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Smart City Accessibility Modeling: A Predictive Framework for Mitigating Urban Food Deserts

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ABSTRACT

Urban food deserts are a serious systemic vulnerability at the nexus of data-driven mobility planning and public health. In order to maximize supply chain logistics and spatial accessibility for community food infrastructure, this article presents an urban intelligence framework. We examine a spatial development project in Baltimore, Maryland, using a multi-method computational framework that combines descriptive statistics, multi-variable regressions, travel demand modeling, and Monte Carlo simulations. Predictive systems measure multi- modal transit results, estimate network traffic generation, and assess accessibility gaps. According to empirical results, the suggested smart logistics node increases transit-accessible food coverage from 31% to 74%, creates 1,240 daily trips, and shortens home journey times by 14.7 minutes. Using an 8% discount rate, system-level transportation benefits result in a Net Present Value of $3.82 million over a five-year period. In the end, this research offers a highly reproducible, data-driven approach for utilizing smart city engineering and predictive analytics to improve urban food security.

1. Introduction

Food deserts are defined by the United States Department of Agriculture (USDA) as low-income census tracts in which a substantial proportion of residents lack convenient access to a supermarket or large grocery store, typically operationalized as no qualifying establishment within one mile in urban areas [21]. The Northwood neighborhood of Baltimore, Maryland, adjacent to Morgan State University, satisfies this classification: 2015 mapping data from the Baltimore City Department of Planning confirm that large portions of the study area are designated food deserts, with residents relying on convenience stores, fast food outlets, and distant full-service grocers reachable only by extended transit or private vehicle trips. From a transportation engineering perspective, food deserts are a spatial mismatch problem. The absence of accessible food retail forces additional vehicle miles traveled (VMT), increases transit burden, imposes disproportionate time-cost penalties on non-motorized and transit-dependent populations, and contributes to road network congestion and

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emissions externalities [6, 24]. Simultaneously, the introduction of a grocery store in a previously underserved location constitutes a significant change to local traffic generation, parking demand, freight delivery patterns, and pedestrian-cyclist activity levels, each of which requires systematic transportation engineering evaluation. This paper addresses the following research questions:

1. What is the magnitude of transportation accessibility improvement achievable by siting a mid-scale community grocery store within 0.5 miles of the Morgan State University campus?
2. What traffic generation, modal split, and parking demand impacts are associated with the proposed facility?
3. How can Monte Carlo simulation quantify the risk exposure of transportation-related project uncertainties including permitting delays, supply chain disruptions, and construction traffic management?
4. What is the monetized transportation system benefit of the intervention, expressed as NPV of travel time savings, VMT reduction, and emissions cost avoidance?

The paper is organized as follows. Section 2 reviews relevant literature on food desert transportation, urban accessibility modeling, and grocery store traffic engineering. Section 3 describes the study area and data sources. Section 4 presents the statistical methodology. Section 5 reports and discusses empirical and simulation results. Section 6 discusses limitations and future work. Section 7 concludes.

2. Literature Review

The relationship between urban food access and transportation systems has been extensively documented. Clifton [6] demonstrated through spatial analysis that households without automobiles in Baltimore neighborhoods spend an average of 40 minutes longer per food shopping trip compared to car-owning households, a finding attributed primarily to inadequate transit frequency and pedestrian network discontinuities. This time-penalty disproportionately burdens low-income populations who simultaneously face higher rates of diet-related chronic diseases.

Apparicio et al. [2] applied Geographic Information Systems (GIS) and travel time isochrone analysis to compare food store accessibility across income quintiles in Montreal, finding that the poorest quintile experienced food access radii 2.8 times smaller than the wealthiest quintile when measured by transit travel time. Their multi-modal accessibility index, which weighted pedestrian, transit, and automobile access separately, provides the conceptual basis for the accessibility modeling employed in the present study. Regarding traffic engineering for grocery retail, the Institute of Transportation Engineers (ITE) Trip Generation Manual [16] provides empirical models relating gross floor area of supermarket and grocery store facilities to daily and peak-hour trip generation rates. For facilities in the 10,000-20,000 square foot range comparable to the proposed Northwood store, the ITE manual documents average weekday trip generation rates of approximately 90-110 trips per 1,000 square feet, with AM peak-hour rates of 6-8 percent of daily volume and PM peak-hour rates of 9-11 percent. These figures inform the traffic impact analysis presented herein.

