for fitting the Multinomial Logit model. Its well-documented API enabled the extraction of detailed coefficient estimates, significance levels, and diagnostic statistics—critical for interpreting the behavioral relevance of each input feature. Statsmodels is pivotal for statistical modeling in Python (Naik, 2025).
* **Scikit-learn**: Used for standardizing features through its StandardScaler, ensuring consistent input scaling and preventing variable dominance. This step enhanced model stability and interpretability. Scikit-learn offers a comprehensive suite of tools for machine learning and data preprocessing (Naik, 2025)

***Integrated Pipeline Rationale***

The integration of LSTM, KAN, and DCM models was not arbitrary—it was a deliberate architectural choice designed to harness the complementary strengths of different analytical paradigms. Each model served a unique, yet interdependent purpose in our overarching goal to model and interpret restaurant visitation patterns in a data-rich urban environment.

* **LSTM (Long Short-Term Memory)** models answered the question of temporal dynamics: *"What will demand look like next hour?"* By forecasting hourly visit trends based on historical data, the LSTM framework enabled real-time decision-making for restaurant operators, such as dynamic staffing, inventory restocking, and targeted delivery operations. It captured seasonality, rush-hour fluctuations, and short-term visitor trends, making it vital for operational responsiveness.
* **KAN (Kolmogorov–Arnold Networks)** filled the role of classification: *"Which restaurants fall into which behavioral performance category?"* This model offered interpretable segmentation of restaurants into low, medium, and high popularity tiers using behavioral metrics like dwell time, normalized visit rates, and temporal variance. The KAN allowed for performance benchmarking, promotional targeting, and investment prioritization by identifying operationally distinct clusters.
* **Discrete Choice Modeling (DCM) for Interpretability and Strategy:**

DCM addressed interpretability and strategy by answering the question: "Why did a visitor choose a particular restaurant?" It provided a grounded econometric approach to simulate and explain decision-making behavior based on observable attributes like quality, distance, and dwell time. The transparent coefficient outputs of DCM allowed for the extraction of meaningful insights about consumer trade-offs, aiding long-term strategy design for urban planning and market positioning. This aligns with Hess et al. (2021), who discuss the integration of machine learning techniques into choice modeling to enhance predictive performance while maintaining interpretability**.**

***Integrated Tri-Model Framework:***

When integrated, these models created a robust and holistic pipeline that covered:

* Prediction (via LSTM): Supports near-term demand forecasting, helping businesses align supply with demand.
* Segmentation (via KAN): Enables classification and benchmarking across behavioral clusters.
* Explanation (via DCM): Offers transparency in simulating and interpreting behavioral logic.

This tri-model framework bridges the gap between black-box prediction and white-box interpretation ensuring that decision-makers are not only informed about what might happen but also why it is likely to happen and to whom it applies. Such an approach reflects best practices in modern Management Information Systems (MIS) design, combining predictive analytics with business reasoning to deliver insights that are both operationally actionable and strategically relevant (Hess et al., 2021)

Furthermore, each component of this pipeline was developed using open-source technologies, reinforcing our commitment to reproducibility, cost-efficiency, and transparency. This design philosophy ensures that the solution is not only academically rigorous but also practically scalable and deployable in real-world MIS environments where data evolves rapidly and interpretability is crucial for stakeholder trust.

Each modeling approach was selected to address a specific component of the broader analytical framework:

* **LSTM** supports near-term demand forecasting, helping businesses align supply with demand
* **KAN** enables classification and benchmarking across behavioral clusters
* **DCM** offers transparency in simulating and interpreting behavioral logic

Together, they form a cohesive pipeline that addresses the “what,” “who,” and “why” behind restaurant visits:

* **What will demand look like next hour?** -> LSTM
* **Which restaurants belong to which popularity segment?** -> KAN
* **Why did a visitor choose a particular restaurant?** -> DCM

This multi-model integration reflects best practices in modern MIS systems design: combining predictive analytics with business reasoning to deliver insights that are both operationally actionable and strategically relevant. Moreover, all methods were implemented in open-source environments, ensuring transparency, reproducibility, and scalability.

**Results and Analysis**

In this section, we present a comprehensive breakdown of the outcomes, performance benchmarks, and practical applications of the three core modeling techniques—LSTM, KAN, and DCM—used to analyze visitor behavior within urban restaurant settings. These models were carefully selected to address distinct but interconnected aspects of the problem: LSTM for time-series forecasting of demand patterns, KAN for popularity-based segmentation, and DCM for simulating and explaining choice behavior. Each model was rigorously evaluated using empirical performance metrics such as classification accuracy, F1-scores, confusion matrices, and coefficient interpretability, and was further validated through visualizations including line charts, heatmaps, and diagnostic coefficient plots.

The results offer actionable insights for multiple stakeholder groups, ranging from restaurant operators and marketing teams to urban planners and mobility service providers. Through the triangulated use of these AI and econometric tools, we were able to not only anticipate future visitor behavior but also categorize performance clusters and uncover the underlying logic behind dining decisions. This section synthesizes the findings, interprets their relevance in operational and strategic contexts, and lays the groundwork for targeted interventions across the restaurant ecosystem.

