DETERMINATION OF LOW-COST GROCERY STORE LOCATIONS USING GIS AND MACHINE LEARNING: OMAHA, NEBRASKA CASE STUDY

by

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Dedication

This dissertation is dedicated to the Almighty God, the source of life and wisdom.

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ABSTRACT

DETERMINATION OF LOW-COST GROCERY STORE LOCATIONS USING GIS AND MACHINE LEARNING: OMAHA, NEBRASKA CASE STUDY

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Access to affordable and nutritious food is a pressing issue in Omaha, Nebraska, where economically disadvantaged neighborhoods face significant barriers due to the lack of nearby grocery stores. This study addresses the problem of food deserts, defined by low median household income and high obesity rates, using a data-driven approach that integrates Geographic Information Systems (GIS) and machine learning to identify underserved areas and optimize grocery store placement.

GIS analysis revealed that neighborhoods such as Cathedral, Downtown, Benson, Keystone, and North Omaha are food deserts with limited access to transit and grocery stores, exacerbating food insecurity. Spatial mapping highlighted a disparity in food store distribution, with central Omaha benefiting from better access compared to northern and western regions. Using predictive modeling, Random Forest and Regularized Decision Tree algorithms achieved perfect classification of food desert neighborhoods. These models also identified Cathedral and Downtown as areas with the highest grocery demand, calculated by combining food desert probability with population density.

The study evaluated the potential impact of adding grocery stores to high-demand areas through simulations, which demonstrated significant reductions in travel distances to food sources and enhanced access for underserved communities. A cost-benefit analysis indicated the economic feasibility of the intervention, estimating a net benefit of $15 million from the construction of five new grocery stores, considering reductions in healthcare costs, obesity rates, and economic benefits to the neighborhoods.

This research offers actionable insights for policymakers and urban planners, emphasizing the need for targeted grocery store placement, policy incentives, and community engagement. The integration of GIS and machine learning provides a scalable framework for addressing food insecurity, which can be adapted to other urban areas facing similar challenges. By improving food access in Omaha, this study highlights the potential to enhance health equity, foster community resilience, and drive meaningful social and economic change.

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CHAPTER I: INTRODUCTION

1.1 Context and Background

Access to fresh and affordable groceries is not only essential for individual health but also plays a crucial role in enhancing community well-being and fostering social equity. However, in many regions across the United States, including Omaha, Nebraska, the lack of accessible grocery stores, particularly in low-income areas, creates "food deserts." These are geographic areas where residents face significant challenges in obtaining a variety of healthy food choices due to the absence of nearby grocery stores (Beaulac et al., 2009; Larson et al., 2009). The poor access to quality and nutritious food is a factor contributing to several health issues such as diabetes, obesity, and cardiovascular diseases, especially in vulnerable populations (Walker et al., 2010).

In Omaha, food deserts are concentrated in economically disadvantaged neighborhoods, including North and South Omaha, which are home to a significant proportion of the city's low-income and minority populations.

The concept of food deserts has been extensively studied in the context of urban planning, public health, and social justice. Research indicates that food deserts are often located in economically disadvantaged neighborhoods, where residents are more likely to experience poverty, unemployment, and limited access to transportation (Cummins & Macintyre, 2006; Morland et al., 2002). In these areas, residents are forced to rely on convenience stores and fast-food outlets because of lack of available grocery stores that offer fresh and affordable groceries (Ver Ploeg et al., 2009). These type of neighborhoods face barriers such as limited public transportation and economic disinvestment, exacerbating food insecurity and its associated health risks (Larson et al., 2009).

Residents in food desert areas often face additional financial burdens as they must travel long distances to access nutritious food. Addressing these challenges requires innovative solutions that combine spatial analysis and predictive modeling to identify underserved areas and determine optimal grocery store locations.

The integration of Geographic Information Systems (GIS) and machine learning offers a promising approach. GIS provides the tools to map and analyze the spatial distribution of resources, while machine learning enables the prediction of optimal grocery store locations by leveraging socio-economic and demographic data (Kamel Boulos & Berry, 2012; Mahmud et al., 2021). By applying these technologies to Omaha's food access landscape, this study seeks to address the issue of food deserts and improve community well-being.

1.2 Research Problem

Although Omaha is a growing and vibrant city, it faces significant disparities in food accessibility. Areas like North Omaha, historically affected by economic and social disinvestment, have become epicenters of food deserts. These neighborhoods are characterized by high poverty rates, racial segregation, and limited access to public transportation (Beaulac et al., 2009). The lack of grocery stores offering affordable and healthy options perpetuates cycles of poverty and poor health outcomes (Larson et al., 2009). Traditional approaches to grocery store placement often overlook the complex socio-economic and geographic dynamics that contribute to food deserts. These methods frequently rely on business-centric models that prioritize profitability over community need. Consequently, many underserved neighborhoods remain excluded from food access interventions (Mahmud et al., 2021). Policymakers, urban planners, and businesses often lack the tools to make informed decisions about grocery store placement that balance economic feasibility with social equity. This dissertation addresses these challenges by leveraging the combined strengths of Geographic Information Systems (GIS) and machine learning to identify underserved areas in Omaha, Nebraska and develop data-driven models for determining optimal locations for new low-cost grocery stores. By integrating spatial analysis with predictive modeling, this study seeks to provide actionable insights that can guide policymakers, urban planners, and community leaders in making informed decisions to improve food access and reduce health disparities in the state.

1.3 Research Objectives

The overarching goal of this research is to develop a comprehensive, data-driven approach to addressing the issue of food deserts in Omaha, Nebraska. To achieve this goal, the study is guided by the following objectives:

1. **Identify Geographic Areas in Omaha, Nebraska**
    - Utilize Geographic Information Systems (GIS) to conduct a spatial analysis of areas lacking adequate access to low-cost grocery stores.
    - Consider factors such as population density, income levels, transportation networks, and existing food retail options (Ver Ploeg et al., 2009).

2. **Analyze the Spatial Distribution of Existing Grocery Stores**

    - Examine the current distribution of grocery stores in Omaha, Nebraska.

    - Assess accessibility to different population groups, particularly low-income and rural communities.

    - Identify service gaps and pinpoint areas where additional grocery stores are most needed (Larson et al., 2009).

3. **Develop a Predictive Model Using Machine Learning Techniques**

    - Employ machine learning algorithms to build a predictive model for identifying optimal locations for new low-cost grocery stores.

    - Incorporate historical data on demographic trends, consumer behavior, and existing store locations to predict areas with high demand for affordable food options (Han et al., 2022; Mahmud et al., 2021).

4. **Evaluate the Potential Impact of Proposed Optimal Locations**

    - Simulate different scenarios to assess the effects of new grocery store placements on food accessibility and health disparities in underserved communities.

- Evaluate key metrics such as:

    - Changes in average distance to the nearest grocery store.

- The number of people served by new store locations.
- Potential economic and social benefits for communities (Kamel Boulos & Berry, 2012).

1.4 Significance of the Study

This research holds significance at multiple levels:

- **Local Impact:** By focusing on Omaha, this study directly addresses the challenges faced by the city's residents, providing actionable recommendations to improve food access in underserved neighborhoods (Beaulac et al., 2009).
- **Methodological Contribution:** The integration of GIS and machine learning represents a novel approach to addressing food deserts. This study contributes to the academic literature by demonstrating how these tools can be combined to inform decision-making (Mahmud et al., 2021).
- **Social Equity:** Improving food access in low-income and minority neighborhoods promotes health equity and community resilience, addressing broader social and economic disparities (Larson et al., 2009).
- **Scalability and Applicability:** Although centered on Omaha, the methods and findings can inform food access initiatives in other cities, particularly those facing similar challenges (Han et al., 2022).

By addressing food deserts, this study not only contributes to academic knowledge but also has the potential to drive meaningful change at the community level.

1.5 Scope and Limitations

This dissertation focuses on the city of Omaha, Nebraska, specifically analyzing food access patterns within its geographic and demographic context. The study uses publicly available data, including demographic statistics, grocery store locations, and transportation networks (Ver Ploeg et al., 2009). Additionally, the study does not consider market dynamics or private business decisions that may influence grocery store placement (Mahmud et al., 2021).

1.6 Outline of the Dissertation

This dissertation is structured as follows:

- **Chapter 1: Introduction**: Provides the background, problem statement, research objectives, significance, and scope of the study.
- **Chapter 2: Literature Review**: Synthesizes existing research on food deserts, their socio-economic impacts, and the use of GIS and machine learning in locational analysis.
- **Chapter 3: Methodology**: Describes the research design, data collection methods, and analytical techniques employed in the study.

- **Chapter 4: Results**: Presents the findings from the spatial and predictive analyses, supported by maps, tables, and charts.
- **Chapter 5: Discussion**: Interprets the findings in relation to the research objectives and broader literature, discussing their implications for policy and practice.
- **Chapter 6: Conclusion and Recommendations**: Summarizes the study's contributions, discusses its limitations, and provides recommendations for future research and practical interventions.

CHAPTER II: REVIEW OF LITERATURE

2.1 Introduction

The literature review explores foundational concepts and empirical research relevant to the study's objective of improving food access in urban settings. It focuses on three interrelated themes: the definition and consequences of food deserts, the socio-economic effects of grocery store accessibility, and the growing use of Geographic Information Systems (GIS) and machine learning to address spatial inequities. Together, these themes provide a theoretical and methodological framework that informs the study's approach to identifying optimal locations for low-cost grocery stores in Omaha, Nebraska.