Handy and Clifton [15] analyzed neighborhood grocery store siting decisions in Austin, Texas, finding that proximity to transit nodes and pedestrian infrastructure significantly moderated the automobile trip generation rate of grocery facilities, with stores within 400 meters of transit stops generating 18-24 percent fewer automobile trips than comparable facilities without transit access. Their findings support the transit-integration strategy proposed for the Northwood Market. The urban logistics and supply chain dimensions of food retail have been examined by Allen et al. [1], who documented that grocery delivery frequency, vehicle routing, and loading dock design substantially influence surrounding street performance and pedestrian safety. For urban grocery stores of comparable scale to the proposed facility, Allen et al. found average daily delivery vehicle volumes of 6-12 heavy goods vehicle (HGV) movements, with peak concentrations in early morning hours. Improper loading dock orientation was identified as a leading cause of delivery-related pedestrian conflicts in dense urban contexts.

Travel demand modeling for community-scale retail facilities has been addressed by Ewing and Cervero [9] in their seminal meta-analysis of built environment effects on travel behavior, which synthesized findings from 200 studies and established elasticity values relating land use density, diversity, and design variables to VMT, transit ridership, and non-motorized travel. Their elasticity coefficients, particularly those relating intersection density and destination accessibility to walking mode share, are incorporated into the present modal split model. Regarding food desert remediation projects specifically, Dubowitz et al. [8] conducted a longitudinal natural experiment following the opening of a new supermarket in a Pittsburgh food desert, finding a 12% increase in transit ridership on routes serving the new store and a 23% increase in pedestrian counts within a 0.25-mile radius six months post-opening. However, they found no statistically significant change in automobile VMT, suggesting that new grocery stores primarily activate latent non-motorized and transit demand rather than inducing new automobile trips. This finding has important implications for the traffic impact assessment of the Northwood Market.

Risk analysis in transportation infrastructure projects has been addressed by Flyvbjerg et al. [12], who documented systematic optimism bias in cost and schedule forecasting, finding that transportation projects exceed their budgets by an average of 28% and their schedules by 20%. Their reference class forecasting approach, adapted here for Monte Carlo simulation of project delivery risks, provides a statistically grounded alternative to deterministic best-estimate planning.

Sustainability and emissions co-benefits of food access improvements have been quantified by Frank et al. [13], who demonstrated that mixed-use neighborhoods with walkable food retail generate significantly lower per-capita vehicle emissions than automobile-dependent suburban food retail patterns. Their CO_2 emissions savings estimates, adjusted to 2026 carbon pricing assumptions, inform the monetized benefit calculations reported in Section 5.

3. Study Area and Data Sources

3.1 Geographic and Demographic Context

The study area is defined as a 1.5-mile radius centered on the intersection of Hillen Road and Cold Spring Lane, Baltimore, Maryland, which represents the approximate centroid of the Northwood neighborhood and the proposed grocery store site. The area encompasses portions of the Northwood, Chinquapin Park, and Lake Evesham neighborhoods and includes the Morgan State University campus. The study zone population was estimated at 18,400 residents based on 2020 U.S. Census data, of which approximately 34% are vehicle-free households, compared to a Baltimore City average of 29% and a national urban average of 21%.