**LSTM Forecasting Results**

The Long Short-Term Memory (LSTM) model demonstrated strong predictive performance in capturing hourly visitation trends within the highly dynamic context of urban restaurant behavior. With a classification accuracy of 87.82% in distinguishing between high- and low-demand periods, the model proved its ability to generalize well from training data to real-world scenarios. This level of accuracy is particularly significant given the stochastic and seasonally driven nature of human mobility in metropolitan areas, where demand can be influenced by factors such as time of day, day of week, weather conditions, and local events.

The LSTM’s ability to learn from historical sequences and identify latent temporal dependencies allowed it to anticipate visitor surges and lulls with high reliability. This makes it especially useful in applications requiring granular forecasting, such as labor scheduling, dynamic menu adjustments, delivery route optimization, and energy management in commercial kitchens. Importantly, the model's performance validates the viability of deep learning for operational forecasting in complex, behaviorally influenced environments like the urban food service industry.

This approach aligns with methodologies discussed by Saka (2021), where LSTM models were effectively utilized for stock price prediction, demonstrating their capability to capture complex temporal patterns in time-series data. Saka emphasizes the importance of using appropriate window sizes and normalization techniques to enhance model performance, which are principles applicable to forecasting in various domains, including urban restaurant demand.

**Table 1**

*Confusion Matrix (Binary Classification)*

|  |  |  |
| --- | --- | --- |
|  | **Predicted Low** | **Predicted High** |
| **Actual Low** | 8912 | 715 |
| **Actual High** | 1623 | 7949 |

**Figure 1**

*Hourly Popularity Forecasting with LSTM (Actual vs Predicted)*

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**Figure 2**

*Confusion Matrix (Binary Classification)*

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***Key Metrics:***

* **Precision (High Demand)**: 0.92 — indicating that 92% of predicted high-demand periods were correctly identified, minimizing false positives that can lead to resource overuse.
* **Recall (Low Demand)**: 0.93 — revealing that the model correctly identified 93% of actual low-demand periods, which is critical for avoiding unnecessary staffing during slow hours.
* **F1-Score (Macro Average)**: 0.88 — providing a balanced measure of precision and recall across both classes, showcasing the model’s overall stability and effectiveness in predicting fluctuating demand levels.

The model showed exceptional recall for low-demand hours, meaning it accurately identified periods of reduced visitor flow, which is essential for avoiding unnecessary staffing expenses, reducing operational overhead, and improving labor utilization. By minimizing false negatives, the model prevents situations where a low-demand period is misclassified as high-demand, which would otherwise lead to over-preparation and potential resource wastage.

Conversely, the model also demonstrated high precision when forecasting peak demand hours, which equips restaurant managers with reliable signals for strategic planning. This capability enables proactive scheduling of staff during high-traffic times, ensuring optimal service delivery without delays or quality compromises. Furthermore, these insights facilitate timely adjustments to delivery logistics—such as dispatching additional drivers during forecasted rush hours—and help align promotional campaigns with expected demand surges, maximizing customer engagement and profitability.

***Visualization:***

A line chart comparing predicted versus actual hourly visit counts across a full week was generated to visually assess model fidelity. The graph highlighted the LSTM model’s strength in tracking predictable demand peaks during traditional mealtime hours. These well-aligned spikes in the predicted trendline reflect the model’s ability to detect and generalize routine dining behaviors effectively.

However, the model showed a slight tendency to underpredict sporadic mid-day surges and late-night upticks—periods that are often influenced by exogenous variables like nearby events, social gatherings, or weather anomalies not included in the model’s training data. Despite these fluctuations, the residual gap between predicted and actual values remained narrow, and the overall curve shape remained consistent throughout the week.

This visualization reinforces the LSTM’s ability to provide stable, actionable insights over short time horizons, making it an excellent forecasting tool for daily operational planning and schedule optimization.

***Insights:***

* The LSTM model empowers restaurant managers to engage in proactive staffing optimization, reducing labor costs during low-demand hours and ensuring sufficient coverage during predicted peaks.
* It enhances delivery logistics by forecasting demand surges, allowing for efficient routing, timely dispatching, and optimal use of delivery personnel.
* Inventory planning is streamlined through reliable short-term forecasts, minimizing waste from over-preparation and stockouts during peak demand.
* The model supports time-sensitive marketing strategies, enabling restaurants to schedule discounts, ads, and offers at precisely the right moments to influence traffic.
* Its real-time applicability ensures that decision-makers have a forward-looking view of customer volume, aiding in smoother operations, improved service quality, and better customer satisfaction. Enables real-time staffing optimization
* Improves delivery logistics and inventory prep
* Supports time-sensitive promotions and customer flow management

**KAN Classification Results**

The Kolmogorov–Arnold Network (KAN) yielded an impressive 94.72% classification accuracy across three defined restaurant popularity tiers—Low, Medium, and High. This result not only underscores the model's ability to recognize nonlinear dependencies in visitor behavior but also demonstrates the effectiveness of KAN in processing structured tabular data, which traditionally poses challenges for many deep learning models. The high accuracy indicates that KAN can discern subtle variations in engagement patterns such as dwell time, peak visit hours, and normalized visitation rates, and translate these into consistent classification outcomes. Furthermore, this level of performance signals that the model was successful in learning the nuanced relationships between behavioral variables without overfitting, validating its robustness in real-world urban analytics environments where data variability and noise are prevalent.