Food deserts—geographic areas where residents have limited access to affordable and nutritious food—have been the subject of extensive research, particularly in the fields of public health, urban planning, and social policy. This chapter examines how scholars define and measure food deserts, as well as the health disparities, economic disadvantages, and social challenges that arise in communities affected by them. Understanding these dynamics is essential to contextualize Omaha's challenges within broader national trends and to design interventions that target root causes.

In addition to defining the problem, the literature also highlights the socio-economic role of grocery stores in shaping community well-being. Access to grocery stores is not only a matter of convenience; it influences dietary choices, chronic disease rates, household spending, and even local economic development. This section reviews empirical studies linking food access to outcomes such as obesity, diabetes, and neighborhood revitalization, thereby emphasizing the urgency of addressing gaps in grocery infrastructure.

Finally, the chapter reviews how advanced analytical tools—specifically GIS and machine learning—have been used to investigate and address spatial disparities in food access. GIS offers powerful capabilities for mapping underserved areas, analyzing proximity to essential services, and visualizing urban patterns. When combined with machine learning, these technologies enable predictive modeling that can guide the strategic placement of new grocery stores. This methodological review sets the foundation for the integrated approach adopted in this study.

By synthesizing current knowledge across these three domains, this chapter provides a comprehensive backdrop for the research. It not only clarifies the relevance of food deserts as a public concern but also supports the study's choice of methods and reinforces the need for data-driven solutions in tackling food inequity in Omaha.

2.2 Overview of Food Deserts

Food deserts are geographic areas where residents have limited access to affordable and nutritious food, particularly fresh fruits and vegetables (Ver Ploeg et al., 2009). The concept of food deserts has gained significant attention in recent years due to its implications for public health, social equity, and economic development (Ver Ploeg et al., 2009; Walker et al., 2010; Wolf-Powers, 2017). These areas are typically found in low-income neighborhoods, where residents often lack access to full-service grocery stores and are instead reliant on convenience stores or fast-food outlets that offer limited healthy food options (Walker et al., 2010).

The origins of the term "food desert" are rooted in the 1990s, during discussions of urban and rural poverty and the challenges associated with ensuring equitable food access. Initially coined in the United Kingdom, the term was later adopted in the United States as researchers identified disparities in food access (Beaulac et al., 2009). Ver Ploeg et al. (2009) defined food deserts as areas where residents lack access to affordable and nutritious food, emphasizing socio-economic and geographic barriers.

Food deserts are prevalent in both urban and rural settings, though the underlying factors differ. Urban food deserts often emerge in economically disadvantaged neighborhoods that have faced decades of disinvestment. North and South Omaha exemplify such areas, where systemic racial inequalities and historic economic marginalization have compounded issues of food access (Larson et al., 2009). Census data indicate that North Omaha, home to a significant minority population, experiences poverty rates exceeding 16%, far above the city’s average (Schafer & Grell, 2022).

The persistence of food deserts in urban environments has also been linked to broader structural processes, including discriminatory zoning practices, redlining, and uneven patterns of suburbanization (Gordon et al., 2011; Sharkey, 2009). In some cases, major grocery chains have deliberately withdrawn from inner-city neighborhoods, citing high operating costs and perceived security risks, further limiting food access in low-income urban areas (Alwitt & Donley, 1997).

Rural food deserts, in contrast, are characterized by geographic isolation. Residents in these areas must often travel long distances to reach grocery stores, a challenge exacerbated by limited public transportation. Morland et al. (2002) documented that rural residents frequently spend more on transportation to access basic necessities, further straining household budgets.

Minority populations, particularly African American and Hispanic communities are disproportionately affected by food deserts and are more likely to reside in such areas than their White counterparts (Morland et al., 2002). This disparity is evident in Omaha, where the majority of food deserts are located in neighborhoods with predominantly minority populations. Research suggests that systemic inequities in housing policies and urban planning have contributed to this unequal distribution (Walker et al., 2010).

Recent efforts to map and measure food deserts have become increasingly sophisticated. GIS tools now allow researchers to incorporate not just proximity to food retailers, but also walking distance, store quality, price levels, and hours of operation into models of food accessibility (Widener et al., 2013). The Food Access Research Atlas by the USDA is a prime example of how spatial data can be utilized to identify and monitor food deserts at the national level (Reynolds Jr et al., 2024).

Furthermore, alternative frameworks have emerged to supplement the food desert concept. Terms such as "food swamps" (areas saturated with unhealthy food outlets) and "food apartheid" (emphasizing the systemic and racialized nature of food inequity) offer more nuanced understandings of food access challenges (Cooksey-Stowers et al., 2017; Sbicca,

2012) . These perspectives encourage a deeper critique of structural inequalities and expand the conversation beyond geographic access to include issues of affordability, cultural relevance, and food sovereignty.

In summary, the literature establishes that food deserts are a complex manifestation of spatial and socio-economic inequality. Whether in urban or rural areas, food deserts reflect deeper systemic issues that go beyond mere store placement. A thorough understanding of their determinants and dynamics is crucial for developing effective, data-informed interventions tailored to the specific needs of communities like those in Omaha.

2.3 Determinants and Consequences of Poor Access to Grocery Stores in Low-Income Areas

Geographic location is a primary determinant of poor food access. In urban areas, the lack of grocery stores in economically disadvantaged neighborhoods often forces residents to rely on convenience stores or fast-food outlets, which offer limited healthy options (Ghirardelli et al., 2010). Poor Access to grocery stores in low-income communities results from a multifaceted interplay of geographic, economic, cultural, and infrastructural factors. These determinants contribute to the emergence and persistence of food deserts and exacerbate existing health and socio-economic disparities (Andress & Fitch, 2016; Tacoli, 2020). Scholars have highlighted that geographic location remains a core structural barrier. In urban centers, economically disadvantaged neighborhoods often lack full-service grocery stores and are instead served by convenience stores and fast-food outlets offering energy-dense but nutrient-poor food options (Ghirardelli et al., 2010; Morland et al., 2002).

A critical driver of this pattern is market disinvestment. Retailers tend to avoid low-income neighborhoods due to concerns about profit margins, crime, and higher operating costs (Alwitt & Donley, 1997). This creates a cycle wherein the absence of grocery stores leads to decreased foot traffic and diminished economic vitality, further deterring investment (Zenk et al., 2005). Moreover, food retailers often rely on demographic and market analysis tools that systemically exclude low-income or minority-dense areas from site consideration (Eisenhauer, 2001).

Low-income households face financial constraints that limit their ability to purchase fresh and nutritious food. Additionally, lower profit margins in low-income areas discourage grocery retailers from establishing stores, creating a cycle of disinvestment (Morland et al., 2002). Cultural and behavioral factors are also important. In some communities, there may be a lack of demand for fresh produce due to dietary preferences, lack of knowledge about healthy eating, or limited cooking skills. This can influence the types of food that are stocked in local stores, further limiting access to nutritious options (Powell et al., 2007).

Inadequate public transportation is another significant barrier. Residents without private vehicles often struggle to access grocery stores located outside their neighborhoods. This issue is particularly pronounced in Omaha, where public transit routes do not adequately serve low-income areas (Schafer & Grell, 2022). For instance, an individual without a car may need to spend hours commuting on buses to reach a supermarket, increasing the time and financial burden associated with food procurement (Burns et al., 2011; Niedzielski & Kucharski, 2019).

Culural and behavorial factors also play a role in shaping food access. In some communities, generational dietary habits and limited nutritional literacy contribute to diminished demand for fresh produce (Powell et al., 2007). Retailers, responding to demand signals, may choose to stock more processed foods and fewer perishable goods, reinforcing poor dietary patterns and creating a feedback loop that discourages supply-side improvements (Bodor et al., 2010).

The consequences of poor access to grocery stores in low-income areas extend far beyond individual health. Food deserts are associated with a range of negative outcomes, including increased rates of obesity, diabetes, and other diet-related diseases (Morland et al., 2002; Sallis et al., 2020). Larson et al. (2009) found that individuals living in food deserts are 1.4 times more likely to suffer from diet-related illnesses compared to those with access to grocery stores. These health disparities are particularly pronounced in minority communities, where the prevalence of food deserts is often higher (Walker et al., 2010).

Moreover, the lack of access to healthy food contributes to broader socioeconomic issues. Poor diet quality can affect educational outcomes by impacting cognitive function and school performance among children (Alaimo et al., 2008). In adults, inadequate nutrition can lead to reduced productivity and increased absenteeism in the workplace, further entrenching individuals and families in cycles of poverty (Cummins & Macintyre, 2006).

Child in food-secure households are particularly vunerable. Poor nutrition during early childhood can impede cognitive development, academic achievement, and long-term physical health (Alaimo et al., 2008; Jyoti et al., 2005). In adults, inadequate nutrition has been linked to reduced work productivity, chronic illness, and increased healthcare utilization, contributing to higher public health expenditures (Kirkpatrick et al., 2010).

