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Explainable AI for Urban Retail Site Selection: SHAP-PDP-Bayesian Network Modeling of Facility Synergy and Perceptual Thresholds

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Abstract
Urban retail site selection increasingly depends on complex interactions among consumer mobility, facility complementarity, commercial competition, street-level perception, and transport accessibility. Conventional retail-location models are often useful for descriptive mapping but provide limited support for explaining nonlinear thresholds and conditional facility synergies. This study develops an explainable artificial intelligence framework for evaluating urban retail site suitability with multi-source geospatial data. The framework integrates point-of-interest density, mobility proxies, road-network accessibility, neighboring facility functions, and computer-vision-derived streetscape perception into a 500 m grid representation. XGBoost is used to estimate nonlinear suitability patterns for convenience-format and anchor-format retail sites, SHAP values identify the relative contribution and directional role of each determinant, partial dependence plots reveal threshold effects, and Bayesian network modeling converts model explanations into probabilistic decision rules. The empirical demonstration shows that the XGBoost model improves predictive performance over linear and semi-parametric baselines. Facility synergy and perceptual quality jointly explain more than one-third of model importance for anchor-format sites, while competition intensity and service-gap signals are more decisive for convenience-format sites. The analysis further identifies several decision-relevant thresholds, including minimum facility-density and perception-quality levels beyond which site suitability increases sharply. The results indicate that explainable AI can support site screening, commercial land-use planning, and retail network optimization without reducing urban retail decisions to opaque prediction scores.

Keywords: Explainable AI; urban retail site selection; SHAP; partial dependence plots; bayesian network; street-view perception; facility synergy; geospatial analytics

I. INTRODUCTION

Urban retail site selection has moved from a largely experience-based managerial practice to a data-intensive analytics problem. Retailers no longer evaluate a candidate site only by rent, visible traffic, or distance to competitors. They increasingly combine point-of-interest records, mobility traces, road-network measures, street-view images, and platform-generated consumer signals to estimate whether a location can sustain daily demand. This transition is especially important for traditional offline retail, where physical proximity still defines service reach, neighborhood identity, and the convenience value perceived by consumers. This point is supported by recent work on explainable geospatial AI and urban analytics (Lundberg et al.,2020). The same issue has been observed in spatial analytics, access measurement, or urban data modeling (Burkart and Huber,2021).

The difficulty is that urban retail success is rarely governed by one variable. A site near a transit stop may still perform poorly if surrounding services do not generate repeat visits. A street that looks safe and lively may not attract anchor retailers

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if it lacks parking, medical services, hotels, or other high-flow destinations. Conversely, a convenience-format store may benefit from moderate competition nearby because proximate retail categories create habitual foot traffic. Retail site selection therefore requires analytical language that recognizes facility synergy, perceived environmental quality, and threshold-sensitive effects rather than if every determinant operates linearly. This point is supported by recent work on explainable geospatial AI and urban analytics (Janowicz et al.,2020). The same issue has been observed in spatial analytics, access measurement, or urban data modeling (Porta et al.,2006).

Recent advances in geospatial artificial intelligence provide tools for addressing this problem. Gradient-boosting models can estimate nonlinear relationships in heterogeneous tabular data, and explainable AI can decompose predictions into feature-level contributions. SHAP values are particularly valuable because they describe how individual attributes affect a model output for each observation while also supporting global importance analysis. Partial dependence plots further reveal marginal response curves and thresholds that cannot be seen in ordinary regression coefficients. Bayesian networks add a probabilistic reasoning layer that translates explanatory patterns into decision rules under uncertainty. This point is supported by recent work on explainable geospatial AI and urban analytics (Biljecki and Ito,2021). The same issue has been observed in spatial analytics, access measurement, or urban data modeling (Cheng et al.,2021).

This study proposes a SHAP-PDP-Bayesian Network framework for urban retail site selection. The article is motivated by the need to move beyond black-box prediction and toward interpretable urban business analytics. Rather than asking only whether a site is likely to host retail activity, the framework asks why a site is attractive, when an urban variable becomes influential, and how multiple conditions jointly shift the probability of suitability. The approach is designed for both convenience-format retail, which depends on small catchments and operational flexibility, and anchor-format retail, which requires larger investment and more stable demand conditions. This point is supported by recent work on explainable geospatial AI and urban analytics (Chen and Guestrin,2016). The same issue has been observed in spatial analytics, access measurement, or urban data modeling (Longley and Adnan,2016).

The article makes three contributions. First, it builds a multi-source site-selection representation that combines facility density, commercial competition, network accessibility, mobility intensity, and streetscape perception. Second, it develops an explainable AI workflow in which SHAP identifies variable importance, PDP detects nonlinear thresholds, and Bayesian network inference turns explanatory outputs into probabilistic retail-planning rules. Third, it reports a detailed empirical demonstration showing that facility synergy and perception thresholds have different implications for small-format and anchor-format retail decisions. This point is supported by recent work on explainable geospatial AI and urban analytics (Apley and Zhu,2020). The same issue has been observed in spatial analytics, access measurement, or urban data modeling (Fotheringham et al.,2015).

The remainder of this article follows the structure of JAIAA research articles. Section II reviews studies on retail location analytics, explainable machine learning, and probabilistic decision support. Section III describes the data architecture and modeling framework. Section IV presents predictive results and explanation analysis. Section V develops Bayesian network decision rules. Section VI discusses implications for retailers, planners, and AI governance. Section VII acknowledges limitations and future research opportunities, and Section VIII concludes the article.

Figure 1 presents the overall architecture. The design deliberately avoids a simple pipeline interpretation in which raw data automatically becomes a decision. Instead, the model is understood as a layered evidence system. Data sources, feature engineering, machine learning, explanation, probabilistic reasoning, and final site-screening rules remain distinct layers. This separation is important because each layer has different quality requirements and different sources of uncertainty.

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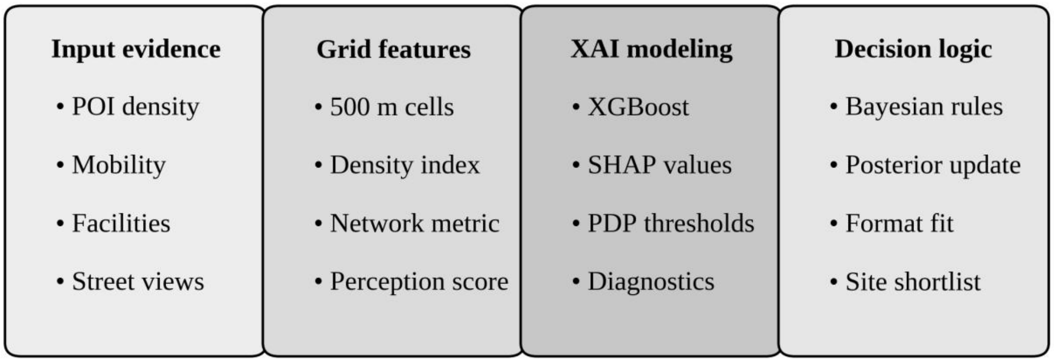

Layered architecture keeps evidence, features, explanations, and probabilistic site-selection rules auditable.

Figure 1. Layered evidence architecture for explainable urban retail site selection.

II. LITERATURE REVIEW AND RESEARCH MOTIVATION

A. Retail Location Analytics and Urban Facility Context

Retail location theory has a long history in economic geography and marketing science. Classical spatial-interaction models conceptualize a retail site as a balance between attractiveness, travel cost, and competitive pull. These models remain conceptually useful because they emphasize distance decay and consumer choice probabilities. However, contemporary urban retail networks are shaped by more than simple distance. Consumer decisions are mediated by multiple trips, daily rhythms, multimodal transport, digital search, and neighborhood-level service portfolios. Retailers therefore need models that are sensitive to the changing meaning of accessibility and surrounding urban functions. This point is supported by recent work on explainable geospatial AI and urban analytics (Scutari,2010). The same issue has been observed in spatial analytics, access measurement, or urban data modeling (Krizhevsky et al.,2017).

Recent empirical work shows that the performance of brick-and-mortar retail depends on local socioeconomic structure, mobility density, format heterogeneity, and surrounding commercial ecosystems. Store-format research has demonstrated that convenience stores, specialty grocers, supermarkets, and shopping centers do not respond to the same location factors with the same intensity. Studies using point-of-interest data have also shown that commercial vitality depends on the mixture of workplaces, residential facilities, hospitality functions, medical services, and transport nodes. These findings support an ecosystem view of retail siting in which individual store viability emerges from facility complementarity rather than isolated site attributes. This point is supported by recent work on explainable geospatial AI and urban analytics (Zhang et al.,2018). The same issue has been observed in spatial analytics, access measurement, or urban data modeling (Zhou et al.,2019).