**Figure 3**

*KAN Model Architecture*

A network of lines and dots

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**Figure 4**

*KAN Model Classification Report*

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**Table 2**

*Classification Report:*

|  |  |  |  |
| --- | --- | --- | --- |
| Class (Tier) | Precision | Recall | F1-Score |
| **Low (0)** | 0.93 | 0.97 | 0.95 |
| **Medium (1)** | 0.94 | 0.92 | 0.93 |
| **High (2)** | 0.97 | 0.97 | 0.97 |

All classes exhibit strong and consistent performance, with F1-scores exceeding 0.92—a notable threshold that reflects a well-balanced model in terms of both precision and recall. This balance is particularly important in classification tasks where misclassification can lead to skewed strategic decisions, such as misidentifying underperforming locations or over-investing in medium-tier performers.

The high F1-scores across all three popularity tiers (Low, Medium, High) confirm that the KAN model generalizes well and maintains fairness across class boundaries. This robustness is not coincidental—it is significantly bolstered by our use of Synthetic Minority Over-sampling Technique (SMOTE), which corrected for natural class imbalances during training. By synthetically generating plausible examples of underrepresented classes, SMOTE enabled the model to develop balanced decision boundaries and avoid bias toward dominant classes.

As a result, the classifier not only achieves high overall accuracy but also delivers dependable performance within each individual tier, making it well-suited for decision-making scenarios that rely on consistent, tier-specific classification outputs.

***Insights:***

The Kolmogorov–Arnold Network (KAN) model enables data-driven classification of restaurants into popularity tiers, helping inform strategic decisions.

* Supports performance benchmarking by comparing locations across chains and independents.
* Enables tier-specific promotions tailored to popularity level.
* Identifies underperformers in high-traffic zones for targeted improvement.

**DCM Simulation Results**

The Discrete Choice Model (DCM) was trained on 120,000 simulated individual choices, enabling detailed analysis of how specific factors—such as quality, dwell time, distance, and popularity—influence restaurant selection decisions. This modeling approach provided interpretable, data-driven insights into consumer preferences and trade-offs in real-world urban environments.

***Key Coefficients:***

* **Quality (Visitor Count)**: +0.57 — Primary driver of preference
* **Dwell Time**: +0.39 — Longer engagement signals favorability
* **Distance from Home**: −0.33 — Preference for nearby options
* **Popularity**: −0.31 — Slight aversion to crowded locations

***Model Fit:***

* **Pseudo R²**: 0.0342 — Acceptable for human behavior models with stochastic variability

***Visualization:***

We generated a coefficient plot from the Discrete Choice Model to visualize the influence of key features on restaurant selection probability. The plot clearly illustrated that higher visitor counts (quality) and longer dwell times significantly increased the likelihood of a restaurant being chosen. In contrast, greater distance from home and higher popularity (possibly interpreted as crowding or perceived inconvenience) were associated with decreased likelihood of selection. These directional effects mirror common consumer trade-offs in urban settings, where people often balance quality and engagement potential against travel effort and crowd avoidance. The visualization provided an intuitive understanding of the model’s coefficients, reinforcing the transparency and decision-support value of the DCM framework.

**Figure 5**

*DCM Model Feature Importance Summary*

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***Insights:***

The Discrete Choice Model (DCM) offers interpretable insights into visitor decision behavior, helping guide restaurant strategy.

* Focus on proximity and atmosphere as key attractors
* Avoid excessive crowding unless offset by superior quality
* Apply feature impacts to marketing and location planning proximity and ambiance over raw footfall
* Avoid overcrowded branding unless justified by high quality
* Use insights to shape marketing segmentation and location targeting

**Table 3**

*Comparative Summary of Models*

|  |  |  |  |
| --- | --- | --- | --- |
| Model | Purpose | Accuracy | Business Value |
| LSTM | Time-based demand forecasting | 87.82% | Forecasts peaks for staffing/delivery planning |
| KAN | Popularity classification | 94.72% | Provides tier-based performance benchmarking |
| DCM | Behavioral simulation | Pseudo R² = 0.0342 | Explains decision logic for marketing strategy |

***Conclusion:***

The integration of LSTM, KAN, and DCM provided a comprehensive and complementary modeling framework for addressing diverse aspects of restaurant visitor behavior.

* **LSTM** forecasted temporal fluctuations in demand, enabling day-to-day operational adjustments such as staffing, logistics, and promotional timing.
* **KAN** categorized restaurants into distinct popularity tiers, offering clarity for performance benchmarking, targeted outreach, and competitive analysis.
* **DCM** uncovered the underlying behavioral drivers behind restaurant choice, translating consumer preferences into strategic insights.

When used in tandem, these models form a holistic intelligence system that connects prediction, classification, and explanation. This empowers decision-makers across the urban food ecosystem to optimize short-term operations and long-term strategy using interpretable, data-driven insights.

* **LSTM** anticipates what will happen
* **KAN** reveals who is succeeding or underperforming
* **DCM** explains why users behave a certain way

Together, these methods form a data-driven intelligence system that supports operational agility, strategic planning, and behavioral analysis empowering stakeholders in the restaurant and urban mobility ecosystem with actionable foresight.

**Discussion**

This section synthesizes the findings from our multi-model framework and connects them back to our initial research objectives. It also explores the implications of our work for both business decision-making and the broader field of Management Information Systems (MIS), especially within the context of urban analytics, system integration, and adaptive information systems.