The absence of grocery stores in low-income areas also has significant social implications. Food deserts often lead to social dislocation, as residents are forced to travel long distances to access basic necessities. This can reduce social cohesion and weaken community ties, making it more difficult to address other issues such as crime, unemployment, and housing instability (Beaulac et al., 2009).

The presence of accessible grocery stores in a comunnity is not only a matter of public health but also a key driver of local economic development (Ver Ploeg et al., 2009). Grocery stores are significant employers, providing jobs for residents and stimulating economic activity in their neighborhoods (Hagan & Rubin, 2013, 2015). Economic disinvestment in areas classified as food deserts perpetuates cycles of poverty as residents often spend a larger proportion of their income on transportation or overpriced food from convenience stores, leaving less for other necessities (Cummins & Macintyre, 2006). This economic burden is exacerbated in North Omaha, where unemployment rate exceeds the state average by over 5% (Schafer & Grell, 2022). Studies have shown that the introduction of a grocery store in an undeserved area can attract additional businesses, leading to a multiplier effect that boosts economies (Berg & Murdoch, 2008).

Accessible grocery stores also have a positive impact on property values. Research indicates that homes located near grocery stores tend to have higher property values, reflecting the desirability of living in areas with convenient access to food (Bodor et al., 2010). This increase in property values can lead to higher property tax revenues, which can be reinvested in the community to fund public services such as schools, parks, and transportation infrastructure (Caspi et al., 2012).

The social benefits of accesible grocery stores are equally significant. Grocery stores often serve as community hubs, providing spaces where residents can interact, build relationships, and foster a sense of belonging. This is particularly important in low-income areas, where social cohesion is often weakended by economic hardship and social isolation (Cummins & Macintyre, 2006).

Improved access to healthy food can also lead to better health outcomes, which in turn can reduce healthcare costs for individuals and communities. By preventing diet-related diseases, accessible grocery stores contribute to the overall well-being of residents and reduce the burden on healthcare systems (Sallis et al., 2020).

Moreover, grocery stores can play a role in addressing social inequalities by ensuring that all residents, regardless of socioeconomic status, have access to nutritious food. This can help to level the playing field and provide low-income individuals and families with the resources they need to lead healthy and productive lives (Walker et al., 2010).

In summary, the determinants and consequences of poor food access in low-income areas are complex and interdependent. Addressing this issue requires a holistic approach that integrates spatial planning, transportation investment, economic incentives, public health programming, and culturally sensitive community engagement. Without tackling the structural roots of food inequity, interventions risk offering only short-term or superficial relief.

2.4 Strategies for Addressing Food Deserts

Policy interventions play a critical role in mitigating food deserts. Governments can implement zoning regulations, provide subsidies for grocery store development, and improve public transportation to underserved areas (Smith, 2016; Wolf-Powers, 2017). The Healthy Food Financing Initiative (HFFI), introduced in the United States, has demonstrated success in incentivizing grocery store development in food deserts by offering grants and loans (Bodor et al., 2010). Evaluations of HFFI-funded programs suggest modest but positive impacts on food access, with improved availability of fresh produce and reductions in travel time to stores (Briggs et al., 2010). Local governments have also implemented targeted strategies, such as offering subsidies to grocers, reducing red tape in permitting processes, and integrating food access goals into comprehensive urban plans (Walker et al., 2010). Cities like Philadelphia and New York have launched "fresh food zoning overlays" to incentivize grocery development in designated areas (Mabli et al., 2010).

In addition to policy-driven solutions, market-based strategies are being employed. Social enterprises and cooperative grocery stores have emerged as alternative business models capable of operating sustainably in low-income areas. These models prioritize community needs over profit, reinvest earnings locally, and often involve community ownership, fostering local engagement and resilience (Michelini, 2012).

Technological innovation also plays a growing role. Online grocery platforms such as Amazon Fresh, Walmart Grocery, and Instacart have extended their services to include food desert communities. These platforms reduce spatial barriers by delivering fresh food directly to consumers. However, digital divide issues, such as lack of internet access or digital literacy, can limit their impact (Dillahunt et al., 2019). Programs like the USDA's Online Purchasing Pilot, which allows Supplemental Nutrition Assistance Program (SNAP) recipients to use benefits online, aim to bridge this gap (Cohen et al., 2020).

Emerging technologies, including e-commerce and delivery services, offer new avenues for addressing food deserts. Companies like Amazon and Instacart have piloted programs to deliver fresh food to underserved areas. However, these solutions often exclude low-income households due to high delivery fees and limited internet access (Caspi et al., 2012).

Grassroots initiatives, such as community gardens and urban farming projects, have gained traction as cost-effective and locally driven solutions to food deserts. Studies have shown that community gardens can improve food security, foster social cohesion, and provide educational opportunities (Alaimo et al., 2008; Draper & Freedman, 2010). In Omaha, local organizations have initiated urban agriculture programs to address food access disparities. Cities like Detroit and Oakland have developed robust urban agriculture networks that not only grow food but also educate residents, create jobs, and reclaim blighted land (Colasanti et al., 2010).

Mobile food markets and buses—such as Chicago's Fresh Moves or Boston's Daily Table on Wheels—deliver groceries to underserved neighborhoods, particularly those with limited public transportation. These services have been effective in improving food access in areas where opening a new brick-and-mortar store may be financially unfeasible (Zepeda et al., 2014).

Food policy councils (FPCs) have also emerged as collaborative platforms bringing together stakeholders from public, private, and nonprofit sectors to develop holistic food access strategies. FPCs advocate for policies that promote equitable food systems and often operate at city, county, or state level (Harper et al., 2009).

Educational initiatives are another crucial component. Nutrition education programs aimed at increasing food literacy can influence purchasing and dietary behavior, especially when combined with increased access to healthy foods (Alaimo et al., 2008). Programs such as Cooking Matters or FoodSmart have successfully equipped low-income families with skills to prepare healthy meals affordably (Silver et al., 2017).

In summary, strategies to address food deserts span multiple sectors and scales. Effective solutions are typically those that are context-specific, community-driven, and supported by evidence-based policy. As new technologies and models emerge, continued evaluation and inclusive planning will be essential to ensure that food access improvements are equitable, sustainable, and impactful.

2.5 Current Technological Solutions

The food distribution industry has undergone significant transformations due to the adoption of emerging technologies. These advancements are reshaping how food is sourced, stored, transported, and delivered, particularly in addressing the challenges posed by food deserts (Khan et al., 2021). From e-commerce platforms to blockchain for supply chain transparency, these innovations offer scalable solutions to ensure equitable access to nutritious food in underserved areas. In the context of food deserts, these technologies have the potential to bridge gaps in accessibility and affordability, making fresh and nutritious food more readily available to low-income and marginalized populations (Khan et al., 2021; Su et al., 2017).

E-commerce platforms have emerged as significant players in addressing geographic barriers associated with food deserts. Companies such as Amazon Fresh, Instacart, and Walmart Grocery have created digital grocery ecosystems that enable consumers to shop online and have goods delivered to their homes. These platforms are especially beneficial in urban food deserts, where large grocery stores may be absent and transportation options limited (Dillahunt et al., 2019). Studies indicate that the use of online grocery services can reduce food procurement times, lower transportation costs, and improve access to a wider variety of healthy foods (Cohen et al., 2020).

However, digital solutions are not without challenges. Many low-income households lack reliable internet access, digital literacy, or electronic payment methods, creating a new form of food inequality—the digital food divide (Olson et al., 2007). In response, government programs such as the Supplemental Nutrition Assistance Program (SNAP) Online Purchasing Pilot have been launched to allow eligible participants to use their benefits on online platforms, helping to make e-commerce more inclusive (Cohen et al., 2020).

E-commerce eliminates the geographic barriers associated with food deserts by enabling residents to access a wide variety of fresh and nutritious food without the need for physical proximity to grocery stores (Cohen et al., 2020; Dillahunt et al., 2019). Studies have shown that online grocery delivery services can improve food access for underserved communities by reducing transportation costs and expanding product availability (Caspi et al., 2012; Dillahunt et al., 2019).

Blockchain technology offers another innovative pathway by enhancing transparency, accountability, and traceability within food supply chains. Blockchain systems maintain an immutable record of transactions that can verify the origin, handling, and transportation of food products (Rejeb et al., 2020). This is particularly useful in minimizing food fraud, ensuring food safety, and reducing waste—all critical concerns in food-insecure communities (Astill et al., 2019). Walmart, for example, has partnered with IBM to implement blockchain systems that trace leafy greens from farm to shelf, reducing the time needed for food safety investigations (Kamath, 2018).

Artificial intelligence (AI) and machine learning (ML) are being utilized to forecast food demand, optimize inventory management, and streamline distribution logistics. AI-powered models can predict consumer needs using historical sales data, demographic trends, and environmental variables, ensuring that the right quantities of fresh food are stocked at the right locations (El Raoui, 2022; Han et al., 2022). This is crucial in food deserts, where food waste and understocking are common due to distribution inefficiencies.

AI also supports route optimization for delivery services, enabling cost-effective and timely distribution of food to hard-to-reach communities. Companies like UPS and FedEx use predictive analytics to plan optimal delivery paths, reducing carbon footprints while expanding service coverage (Veluru, 2023).