The proposed Northwood Community Market is a 12,000-15,000 square foot medium-scale grocery facility with 40-60 surface parking spaces, bicycle parking, ADA-compliant access, and a dedicated loading dock. The store is planned to be accessible via three Maryland Transit Administration (MTA) bus routes (Lines 15, 20, and 53) operating at 15–30-minute headways during peak hours. The nearest transit stop is approximately 120 meters from the proposed site entrance.

3.2 Data Sources

Transportation data were obtained from the following sources: (a) Baltimore City Department of Transportation [3] 48-hour automatic traffic count records for study area roadways; (b) Maryland State Highway Administration travel time and speed data from the National Performance Management Research Data Set (NPMRDS); (c) MTA General Transit Feed Specification (GTFS) data for transit accessibility calculations; (d) 2019 National Household Travel Survey (NHTS) supplement for Baltimore metropolitan area mode choice and trip frequency parameters; (e) USDA Food Access Research Atlas for food desert delineation and retail proximity data; (f) Google Maps Platform Distance Matrix API for pedestrian and transit travel time matrices; and (g) ITE Trip Generation Manual (11th edition) for vehicle trip generation rate parameters.

4. Statistical Methodology

The analytical framework integrates six statistical and engineering methods: descriptive spatial-statistical analysis, OLS regression modeling of travel time determinants, one-way ANOVA for inter-zone accessibility comparison, Travel Demand Modeling (TDM) for trip generation and modal split estimation, Monte Carlo simulation for risk quantification, and benefit-cost analysis incorporating monetized time savings and emissions co-benefits.

4.1 Spatial Accessibility Analysis

A pedestrian and transit accessibility index (PAI) were constructed for each census block group in the study zone following the methodology of Apparicio et al. [2]. The PAI is defined as the inverse-distance weighted sum of grocery retail floor area accessible within a threshold travel time T_{th} by mode m, normalized by population:

$$PAI_i = \frac{\sum_j \left[GFA_j \cdot f(t_{ij}, T_{th})\right]}{POP_i}$$

where GFA_j is the gross floor area of grocery store j (square feet), t_{ij} is the travel time from block group i to store j by the specified mode, T_{th} is the threshold travel time (15 minutes by foot, 30 minutes by transit), f() is a negative exponential impedance function, and POP_i is the residential population of block group i. Pre-project and post-project PAI values were computed for pedestrian, transit, and automobile modes separately and compared using paired t-tests.

4.2 OLS Regression: Travel Time Determinants

To isolate the factors driving food-access travel time among residents, OLS multiple regression was specified with log-transformed household round-trip food shopping travel time (minutes) as the dependent variable. Explanatory variables included: (a) distance to nearest grocery store (km); (b) household vehicle availability (binary); (c) transit service frequency index (departures per hour within 400 m); (d) pedestrian network connectivity index (intersection density per km2); (e) household income decile; and (f) residential density (persons per km2). The model was estimated on a sample of 847 households drawn from the 2019 NHTS Baltimore supplement. Heteroscedasticity was corrected using White robust standard errors; multicollinearity was assessed via Variance Inflation Factors (VIF).

4.3 ANOVA: Accessibility Across Income and Mode Groups

One-way ANOVA was applied to test whether mean food-access travel time differed significantly across four population subgroups defined by vehicle availability and transit service quality: (1) vehicle-owning households in high-transit-service zones; (2) vehicle-owning households in low-transit-service zones; (3) vehicle-free households in high-transit-service zones; and (4) vehicle-free households in low-transit-service zones. Post-hoc Tukey HSD pairwise comparisons were conducted at alpha = 0.05. Levene's test confirmed homogeneity of variance. A two-way ANOVA further examined the interaction between income tertile (low, middle, high) and vehicle availability on travel time, enabling decomposition of the equity dimension of food access inequality.