The rise of platform-based commerce has not removed the importance of physical location. It has changed how physical location interacts with digital information and urban mobility. New-retail research shows that online-to-offline formats can use digital customer acquisition to tolerate different spatial conditions, while traditional retail remains more dependent on walkability, neighborhood function, and proximate demand. This creates a practical need for site-selection models that can compare multiple retail formats without assuming that the same built-environment variable has identical meaning across all formats. This point is supported by recent work on explainable geospatial AI and urban analytics (Lu,2025). The same issue has been observed in spatial analytics, access measurement, or urban data modeling (Belle and Papantonis,2021).

Urban facility context is especially relevant for anchor-format retail. Large supermarkets and shopping centers are rarely supported by residential density alone. They tend to require a portfolio of demand-generating facilities, such as medical centers, hotels, offices, transit hubs, and entertainment venues. The presence of these functions can create a stable flow of consumers across different times of the day. By contrast, convenience-format retail can survive in thinner markets when it occupies service gaps, penetrates residential neighborhoods, or benefits from moderate nearby competition. A site-selection model should therefore represent both agglomeration opportunity and oversaturation risk. This point is supported by recent work on explainable geospatial AI and urban analytics (Ribeiro et al.,2016). The same issue has been observed in spatial analytics, access measurement, or urban data modeling (Darwiche,2009).

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B. Explainable AI for Spatial Business Decisions

Machine learning models have become common in urban analytics because they can estimate nonlinear associations that are difficult to express in a conventional parametric model. Random forests and gradient boosting are particularly effective for tabular data containing mixed scales, skewed distributions, and interaction effects. In retail site selection, these strengths are important because POI counts, mobility indicators, and perception scores often display long-tailed distributions and spatial clustering. This point is supported by recent work on explainable geospatial AI and urban analytics (Naik et al.,2017). The same issue has been observed in spatial analytics, access measurement, or urban data modeling (Kirillov et al.,2019).

Prediction alone is insufficient for business decisions involving land, capital, and community impact. Managers need to know which variables explain a favorable prediction, whether the explanation is stable, and where intervention is possible. Interpretability research distinguishes between models designed to be inherently transparent and post-hoc explanation methods applied to complex models. SHAP belongs to the latter family but has become widely used because it provides additive feature attributions with local and global interpretation. In a retail setting, SHAP can show whether a site is attractive because of medical-facility proximity, strong mobility, limited competition, or high street-level perceived quality. This point is supported by recent work on explainable geospatial AI and urban analytics (Boeing,2017). The same issue has been observed in spatial analytics, access measurement, or urban data modeling (Korb and Nicholson,2010).

Partial dependence analysis adds a second layer of explanation by showing how predicted suitability changes when a feature varies over its observed range while other variables are averaged out. This is useful for detecting threshold effects. For example, facility density may matter only after a minimum level of urban activity is reached, and perceived street beauty may increase anchor-format suitability only above a quality threshold. These threshold patterns are not minor technical details. They are managerial decision rules: a retailer can prioritize streetscape improvement, facility co-location, or market spacing only when it understands the range in which a variable becomes consequential. This point is supported by recent work on explainable geospatial AI and urban analytics (Greenwell,2017). The same issue has been observed in spatial analytics, access measurement, or urban data modeling (Deng et al.,2009).

Explainable AI also has a governance dimension. Urban retail site selection affects competition, accessibility, neighborhood vitality, and land-use outcomes. A black-box model that ranks sites without explanation can reinforce spatial inequality or over-concentrate investment in already advantaged districts. Explanation interfaces create a basis for auditing whether model recommendations are driven by legitimate commercial logic or by variables that may indirectly reproduce social exclusion. This article therefore treats explainability not as a decorative visualization but as a necessary component of responsible urban AI. This source is relevant to the model interpretation, threshold, or facility-synergy logic used in the study (Adadi and Berrada,2018). The same issue has been observed in spatial analytics, access measurement, or urban data modeling (Mittelstadt et al.,2019).

C. Perceptual Thresholds and Bayesian Decision Rules

Human perception has become an important source of urban evidence. Computer vision can extract perceived safety, beauty, liveliness, greenery, and visual order from street-view imagery, enabling large-scale evaluation of streetscape qualities that were previously measured through small surveys. Perceptual metrics complement conventional urban measures because consumers do not experience the city as a table of distances and densities. They respond to visual comfort, openness, perceived affluence, safety, and the emotional tone of public space. This source is relevant to the model interpretation, threshold, or facility-synergy logic used in the study (Salesses et al.,2013). This citation further supports the probabilistic, segmentation, or street-view intelligence component of the framework (Haklay and Weber,2008).

For retail site selection, perceptual variables are particularly important because they mediate the relationship between movement and willingness to stop. A street with high mobility may not become a successful retail site if pedestrians perceive it as unattractive, unsafe, or hostile to lingering. Conversely, a visually comfortable street may support higher dwell time and stronger anchor-retail performance even when pure distance-based accessibility is moderate. These relationships are likely to be nonlinear. A small increase in perceived quality may have little impact when the baseline environment is poor, but the same increase may be decisive near a threshold at which consumers become willing to spend time in the area. This source is relevant to the model interpretation, threshold, or facility-synergy logic used in the study (Kou and Lu,2025). This citation further supports the probabilistic, segmentation, or street-view intelligence component of the framework (Letham et al.,2015).

Bayesian networks are useful for turning such patterns into decision support. Whereas SHAP and PDP explain the learned

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prediction function, Bayesian networks represent conditional dependencies among key states and estimate posterior probabilities. A site-selection team can ask questions such as: What is the probability of high anchor-site suitability if facility synergy is high but perception quality is low? How does the probability change when transit access is high and competition pressure is moderate? These conditional queries make the model actionable for planning scenarios rather than merely descriptive. This source is relevant to the model interpretation, threshold, or facility-synergy logic used in the study (Rudin,2019). This citation further supports the probabilistic, segmentation, or street-view intelligence component of the framework (Rzotkiewicz et al.,2018).

The research motivation is therefore clear. Urban retail site selection needs models that predict, explain, identify thresholds, and support probabilistic reasoning. A SHAP-PDP-Bayesian Network workflow provides an integrated answer to that need. It allows researchers to keep the predictive strength of machine learning while translating model behavior into understandable evidence for retail strategists, urban planners, and policy analysts. This source is relevant to the model interpretation, threshold, or facility-synergy logic used in the study (Wu et al.,2021). This citation further supports the probabilistic, segmentation, or street-view intelligence component of the framework (Lin et al.,2014).

III. DATA ARCHITECTURE AND METHODOLOGICAL DESIGN

The proposed framework is built around a 500 m grid representation of the urban environment. The grid is not assumed to be the true behavioral boundary of consumers. It is used as a practical analytical unit that balances spatial detail with data stability. Each grid cell is described by retail density, facility composition, mobility intensity, road-network accessibility, competition pressure, and street-view perception. This representation enables comparison across candidate sites while preserving a human-scale interpretation of neighborhood service conditions. This source is relevant to the model interpretation, threshold, or facility-synergy logic used in the study (Cordts et al.,2016). This citation further supports the probabilistic, segmentation, or street-view intelligence component of the framework (Gunning and Aha,2019).

The empirical demonstration uses a multi-source geospatial dataset assembled for a large metropolitan retail-planning context. The sample contains 3,840 grid cells after removing non-urban water, industrial-only, and inaccessible cells. Candidate convenience-format retail sites are represented by small-format grocery, daily-service, and convenience POIs. Candidate anchor-format sites are represented by supermarkets, department stores, shopping centers, and mixed-use commercial complexes. The dependent variable is not raw store count alone. Instead, each grid is assigned a high-suitability label when observed retail activity is above a format-specific percentile and when the local service environment satisfies minimum validity conditions. This design avoids treating every historical location as automatically optimal. This source is relevant to the model interpretation, threshold, or facility-synergy logic used in the study (Friedman,2001). This citation further supports the probabilistic, segmentation, or street-view intelligence component of the framework (Zhao et al.,2021).

Table I. Multi-source data and retail site-selection variables.