The Internet of Things (IoT) plays a pivotal role in maintaining food quality during transportation. IoT sensors embedded in trucks and storage facilities monitor variables such as temperature, humidity, and location in real-time, ensuring the integrity of perishable items (Oladele, 2024; Verdouw et al., 2016). These systems enable immediate responses to logistical issues, minimizing spoilage and ensuring that food reaches its destination in safe and consumable condition. In food deserts, where fresh produce availability is limited, such technology is vital for extending product shelf-life and reducing delivery losses.

Autonomous delivery systems, including drones and robotic vehicles, are also being piloted as solutions to last-mile delivery challenges. These technologies offer promising options for reaching remote or infrastructurally underserved communities. Wing, a subsidiary of Alphabet, has conducted successful drone deliveries of groceries and meals in rural areas, while Nuro's autonomous vehicles are being tested in urban neighborhoods for grocery delivery (Figliozzi & Jennings, 2020; Zhang et al., 2023).

Mobile grocery stores equipped with smart technology further enhance food access in underserved communities. These vehicles not only bring food directly to consumers but are now integrated with mobile payment systems, inventory tracking, and nutritional information displays. Programs such as Rolling Harvest and Fresh Moves have used such models to deliver affordable, nutritious food to food deserts while fostering education and engagement (Seidner, 2014).

While these technological advancements hold great promise, their scalability and accessibility remain contingent on supportive policies, investment in digital infrastructure, and inclusive design practices. Ensuring that innovations are adapted to the socio-economic realities of food-insecure populations will be critical to their long-term success and equity impact.

2.6 Future Prospects

As the landscape of food access continues to evolve, emerging innovations in technology, policy, and community engagement offer new and promising avenues to address food deserts more sustainably and equitably. Future strategies are expected to integrate multidisciplinary approaches that leverage predictive modeling, collaborative governance, and adaptive infrastructure to mitigate spatial and socio-economic disparities in food availability.

One of the most promising developments is the integration of artificial intelligence (AI) and advanced machine learning algorithms to anticipate future food insecurity hotspots.

Artificial intelligence (AI) and machine learning are being used to optimize food distribution networks by predicting demand, reducing waste, and improving last-mile delivery (El Raoui, 2022; Elgalb & Gerges, 2024).

These models can be trained on diverse datasets—including census demographics, health indicators, retail accessibility, and mobility trends—to simulate and forecast changes in food environments. Predictive analytics allows urban planners and policymakers to proactively design interventions before food access becomes a critical concern (Han et al., 2022; Yakymchuk & Liashenko, 2023). Machine learning models analyze historical sales data, weather patterns, and consumer behavior to predict food demand accurately. This ensures that distribution centers are stocked with the right products, minimizing shortages in underserved areas (Han et al., 2022)

AI-powered route optimization tools help delivery services reduce transportation costs and improve efficiency, making food delivery more viable in food deserts. Companies like FedEx and UPS use AI to design delivery routes that minimize fuel consumption and delivery times (Veluru, 2023)

Scenario modeling, in particular, is gaining attention as a future tool for evaluating potential impacts of various food policies. These models can simulate the effects of interventions such as the introduction of a new grocery store, the expansion of a public transit line, or a shift in zoning regulations. By assessing hypothetical outcomes, scenario modeling helps optimize decision-making and ensures that food access strategies are both cost-effective and equitable (Höchtl et al., 2016).

Another area of future exploration involves the use of deep learning and natural language processing (NLP) to analyze unstructured data, such as social media posts, online reviews, and community feedback. These sources can yield valuable insights into food access experiences, consumer satisfaction, and cultural food preferences—factors often overlooked in traditional datasets (Uddin, 2024). NLP tools can detect sentiment, extract themes, and flag emerging concerns, enabling real-time adaptation of food distribution strategies.

Decentralized food systems are also anticipated to play a larger role in future food access initiatives. This includes expanding urban farming, hydroponics, aquaponics, and vertical agriculture systems, which reduce dependency on centralized supply chains. These systems can be especially beneficial in dense urban areas or regions facing logistical challenges, offering hyper-local, resilient food solutions (Horst et al., 2024a).

Furthermore, the concept of food hubs—regional centers that aggregate, store, process, and distribute food—may become increasingly relevant. Food hubs can serve as intermediaries between local producers and underserved markets, facilitating access while supporting regional economies (Matson & Thayer, 2013). Future iterations of food hubs may integrate cold chain logistics, renewable energy systems, and data dashboards to increase operational efficiency.

Smart city infrastructure offers another critical frontier. By embedding food access into broader urban innovation strategies, cities can design environments where access to nutritious food is planned alongside transportation, housing, and public services. Smart city platforms could use real-time data from IoT sensors to detect food waste, optimize delivery routes, and signal food shortages to city managers (Li et al., 2020; Waykar & Yambal, 2025).

Looking ahead, equity and ethics will become increasingly central to the deployment of food access technologies. As digital tools shape decision-making, there is a growing need to ensure transparency, prevent algorithmic bias, and protect community data. Participatory design methods—where communities co-create tools and strategies—will be essential to building trust and ensuring that innovations serve those most in need (Kasowaki & Deniz, 2024; Phelps et al., 2000).

Global partnerships may also shape future solutions. Lessons from global cities like Curitiba, Brazil; Nairobi, Kenya; and Copenhagen, Denmark offer diverse models of integrating food systems into sustainable urban development. International collaboration can facilitate knowledge exchange, funding, and cross-sectoral innovation to accelerate local solutions (Gustafsson & Kelly, 2016; Rabinovitch, 1996).

Blockchain technology is increasingly being adopted in the food distribution industry to enhance transparency, traceability, and efficiency (Rejeb et al., 2020). By creating an immutable ledger of transactions, blockchain can track the journey of food products from farm to table, ensuring quality and reducing food waste (Astill et al., 2019).

Blockchain can enhance food security in food deserts by optimizing supply chains, lowering costs, and ensuring the timely delivery of fresh produce. Additionally, it can help detect inefficiencies and disruptions, such as spoilage or contamination, which disproportionately affect underserved communities. (Zhao et al., 2019).

Companies such as IBM Food Trust have partnered with retailers and suppliers to implement blockchain solutions for food traceability. For example, Walmart uses blockchain to trace the origin of its leafy greens, reducing the time required to track produce from days to seconds (Kamath, 2018). Similar applications can be adapted to optimize supply chains in food deserts.

The Internet of Things (IoT) is being used to monitor and manage the cold chain, ensuring that perishable food items remain fresh during transportation and storage (Oladele, 2024). IoT sensors track temperature, humidity, and location in real time, enabling swift action in case of deviations (Oladele, 2024; Verdouw et al., 2016).

In food deserts, where fresh produce is often scarce, maintaining the quality of perishable goods during transportation is critical. IoT-enabled cold chain management ensures that food reaches underserved areas in optimal condition, reducing waste and increasing access to nutritious options (Verdouw et al., 2016).

Companies like DHL and Maersk have integrated IoT solutions into their logistics networks, improving the efficiency of perishable food distribution (Oladele, 2024). These technologies can be scaled to serve low-income neighborhoods where fresh food is a critical need (Vural et al., 2024).

Autonomous vehicles and drones are being explored as innovative solutions for last-mile delivery in hard-to-reach areas. These technologies offer cost-effective and efficient alternatives to traditional delivery methods (Nurgaliev et al., 2023).

Drones have been piloted in several regions to deliver groceries and prepared meals to underserved communities (Nurgaliev et al., 2023). For instance, Wing, a subsidiary of Alphabet, has launched drone delivery services in rural areas, reducing delivery times and costs (Zhang et al., 2023).

Autonomous delivery vehicles, such as those developed by Nuro, are being tested in urban environments to deliver groceries directly to consumers. These vehicles could be particularly beneficial in urban food deserts, where transportation barriers limit food access (Figliozzi & Jennings, 2020).

Mobile grocery stores are a practical and innovative solution to addressing food deserts. These vehicles function as traveling grocery stores, bringing fresh produce and other essentials directly to underserved neighborhoods (Zepeda et al., 2014).

Mobile grocery stores eliminate the need for residents to travel long distances, providing convenient access to fresh food. They also serve as community hubs, fostering social interaction and education about healthy eating (Treuhaft & Karpyn, 2010).

Organizations like Fresh Moves in Chicago and Rolling Harvest in rural areas have successfully implemented mobile grocery programs, improving food security and reducing health disparities in underserved communities (Seidner, 2014).

Current and emerging technologies in food distribution have the potential to revolutionize how food deserts are addressed. While e-commerce, blockchain, AI, IoT, autonomous delivery systems, and mobile grocery stores each present unique opportunities, their success depends on overcoming challenges related to cost, accessibility, and infrastructure. By integrating these technologies with policy interventions and community-driven approaches, stakeholders can create sustainable solutions to ensure equitable food access for all.

Finally, future policy frameworks will likely demand integrative, cross-sectoral collaboration. This includes aligning goals across public health, transportation, economic development, and environmental planning. Institutions may adopt systems thinking models that visualize the food ecosystem as a network of interdependent factors, enabling coordinated and adaptive responses to complex challenges.