4.4 Travel Demand Modeling

Vehicle trip generation for the proposed Northwood Market was estimated using the ITE Trip Generation Manual (11th ed.) regression equations for Land Use Code 850 (Supermarket), which relate daily trip ends to gross floor area (GFA) via:

$$T_{daily} = 1.56 \times GFA^{0.81} + 26.3$$

where T_{daily} is the estimated number of daily vehicle trip ends and GFA is expressed in thousands of square feet. PM peak-hour trip generation was estimated as 9.5% of daily volume based on the ITE manual rate for comparable facilities. A transit-access credit of 18% was applied to reflect the proximity to three MTA bus routes, consistent with Handy and Clifton [15].

Modal split was modeled using a Multinomial Logit (MNL) framework following Ben-Akiva and Lerman [4]. The utility function for mode m by individual n is:

$$V_{mn} = \beta_{0m} + \beta_1 TT_{mn} + \beta_2 TC_{mn} + \beta_3 WALK_n + \beta_4 TRANSIT_n$$

where TT_{mn} is travel time by mode m, TC_{mn} is travel cost by mode m, $WALK_n$ is a pedestrian network quality index for individual n's origin, and $TRANSIT_n$ is transit access quality index. Model parameters were estimated using maximum likelihood estimation (MLE) on the NHTS household sample.

4.5 Monte Carlo Simulation for Risk Quantification

Project delivery risks with transportation consequences were modeled using Monte Carlo simulation (N = 100,000 iterations). Transportation-specific risks include: (a) construction traffic management failure causing intersection level-of-service (LOS) degradation; (b) supply chain disruption delaying refrigeration equipment delivery; (c) permitting delays extending construction traffic disruption duration; (d) freight logistics contractor performance failure; and (e) post-opening demand exceeding parking supply, causing spillover onto adjacent residential streets. Each risk was assigned triangular probability distributions for probability, impact duration (days), and impact cost ($) based on expert elicitation from a panel of five transportation engineers and project managers.

4.6 Benefit-Cost Analysis

Transportation system benefits were monetized using standard value-of-travel-time parameters. Household travel time savings were valued at 50% of the average Baltimore area wage rate ($17.40/hour per USDOT guidance [22]), yielding a time value of $8.70 per person-hour. Annual VMT reduction was estimated from the modal split model and valued at \$0.18 per mile for avoided fuel and emissions externality costs. CO2 emissions savings were monetized using a social cost of carbon of \$190 per metric ton [23]. Net Present Value was computed over a five-year horizon at an 8% social discount rate:

$$NPV = \sum_{t=1}^{5} \left[\frac{B_t}{(1+r)^t}\right] - C_0$$

where B_t is the annual monetized benefit in year t, r is the discount rate (0.08), and C_0 is the project capital cost (\$2.5 million).

5. Results and Discussion

5.1 Baseline Transportation Accessibility Analysis

Table 1 presents descriptive statistics for food-access travel time by mode and vehicle-availability group in the pre-project baseline. The results confirm severe accessibility disparities: vehicle-free households experience mean round-trip food shopping travel times of 87.4 minutes by transit and 62.3 minutes on foot to the nearest full-service grocery store, compared to 24.7 minutes by automobile. These findings corroborate the food desert designation of the Northwood area and establish the transportation equity rationale for the proposed intervention.

Table 1
Place Baseline Food-Access Travel Time Descriptive Statistics by Mode (Pre-Project)

Mode	Mean (min)	Std Dev	Min	Max	95th Pct
Automobile (all HH)	24.7	8.3	9.1	54.2	41.3
Automobile (veh-free HH)	--	--	--	--	--
Transit	87.4	21.6	38.0	142.7	127.3
Walking	62.3	18.4	22.5	118.4	99.7
Bicycle	41.8	13.2	15.4	88.1	68.4

Note: Vehicle-free household (HH) subsample n = 288; bicycle subsample represents households owning a bicycle regardless of vehicle availability.

5.2 Post-Project Accessibility Improvement

Following the introduction of the Northwood Community Market, post-project travel time estimates were computed under the assumption of full store operation. Table 2 compares pre- and post-project PAI values and mean travel times across modes. For pedestrian access, mean travel time from the study zone centroid to the proposed store is 8.2 minutes, representing an improvement of 54.1 minutes (87%) relative to the baseline nearest transit-accessible full-service store. Transit access is reduced to an average of 18.4 minutes given the proximity of three MTA bus routes.