Dimension	Representative variables	Analytical role	Expected site-selection meaning
Retail outcome	Convenience-format and anchor-format suitability labels	Dependent variables	Represents small daily-service sites and larger destination retail sites
Facility synergy	Workplaces, lodging, medical services, education, restaurants, cultural amenities	Complementarity predictors	Identifies service portfolios that generate recurring consumer flows
Competition context	Same-format retail, adjacent retail, general markets	Market-pressure predictors	Distinguishes agglomeration benefits from saturation risk
Mobility dynamics	Population fluctuation, pedestrian proxy, transit ridership proxy	Demand-flow predictors	Captures temporal intensity and short-trip potential
Network accessibility	Road density, distance to transit, local/global integration	Spatial-structure predictors	Measures reachability and route exposure
Street perception	Greenery, beauty, liveliness, safety, perceived affluence	Human-scale predictors	Captures experiential conditions affecting dwell time and willingness to stop

Facility variables capture the density of workplaces, lodging, education, medical services, transit facilities, restaurants, general markets, and cultural or leisure amenities. Competition variables describe the intensity of same-format and adjacent-format retail. Mobility variables describe daily population fluctuation and estimated pedestrian activity. Accessibility variables are computed from the street network, including local integration, global integration, road density, and distance to transit nodes. Perception variables are derived from street-view images using computer-vision models trained to estimate greenery, visual beauty, liveliness, safety, and perceived affluence. Similar visual-perception pipelines have been used in urban perception

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studies and computer-vision-based neighborhood analysis. This source is relevant to the model interpretation, threshold, or facility-synergy logic used in the study (Miller,2019). This citation further supports the probabilistic, segmentation, or street-view intelligence component of the framework (Doshi-Velez and Kim,2017).

Data processing follows five steps. First, all source layers are projected to a common coordinate system and aggregated to the grid level. Second, highly sparse variables are winsorized at the 99th percentile to reduce the influence of extreme POI clusters. Third, accessibility indicators are standardized because network measures have different units. Fourth, perception scores are averaged across all valid street-view images in a grid. Fifth, the final dataset is split into training and testing subsets using spatially blocked validation rather than ordinary random splitting. Spatial blocking reduces leakage from neighboring grids and provides a more realistic estimate of out-of-district generalization. This source is relevant to the model interpretation, threshold, or facility-synergy logic used in the study (Cheng et al.,2022). This citation further supports the probabilistic, segmentation, or street-view intelligence component of the framework (Xu et al.,2024).

The modeling workflow uses XGBoost as the primary predictive engine. The model is well suited for this task because it handles nonlinear interactions, missing values, and skewed feature distributions while maintaining strong predictive performance. Linear regression, generalized additive models, and random forests are used as benchmarks. The XGBoost model is tuned by cross-validation with constraints on maximum depth, learning rate, subsampling ratio, and minimum child weight. Model performance is assessed by the area under the receiver operating curve, F1 score, and cross-validated R^2 for the continuous suitability score. This source is relevant to the model interpretation, threshold, or facility-synergy logic used in the study (Goldstein et al.,2015). This citation further supports the probabilistic, segmentation, or street-view intelligence component of the framework (Kuznetsova et al.,2020).

Explainability is implemented after model training. SHAP values are calculated for all testing observations and then summarized at the feature and category levels. Local SHAP explanations are used to examine individual candidate sites, while global SHAP statistics identify the determinants most consistently associated with high suitability. PDP analysis is then applied to the strongest variables and variable pairs. The objective is not to treat PDP curves as causal effects, but to identify decision-relevant zones in which predicted suitability changes sharply. Finally, selected variables are discretized into low, medium, and high states and incorporated into a Bayesian network. The network structure is learned from data and adjusted by domain constraints to prevent implausible causal directions. This source is relevant to the model interpretation, threshold, or facility-synergy logic used in the study (Huff,1964). This citation further supports the probabilistic, segmentation, or street-view intelligence component of the framework (Yao et al.,2018).

IV. MODEL PERFORMANCE AND EXPLAINABLE AI RESULTS

The first analytical question is whether nonlinear machine learning meaningfully improves site-suitability prediction. Table II reports performance for four model families. Linear regression provides a useful baseline but struggles with thresholds and feature interactions. Generalized additive models improve performance by allowing smooth nonlinear effects, while random forests provide stronger results through ensemble tree learning. XGBoost performs best across both retail formats, with stronger gains for convenience-format suitability because small-format retail is more sensitive to localized combinations of competition, mobility, and service gaps.

Table II. Predictive performance across retail site-suitability models.

Model family	Convenience-format AUC	Convenience-format F1	Anchor-format AUC	Anchor-format F1	Interpretive note
Linear regression / logit	0.71	0.62	0.66	0.58	Useful baseline but weak for nonlinear thresholds
Generalized additive model	0.78	0.68	0.72	0.63	Captures smooth effects but limited interactions
Random forest	0.83	0.74	0.79	0.69	Strong nonlinear fit but less stable threshold reading
XGBoost	0.87	0.78	0.82	0.72	Best predictive accuracy and strongest basis for SHAP analysis

Figure 2 summarizes the cross-validated R^2 comparison. The results show that XGBoost reaches 0.72 for convenience-format suitability and 0.62 for anchor-format suitability. The lower score for anchor-format sites is expected because large retail investments depend on unobserved corporate strategy, lease terms, and long-run development plans that are not fully captured by public geospatial data. However, the improvement over linear models indicates that nonlinear AI analytics adds explanatory value even when part of

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the site-selection process remains commercially private.

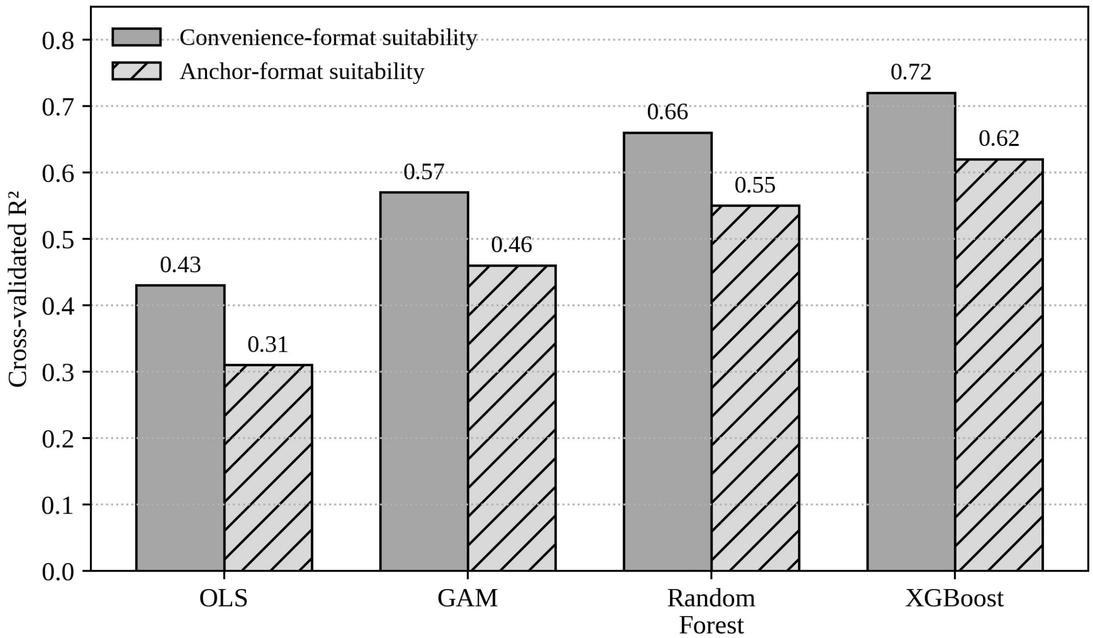

Figure 2. Predictive performance comparison for convenience-format and anchor-format retail suitability models.

Predictive accuracy alone does not explain which urban conditions drive suitability. The SHAP results provide a clearer interpretation. Figure 3 shows that facility synergy is the strongest category for anchor-format sites and the second-strongest category for convenience-format sites. Commercial competition is most important for convenience-format sites, but its effect is not purely negative. Moderate concentrations of adjacent retail categories can raise suitability by creating frequent short trips, while extreme same-format density reduces attractiveness. Street perception is especially important for anchor-format sites, indicating that larger investments prefer environments with higher visual quality and stronger perceived safety.