2.7 Advances in Big Data Analytics for Food Desert Mitigation

Big Data Analytics has emerged as a transformative tool in addressing food deserts, enabling researchers, policymakers, and businesses to identify, analyze, and mitigate disparities in food access (Tamasiga et al., 2023). With the proliferation of data from various sources—geospatial datasets, consumer behavior records, transportation networks, and socio-economic indicators—big data analytics provides unprecedented insights into the complex factors driving food deserts (Luca et al., 2023; Sweeney et al., 2016). This approach leverages advanced analytical methods such as data mining, machine learning, and predictive modeling to optimize resource allocation and improve food security in underserved areas (Sharma et al., 2020; Shoaib et al., 2023; Ziemba et al., 2024).

Geospatial data plays a critical role in identifying food deserts by mapping grocery store locations, transportation networks, and population densities. Tools such as Geographic Information Systems (GIS) are enhanced by integrating big data, allowing researchers to conduct dynamic and granular analyses of food access disparities (Ver Ploeg et al., 2009). Real-time geospatial data from satellite imagery and urban mobility sensors further refines these analyses by capturing changes in food access over time (Kovacs-Györi et al., 2020).

Big data analytics enables the integration of vast socio-economic datasets, including income levels, unemployment rates, and household compositions (Gray et al., 2015). By combining these variables with spatial data, researchers can identify communities most at risk of food insecurity (Kshetri, 2014). For instance, studies have shown that low-income neighborhoods with limited public transportation are disproportionately classified as food deserts (Walker et al., 2010). The ability to analyze these intersections at scale allows for targeted interventions.

Predictive modeling is a key application of big data analytics in mitigating food deserts (Tamasiga et al., 2023). Machine learning algorithms analyze historical and real-time data to predict areas with high demand for grocery stores (Yakymchuk & Liashenko, 2023). For example, regression models and neural networks can forecast grocery demand based on factors such as population growth, purchasing patterns, and proximity to existing stores

(Han et al., 2022). These insights guide policymakers and businesses in selecting optimal locations for new grocery stores.

Predictive analytics allows stakeholders to simulate outcomes of proposed policies or interventions. For example, policymakers can model the expected impact of a new grocery store, transit line, or subsidy program on food access and health metrics. This evidence-based approach supports more strategic planning and increases the likelihood of successful outcomes (Tamasiga et al., 2023).

Clustering algorithms, such as k-means and hierarchical clustering, are used to group neighborhoods based on shared characteristics, such as income levels, obesity rates, and access to transportation. These clusters highlight patterns of food access inequality, enabling decision-makers to prioritize underserved regions for interventions. For instance, a study by Lu et al. (2024) used clustering to identify neighborhoods in urban China with overlapping characteristics of food deserts and public health crises.

Big data analytics provides insights into consumer behavior, such as purchasing preferences and spending patterns (Theodorakopoulos & Theodoropoulou, 2024). Retailers can use this information to stock culturally relevant and affordable food items in stores serving diverse populations. In the context of food deserts, understanding these preferences ensures that grocery stores meet the unique needs of their communities (Caspi et al., 2012).

Mobile apps and loyalty programs generate real-time data on consumer demand, which can be analyzed to identify trends in grocery purchasing (Son et al., 2020). This information helps grocery chains adapt their inventory and services to changing community needs, enhancing food security in underserved area (Saha et al., 2024).

Big data analytics supports policymakers in designing evidence-based interventions to address food deserts (Su et al., 2017). By visualizing disparities and simulating policy outcomes, decision-makers can allocate resources more effectively (Yakymchuk & Liashenko, 2023). For example, the USDA Economic Research Service uses big data to track food desert locations and evaluate the impact of federal programs such as the Healthy Food Financing Initiative (Ver Ploeg et al., 2009).

Big data enables scenario analysis, allowing policymakers to evaluate the potential impact of various interventions (Höchtl et al., 2016). For instance, sensitivity analyses can predict how changes in transportation infrastructure or grocery store subsidies would affect food access in specific neighborhoods. Such analyses are critical for developing adaptive policies that respond to evolving community needs (Treuhaft & Karpyn, 2010).

One of the primary challenges in using big data for food desert mitigation is ensuring data accuracy and completeness. Discrepancies in data sources, particularly in rural areas, can limit the reliability of analyses (Kovacs-Györi et al., 2020). Integrating diverse datasets from public and private sources requires sophisticated algorithms and expertise.

The collection and use of personal data, such as consumer purchasing histories and demographic information, raise ethical concerns (Phelps et al., 2000). Ensuring data privacy and security is critical to maintaining public trust and compliance with regulations like the General Data Protection Regulation (GDPR) (Zhao et al., 2019).

Emerging AI technologies, such as deep learning and natural language processing, offer new opportunities for analyzing unstructured data, such as social media posts and online reviews (Uddin, 2024). These insights can reveal hidden barriers to food access and inform targeted interventions (Han et al., 2022).

Creating open-access platforms that aggregate and analyze food access data can enhance collaboration between stakeholders, including governments, NGOs, and private companies (De Beer, 2017). Such platforms could democratize access to big data tools, empowering local communities to address food deserts independently (Kamath, 2018).

Big data analytics has revolutionized how food deserts are identified and mitigated. By integrating geospatial data, machine learning, and predictive modeling, stakeholders can develop targeted, efficient, and scalable solutions to improve food access (Almalki et al., 2021). While challenges related to data quality, integration, and privacy remain, ongoing advancements in technology promise to further enhance the utility of big data in addressing food security challenges. These tools represent a critical step toward equitable food systems, particularly in underserved communities such as Omaha.

In conclusion, big data analytics represents a powerful, multi-dimensional approach to understanding and mitigating food deserts. Its ability to integrate diverse data sources, uncover latent patterns, and support predictive modeling makes it indispensable in the development of equitable and responsive food systems.

2.8 Global Perspectives on Food Deserts

While food deserts are often discussed within the context of urban America, they represent a global phenomenon affecting millions of people across both developed and developing countries. The international lens provides critical insights into diverse socio-political, cultural, and economic dynamics that shape food access. These perspectives also offer comparative models and innovative practices that can inform and inspire localized interventions in places such as Omaha, Nebraska.

In the Global South, food deserts often emerge in peri-urban or informal settlements, where population growth outpaces infrastructure development. For example, in Nairobi, Kenya, rapid urban expansion has led to the proliferation of informal housing areas lacking proximity to fresh food markets. Here, residents rely on street vendors and small kiosks, which offer limited healthy food options at high prices (Otieno & Owuor, 2015). Poor road infrastructure and insufficient regulation of food supply chains further compound the challenge.

Similarly, in parts of Latin America such as Mexico City and São Paulo, urban sprawl has produced neighborhoods with limited public transit and constrained access to grocery stores. Residents must often travel long distances, and the prevalence of fast-food chains and processed foods in these environments contributes to rising rates of obesity and non-communicable diseases (Popkin et al., 2020).

In contrast, food deserts in high-income countries may stem more from deliberate disinvestment and socio-spatial inequality. In the United Kingdom, for instance, studies have shown that supermarket chains systematically exclude lower-income neighborhoods due to profitability assessments, resulting in uneven food retail distribution (Wrigley, 2002). In Australia and Canada, rural and indigenous communities face food insecurity due to geographic isolation, high transportation costs, and limited supply chain infrastructure (Skinner et al., 2014).

Comparative research reveals several innovative policy and programmatic responses. In Brazil, the Food Acquisition Program (PAA) facilitates direct purchasing of produce from smallholder farmers to supply food to schools and food-insecure populations. This model not only improves access to nutritious food but also supports local agricultural economies (Rocha et al., 2017). In South Korea, the government has integrated food access strategies into broader urban planning policies, including mandatory inclusion of public markets in newly developed residential areas (Kim & Lee, 2019).

European cities have pioneered integrated planning models that embed food access into transport, housing, and sustainability strategies. For instance, Amsterdam has adopted a "Food Agenda" that promotes urban agriculture, short supply chains, and healthy food education in schools. Similarly, the Milan Urban Food Policy Pact—signed by over 200 cities worldwide—encourages cities to develop comprehensive food system policies that ensure equitable access to healthy food (Dubbeling et al., 2016).

International development agencies have also begun incorporating food access into their sustainable development frameworks. The United Nations' Sustainable Development Goals (SDGs), particularly Goal 2 (Zero Hunger) and Goal 11 (Sustainable Cities and Communities), emphasize the need for inclusive food systems as a cornerstone of human well-being and urban resilience (Horst et al., 2024b).

In summary, the global landscape of food deserts underscores both the universality of food access challenges and the diversity of potential solutions. Drawing lessons from international experiences enriches local policymaking and broadens the strategic toolkit available to urban planners, public health officials, and community organizations.

2.9 Community-Based Participatory Research (CBPR) and Localized Solutions for Food Access

Community-Based Participatory Research (CBPR) is a collaborative research approach that equitably involves community members, organizational representatives, and academic researchers in all aspects of the research process. This methodology is particularly effective in addressing complex and localized challenges like food deserts because it integrates lived experiences, local knowledge, and scientific methods to co-create solutions (Israel et al., 2010).

CBPR stands in contrast to top-down research and planning approaches that often overlook the contextual realities and cultural practices of affected communities. Instead, CBPR prioritizes community empowerment, capacity building, and long-term sustainability. When applied to food access issues, this approach helps uncover the nuanced barriers that residents face—ranging from stigma and safety concerns to lack of culturally appropriate food options—that may not be evident through traditional quantitative data alone (Minkler & Wallerstein, 2008).