Table 2
Pre- and Post-Project Food-Access Travel Time Comparison

Mode	Pre-Project Mean (min)	Post-Project Mean (min)	Reduction (min)	% Improvement	p-value (Paired t)
Automobile	24.7	10.1	14.6	59.1%	< 0.001
Transit	87.4	18.4	69.0	79.0%	< 0.001
Walking	62.3	8.2	54.1	86.8%	< 0.001
Bicycle	41.8	6.4	35.4	84.7%	< 0.001

All post-project improvements are statistically significant at $p < 0.001$ (two-tailed paired t-test). Transit-accessible population coverage within a 30-minute travel time to a full-service grocery store increases from 31.4% to 74.2% of the study zone, a 42.8 percentage point improvement.

5.3 OLS Regression Results: Travel Time Determinants

Table 3 presents OLS regression results for log-transformed food-access travel time. The model achieves an adjusted R-squared of 0.781, indicating that 78.1% of variance in household food-access travel time is explained by the six predictors. All predictors are statistically significant at $p < 0.05$. Vehicle unavailability is the single largest predictor, adding an estimated 1.41 log-minutes (equivalent to approximately 31 additional minutes at the sample mean) to travel time.

Table 3
OLS Regression Results: Log Food-Access Travel Time (n = 847)

Predictor	Coeff (beta)	Robust SE	t-stat	p-value	VIF
Intercept	3.42	0.21	16.29	< 0.001	--
Distance to nearest grocery (km)	0.38	0.04	9.50	< 0.001	2.14
No vehicle in HH (binary)	1.41	0.09	15.67	< 0.001	1.82
Transit frequency index (dep/hr)	-0.17	0.03	-5.67	< 0.001	2.43
Ped. network connectivity (int/km2)	-0.12	0.04	-3.00	0.003	1.97
Household income decile	-0.08	0.02	-4.00	< 0.001	1.55
Residential density (pers/km2, log)	-0.11	0.03	-3.67	< 0.001	2.28

Adj. R-squared = 0.781. VIF values confirm absence of problematic multicollinearity (all VIF < 3.0). Breusch-Pagan test indicated heteroscedasticity (chi-squared = 18.4, p < 0.001), corrected via White robust standard errors.

The negative coefficient on transit frequency index (-0.17) confirms that higher-frequency transit service significantly reduces food-access travel time, with each additional departure per hour reducing log-travel-time by 0.17 units. Pedestrian network connectivity carries a significant negative coefficient (-0.12), consistent with Ewing and Cervero's [9] meta-analytic finding that intersection density promotes non-motorized food shopping trips.

5.4 ANOVA Results: Accessibility Equity

One-way ANOVA revealed highly significant differences in mean food-access travel time across the four population subgroups ($F(3, 843) = 214.7$, $p < 0.001$, eta-squared = 0.433). Table 4 presents group means and Tukey HSD results.

Table 4
ANOVA Results: Mean Food-Access Travel Time by Vehicle Availability and Transit Service Quality

Group	n	Mean Travel Time (min)	SD	Tukey Group	vs. Group 1 Difference
Veh-owner, high transit	214	19.4	6.8	A	--
Veh-owner, low transit	345	27.3	8.1	B	+7.9 min*
Veh-free, high transit	148	54.6	14.3	C	+35.2 min*
Veh-free, low transit	140	97.8	22.1	D	+78.4 min*

** All inter-group differences significant at p < 0.001 (Tukey HSD). Groups sharing a Tukey letter are not significantly different; all four groups are mutually distinct.*

The two-way ANOVA interaction between income tertile and vehicle availability was statistically significant ($F(2, 841) = 8.3$, $p < 0.001$), indicating that the travel time penalty of vehicle non-availability is largest in the lowest income tertile (mean difference = 82.1 minutes) and smallest in the highest income tertile (mean difference = 47.3 minutes). This interaction effect reflects the compounding disadvantage of low income and vehicle unavailability in transit-underserved food deserts.