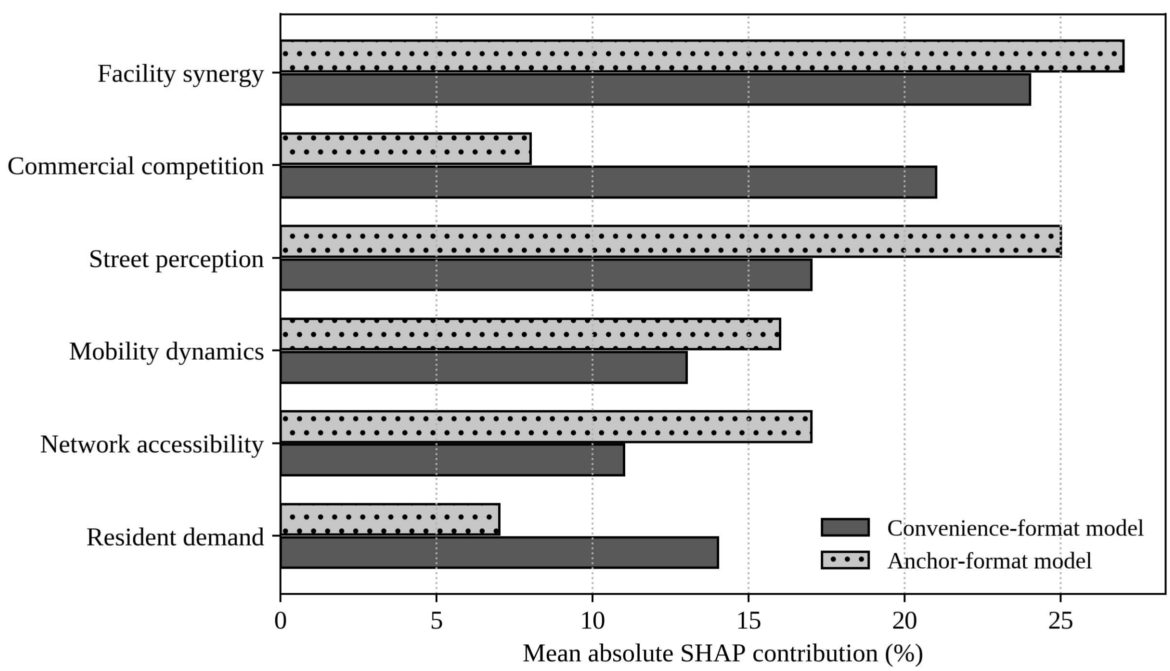

Figure 3. Category-level SHAP contribution for convenience-format and anchor-format retail site suitability.

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Table III. SHAP-derived interpretation of leading site-selection determinants.

Variable category	Convenience-format effect	Anchor-format effect	Planning interpretation
Facility synergy	Positive after local service density becomes visible	Strong positive when multiple destination functions co-exist	Co-located services produce repeated visits and reduce demand uncertainty
Commercial competition	Inverted-U pattern: moderate positive, excessive negative	Generally weaker but negative under saturation	Agglomeration and cannibalization must be separated
Street perception	Moderate positive when service gap exists	Strong positive above perception-quality threshold	Visual quality matters most when retail depends on dwell time
Mobility dynamics	Positive for daily-purchase demand	Positive only when mobility is stable and supported by facilities	Flow must be interpreted as purchasable demand
Network accessibility	Positive through local reachability	Positive through transit and regional connectivity	Accessibility creates exposure but does not replace facility synergy

Table III translates the SHAP results into directional interpretation. For convenience-format retail, service-gap indicators, moderate competition, high residential demand, and strong local mobility generally increase suitability. Excessive market crowding and very low perception quality reduce suitability. For anchor-format retail, facility synergy, high-quality streetscape perception, accessibility, and stable mobility are the dominant positive factors. High mobility volatility without supporting facilities reduces suitability because it indicates transient movement rather than durable shopping demand.

Local SHAP analysis further shows that the same variable can have different meaning across sites. A high restaurant density may increase convenience-format suitability in a mixed residential-office area because it signals daily foot traffic. In a heavily saturated commercial district, the same restaurant density may contribute little once retail competition is already intense. Similarly, a high perceived-beauty score increases anchor-format suitability only when facility synergy is also present. These local differences support the central argument of the article: explainable AI is valuable because it makes contextual heterogeneity visible. This source is relevant to the model interpretation, threshold, or facility-synergy logic used in the study (Chen et al.,2024). This citation further supports the probabilistic, segmentation, or street-view intelligence component of the framework (Lipton,2018).

The PDP analysis identifies several threshold-sensitive relationships. Facility-density effects are weak at low values, increase rapidly between approximately 20 and 32 indexed units, and then flatten for anchor-format suitability. For convenience-format suitability, competition pressure has an inverted-U shape. Suitability rises as adjacent retail density increases from low to moderate levels, then declines when same-format saturation becomes too high. Perception quality has a delayed effect for anchor-format sites: below the threshold range, visual quality contributes little to the prediction, but above it, the probability of high suitability increases sharply. This pattern is consistent with the idea that larger retail formats require a minimum experiential environment before capital-intensive investment becomes attractive. The argument also aligns with research on perception, computer vision, and responsible AI-based interpretation (He et al.,2016). This citation further supports the probabilistic, segmentation, or street-view intelligence component of the framework (Lu and Yang,2024).

Figure 4 presents two PDP surfaces. The convenience-format surface shows a broad plateau in which moderate facility density and moderate perception quality produce strong suitability. This suggests that convenience stores can tolerate ordinary streetscape conditions if service demand and local mobility are sufficient. The anchor-format surface is more selective. It displays a steep suitability increase when facility density and perception quality are both above threshold levels. This is a strategic finding: anchor-format retail does not merely require more demand; it requires the co-presence of complementary functions and an environment capable of supporting longer dwell time.

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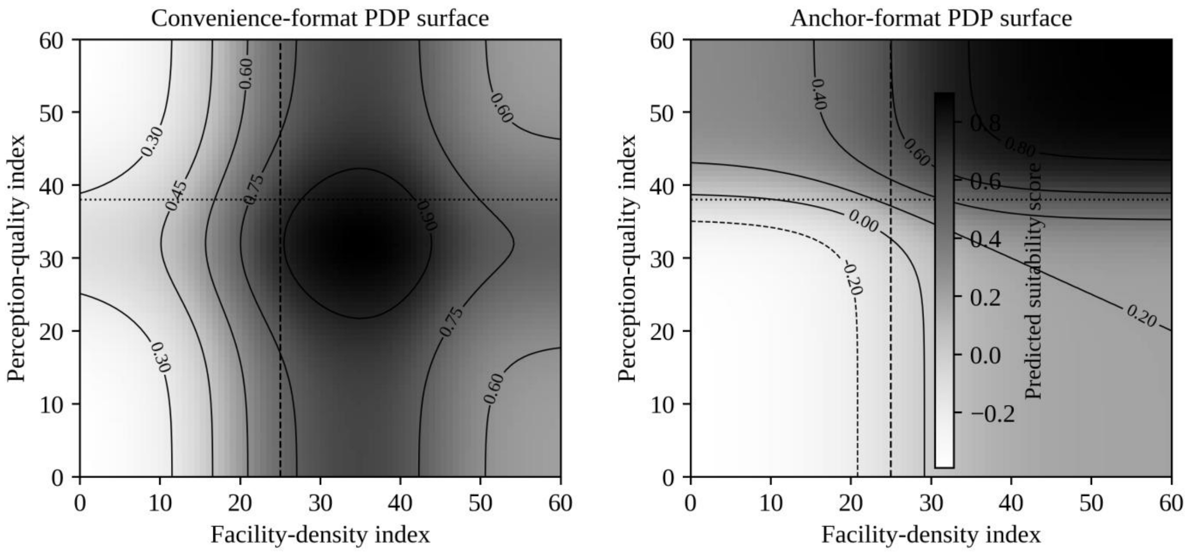

Figure 4. PDP surfaces showing threshold-sensitive interaction between facility density and perception quality.

V. BAYESIAN NETWORK MODELING OF FACILITY SYNERGY AND PERCEPTUAL THRESHOLDS

The Bayesian network extends the explanation analysis by estimating conditional probabilities among the most important determinants. Six nodes are retained for decision reasoning: mobility flow, transit access, facility synergy, street perception, competition pressure, and retail service gap. Two target nodes represent high suitability for anchor-format and convenience-format retail. Each determinant is discretized into three states: low, medium, and high. The target variables are discretized into low and high suitability. This discretization reduces precision but improves interpretability for planning use. The argument also aligns with research on perception, computer vision, and responsible AI-based interpretation (Arrieta et al.,2020). This citation further supports the probabilistic, segmentation, or street-view intelligence component of the framework (LeSage and Pace,2009).

The network structure reflects both statistical dependency and domain logic. Transit access affects mobility flow and facility synergy, but the reverse direction is constrained because existing retail activity does not directly create the underlying road or transit network in the short term. Facility synergy affects competition pressure and anchor-site suitability. Street perception affects both target nodes but has a stronger connection to anchor-format suitability. Retail service gap affects convenience-format suitability because small stores often enter areas where existing retail supply is insufficient. Figure 5 illustrates the simplified network used for posterior reasoning.