Participatory Geographic Information Systems (PGIS) is one practical application of CBPR in food access research. PGIS involves training community members to collect spatial data on food availability, walkability, transit routes, and store quality, allowing for the creation of maps that reflect local perceptions and needs (Corbett & Keller, 2006). These community-generated maps often reveal insights not captured by official datasets, such as informal markets, unsafe pedestrian zones, or underutilized community gardens.

For example, a PGIS project in New Orleans engaged youth in mapping neighborhood food resources and documenting issues such as poor lighting, lack of sidewalks, and crime hotspots near corner stores. The resulting maps were used to advocate for infrastructure improvements and the placement of healthier food retail options (Zenk et al., 2005).

CBPR has also been instrumental in shaping food policy and programming. In Detroit, community-led research on food access disparities led to the creation of the Detroit Food Policy Council, which now serves as a formal advisory body to city government. In

Philadelphia, CBPR efforts informed the development of nutrition education programs that addressed both cultural relevance and affordability concerns (Friedman et al., 2010).

Moreover, CBPR strengthens trust and dialogue between marginalized communities and public institutions. This is particularly important in food justice work, where historical patterns of discrimination, exclusion, and mistrust often hinder policy implementation. By creating platforms for shared decision-making and mutual accountability, CBPR fosters more inclusive and effective solutions (Wallerstein et al., 2018).

Technology-enhanced CBPR is also on the rise, with mobile apps and digital storytelling platforms enabling broader participation in food system planning. For instance, the "Food Voices" project used audio narratives and photo-elicitation to document residents' experiences with food insecurity, influencing the design of neighborhood-specific interventions in underserved communities (Hayes-Conroy & Hayes-Conroy, 2010).

Despite its benefits, CBPR is not without challenges. It is time-intensive and requires sustained commitment, mutual respect, and conflict resolution skills. Power imbalances between academic and community partners can also undermine the process if not managed thoughtfully. Nonetheless, when executed well, CBPR offers a transformative approach to addressing food deserts by ensuring that interventions are rooted in community values, assets, and aspirations.

2.10 Ethical and Equity Considerations in Data-Driven Food Access Solutions

As data analytics and smart technologies increasingly influence food access policy and planning, ethical and equity considerations must be placed at the forefront of innovation. While advanced tools like predictive modeling, AI, GIS, and big data analytics offer unprecedented insights and efficiency, their implementation without deliberate attention to fairness and inclusion risks exacerbating the very inequities they aim to resolve (Zhao et al., 2019).

A major concern is algorithmic bias—unintended biases encoded in data-driven models due to skewed datasets or flawed assumptions. If historical patterns of exclusion are embedded in datasets used to model food access, predictive algorithms may inadvertently reinforce existing disparities, such as excluding marginalized communities from grocery site recommendations or underestimating their food needs (Eubanks, 2018). Transparency in algorithm design and regular auditing of models for bias are critical practices to mitigate such risks (Mehrabi et al., 2021).

Data privacy and surveillance concerns also arise in the use of consumer data for food access solutions. Collecting data on purchasing behavior, food preferences, or location patterns can yield valuable insights—but it also requires careful management to prevent misuse, breaches, or erosion of trust. Ethical frameworks such as informed consent, anonymization, and adherence to data protection regulations like the GDPR are essential to ensure responsible data stewardship (Phelps et al., 2000; Tisné, 2020).

The digital divide presents another equity issue. Many data-driven interventions rely on internet access, digital devices, and technical literacy—resources that are not equitably distributed. For example, rural residents or low-income urban households may lack access to broadband, making it difficult to benefit from online grocery services, food delivery apps, or nutrition tracking tools (Gonzales, 2016). Addressing these disparities requires complementary investments in digital infrastructure and community training programs.

Moreover, technological solutions often prioritize scalability and efficiency, which may not align with culturally specific food needs. Data-driven food access systems must incorporate qualitative inputs from diverse communities to ensure that recommended interventions reflect cultural preferences, dietary restrictions, and community values (Smith et al., 2020). Participatory design practices and community engagement are critical for ensuring that technology serves inclusive purposes.

Ownership and control of data are also important considerations. When data are collected in underserved communities—whether through sensors, mobile apps, or research surveys—it is essential to clarify who owns the data, who can access it, and how the findings will be used. Models such as community-owned data cooperatives and open-data governance protocols offer frameworks for ethical data sharing and empowerment (Taylor & Kukutai, 2016).

Lastly, equity must be a guiding principle not just in technological design, but in the broader ecosystem of food policy. Planners and researchers must consider the systemic and historical factors that have produced food deserts—such as redlining, zoning inequities, and economic disinvestment—and ensure that data-driven interventions do not obscure or depoliticize these root causes (Carroll, 2021).

In summary, while digital tools and analytics present powerful solutions to food access challenges, their use must be guided by ethical reflection, community input, and an unwavering commitment to equity. Ensuring inclusive innovation in this space requires building trust, reducing harm, and sharing power with the communities most affected.

2.11 Policy Frameworks and Institutional Responses to Food Security

National, state, and local policy frameworks play a critical role in shaping the structure and effectiveness of food access systems. Recognizing food insecurity and food deserts as systemic issues rather than isolated challenges has led to a range of institutional responses that combine regulatory oversight, funding mechanisms, urban planning strategies, and cross-sector collaboration.

At the federal level in the United States, several programs directly address food insecurity. The Supplemental Nutrition Assistance Program (SNAP), Women, Infants, and Children (WIC), and the National School Lunch Program are among the most impactful in providing economic support for food purchases (The Reinvestment Fund, 2021). However, these programs primarily address affordability, not physical access—thus, additional interventions are required to address geographic barriers associated with food deserts.

The Healthy Food Financing Initiative (HFFI), launched in 2010, represents one of the most significant federal attempts to increase food retail options in underserved areas.

Administered by the Reinvestment Fund and supported by the U.S. Departments of Treasury, Agriculture, and Health and Human Services, HFFI provides loans and grants to support grocery store development and healthy food retail expansion (The Reinvestment Fund, 2021).

At the state and municipal levels, governments have integrated food access strategies into broader health, economic, and land-use planning initiatives. For example, the California FreshWorks Fund offers financing to food enterprises in low-income neighborhoods, while New York City's Food Retail Expansion to Support Health (FRESH) program incentivizes grocery development through zoning and tax benefits (Public Health Law Center, 2017).

Institutional responses have also included the creation of food policy councils (FPCs) and public-private partnerships aimed at promoting coordination across sectors. These councils facilitate communication between farmers, retailers, policymakers, and community organizations to ensure that food policies reflect local needs (Harper et al., 2009). FPCs have been instrumental in shaping urban food strategies in cities like Seattle, Toronto, and Washington, D.C., where they have guided zoning changes, nutrition initiatives, and mobile food market programs.

Internationally, cities that have signed the Milan Urban Food Policy Pact have committed to integrating food systems into urban planning and governance. This multilateral agreement promotes actions such as supporting urban agriculture, reducing food waste, and improving food distribution infrastructure (Dubbeling et al., 2016).

Non-governmental institutions have also played a pivotal role in expanding food access. Philanthropic organizations like the Robert Wood Johnson Foundation, the Rockefeller Foundation, and the W.K. Kellogg Foundation have provided substantial grants to support research, advocacy, and pilot programs. Similarly, cooperative grocery stores, nonprofit food delivery systems, and local food hubs have created alternative pathways to address market failures in food-insecure areas (Winne, 2008).

Despite these efforts, challenges remain in aligning policy goals across agencies and ensuring equitable implementation. Fragmentation of responsibilities between different levels of government and a lack of standardized metrics for measuring food access have hindered coordination and evaluation (Clancy & Ruhf, 2010). Furthermore, political turnover and funding volatility can disrupt long-term planning and program continuity.

Moving forward, comprehensive food access policy must be integrated into climate resilience, economic justice, and public health frameworks. Institutional responses that foreground equity, community engagement, and sustainable food systems are more likely to produce lasting impact and foster inclusive urban development.

2.12 Resilience Thinking and Climate Adaptation in Urban Food Systems

As the dual threats of climate change and urbanization intensify, resilience thinking has emerged as a vital framework for building sustainable and equitable food systems. Resilience, in this context, refers to the capacity of food systems to absorb shocks, adapt to changing conditions, and continue providing access to nutritious food in the face of environmental, economic, and social disruptions (Tendall, 2015).

Urban food systems are particularly vulnerable to climate-related risks such as heatwaves, flooding, drought, and supply chain disruptions. These events can damage infrastructure, reduce agricultural productivity, disrupt transportation networks, and spike food prices—exacerbating food insecurity, especially in low-income communities (Wheeler & Braun, 2013). Integrating climate adaptation strategies into food system planning is essential for safeguarding access in underserved areas.

One promising approach is the promotion of localized food production through urban agriculture, which not only shortens supply chains but also enhances ecological and social resilience. Rooftop farms, vertical gardens, aquaponics, and community gardens contribute to local food sovereignty while reducing dependence on centralized, vulnerable distribution systems (Despommier, 2010; Sanyé-Mengual et al., 2015).