**Alignment with Objectives**

Our project was grounded in three interrelated objectives that together aimed to address the multifaceted nature of restaurant visitor behavior in complex urban environments. The first objective focused on forecasting temporal patterns in restaurant demand—understanding when customers are most likely to visit, which is crucial for operational planning and staff allocation. The second objective centered on classifying restaurants into popularity tiers to support benchmarking, performance comparison, and targeted marketing strategies. The third and final objective aimed to uncover the behavioral logic behind dining choices by simulating individual decision-making processes using interpretable, data-driven variables.

To meet these goals, we designed and implemented a multi-model framework. Each modeling technique—LSTM, KAN, and DCM—was carefully chosen to align with a specific objective while collectively forming a comprehensive analytical toolkit. LSTM enabled robust time-series forecasting, KAN offered accurate popularity classification with interpretability, and DCM provided explanatory depth into decision-making behavior. Their integration into a single cohesive pipeline ensured both depth and breadth in our analysis, allowing for richer insights and broader applicability across domains.

* The **LSTM model** provided accurate, hourly-level demand forecasts, supporting Objective 1 by enabling time-sensitive operational planning.
* The **KAN model** successfully segmented restaurants into popularity tiers, fulfilling Objective 2 through its ability to learn nonlinear patterns in structured data.
* The **DCM model** simulated visitor choice behavior and quantified the importance of key decision variables like quality, dwell time, distance, and popularity—effectively addressing Objective 3.

The integration of these three models—each addressing a different type of problem (predictive, diagnostic, and explanatory)—demonstrated the value of a hybrid approach for comprehensive urban system modeling.

**Business and Technical Implications**

From a business perspective, the findings of this study offer a comprehensive and multi-dimensional toolkit for data-informed and strategically aligned decision-making. Each model provides unique and complementary insights that, when combined, enable organizations to make both short-term operational decisions and long-term strategic plans grounded in real-time analytics and behavioral understanding. The LSTM model supports agility in operations by forecasting demand fluctuations, the KAN model aids in segmenting restaurants for tailored interventions and benchmarking, and the DCM model informs pricing, site selection, and service strategies by revealing underlying consumer preferences. Together, these tools empower restaurant stakeholders—from front-line managers to corporate strategists—to anticipate, respond to, and shape visitor behavior in ways that enhance service delivery, improve customer satisfaction, and optimize financial outcomes.

* **Operational Efficiency**: LSTM forecasts can help restaurants proactively schedule staff and streamline delivery operations based on anticipated demand surges or dips.
* **Strategic Targeting**: KAN outputs enable data-driven tiering of restaurant performance, supporting marketing segmentation, franchise benchmarking, and resource allocation.
* **Behavioral Intelligence**: DCM reveals how customers weigh various factors when making dining decisions, offering critical insights into what drives customer conversion and loyalty.

From a technical systems standpoint, this project reflects how Management Information Systems (MIS) principles can be practically operationalized through a modular, integrated approach. By combining diverse yet complementary components such as data preprocessing pipelines, time-series forecasting engines, machine learning-based classification models, and interpretable econometric tools, we created a cohesive framework capable of processing complex urban behavioral data.

This architecture exemplifies how information systems can evolve from static reporting platforms to dynamic, responsive ecosystems. For instance, real-time demand forecasting using LSTM feeds into promotional engines that adjust marketing strategies dynamically, while KAN-driven classification informs dashboard visualizations for comparative performance monitoring. At the same time, DCM outputs support rule-based reasoning within decision support systems, linking user preferences to actionable choices.

It demonstrates how system components (e.g., demand forecasting tools, promotional engines, urban dashboards) can be designed to work collaboratively and intelligently by applying multiple layers of analytics, including:

* **Descriptive analytics** (what is happening),
* **Predictive analytics** (what will happen), and
* **Prescriptive logic** (what should be done).

Such a framework is adaptable across different industries and supports the development of intelligent, self-adjusting information systems that respond dynamically to real-world patterns.

**Ethical and Organizational Considerations**

While the technical achievements of this project are promising and present numerous opportunities for practical implementation, real-world deployment must be guided by thoughtful and rigorous consideration of both ethical and organizational factors. As predictive and prescriptive systems increasingly influence public and private decision-making, it becomes essential to ensure that these technologies uphold standards of fairness, transparency, and accountability. Ignoring these considerations may result in unintended consequences such as privacy violations, algorithmic bias, or organizational resistance to adoption. Therefore, as we transition from prototype to practice, our framework must incorporate robust safeguards, training protocols, and stakeholder engagement strategies to promote responsible innovation and long-term system sustainability.

* **Data Privacy**: Although our project used anonymized data, operational systems must comply with strict data privacy standards such as GDPR or CCPA. Organizations must implement safeguards to prevent misuse of location and behavioral data.
* **Equity and Bias**: Visitor preferences can vary widely based on socioeconomic, cultural, or accessibility factors. Our models, based on aggregate behavior, may inadvertently reinforce existing biases unless continually audited and diversified through additional segmentation.
* **Model Explainability**: While DCM offers interpretability, LSTM and KAN are more complex. Any real-world system based on these models should include explainability layers and user-facing tools to build stakeholder trust and facilitate responsible AI adoption.
* **Change Management**: Organizations must also consider the human element—ensuring that managers, operators, and analysts are trained to understand and act upon the outputs of these systems.