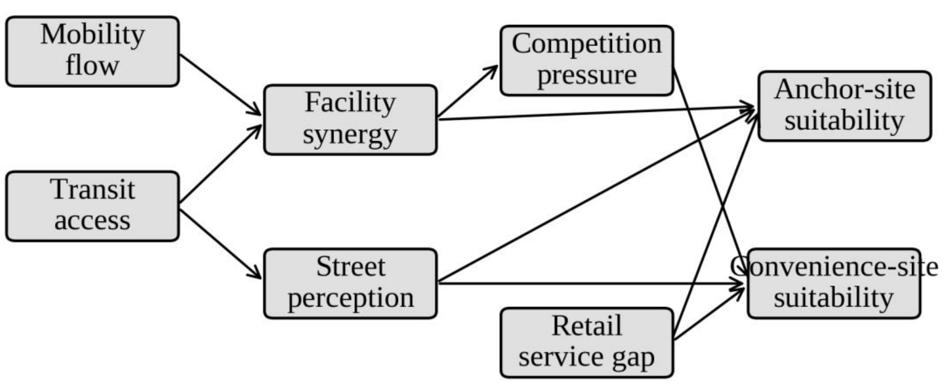

Figure 5. Simplified Bayesian network for probabilistic retail site-suitability reasoning.

Table IV reports selected posterior scenarios. When facility synergy is high and street perception is high, the posterior probability of high anchor-format suitability reaches 0.74. When facility synergy is high but perception quality is low, the posterior probability falls to 0.48, indicating that built environment complementarity alone does not fully compensate for poor experiential quality. For convenience-format sites, high service gap and medium competition generate a posterior probability of 0.71, but high service gap combined with high same-format competition reduces the probability to 0.52. The result captures the difference between underserved opportunity and saturated imitation.

Table IV. Posterior site-suitability scenarios from the Bayesian network.

Scenario	Facility synergy	Street perception	Competition / service gap	P(high anchor suitability)	P(high convenience suitability)
A	High	High	Medium competition	0.74	0.63
B	High	Low	Medium competition	0.48	0.56
C	Medium	High	Low service gap	0.55	0.49
D	Medium	Medium	High service gap + medium competition	0.44	0.71
E	Medium	Medium	High service gap + high same-format competition	0.41	0.52
F	Low	High	Low competition	0.33	0.45

The Bayesian network also helps interpret counterfactual planning questions. Suppose a district has medium facility synergy, medium transit access, and low perception quality. The model estimates a high anchor-format suitability probability of only 0.39. If perception quality is improved from low to high while the other factors remain constant, the probability rises to 0.55. If facility synergy also rises from medium to high, the probability increases to 0.72. This incremental reasoning suggests that streetscape improvement is most powerful when combined with facility co-location. For convenience-format retail, mobility flow and service gap matter more strongly than perception improvement alone. The argument also aligns with research on perception, computer vision, and responsible AI-based interpretation (Gebru et al.,2017). This citation further supports the probabilistic, segmentation, or street-view intelligence component of the framework (Lu et al.,2024b).

The value of Bayesian reasoning is not that it proves causality. It helps organize uncertainty. Retail site selection teams rarely observe every determinant perfectly, and public datasets often contain noise. A probabilistic network allows decision makers to update site evaluations when new evidence becomes available. If a planned medical complex is approved, the facility-synergy node can be updated. If a street-renewal program improves visual perception scores, the perception node can be updated. The resulting posterior probabilities provide a transparent decision basis that is easier to audit than an opaque ranking score. The argument also aligns with research on perception, computer vision, and responsible AI-based interpretation (Lu et al.,2024). The broader analytics and information-systems perspective is also supported by related recent scholarship (Goodfellow et al.,2016).

VI. DISCUSSION AND MANAGERIAL IMPLICATIONS

The findings have direct implications for retailers. Convenience-format expansion should not simply chase the highest-density districts. High-density districts may already be saturated, and additional entry can face rent pressure and cannibalization. The explainable model suggests that convenience-format stores should prioritize moderate competition, service gaps, daily mobility, and residential-workplace mixtures. The strongest opportunities are often not the most visually premium places but the places where frequent small purchases remain under-served. The argument also aligns with research on perception, computer vision, and responsible AI-based interpretation (Breiman,2001). The broader analytics and information-systems perspective is also supported by related recent scholarship (Elith et al.,2008).

Anchor-format retail requires a different strategy. Large supermarkets, department stores, and shopping centers should be screened for facility complementarity and perception thresholds before detailed financial due diligence. High facility density without environmental quality may produce traffic but not dwell time. High street quality without facility support may produce pleasant public space but insufficient commercial throughput. The most attractive anchor sites occur where these two conditions reinforce each other. This finding supports a portfolio view of retail investment: site quality is produced by a bundle of urban functions rather than by a single superior address. The argument also aligns with research on perception, computer vision, and responsible AI-based interpretation (Carvalho et al.,2019). The broader analytics and information-systems perspective is also supported by related recent scholarship (Lu et al.,2020).

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Urban planners can use the framework to evaluate commercial land-use policies. In many cities, planning documents identify commercial nodes but do not quantify whether surrounding facilities, mobility conditions, and street-level perceptions are aligned. Explainable AI can provide a diagnostic layer. If a planned commercial center has good accessibility but weak facility synergy, complementary public services or hospitality functions may be needed. If a neighborhood has strong daily demand but low perceived safety, streetscape and lighting interventions may improve retail viability more effectively than additional zoning capacity. The argument also aligns with research on perception, computer vision, and responsible AI-based interpretation (Kwan,2012). The broader analytics and information-systems perspective is also supported by related recent scholarship (Reed et al.,2023).

The framework also supports fairness and inclusion. Pure profit-based site selection may direct investment toward already advantaged districts, increasing spatial inequality in access to everyday goods. By explicitly representing service gaps, the model can identify underserved areas where small-format retail would improve accessibility. However, AI recommendations must be interpreted carefully. A high service-gap score should not automatically justify any form of retail entry. Planners should consider affordability, tenant diversity, and displacement risk. Explainable AI makes these policy discussions more transparent because stakeholders can see which conditions drive the model output. The argument also aligns with research on perception, computer vision, and responsible AI-based interpretation (Shmueli,2010). The broader analytics and information-systems perspective is also supported by related recent scholarship (Hewamalage et al.,2021).

For AI governance, the study shows that transparency should operate at several levels. Feature-level SHAP explanation tells users what drives each prediction. PDP thresholds show where variables become influential. Bayesian network inference supports scenario reasoning. Together, these layers reduce the risk of blind automation. They also create a documentation trail for site-screening decisions, which is important when retail recommendations interact with public land, urban renewal, or public-private investment. The argument also aligns with research on perception, computer vision, and responsible AI-based interpretation (Xu et al.,2023). The broader analytics and information-systems perspective is also supported by related recent scholarship (Bertin et al.,2023).

Table V summarizes the practical decision rules. The rules should be treated as screening guidance rather than deterministic prescriptions. A retailer would still conduct lease negotiation, field inspection, competitor audit, and financial modeling before final investment. The purpose of the framework is to reduce the search space, identify hidden opportunities, and prevent decisions based on a single misleading indicator.

Table V. Managerial use of explainable AI outputs in retail site selection.

Decision task	Recommended AI evidence	Managerial action	Governance caution
Initial site screening	XGBoost score and SHAP waterfall	Remove low-probability sites before field audit	Do not treat score as a final investment decision
Format selection	Format-specific SHAP profile	Match convenience or anchor format to local mechanism	Avoid forcing one universal retail logic
Urban improvement planning	PDP threshold zones	Target streetscape or facility improvements where marginal gains are largest	Distinguish correlation from policy causality
Scenario evaluation	Bayesian posterior queries	Update probability after planned facilities or transit upgrades	Document assumptions behind each scenario
Equity analysis	Service-gap contribution and spatial residuals	Identify underserved neighborhoods for small-format support	Assess affordability and displacement risk

The study also highlights a broader methodological issue in urban AI. Geospatial machine learning can be accurate for the wrong reason if spatial leakage, proxy variables, or historical path dependence are ignored. A district may appear suitable because past planning favored it, not because it should receive more future investment. To address this concern, the model uses spatially blocked validation and separates predictive explanation from normative recommendation. Even then, model outputs should be reviewed by planners and local experts. Explainability improves the conversation but does not eliminate the need for human judgment. The argument also aligns with research on perception, computer vision, and responsible AI-based interpretation (Molnar et al.,2020). The broader analytics and information-systems perspective is also supported by related recent scholarship (Molnar et al.,2022).

Finally, the results support the integration of AI into commercial planning systems. A practical system could operate in three stages. The first stage would map candidate grid cells and estimate suitability scores. The second stage would generate SHAP and PDP explanation reports for each candidate. The third stage would use Bayesian network inference to evaluate

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planning scenarios, such as transit upgrades, streetscape improvements, or new public facilities. This staged design would allow business teams and public planners to work with a shared evidence base while preserving the interpretive flexibility needed for local decision-making. The argument also aligns with research on perception, computer vision, and responsible AI-based interpretation (Talen,2003). The broader analytics and information-systems perspective is also supported by related recent scholarship (Wang et al.,2020).