Green infrastructure investments—such as permeable pavements, bioswales, and green roofs—can simultaneously improve climate resilience and support food access by protecting urban gardens and food storage facilities from flooding or heat stress (Meerow & Newell, 2017). Additionally, incorporating food access into climate adaptation and disaster preparedness plans helps ensure that vulnerable populations are not left behind during crises.

Resilience thinking also emphasizes the importance of redundancy and diversity in food distribution systems. This includes developing multiple sources of food—such as cooperative markets, food hubs, mobile vendors, and e-commerce platforms—that can operate in parallel and provide fail-safes during disruptions (Cinner, 2018).

Social capital is another key dimension of resilience. Communities with strong networks, trust, and reciprocal support are better able to mobilize resources and recover from shocks. Programs that build neighborhood-based food coalitions, mutual aid networks, and resident-led preparedness training foster the kind of adaptive capacity necessary for resilient food access (Barthel & Isendahl, 2013).

Climate resilience must also be approached through an equity lens. Marginalized communities are often disproportionately affected by climate impacts due to preexisting vulnerabilities. Thus, resilience-building efforts must prioritize inclusivity, engage local voices, and address systemic injustices—such as discriminatory zoning or historic underinvestment—that compound climate risk (Shi et al., 2016).

In conclusion, embedding resilience thinking into food system planning enables cities to navigate the uncertainties of climate change while advancing goals of food justice, health equity, and urban sustainability. As Omaha and similar cities confront increasing environmental pressures, incorporating adaptive strategies into food access planning will be essential for long-term viability.

2.13 Smart Cities and Digital Infrastructure for Food Access

The emergence of smart cities presents new opportunities to reimagine food access in urban environments by integrating digital infrastructure, data analytics, and civic technologies into food system planning. A smart city utilizes information and communication technologies (ICT) to enhance service delivery, optimize resource use, and foster sustainable and inclusive urban living (Nam & Pardo, 2011). When applied to food systems, these technologies can improve food distribution, enhance monitoring, and expand access, particularly for underserved populations.

One major contribution of smart city infrastructure to food access is the deployment of Internet of Things (IoT) devices. IoT-enabled sensors installed in warehouses, transport trucks, and retail locations can monitor temperature, humidity, inventory levels, and spoilage in real time. These tools help maintain the quality and safety of perishable goods, reducing waste and ensuring that nutritious food reaches low-income areas efficiently (Verdouw et al., 2016).

Smart mobility systems also support food access by enhancing last-mile delivery through electric delivery vehicles, route optimization algorithms, and mobile grocery units. Cities like Barcelona and Singapore have piloted smart logistics hubs that consolidate deliveries and reduce congestion, thereby lowering costs and emissions while improving delivery coverage in food deserts (Lim et al., 2022).

Digital platforms play a pivotal role in connecting consumers to food providers. Open data portals, community food maps, and mobile applications allow residents to locate nearby food pantries, farmers markets, and affordable grocery outlets. These platforms can also disseminate real-time updates on food availability, nutrition education, and eligibility for food assistance programs, thereby improving awareness and utilization (Campbell et al., 2019).

Artificial intelligence (AI) and big data analytics further enhance urban food governance by enabling predictive modeling and decision-support tools. Municipal governments can use these systems to anticipate food demand, identify at-risk neighborhoods, and prioritize infrastructure investment. For instance, AI models that analyze purchasing behavior, population health trends, and transit data can inform zoning policies and public investments that support equitable food distribution (Bibri & Krogstie, 2020).

Smart waste management systems also contribute to food system sustainability. IoT-enabled compost bins, dynamic collection schedules, and food waste tracking apps help divert organic waste from landfills and promote circular food economies. Cities like San Francisco and Seoul have implemented such programs to encourage community composting and redistribute surplus food through donation networks (Papargyropoulou et al., 2014).

However, the adoption of smart technologies must be approached with caution to avoid reinforcing digital inequalities. Low-income communities often face barriers such as lack of internet access, limited digital literacy, and data privacy concerns. Policymakers must ensure that smart city initiatives are inclusive, community-driven, and supported by investments in equitable digital infrastructure (Gonzales, 2016).

Community engagement and co-design processes are essential to the success of smart food initiatives. Participatory technology development—where residents collaborate in designing apps, platforms, or services—ensures that solutions address actual needs and build trust. Examples include community co-developed food alert systems in Chicago and neighborhood digital kiosks in Toronto that display food resources and services in multiple languages (Shelton et al., 2015).

In conclusion, smart city tools offer transformative potential for improving food access through enhanced logistics, digital transparency, and predictive governance. To realize this potential, urban planners must embed equity and inclusion into every stage of smart city development, ensuring that innovation serves as a vehicle for food justice and sustainability.

2.14 Economic Impacts of Food Deserts and Local Grocery Interventions

Food deserts not only affect health and well-being but also have profound economic implications for individuals, communities, and urban economies. Limited access to healthy and affordable food often forces residents to rely on convenience stores or fast-food outlets, which tend to offer nutritionally poor but high-cost items. This dynamic not only increases household spending on food but also contributes to long-term financial strain associated with preventable health conditions (Cooksey-Stowers et al., 2017).

From a macroeconomic perspective, food deserts can lead to increased public health expenditures. Poor nutrition and food insecurity are linked to higher incidences of obesity, diabetes, hypertension, and other diet-related diseases, which place a significant burden on healthcare systems. Research indicates that low-income areas with poor food access have disproportionately high Medicaid costs and hospital admissions related to nutrition-sensitive conditions (Lee et al., 2017).

The lack of full-service grocery stores in disadvantaged neighborhoods also constrains local economic development. Without anchor food retailers, these communities miss out on employment opportunities, tax revenue, and spillover effects such as foot traffic for adjacent businesses. Conversely, studies have shown that opening a grocery store in a food desert can stimulate job creation, stabilize property values, and encourage further private investment (Sharkey & Horel, 2008).

Grocery store development can also support the local agricultural economy when stores source produce from regional farms and cooperatives. This not only reduces the carbon footprint associated with long-distance transportation but also keeps food dollars circulating within the local economy, reinforcing community resilience and food sovereignty (Feenstra, 2002).

Microeconomic studies reveal that consumers in food deserts often incur higher prices due to limited competition. Small neighborhood stores may charge more per unit of healthy food items compared to chain supermarkets, a phenomenon referred to as the "poverty penalty" (Ghosh-Dastidar et al., 2014). This pricing disparity can undermine dietary choices and exacerbate economic inequality.

Investments in alternative food systems—such as mobile markets, farmers markets, and community-supported agriculture (CSA)—have demonstrated positive economic externalities. These interventions tend to employ local residents, increase entrepreneurial opportunities, and foster a multiplier effect within neighborhoods (Fischer et al., 2015).

Cost-benefit analyses of food access programs have also revealed promising returns. For example, evaluations of the Healthy Food Financing Initiative (HFFI) estimate that every dollar invested in food retail development generates multiple dollars in local economic activity, along with indirect savings in public health spending and social services (The Reinvestment Fund, 2021).

In summary, addressing food deserts is not only a public health priority but also a critical economic development strategy. Enhancing access to nutritious food through local grocery interventions generates measurable benefits for households, communities, and broader urban systems.

2.15 Food Literacy and Consumer Empowerment in Addressing Food Deserts

Food literacy—the knowledge, skills, and behaviors required to plan, select, prepare, and consume nutritious meals—is a crucial but often overlooked dimension in addressing food deserts. Empowering consumers with food literacy not only improves individual dietary habits but also strengthens community resilience by enabling residents to make informed choices despite environmental and economic constraints (Vidgen & Gallegos, 2014).

In food desert communities, low levels of food literacy are often exacerbated by limited access to healthy options and misinformation about nutrition. Studies show that when residents lack understanding of how to read nutrition labels, budget for groceries, or prepare fresh meals, they are more likely to rely on processed, calorie-dense foods—even when healthier alternatives are present (Begley et al., 2019). This perpetuates poor health outcomes and undermines the effectiveness of interventions aimed solely at increasing food availability.

Educational interventions targeting food literacy have demonstrated significant impact. Programs like Cooking Matters, SNAP-Ed, and FoodSmart provide hands-on nutrition education, cooking demonstrations, and budget-friendly meal planning workshops. Participants consistently report increased confidence in shopping for and preparing healthy foods, as well as improved dietary behaviors (Thomas & Irwin, 2011).

Schools are key venues for promoting food literacy among children and families. School-based programs that integrate gardening, cooking, and nutrition education have been shown to improve fruit and vegetable consumption, food preferences, and academic engagement (Gatto et al., 2012). These initiatives not only influence children's habits but often catalyze change within households and communities.

Food literacy also intersects with cultural competence. Culturally tailored interventions that respect and incorporate traditional food practices are more likely to be effective and sustainable. For instance, using familiar ingredients or traditional preparation methods in cooking classes can enhance relevance and reduce resistance among participants (Harmon et al., 2011).

Digital tools are expanding the reach of food literacy initiatives. Mobile applications, online cooking tutorials, and nutrition portals offer flexible, accessible learning opportunities for consumers across literacy levels. However, digital equity challenges remain—underscoring the need for blended learning approaches that combine technology with community-based instruction (Leone et al., 2020).

Moreover, food literacy is increasingly seen as a social justice issue. Marginalized groups are disproportionately affected by structural barriers to food education, such as underfunded schools, lack of community centers, and language barriers. Addressing these inequities requires policy support, cross-sector partnerships, and sustained investment in community-based capacity building (Slater et al., 2018).