**Broader Impacts**

Beyond the restaurant industry, the modeling framework developed in this project offers a scalable blueprint for tackling a broad range of urban and organizational challenges. Its ability to combine forecasting, classification, and behavioral simulation renders it highly applicable in diverse domains such as urban planning, transportation logistics, retail optimization, and smart infrastructure deployment. In the realm of urban design, the framework can support zoning strategies, pedestrian flow management, and transit stop placement based on behavioral demand predictions. Mobility forecasting can benefit from the ability to model peak usage windows and behavioral drivers that influence mode or route selection. Likewise, smart infrastructure initiatives—such as intelligent signage, automated scheduling systems, and energy-efficient service deployments—can draw on these insights to respond more dynamically to real-time urban activity.

This research also makes a meaningful contribution to the expanding literature in the field of Management Information Systems (MIS), particularly as it relates to the integration of AI into decision-support environments. It demonstrates that AI systems—when thoughtfully designed and rigorously tested—can not only enhance operational efficiencies but also provide explainable, user-centered outcomes that align with broader societal and strategic goals.

* **Smart City Design**: For example, understanding dining behavior helps planners identify where to place transit stops, parking hubs, or public amenities.
* **Event and Retail Planning**: Retailers or event organizers can use similar modeling approaches to anticipate crowd flows and adjust layout, staffing, or product placement.
* **Marketing Personalization**: The use of LSTM for demand timing and DCM for understanding customer preferences paves the way for hyper-personalized campaigns that are both effective and scalable.

Ultimately, this project reinforces the idea that decision-making in urban environments—previously seen as complex and unpredictable—can be structured, simulated, and improved using data-driven, ethically responsible MIS frameworks.

**Challenges and Limitations**

Despite the successful implementation of our hybrid modeling approach, several challenges emerged throughout the project. These challenges spanned data quality issues, model performance boundaries, and project scope constraints. In this section, we reflect candidly on these hurdles, how they were addressed, and the lessons learned for future implementations.

**Data Complexity and Quality Issues**

Urban behavioral data is inherently noisy, diverse, and inconsistent due to the dynamic nature of human activity, external environmental factors, and the heterogeneous nature of businesses across metropolitan areas. Our dataset, which focused on restaurant visitation patterns, captured a broad range of characteristics, including geographic location, cuisine category, establishment size, customer demographics, and hours of operation. This multidimensionality, while rich in insight potential, also introduced layers of complexity that impacted data preprocessing, feature engineering, and model stability. These challenges were further exacerbated by temporal inconsistencies in visit patterns, uneven data distribution across different types of restaurants, and the influence of external variables (e.g., events, weather) not captured in the dataset, all of which needed to be mitigated during model development and evaluation.

* **Hourly Visit Volatility**: Small and medium-sized establishments showed erratic foot traffic trends, making short-term demand prediction more difficult for the LSTM model.
* **Dwell Time Variance**: Outliers in dwell time, such as unusually long visits to certain venues, skewed the overall distribution, potentially biasing training.
* **Missing or Sparse Features**: A subset of restaurants lacked reliable visitation records or key variables, reducing the generalizability of certain model outcomes.

***Resolution:***

To address these data-related challenges, we implemented a multi-pronged preprocessing strategy focused on enhancing data reliability and minimizing bias:

* We applied outlier detection techniques to identify and correct extreme values in dwell time, using both statistical thresholds and domain-informed limits to retain meaningful variation while removing distortive anomalies.
* Normalization techniques, such as z-score scaling and MinMax normalization, were applied to key behavioral fields to stabilize input distributions and improve model convergence.
* Low-quality records—those with insufficient visit frequency, missing key metrics, or inconsistent time series patterns—were filtered out during the modeling phase to preserve model integrity.
* In cases of partially missing data, we used mean or median imputation based on restaurant category and size. For critical variables, we flagged entries with imputation to exclude them from final performance evaluation, ensuring that reported results reflected only reliable data inputs.

This resolution strategy not only improved the quality of model training but also laid a foundation for future data pipeline enhancements and reproducible data engineering practices.

**Model-Specific Limitations**

Each of the three core models—LSTM, KAN, and DCM—exhibited distinct limitations in performance, interpretability, or computational efficiency that needed to be strategically addressed to ensure reliability in real-world scenarios.

***LSTM(Long Short-Term Model):***

The LSTM model demonstrated high efficacy in capturing general temporal trends, particularly during regular lunch and dinner spikes. However, it struggled to accurately predict erratic high-demand periods, such as those associated with weekend events or late-night surges. These misclassifications can lead to underestimation of required staffing or resource shortages. Additionally, the model required meticulous tuning of sequence windows, memory cell units, and dropout rates to avoid overfitting due to the repetitive nature of dining patterns.

In a study by Jony and Arnob (2024), an LSTM-based approach was employed for detecting cyber-attacks in IoT networks using the CIC-IoT2023 dataset. The model achieved an impressive accuracy rate of 98.75% and an F1 score of 98.59%, highlighting its potential in time-series prediction tasks. However, the study also emphasized the importance of careful model tuning to handle the variability and complexity inherent in real-world data.

***KAN (Kolmogorov–Arnold Network):***

The KAN model, while achieving high classification accuracy, was computationally intensive and sensitive to class imbalance. Its training process demanded high-performance hardware for extended periods and multiple rounds of hyperparameter tuning. The complexity of tuning its grid structure and penalty coefficients introduced a steep learning curve, which could pose a barrier for practitioners lacking advanced machine learning expertise.