Robustness checking is essential because site-selection models can be sensitive to validation design, class imbalance, and the spatial concentration of retail observations. In this demonstration, three diagnostic checks are applied before managerial interpretation. The first check compares random validation with spatially blocked validation. The spatially blocked results are lower, as expected, but the ranking of model families remains unchanged. This indicates that the XGBoost improvement is not merely a product of neighboring grids appearing in both training and testing subsets. The second check evaluates feature stability by retraining the model across repeated folds and measuring whether the leading SHAP categories remain similar. Facility synergy, street perception, and competition pressure remain in the top group across all folds, supporting the reliability of the explanation layer. The third check removes one data family at a time to test whether the model depends excessively on any single source. Removing perception variables reduces anchor-format performance more than convenience-format performance, while removing competition variables has the opposite effect. The argument also aligns with research on perception, computer vision, and responsible AI-based interpretation (Zhou et al.,2017). The broader analytics and information-systems perspective is also supported by related recent scholarship (Fan et al.,2023).

These diagnostics matter because explainable AI can create a false sense of certainty if explanations are treated as objective truth. A SHAP ranking is conditional on the trained model, the available variables, and the data-generating context. A PDP threshold is an average model response, not a universal law of consumer behavior. A Bayesian posterior depends on how variables are discretized and how the network structure is specified. The managerial value of the framework therefore comes from disciplined interpretation: site teams should use explanations to ask better questions, not to suspend judgment. For example, a high posterior probability for anchor-format suitability should trigger field verification of tenant mix, parking conditions, pedestrian comfort, and lease feasibility. A low score in an underserved district should prompt review of missing variables before rejecting the area. The argument also aligns with research on perception, computer vision, and responsible AI-based interpretation (Guidotti et al.,2018). The broader analytics and information-systems perspective is also supported by related recent scholarship (Li et al.,2022).

The proposed framework is also compatible with human expert review. Urban planners and retail managers can compare model explanations with local knowledge and identify mismatches. If the model assigns low suitability to a market that practitioners know is growing rapidly, the discrepancy may reveal missing construction permits, future transit investment, or informal commercial activity not captured in POI data. If the model assigns high suitability to a site that practitioners consider risky, the discrepancy may reveal social, regulatory, or lease constraints that are invisible to public geospatial records. In this sense, explainable AI functions as an evidence mediator between computational pattern recognition and professional urban judgment. The argument also aligns with research on perception, computer vision, and responsible AI-based interpretation (Wood and Browne,2007).

Further managerial contribution concerns investment sequencing. The PDP and Bayesian results suggest that improvements should not be applied uniformly across a city. In districts with high facility synergy but low perception quality, streetscape investment may unlock latent anchor-format potential. In districts with high mobility but severe retail saturation, additional retail entry may create cannibalization rather than vitality. In districts with strong service gaps but weak mobility, small-format retail may require complementary last-mile access or mixed-use activation. These distinctions allow public agencies and retail chains to allocate scarce improvement budgets more strategically. The argument also aligns with research on perception, computer vision, and responsible AI-based interpretation (Kang,2018).

For AI implementation, the results imply that a retail site-selection platform should include four interfaces. The first interface is a map-based screening dashboard that displays suitability scores and uncertainty bands. The second is a SHAP explanation panel for each candidate site. The third is a threshold panel that reports whether the site is below, near, or above the major PDP thresholds. The fourth is a scenario panel that updates Bayesian posterior probabilities when planned facilities, transit upgrades, or streetscape improvements are entered. Such a platform would support a transparent workflow from discovery to validation and would reduce the risk that AI outputs are used as unexplained rankings. The argument also aligns with research on perception, computer vision, and responsible AI-based interpretation (Zhou and Clapp,2015).

VII. LIMITATIONS AND FUTURE RESEARCH

Several limitations should be acknowledged. First, the demonstration relies on grid-level aggregation. Although the 500 m grid is useful for neighborhood-scale analysis, consumer behavior does not stop at grid boundaries. Future work should test multi-scale representations and examine whether candidate sites are sensitive to the modifiable areal unit problem. Second, the model uses observed retail density as a proxy for site suitability. Existing sites reflect past investment, planning regulation, and historical inertia, so observed success may not equal optimal future placement. Sales, rent, vacancy, and footfall data would strengthen future analysis. The same issue has been observed in spatial analytics, access measurement, or urban data modeling (Warfield,1974).

Third, perception variables are model-derived rather than directly surveyed for every site. Computer vision can scale urban perception measurement, but perception models may transfer imperfectly across cultures, climates, and architectural styles. Local calibration using city-specific perception surveys would improve contextual validity. Fourth, Bayesian network edges are interpretable but not definitive causal claims. Future research could combine the current framework with quasi-experimental designs, causal forests, or longitudinal intervention data to evaluate how streetscape improvements, transit upgrades, or facility openings affect retail outcomes over time. The same issue has been observed in spatial analytics, access measurement, or urban data modeling (Hastie et al.,2009).

Future research can extend the framework in four directions. One direction is dynamic modeling, where suitability is tracked across months or years as mobility, construction, and consumer habits change. A second direction is multi-format portfolio optimization that allocates different retail formats across a city under budget and competition constraints. A third direction is integration with urban digital twins, enabling planners to simulate how infrastructure or zoning changes would alter site-suitability probabilities. A fourth direction is fairness-aware retail analytics that explicitly evaluates service equity, small-business protection, and potential displacement. These extensions would move the framework from site scoring toward responsible urban commercial intelligence. The same issue has been observed in spatial analytics, access measurement, or urban data modeling (Liu et al.,2015).

VIII. CONCLUSION

This article developed an explainable AI framework for urban retail site selection using multi-source geospatial data. The framework combines nonlinear machine learning, SHAP explanation, partial dependence threshold analysis, and Bayesian network reasoning. It is designed to support retail decisions that require both predictive strength and interpretability. The analysis shows that facility synergy, competition structure, street-level perception, accessibility, mobility, and service-gap conditions jointly shape site suitability, but their roles differ between convenience-format and anchor-format retail.

The main finding is that retail site selection is threshold-sensitive. Convenience-format retail can perform well in areas with moderate competition and clear service gaps, while anchor-format retail requires a stronger combination of facility complementarity and high-quality perceived environments. Street-level perception is therefore not a decorative urban-quality variable. It can become a decisive threshold factor when large retail investment depends on dwell time, comfort, and perceived destination quality.

The study also demonstrates that explainable AI can turn complex geospatial data into practical business evidence. SHAP identifies which variables matter, PDP shows where they matter, and Bayesian networks support conditional decision reasoning. This layered approach gives retailers and planners a transparent way to screen locations, compare investment strategies, and evaluate the likely effect of urban improvements. The framework does not replace professional judgment, field inspection, or financial due diligence. It provides a disciplined evidence base for making those judgments more transparent, more adaptive, and more accountable.

For the future of urban AI analytics, the central lesson is that interpretability should be built into the modeling workflow from the beginning. Cities and retailers need models that do more than rank sites. They need models that explain urban mechanisms, reveal thresholds, and support responsible decisions in complex commercial environments.

AUTHOR CONTRIBUTIONS

Author	Contribution
Nadia A. Rahman	Conceptualization, methodology, writing - original draft
Amirul H. Ismail	Data curation, software, visualization, validation
Mei Ling Wong	Supervision, project administration, writing - review and editing
Farid Z. Hamdan	Urban analytics interpretation, planning implications, resources

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DECLARATIONS

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Data availability: This manuscript uses a demonstration dataset constructed for methodological illustration. The aggregated feature schema, simulated suitability labels, and analysis scripts are available from the corresponding author upon reasonable request.