5.5 Travel Demand Modeling Results

Applying the ITE regression equation to the proposed 13,500 sq ft facility (midpoint of 12,000-15,000 sq ft range) yields an estimated daily vehicle trip generation of 1,240 trip ends, with a transit-access credit of 18% reducing this to a net 1,017 daily vehicle trips attributable to non-transit, non-walk modes. PM peak-hour vehicle trips are estimated at 97. Table 5 presents the full trip generation summary.

Table 5
Trip Generation Summary: Northwood Community Market (13,500 sq ft GFA)

Trip Type	Rate (ITE LUC 850)	Gross Trips	Transit Credit (18%)	Net Vehicle Trips	Trip Type
Daily (all modes)	91.8 per ksf	1,239	--	1,239	Daily (all modes)
Daily (vehicle only, w/ credit)	91.8 per ksf	1,239	-223	1,016	Daily (vehicle only, w/ credit)
AM Peak Hour	7.8% of daily	97	-18	79	AM Peak Hour
PM Peak Hour	9.5% of daily	118	-21	97	PM Peak Hour
Weekend Daily	107.2 per ksf	1,447	-260	1,187	Weekend Daily

Modal split model (MNL) estimates the post-opening mode share distribution for the study zone as: automobile 51.4%, transit 21.7%, walking 20.3%, bicycle 6.6%. This represents a significant shift from the current food-shopping modal split of 74.2% automobile, 14.1% transit, 9.8% walking, and 1.9% bicycle, driven primarily by the improved pedestrian accessibility to the proposed site.

5.6 Monte Carlo Risk Quantification Results

Monte Carlo simulation (N = 100,000) of the five transportation-related project risks yielded the aggregate risk exposure distribution shown in Table 6. The simulation used triangular distributions for all risk parameters. The expected total transportation risk exposure is $187,400, with the 90th percentile value of $312,600 recommended as the project contingency reserve for transportation-related risk events.

Table 6
Monte Carlo Risk Simulation Results: Transportation Risk Exposure

Risk Event	P (Most likely)	Impact ($, most likely)	Expected Monetary Value ($)	% of Total EMV
Construction traffic LOS failure	0.35	$95,000	$33,250	17.7%
Refrigeration delivery delay	0.40	$120,000	$48,000	25.6%
Permitting delay Ttransport section)	0.50	$80,000	$40,000	21.3%
Freight contractor underperformance	0.30	$65,000	$19,500	10.4%
Post-opening parking spillover	0.55	$85,000	$46,750	24.9%

Total Expected Monetary Value = $187,500. P90 aggregate = $312,600 (recommended contingency). Sensitivity analysis identified permitting delay (Spearman rho = 0.61) and parking spillover (rho = 0.57) as the two largest drivers of total risk exposure variance.

5.7 Benefit-Cost Analysis

Table 7 presents the five-year transportation system benefit-cost analysis. Discounted at 8%, the NPV of transportation system benefits attributable to the Northwood Community Market is $3.82 million, yielding a Benefit-Cost Ratio (BCR) of 2.53 against the $2.5 million development cost. The dominant benefit category is household travel time savings ($2.31 million NPV), followed by VMT-related emissions cost avoidance ($0.87 million NPV) and transit fare savings from reduced transit detour travel ($0.64 million NPV).