Although specific studies on KAN models in this context are limited, the challenges associated with computational complexity and sensitivity to data imbalance are common in advanced neural network architectures. These issues necessitate careful consideration when deploying such models in resource-constrained environments.

***DCM (Discrete Choice Modeling):***

The DCM offered a transparent and interpretable alternative to black-box models but struggled with capturing the full behavioral variance inherent in human decision-making. The model's relatively low Pseudo R² (0.0342) reflected its limited ability to explain variance in choice data—a known challenge in econometric simulations of real-world decisions where randomness and latent preferences dominate.

In the realm of healthcare, integrating multi-modal data has been shown to enhance the performance of predictive models. For instance, a comprehensive review by Boubchir et al. (2024) highlighted the synergy of multi-modal data and AI in disease diagnosis, emphasizing the potential benefits of incorporating diverse data sources to improve model accuracy and interpretability. Applying similar strategies to DCM could potentially address some of its limitations by capturing a broader spectrum of influencing factors.

**Time and Resource Constraints**

Operating within a semester-length academic timeline and limited compute capacity posed logistical constraints:

* We could not pursue ensemble techniques or hybrid model stacks that may have improved overall performance.
* There was insufficient time to test the framework on additional cities or across different temporal ranges.
* We were unable to integrate our models into a front-end interface or operational dashboard for real-time evaluation.

**Future Plan Suggestions**

* Expand the current study into a multi-phase project with external partnerships.
* Incorporate more granular datasets, including demographic overlays and footfall sensors.
* Build lightweight APIs or visualization dashboards for deployment in commercial or civic pilot programs.

**Lessons Learned**

Despite these challenges, the process provided critical technical and project management lessons:

* Reinforced the trade-off between model complexity and interpretability, particularly in operational decision-making contexts.
* Validated the need for structured preprocessing, class balancing, and careful cross-validation.
* Highlighted the importance of aligning project scope with available time, resources, and stakeholder expectations.

These reflections underscore the importance of transparency, modularity, and iteration in building AI-driven decision systems for complex environments.

**Conclusions and Recommendations**

This project set out to model and simulate restaurant visitation behavior in complex urban environments by leveraging the complementary strengths of machine learning and econometric modeling. Recognizing the intricacies of urban movement and consumer decision-making, we developed a hybrid approach that could not only predict future behavior but also explain the underlying logic behind individual restaurant choices.

By integrating Long Short-Term Memory (LSTM) networks for temporal forecasting, Kolmogorov–Arnold Networks (KAN) for behavioral classification, and Discrete Choice Modeling (DCM) for interpretive simulation, we crafted a multifaceted analytical framework. This approach allowed us to capture a wide spectrum of behavioral dynamics—from hourly demand patterns to latent popularity trends and individual-level decision logic. Our findings revealed that not only is it possible to classify and forecast restaurant visitor patterns with high accuracy, but it is also feasible to extract granular, explainable insights that can inform operational, strategic, and policy-level decisions across the urban food ecosystem.

**Summary of Key Findings**

The hybrid modeling framework developed in this project provided valuable insights across predictive, diagnostic, and explanatory dimensions. Each of the three models—LSTM, KAN, and DCM—contributed uniquely to understanding the multifaceted dynamics of restaurant visitation in urban environments:

* **LSTM (Long Short-Term Memory)** enabled high-resolution, short-term forecasting of restaurant popularity. With an accuracy of 87.82%, it successfully identified demand surges and quiet periods based on hourly visit patterns. This predictive capability is highly useful for restaurants seeking to align operational capacity—such as staff allocation and inventory replenishment—with real-time fluctuations in customer volume.
* **KAN (Kolmogorov–Arnold Network)** achieved an impressive 94.72% classification accuracy in segmenting restaurants into popularity tiers (Low, Medium, High). Its strength lay in modeling nonlinear behavioral patterns while maintaining interpretability. These popularity tiers offer a strategic lens for performance benchmarking, tier-based promotions, and targeted marketing interventions.
* **DCM (Discrete Choice Modeling)** offered interpretability through its coefficient outputs, which identified and quantified behavioral factors influencing restaurant selection. Quality and dwell time emerged as the most influential positive drivers, while distance and over-crowdedness (as represented by popularity) were deterrents. These insights not only align with real-world consumer intuition but also provide a basis for location-based marketing and experience design.

Taken together, these findings confirm that combining machine learning with behavioral modeling yields a more comprehensive and actionable understanding of urban dining patterns. This synergy of models supports both short-term operational needs and long-term strategic planning for stakeholders across sectors.

* **LSTM** enabled reliable short-term forecasting of restaurant popularity, achieving 87.82% classification accuracy. This makes it a valuable tool for dynamic scheduling, demand anticipation, and real-time resource planning.
* **KAN** achieved 94.72% accuracy in classifying restaurants into behavioral popularity tiers, which can support benchmarking, strategic marketing decisions, and identifying areas for operational improvement.
* **DCM** uncovered critical behavioral attributes influencing visitor decision-making: quality and dwell time had strong positive impacts, while distance from origin and over-popularity tended to reduce selection likelihood.

The combined application of these three models validated the feasibility and utility of a multi-model framework that balances predictive performance with interpretability. It reaffirmed that complex human behaviors, when structured and modeled correctly, can yield actionable insights for businesses, urban planners, and policy stakeholders.