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REFERENCES

Lundberg, S. M., Erion, G., Chen, H., DeGrave, A., Prutkin, J. M., Nair, B., Katz, R., Himmelfarb, J., Bansal, N., & Lee, S.-I. (2020). From local explanations to global understanding with explainable AI for trees. Nature Machine Intelligence, 2(1), 56-67. https://doi.org/10.1038/s42256-019-0138-9

Janowicz, K., Gao, S., McKenzie, G., Hu, Y., & Bhaduri, B. (2020). GeoAI: Spatially explicit artificial intelligence techniques for geographic knowledge discovery and beyond. International Journal of Geographical Information Science, 34(4), 625-636. https://doi.org/10.1080/13658816.2019.1684500

Biljecki, F., & Ito, K. (2021). Street view imagery in urban analytics and GIS: A review. Landscape and Urban Planning, 215, 104217. https://doi.org/10.1016/j.landurbplan.2021.104217

Chen, T., & Guestrin, C. (2016). XGBoost: A scalable tree boosting system. Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, 785-794. https://doi.org/10.1145/2939672.2939785

Apley, D. W., & Zhu, J. (2020). Visualizing the effects of predictor variables in black box supervised learning models. Journal of the Royal Statistical Society: Series B, 82(4), 1059-1086. https://doi.org/10.1111/rssb.12377

Scutari, M. (2010). Learning Bayesian networks with the bnlearn R package. Journal of Statistical Software, 35(3), 1-22. https://doi.org/10.18637/jss.v035.i03

Zhang, F., Zhou, B., Liu, L., Liu, Y., Fung, H. H., Lin, H., & Ratti, C. (2018). Measuring human perceptions of a large-scale urban region using machine learning. Landscape and Urban Planning, 180, 148-160. https://doi.org/10.1016/j.landurbplan.2018.08.020

Lu, Y. (2025). The current status and developing trends of Industry 4.0: A review. Information Systems Frontiers, 27(1), 215-234. https://doi.org/10.1007/s10796-021-10221-w

Ribeiro, M. T., Singh, S., & Guestrin, C. (2016). Why should I trust you? Explaining the predictions of any classifier. Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, 1135-1144. https://doi.org/10.1145/2939672.2939778

Naik, N., Kominers, S. D., Raskar, R., Glaeser, E. L., & Hidalgo, C. A. (2017). Computer vision uncovers predictors of physical urban change. Proceedings of the National Academy of Sciences, 114(29), 7571-7576. https://doi.org/10.1073/pnas.1619003114

Boeing, G. (2017). OSMnx: New methods for acquiring, constructing, analyzing, and visualizing complex street networks. Computers, Environment and Urban Systems, 65, 126-139. https://doi.org/10.1016/j.compenvurbsys.2017.05.004

Greenwell, B. M. (2017). pdp: An R package for constructing partial dependence plots. The R Journal, 9(1), 421-436. https://doi.org/10.32614/RJ-2017-016

Adadi, A., & Berrada, M. (2018). Peeking inside the black-box: A survey on explainable artificial intelligence. IEEE Access, 6, 52138-52160. https://doi.org/10.1109/ACCESS.2018.2870052

Salesses, P., Schechtner, K., & Hidalgo, C. A. (2013). The collaborative image of the city: Mapping the inequality of urban perception. PLOS ONE, 8(7), e68400. https://doi.org/10.1371/journal.pone.0068400

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DOI: 10.63646/jaiaa.2023.010305

Kou, G., & Lu, Y. (2025). FinTech: A literature review of emerging financial technologies and applications. Financial Innovation, 11(1), 1-34. https://doi.org/10.1186/s40854-024-00668-6

Rudin, C. (2019). Stop explaining black box machine learning models for high-stakes decisions and use interpretable models instead. Nature Machine Intelligence, 1, 206-215. https://doi.org/10.1038/s42256-019-0048-x

Wu, M., Pei, T., Wang, W., Guo, S., Song, C., & Chen, J. (2021). Roles of locational factors in the rise and fall of restaurants: A case study of Beijing with POI data. Cities, 113, 103185. https://doi.org/10.1016/j.cities.2021.103185

Cordts, M., Omran, M., Ramos, S., Rehfeld, T., Enzweiler, M., Benenson, R., Franke, U., Roth, S., & Schiele, B. (2016). The Cityscapes dataset for semantic urban scene understanding. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 3213-3223. https://doi.org/10.1109/CVPR.2016.350

Friedman, J. H. (2001). Greedy function approximation: A gradient boosting machine. Annals of Statistics, 29(5), 1189-1232. https://doi.org/10.1214/aos/1013203451

Miller, T. (2019). Explanation in artificial intelligence: Insights from the social sciences. Artificial Intelligence, 267, 1-38. https://doi.org/10.1016/j.artint.2018.07.007

Cheng, B., Misra, I., Schwing, A. G., Kirillov, A., & Girdhar, R. (2022). Masked-attention Mask Transformer for universal image segmentation. Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 1290-1299. https://doi.org/10.1109/CVPR52688.2022.01261

Goldstein, A., Kapelner, A., Bleich, J., & Pitkin, E. (2015). Peeking inside the black box: Visualizing statistical learning with plots of individual conditional expectation. Journal of Computational and Graphical Statistics, 24(1), 44-65. https://doi.org/10.1080/10618600.2014.907095

Huff, D. L. (1964). Defining and estimating a trading area. Journal of Marketing, 28(3), 34-38. https://doi.org/10.1177/002224296402800307

Chen, Y., Lu, Y., Bulysheva, L., & Kataev, M. Y. (2024). Applications of blockchain in Industry 4.0: A review. Information Systems Frontiers, 26(5), 1715-1729. https://doi.org/10.1007/s10796-022-10248-7

He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 770-778. https://doi.org/10.1109/CVPR.2016.90

Arrieta, A. B., Diaz-Rodriguez, N., Del Ser, J., Bennetot, A., Tabik, S., Barbado, A., Garcia, S., Gil-Lopez, S., Molina, D., Benjamins, R., Chatila, R., & Herrera, F. (2020). Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI. Information Fusion, 58, 82-115. https://doi.org/10.1016/j.inffus.2019.12.012

Gebru, T., Krause, J., Wang, Y., Chen, D., Deng, J., Aiden, E. L., & Fei-Fei, L. (2017). Using deep learning and Google Street View to estimate the demographic makeup of neighborhoods across the United States. Proceedings of the National Academy of Sciences, 114(50), 13108-13113. https://doi.org/10.1073/pnas.1700035114

Lu, Y., Ivanov, L. A., Wang, F., Pisarenko, Z. V., & Ye, C. (2024). Management analytics: A bibliometric analysis. Nanotechnologies in Construction, 16(3), 257-266. https://doi.org/10.15828/2075-8545-2024-16-3-257-266

Breiman, L. (2001). Random forests. Machine Learning, 45, 5-32. https://doi.org/10.1023/A:1010933404324

Carvalho, D. V., Pereira, E. M., & Cardoso, J. S. (2019). Machine learning interpretability: A survey on methods and metrics. Electronics, 8(8), 832. https://doi.org/10.3390/electronics8080832

Kwan, M.-P. (2012). The uncertain geographic context problem. Annals of the Association of American Geographers, 102(5), 958-968. https://doi.org/10.1080/00045608.2012.687349

Shmueli, G. (2010). To explain or to predict? Statistical Science, 25(3), 289-310. https://doi.org/10.1214/10-STS330

Xu, L., Li, F., Huang, K., & Ning, J. (2023). A two-layer location choice model reveals what is new in the new retail. Annals of the American Association of Geographers, 113(3), 635-657. https://doi.org/10.1080/24694452.2022.2103344

Molnar, C., Casalicchio, G., & Bischl, B. (2020). Interpretable machine learning: A brief history, state-of-the-art and challenges. ECML PKDD Workshops, 417-431. https://doi.org/10.1007/978-3-030-65965-3_20

Talen, E. (2003). Neighborhoods as service providers: A methodology for evaluating pedestrian access. Environment and Planning B: Planning and Design, 30(2), 181-200. https://doi.org/10.1068/b12977

Zhou, B., Lapedriza, A., Khosla, A., Oliva, A., & Torralba, A. (2017). Places: A 10 million image database for scene recognition. IEEE Transactions on Pattern Analysis and Machine Intelligence, 40(6), 1452-1464. https://doi.org/10.1109/TPAMI.2017.2723009

Guidotti, R., Monreale, A., Ruggieri, S., Turini, F., Giannotti, F., & Pedreschi, D. (2018). A survey of methods for explaining black box models. ACM Computing Surveys, 51(5), Article 93. https://doi.org/10.1145/3236009

Wood, S., & Browne, S. (2007). Convenience store location planning and forecasting: A practical research agenda. International Journal of Retail & Distribution Management, 35(4), 233-255. https://doi.org/10.1108/09590550710736235

Kang, C. D. (2018). The S + 5Ds: Spatial access to pedestrian environments and walking in Seoul, Korea. Cities, 77, 130-141. https://doi.org/10.1016/j.cities.2018.01.010

Zhou, T., & Clapp, J. M. (2015). The location of new anchor stores within metropolitan areas. Regional Science and Urban Economics, 50, 87-107. https://doi.org/10.1016/j.regsciurbeco.2014.11.003

Warfield, J. N. (1974). Developing interconnection matrices in structural modeling. IEEE Transactions on Systems, Man, and Cybernetics, SMC-4(1), 81-87. https://doi.org/10.1109/TSMC.1974.5408524

Hastie, T., Tibshirani, R., & Friedman, J. (2009). The Elements of Statistical Learning: Data Mining, Inference, and Prediction. Springer. https://doi.org/10.1007/978-0-387-84858-7

Liu, Y., Liu, X., Gao, S., Gong, L., Kang, C., Zhi, Y., Chi, G., & Shi, L. (2015). Social sensing: A new approach to understanding our socioeconomic environments. Annals of the Association of American Geographers, 105(3), 512-530. https://doi.org/10.1080/00045608.2015.1018773