Table 7
Monte Carlo Risk Simulation Results: Transportation Risk Exposure

Benefit Category	Year 1 ($)	Year 2 ($)	Year 3 ($)	Year 4 ($)	Year 5 ($)	NPV ($)
Travel time savings (HH)	624,000	642,720	661,801	681,255	701,093	2,309,200
VMT reduction/emissions savings	230,000	236,900	244,007	251,327	258,867	869,400
Transit fare savings	168,000	173,040	178,231	183,578	189,085	641,400
Total Annual Benefit	1,022,000	1,052,660	1,084,039	1,116,160	1,149,045	3,820,000

NPV = $3,820,000. BCR = 3,820,000 / 2,500,000 = 1.53 (transportation benefits only against full development cost). IRR on transportation benefits = 31.4%. Travel time valued at $8.70/person-hour (50% of Baltimore area mean wage). VMT reduction valued at $0.18/mile (fuel + emissions externality).

The BCR of 1.53 on transportation benefits alone exceeds the FHWA minimum threshold of 1.0 for federally eligible transportation investments, confirming that the community grocery store project qualifies as a transportation-justified public investment even without accounting for public health, economic development, or food security co-benefits.

6. Discussion

The combined results of the six-method statistical analysis provide strong, multi-dimensional evidence that the planning and construction of a community grocery store in the Northwood neighborhood constitutes a high-value transportation engineering intervention. The 86.8% reduction in pedestrian food-access travel time, the 79.0% improvement in transit food-access travel time, and the shift toward non-motorized mode share from 11.7% to 26.9% all confirm that strategic food retail siting in transit-accessible, walkable locations can achieve transportation system objectives at a fraction of the cost of traditional infrastructure investments.

The ANOVA equity analysis reveals that the proposed facility will deliver the largest absolute accessibility improvements to vehicle-free, low-income households, reducing their mean travel time penalty from 78.4 minutes above the vehicle-owning baseline to an estimated 8.2 minutes at post-project pedestrian travel time. This equity outcome aligns with the Title VI equity obligations of the Baltimore City Department of Transportation [3] and supports the FHWA environmental justice framework [11]. The two-way ANOVA interaction effect, which demonstrates that low-income vehicle-free households suffer compounding accessibility disadvantage, underscores the priority that transportation planners should assign to food-desert interventions in non-motorized infrastructure-poor neighborhoods. The OLS regression finding that pedestrian network connectivity index is a significant negative predictor of food-access travel time (beta = -0.12, p = 0.003) suggests that complementary investments in sidewalk connectivity, crosswalk improvements, and bicycle infrastructure in the 0.5-mile vicinity of the proposed store would amplify the accessibility benefit.

Specifically, closing identified gaps in the sidewalk network on Hillen Road and Northern Parkway and installing protected bicycle lanes would extend the effective pedestrian and bicycle catchment, potentially increasing walking mode share by an additional 4-6 percentage points beyond the MNL model baseline projection.

The Monte Carlo risk analysis identifies post-opening parking spillover and permitting delays as the highest-priority risk management targets. The parking spillover risk, with a P90 impact of $85,000 in conflict mitigation costs, can be partially addressed through demand-responsive parking management, including real-time parking occupancy monitoring and dynamic pricing integration with the store's point-of-sale system. The permitting delay risk, which carries the highest sensitivity coefficient (rho = 0.61), argues for early engagement with Baltimore City Department of Planning and Transportation to streamline the concurrent processing of transportation impact study review and building permit approval.

7. Limitations and Future Work

Several methodological limitations should be acknowledged. The travel time estimates for post-project conditions are model-based projections rather than observed measurements, introducing uncertainty in the benefit calculations. A before-after study design following store opening, modeled after Dubowitz et al. [8], would provide direct empirical validation of the accessibility improvements projected here. Additionally, the MNL modal split model was parameterized using 2019 NHTS data, which predates the post-pandemic shift in urban travel behavior; recalibration using post-2022 household travel survey data would improve mode share projection accuracy. The benefit-cost analysis does not capture several potentially significant co-benefits including reduced emergency medical service calls related to diet-associated chronic disease, improvements in student academic performance linked to improved nutritional access, and economic multiplier effects from local employment creation. Future research should employ a Social Return on Investment (SROI) framework to capture these broader social value streams.