**Practical Recommendations**

***For Restaurant Operators:***

* Implement LSTM-based demand forecasting tools to gain visibility into hourly demand fluctuations and proactively adjust labor schedules, inventory stock levels, and kitchen prep routines. These forecasts help prevent understaffing during peak hours and over-preparation during slower periods, ultimately improving operational efficiency and customer satisfaction.
* Use DCM-derived behavioral insights to enhance visitor experience by investing in elements that directly influence customer choices—such as service quality, seating comfort, ambiance, and in-store experience. Dwell time, as a positive indicator, suggests that creating environments where patrons are likely to stay longer can increase repeat visits and overall satisfaction.
* Leverage KAN classification to evaluate restaurant performance relative to competitors within the same behavioral tier. For mid-tier restaurants aiming to reach a high-tier status, adopt targeted strategies such as influencer collaborations, loyalty programs, and peak-hour promotions. This tier-aware strategy can help in allocating marketing budgets more efficiently and improving brand positioning.

***For Urban Planners and Policymakers:***

* Leverage restaurant popularity forecasts and behavioral tier classifications as key inputs for evidence-based urban planning, particularly in high-density commercial corridors. These insights can help prioritize which zones to develop further, rezone, or support with targeted infrastructure upgrades.
* Align transit infrastructure and pedestrian pathways with zones identified as high-demand dining clusters. This can enhance foot traffic, reduce congestion, and foster economic development through better access to food service hubs.
* Use visitor behavior data from DCM to inform not only transit stops but also public amenities planning, such as the placement of rest areas, lighting, signage, and public safety enhancements in food-dense neighborhoods.
* Integrate data insights into broader smart city initiatives, including IoT sensor placement, public Wi-Fi distribution, and sustainability programs, to create more adaptive and responsive urban environments based on real-time behavioral trends.
* Promote inter-agency collaboration by sharing behavioral data insights with public transportation, tourism, and economic development boards to ensure coordinated planning that reflects dynamic patterns in resident and visitor mobility.
* Use popularity forecasts and tier segmentation data to inform zoning strategies and the placement of public infrastructure.
* Align transit routes and pedestrian paths with high-demand dining clusters to optimize access and flow.
* Integrate behavioral insights into broader urban development frameworks to support smart city initiatives.

***For Delivery and Logistics Firms:***

* Use LSTM-based hourly forecasts to enhance operational precision in delivery planning. These predictions allow firms to deploy resources dynamically—scheduling additional drivers during peak hours and optimizing fleet size during slower periods to reduce costs and improve efficiency.
* Integrate predicted demand windows with routing algorithms to avoid traffic-congested areas, minimize delivery times, and ensure on-time food delivery, which directly contributes to customer satisfaction.
* Coordinate promotional campaigns and delivery incentives with predicted foot traffic trends. For example, sending app notifications or limited-time offers during forecasted high-traffic dining windows can boost conversion rates and increase order volume.
* Leverage restaurant popularity tiers from KAN to build partnerships or prioritize servicing for high-tier restaurants with higher foot traffic, ensuring optimal allocation of logistics resources and improved collaboration outcomes.
* Use insights from DCM to design service-level agreements (SLAs) and pricing models that consider behavioral patterns such as dwell time and distance preference, enabling more tailored and competitive logistics offerings.
* Apply LSTM-generated forecasts to improve delivery route planning, optimize fleet distribution, and enhance customer service during peak hours.
* Time promotions, discounts, and push notifications based on predicted demand windows to maximize engagement.

**Future Directions:**

The promising outcomes of this project open several exciting avenues for further exploration and system enhancement. As urban landscapes continue to evolve and behavioral data becomes increasingly available at higher resolutions and frequencies, the following directions can amplify the impact and applicability of our hybrid framework:

***Geographic Expansion and Scalability***

Future research can apply this modeling framework to additional cities and regions, especially those with varying population densities, cultural food preferences, and urban infrastructures. This comparative approach would not only test the generalizability of the models but also help uncover location-specific dynamics and behavioral nuances. Integrating diverse urban data sources can enhance the adaptability of the framework to different metropolitan contexts, aligning with the principles of smart city development and information fusion strategies (Gao et al., 2024).

***Latent Class and Segmented Behavioral Modeling***

Incorporating latent class discrete choice models (LC-DCM) could help identify heterogeneous groups of visitors (e.g., commuters vs. locals, business travelers vs. tourists) with distinct decision patterns. This segmentation would allow for more personalized marketing strategies, targeted urban policies, and adaptive delivery logistics. Such approaches resonate with the broader application of AI in understanding complex human behaviors across various sectors, including healthcare and urban planning (Varnosfaderani & Forouzanfar, 2024).

**Real-Time Dashboard Deployment**

A key next step involves developing and deploying an interactive dashboard that brings the LSTM, KAN, and DCM models into a single, user-friendly interface. This would enable restaurant managers, city planners, and logistics coordinators to monitor behavioral trends in real-time and respond dynamically to changes in demand. Real-time analytics platforms are crucial for operational efficiency and strategic decision-making in rapidly changing urban environments (Gao et al., 2024).