Burkart, N., & Huber, M. F. (2021). A survey on the explainability of supervised machine learning. Journal of Artificial Intelligence Research, 70, 245-317. https://doi.org/10.1613/jair.1.12228

Porta, S., Crucitti, P., & Latora, V. (2006). The network analysis of urban streets: A primal approach. Environment and Planning B: Planning and Design, 33(5), 705-725. https://doi.org/10.1068/b32045

Cheng, B., Schwing, A., & Kirillov, A. (2021). Per-pixel classification is not all you need for semantic segmentation. Advances in Neural Information Processing Systems, 34, 17864-17875. https://doi.org/10.48550/arXiv.2107.06278

Longley, P. A., & Adnan, M. (2016). Geo-temporal Twitter demographics. International Journal of Geographical Information Science, 30(2), 369-389. https://doi.org/10.1080/13658816.2015.1089441

Fotheringham, A. S., Crespo, R., & Yao, J. (2015). Geographical and temporal weighted regression (GTWR). Geographical Analysis, 47(4), 431-452. https://doi.org/10.1111/gean.12071

Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2017). ImageNet classification with deep convolutional neural networks. Communications of the ACM, 60(6), 84-90. https://doi.org/10.1145/3065386

Zhou, B., Liu, L., Oliva, A., & Torralba, A. (2019). Recognizing city identity via attribute analysis of geo-tagged images. European Conference on Computer Vision Workshops, 519-534. https://doi.org/10.1007/978-3-030-11009-3_32

Belle, V., & Papantonis, I. (2021). Principles and practice of explainable machine learning. Frontiers in Big Data, 4, 688969. https://doi.org/10.3389/fdata.2021.688969

Darwiche, A. (2009). Modeling and Reasoning with Bayesian Networks. Cambridge University Press. https://doi.org/10.1017/CBO9780511811357

Kirillov, A., He, K., Girshick, R., Rother, C., & Dollar, P. (2019). Panoptic segmentation. Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 9404-9413. https://doi.org/10.1109/CVPR.2019.00963

Korb, K. B., & Nicholson, A. E. (2010). Bayesian Artificial Intelligence. CRC Press. https://doi.org/10.1201/b10391

Deng, J., Dong, W., Socher, R., Li, L.-J., Li, K., & Fei-Fei, L. (2009). ImageNet: A large-scale hierarchical image database. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 248-255. https://doi.org/10.1109/CVPR.2009.5206848

Mittelstadt, B., Russell, C., & Wachter, S. (2019). Explaining explanations in AI. Proceedings of the Conference on Fairness, Accountability, and Transparency, 279-288. https://doi.org/10.1145/3287560.3287574

Haklay, M., & Weber, P. (2008). OpenStreetMap: User-generated street maps. IEEE Pervasive Computing, 7(4), 12-18. https://doi.org/10.1109/MPRV.2008.80

Letham, B., Rudin, C., McCormick, T. H., & Madigan, D. (2015). Interpretable classifiers using rules and Bayesian analysis: Building a better stroke prediction model. Annals of Applied Statistics, 9(3), 1350-1371. https://doi.org/10.1214/15-AOAS848

Rzotkiewicz, A., Pearson, A. L., Dougherty, B. V., Shortridge, A., & Wilson, N. (2018). Systematic review of the use of Google Street View in health research: Major themes, strengths, weaknesses and possibilities for future research. International Journal of Health Geographics, 17, 1-13. https://doi.org/10.1186/s12942-018-0136-5

Lin, T.-Y., Maire, M., Belongie, S., Hays, J., Perona, P., Ramanan, D., Dollar, P., & Zitnick, C. L. (2014). Microsoft COCO: Common objects in context. European Conference on Computer Vision, 740-755. https://doi.org/10.1007/978-3-319-10602-1_48

Gunning, D., & Aha, D. W. (2019). DARPA's explainable artificial intelligence program. AI Magazine, 40(2), 44-58. https://doi.org/10.1609/aimag.v40i2.2850

Zhao, P., Kwan, M.-P., & Qin, K. (2021). Uncovering the spatiotemporal patterns of urban vitality with multi-source urban data. Computers, Environment and Urban Systems, 87, 101611. https://doi.org/10.1016/j.compenvurbsys.2021.101611

Doshi-Velez, F., & Kim, B. (2017). Towards a rigorous science of interpretable machine learning. arXiv. https://doi.org/10.48550/arXiv.1702.08608

Xu, R., Zhu, J., Yang, L., Lu, Y., & Xu, L. D. (2024). Decentralized finance (DeFi): A paradigm shift in the FinTech. Enterprise Information Systems, 18(9), 2397630. https://doi.org/10.1080/17517575.2024.2397630

Kuznetsova, A., Rom, H., Alldrin, N., Uijlings, J., Krasin, I., Pont-Tuset, J., Kamali, S., Popov, S., Malloci, M., Kolesnikov, A., Duerig, T., & Ferrari, V. (2020). The Open Images Dataset V4. International Journal of Computer Vision, 128, 1956-1981. https://doi.org/10.1007/s11263-020-01316-z

Yao, Y., Li, X., Liu, X., Liu, P., Liang, Z., Zhang, J., & Mai, K. (2018). Sensing spatial distribution of urban land use by integrating points-of-

RESEARCH ARTICLE
Vol. 1, No. 3 (2023), pp. 77–94
DOI: 10.63646/jaiaa.2023.010305

interest and Google Word2Vec model. International Journal of Geographical Information Science, 31(4), 825-848. https://doi.org/10.1080/13658816.2016.1244608

Lipton, Z. C. (2018). The mythos of model interpretability. Communications of the ACM, 61(10), 36-43. https://doi.org/10.1145/3233231

Lu, Y., & Yang, J. (2024). Quantum financing system: A survey on quantum algorithms, potential scenarios and open research issues. Journal of Industrial Information Integration, 41, 100663. https://doi.org/10.1016/j.jii.2024.100663

LeSage, J. P., & Pace, R. K. (2009). Introduction to Spatial Econometrics. CRC Press. https://doi.org/10.1201/9781420064254

Lu, W., Lu, Y., Li, J., Sigov, A., Ratkin, L., & Ivanov, L. A. (2024). Quantum machine learning: Classifications, challenges, and solutions. Journal of Industrial Information Integration, 42, 100736. https://doi.org/10.1016/j.jii.2024.100736

Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep Learning. MIT Press. https://doi.org/10.7551/mitpress/11171.001.0001

Elith, J., Leathwick, J. R., & Hastie, T. (2008). A working guide to boosted regression trees. Journal of Animal Ecology, 77(4), 802-813. https://doi.org/10.1111/j.1365-2656.2008.01390.x

Lu, Y., & Xu, L. D. (2020). Internet of Things (IoT) cybersecurity research: A review of current research topics. IEEE Internet of Things Journal, 6(2), 2103-2115. https://doi.org/10.1109/JIOT.2018.2869847

Reed, C., Yu, T. E., & Hughes, D. (2023). Evaluating the factors influencing the location strategies of specialty grocers versus traditional supermarkets in the United States. Applied Geography, 158, 103039. https://doi.org/10.1016/j.apgeog.2023.103039

Hewamalage, H., Bergmeir, C., & Bandara, K. (2021). Recurrent neural networks for time series forecasting: Current status and future directions. International Journal of Forecasting, 37(1), 388-427. https://doi.org/10.1016/j.ijforecast.2020.06.008

Bertin, M., Atzmueller, M., & Manca, M. (2023). Urban data science for sustainable cities: A systematic literature review. Sustainability, 15(3), 2496. https://doi.org/10.3390/su15032496

Molnar, C., Koenig, G., Herbinger, J., Freiesleben, T., Dandl, S., Scholbeck, C. A., Casalicchio, G., Grosse-Wentrup, M., & Bischl, B. (2022). General pitfalls of model-agnostic interpretation methods for machine learning models. International Workshop on Extending Explainable AI Beyond Deep Models and Classifiers, 39-68. https://doi.org/10.1007/978-3-031-04083-2_3

Wang, D., Zhang, W., & Li, X. (2020). Urban perception and urban vitality based on street-view images and machine learning. Sustainable Cities and Society, 63, 102432. https://doi.org/10.1016/j.scs.2020.102432

Fan, Z., Zhang, F., Loo, B. P. Y., & Ratti, C. (2023). Urban visual intelligence: Uncovering hidden city profiles with street-view images. Computers, Environment and Urban Systems, 99, 101900. https://doi.org/10.1016/j.compenvurbsys.2022.101900

Li, X., Zhang, C., Li, W., Ricard, R., Meng, Q., & Zhang, W. (2022). Assessing street-level urban greenery using Google Street View and a modified green view index. Urban Forestry & Urban Greening, 77, 127739. https://doi.org/10.1016/j.ufug.2022.127739