Future work should also evaluate the optimal frequency and routing of freight delivery vehicles using vehicle routing optimization algorithms to minimize HGV impact on adjacent residential streets, and should conduct a microsimulation traffic analysis using VISSIM or AIMSUN to model intersection-level performance under projected post-opening volume conditions.

Artificial intelligence methods offer several concrete avenues for strengthening the analytical framework applied here. Machine learning-based forecasting and clustering models could refine the demand and modal-split projections used in this study, extending the kind of predictive and clustering techniques recently applied to renewable-energy and smart-grid planning [20] to food-access travel demand and multi-modal ridership forecasting. Predictive infrastructure models built on AI, as demonstrated for energy-efficient smart buildings [17], could likewise be adapted to anticipate facility-level energy and operational loads for community grocery developments and to optimize their siting relative to transit and pedestrian networks. Explainable physics-informed and machine-learning frameworks, such as those developed for structural and biomedical applications [18, 7], point toward more transparent surrogate models for the travel-demand and risk-simulation components of this study, allowing planners to interpret model outputs with greater confidence. Governance-oriented AI research on institutional and municipal decision systems [14] is also directly relevant to the permitting and inter-agency coordination challenges identified in the Monte Carlo risk analysis, suggesting that AI-supported knowledge-management systems could streamline the concurrent review processes recommended above. Reinforcement-learning-based multi-criteria decision-making frameworks [19] could further improve the vehicle routing and freight-delivery optimization proposed for future work, while AI-augmented fuzzy strategic analysis methods [5] and AI-driven strategic governance frameworks [10] could help evaluate the environmental sustainability and policy trade-offs of food-desert remediation projects at a broader planning scale. Collectively, these AI-enabled approaches could increase the precision, transparency, and adaptability of the transportation engineering methodology presented in this paper.

8. Conclusion

This paper has presented a rigorous, multi-method transportation engineering analysis of the planning and construction of a community grocery store in the food-desert-designated Northwood neighborhood of Baltimore, Maryland. Through spatial accessibility modeling, OLS regression, ANOVA, Travel Demand Modeling, Monte Carlo risk simulation, and benefit-cost analysis, the study demonstrates that the proposed facility delivers substantial and statistically verifiable transportation system benefits. Key quantitative conclusions include: (1) pedestrian food-access travel time is reduced by 86.8% for residents within the 0.5-mile service radius; (2) transit-accessible food retail population coverage increases from 31.4% to 74.2%; (3) vehicle-free, low-income households experience the largest absolute travel time improvements, confirming the equity value of the project; (4) expected daily vehicle trip generation of 1,016 net automobile trips is manageable within the study area road network capacity; (5) walking and cycling mode share increases from 11.7% to 26.9% of food shopping trips; and (6) the five-year NPV of transportation system benefits is $3.82 million against a $2.5 million project cost, yielding a Benefit-Cost Ratio of 1.53.

These findings establish that community food infrastructure investments in strategically sited, transit-accessible locations constitute legitimate and high-return transportation engineering interventions. The methodology presented here provides a reproducible analytical framework applicable to food desert remediation projects in comparable urban contexts nationally.

Author Contributions

Conceptualization, F.J. and R.S.; methodology, F.J.; software, F.J.; validation, F.J. and R.S.; formal analysis, F.J.; investigation, F.J.; resources, F.J. and R.S.; data curation, F.J.; writing original draft preparation, F.J.; writing review and editing, F.J. and R.S.; visualization, F.J.; supervision, F.J. and R.S.; project administration, F.J. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement

The transportation, demographic, and travel-survey data supporting results of this study are derived from publicly available sources cited in Section 3.2, including the U.S. Census Bureau, the USDA Food Access Research Atlas, the 2019 National Household Travel Survey, and MTA GTFS feeds. Derived datasets and analysis code are available from corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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