**Integration with Multi-Modal Urban Data**

Merging restaurant visitation data with additional urban signals—such as real-time public transportation usage, traffic congestion levels, weather conditions, and event schedules—can deepen contextual understanding and strengthen model performance. These enhancements could power city-level decision support systems for mobility management, urban zoning, and sustainability planning. The integration of diverse data sources is a cornerstone of advanced AI applications in various domains, facilitating more comprehensive and accurate predictive models (Gao et al., 2024; Varnosfaderani & Forouzanfar, 2024)

**Temporal Adaptation and Continuous Learning**

As consumer preferences and city dynamics evolve, the ability to retrain and adapt models over time will be crucial. Building pipelines for continuous model updates with live data streams can ensure the system remains relevant, accurate, and responsive in fast-changing urban environments. Continuous learning mechanisms are essential for maintaining the efficacy of AI systems in dynamic settings, as evidenced by their application in energy management and healthcare (Gao et al., 2024; Varnosfaderani & Forouzanfar, 2024).

**Cross-Domain Applications**

Finally, the analytical framework developed here is transferable to other domains beyond restaurants, such as retail site selection, cultural event forecasting, smart tourism systems, and public space utilization studies—wherever human movement, timing, and decision-making intersect. The versatility of AI-driven models underscores their potential to address complex challenges across various sectors, including energy systems and healthcare (Gao et al., 2024; Varnosfaderani & Forouzanfar, 2024).

Pursuing these future directions will not only expand the scope and reliability of the framework but also reinforce its relevance in shaping intelligent, data-driven cities of tomorrow.

In conclusion, this project serves as a robust demonstration of how the core principles of Management Information Systems (MIS) can be applied to a complex, real-world challenge. By transforming raw, multidimensional behavioral data into structured, predictive, and interpretable outputs, we showcased how technology, analytics, and strategy can converge to address urban operational and planning needs. The integration of advanced models—LSTM for forecasting, KAN for segmentation, and DCM for interpretability—provides a comprehensive toolkit for stakeholders aiming to enhance decision-making processes in dynamic urban environments.

KAN for classification, and DCM for behavioral interpretation—illustrates the potential of hybrid systems that combine machine learning with economic reasoning.

These models not only provided accurate predictions but also delivered actionable insights that align with real-world decision-making contexts, enabling smarter planning, optimized logistics, and customer-centric business strategies. Their interpretability and adaptability make them suitable for deployment across a range of industries beyond the restaurant sector, including transportation, public services, retail, and urban development. As cities become increasingly data-driven, the blueprint presented in this study offers a scalable, transferable framework that supports more intelligent, responsive, and equitable systems of service delivery and urban governance.

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**Appendices**

**Appendix A: Sample Dataset Structure**

* RAW\_VISIT\_COUNTS
* DISTANCE\_FROM\_HOME
* MEDIAN\_DWELL
* HOURLY\_MEAN\_VISITS
* NORMALIZED\_VISITS\_BY\_TOTAL\_VISITS

**Appendix B: KAN Feature Matrix**

|  |  |
| --- | --- |
| **Feature** | **Description** |
| hourly\_mean | Avg hourly visit count |
| hourly\_std | Visit variability |
| distance | Visitor origin distance |
| median\_dwell | Avg stay duration |

**Appendix C: DCM Coefficient Table**

|  |  |  |
| --- | --- | --- |
| Variable | Coefficient | Interpretation |
| Quality | +0.57 | Strongly positive effect |
| Dwell | +0.39 | Positive engagement effect |
| Distance | -0.33 | Negative, disincentive |
| Popularity | -0.31 | Slight crowding deterrent |

**Appendix D: Tools and Technologies Used**

* Programming Language: Python 3.10
* Libraries: TensorFlow, PyKAN, Statsmodels, Pandas, NumPy, Scikit-learn, Matplotlib
* IDE: Jupyter Notebook, Visual Studio Code

**Appendix E: KAN Architecture**

A network of lines and dots

AI-generated content may be incorrect.

**Figure : KAN Architecture**

**Appendix F: Acknowledgments** We would like to thank our faculty advisor, Professor Carlos D. Paternina Arboleda, for his guidance and encouragement throughout this project. We also extend gratitude to SDSU’s MIS department and our data source partners for enabling this research. Lastly, we thank our peers and reviewers who provided valuable feedback during development and rehearsal sessions.

**AI Usage Disclaimer**

I acknowledge the use of generative AI tools during the preparation of this final report, titled Modeling Visitor Travel Patterns to Restaurants in Complex Urban Environments. The following details the specific ways in which these tools were utilized:

Writing Support: AI tools (e.g., ChatGPT) were used to paraphrase and enhance language, and to help draft, expand, and refine various sections of the report. All final edits were reviewed and approved by me.

Language & Grammar Enhancement: ChatGPT was used to improve clarity, grammar, and sentence structure throughout the document, especially for professional tone and consistency.

Code Assistance: AI tools were used to help debug, format, and optimize Python code for LSTM, KAN, and DCM model implementation. While AI offered recommendations for improving model efficiency and readability, all code was manually verified, executed, and interpreted by me.

Data Interpretation & Visualization: ChatGPT provided suggestions for interpreting quantitative results and structuring corresponding visualizations. All graphs, charts, and visual summaries were created and validated independently using tools like Matplotlib and Seaborn.

Citation & Formatting Help: AI was consulted to format APA-style citations and to cross-reference sources efficiently. Every citation included in the report was manually reviewed to ensure its accuracy and relevance.

I confirm that these tools were used strictly as support resources. The analysis, decisions, and interpretations in this report reflect my own critical thinking and academic effort. I take full responsibility for the integrity and originality of all submitted work.