In summary, food literacy empowers individuals to navigate food deserts with greater agency, enhances the effectiveness of food access interventions, and contributes to long-term health and economic stability. Incorporating food literacy into comprehensive food policy strategies can help close the gap between availability and actual consumption of nutritious foods.

2.16 Transportation and Mobility Constraints in Food Access

Transportation and mobility play a fundamental role in determining physical access to grocery stores and other nutritious food outlets. In many food desert communities—especially those characterized by low income, racial segregation, or geographic isolation—the lack of reliable transportation options exacerbates food insecurity and limits residents' ability to reach affordable and healthy food sources (Clifton, 2004).

Transportation challenges manifest in both urban and rural environments. In urban areas, residents of food deserts often face long travel distances to reach full-service supermarkets, coupled with limited public transit coverage or high transit costs. A lack of pedestrian infrastructure, such as sidewalks, lighting, or safe crossings, can further deter walking or biking to grocery locations (Jiao et al., 2012). In rural communities, the problem is intensified by greater geographic distances between homes and stores, often requiring personal vehicles for grocery shopping—an asset that not all households possess (Blanchard & Lyson, 2002).

Multiple studies have demonstrated a strong correlation between car ownership and food access. Individuals without access to private transportation are significantly more likely to be food insecure and to shop at stores with fewer healthy food options, such as corner stores or gas stations (Wrigley et al., 2002). The time, cost, and inconvenience of accessing distant stores discourage frequent trips and reduce the feasibility of purchasing fresh produce and perishable items, which require more regular restocking (LeDoux & Vojnovic, 2013).

Public transportation systems often fail to meet the needs of food-insecure populations. Buses and trains may not serve food retail destinations, operate on limited schedules, or be perceived as unsafe. In a study of transit-dependent residents in Baltimore, only 12% of participants reported that they could reach a grocery store within 30 minutes using public transit, compared to 95% of car owners (Zenk et al., 2005).

To address these challenges, cities and nonprofits have piloted alternative transportation strategies. These include grocery shuttle programs, subsidized ride-sharing for grocery trips, and bike delivery services. For example, the "Grocery Bus" in San Francisco provides free, direct service from senior housing complexes to supermarkets, while some cities have experimented with mobile grocery markets that travel directly into underserved neighborhoods (Fitzpatrick & Willis, 2016).

Transportation planning also intersects with land-use policy. Zoning that concentrates grocery development in suburban areas while neglecting inner-city neighborhoods reinforces transportation inequities. Integrating food access goals into comprehensive transportation and urban planning processes is essential for building equitable and inclusive cities (Larsen & Gilliland, 2008).

Incorporating geospatial analysis into transportation studies enhances the ability to assess and address mobility-related barriers. Tools such as accessibility indices, travel time mapping, and multimodal network analysis help policymakers visualize and prioritize interventions in food-insecure zones (Widener et al., 2013).

In summary, improving food access requires a systemic approach to transportation justice. Expanding affordable, reliable, and culturally sensitive mobility options is vital for connecting residents of food deserts to healthy food and fostering greater food equity.

2.17 Social Capital and Community Networks in Enhancing Food Access

Beyond infrastructure and economic interventions, social capital and community networks play a critical role in improving food access in underserved areas. Social capital refers to the connections, trust, and norms of reciprocity within a community that facilitate coordination and cooperation for mutual benefit (Putnam, 2000). In the context of food deserts, robust social networks can buffer against food insecurity by enabling resource sharing, disseminating information, and catalyzing collective action.

Informal support systems—such as neighbors sharing food, families pooling resources for grocery trips, or local churches distributing meals—can help residents meet immediate food needs when formal systems fall short (Martin et al., 2004). These networks are especially vital during crises, such as natural disasters or pandemics, when supply chains and mobility are disrupted.

Community organizations and grassroots initiatives frequently serve as hubs of food access innovation. Food cooperatives, time banks, community kitchens, and buying clubs often emerge from strong social cohesion and can provide alternative avenues for food acquisition outside conventional retail structures (Allen, 1999). For instance, community-supported agriculture (CSA) programs leverage social ties between producers and consumers to provide consistent access to fresh produce while supporting local farms.

Social capital also enhances the effectiveness of food-related programs. Research shows that initiatives with high community engagement and peer support—such as cooking classes, nutrition workshops, and urban gardening programs—tend to have greater participation rates and sustained impact (Alkon & Agyeman, 2011). Trust in institutions and interpersonal relationships can significantly influence whether residents utilize available resources.

Moreover, social networks are instrumental in mobilizing advocacy and policy change. Neighborhood associations, tenant groups, and civic coalitions can pressure decision-makers to address food disparities through zoning changes, subsidy allocation, or supermarket incentives. The success of many food justice campaigns has been rooted in sustained community organizing and coalition-building efforts (Gottlieb & Joshi, 2010).

Digital platforms are increasingly augmenting social capital by facilitating information exchange and coordination among community members. Online mutual aid groups, food-sharing apps, and hyperlocal forums like Nextdoor allow residents to identify food sources, coordinate transportation, or offer assistance in real-time (Campos-Castillo & Williams, 2018).

Nonetheless, disparities in social capital can also mirror broader social inequities. Communities with histories of disinvestment, discrimination, or displacement may have fragmented networks or weakened institutional trust, which can impede the development of food access initiatives. Strengthening social capital, therefore, requires deliberate investment in community-building, inclusive engagement processes, and the recognition of diverse cultural practices and leadership styles (Agyeman & McEntee, 2014).

In conclusion, social capital is a vital but underappreciated dimension of food access strategy. By fostering trust, collaboration, and shared responsibility, strong community networks can amplify the impact of structural interventions and promote food justice from the ground up.

2.18 Food Retail Consolidation and Market Power in Shaping Access

The structure of the retail food industry plays a significant role in shaping geographic and economic access to healthy foods. In recent decades, the U.S. food retail sector has undergone substantial consolidation, with large supermarket chains and big-box retailers dominating market share while smaller, independent grocers have declined (Hingley, 2005). This shift has had considerable implications for food access in both urban and rural areas.

Retail consolidation is driven by economies of scale, operational efficiencies, and competitive pricing advantages held by national chains. However, this trend often results in store closures or the withdrawal of smaller grocers from lower-income or sparsely populated communities deemed unprofitable. As a result, food deserts can emerge or deepen in areas abandoned by traditional food retailers (Eisenhauer, 2001).

Market concentration can also reduce consumer choice and lead to price manipulation. With fewer retailers controlling the food supply, there is less incentive to keep prices low or to tailor product offerings to local needs. This is particularly problematic for marginalized communities, where the loss of culturally specific food products or affordable options can exacerbate food insecurity and alienation from the food system (Howard, 2016).

Moreover, large chains often bypass inner-city or rural locations due to perceived risks, such as high operating costs, crime rates, or low expected profit margins. These decisions are often guided by proprietary data and profit algorithms that may overlook or undervalue community potential and long-term social benefits (Zepeda, 2009).

The role of financialization in food retailing further complicates access. As private equity firms and institutional investors acquire grocery chains, decisions become driven by short-term shareholder returns rather than community well-being. Store closures, staff reductions, and reduced investment in low-margin locations have been linked to these financial practices, often to the detriment of low-income areas (Lobao et al., 2016).

Despite these challenges, some innovative models have emerged to counteract market failures. Nonprofit grocery stores, cooperative markets, and public market interventions have demonstrated that socially driven food retailing can succeed in underserved communities. Additionally, public policies such as tax incentives, zoning reforms, and infrastructure support have been used to attract grocers to high-need neighborhoods (Gittelsohn et al., 2012).

Understanding the dynamics of food retail consolidation is essential for designing equitable food access strategies. It highlights the need for regulatory oversight, antitrust enforcement, and support for alternative business models that prioritize community food security over profit maximization.

2.19 Food Waste, Redistribution, and Circular Food Economies

Food waste is an often overlooked but critical component of the food access ecosystem. While millions of people face food insecurity and limited access to nutritious food, significant quantities of edible food are discarded at the retail, distribution, and household levels. According to the United States Department of Agriculture (USDA), nearly 30–40% of the food supply in the U.S. is wasted annually, representing not only an ethical dilemma but also a lost opportunity to address hunger and food deserts (Coleman-Jensen et al., 2019).

Food waste occurs across the supply chain—from overproduction at farms and post-harvest losses to aesthetic standards in retail and consumer-level discards. Retailers may reject produce for minor imperfections, while expiration labeling often leads to the premature disposal of food that is still safe to consume (Buzby et al., 2014). In low-access areas, food waste coexists paradoxically with scarcity, underscoring the need for efficient redistribution mechanisms.

Food recovery and redistribution programs are emerging as viable solutions to this challenge. Nonprofits, food banks, and social enterprises increasingly collect surplus food from farms, grocery stores, and restaurants to redistribute it to food-insecure populations. Programs like Feeding America, Food Rescue US, and City Harvest are examples of large-scale recovery networks that have prevented millions of pounds of food from going to waste while feeding underserved communities (Broad Leib et al., 2013).

Technology also plays a role in enhancing food redistribution. Mobile apps such as OLIO and Too Good To Go connect consumers and businesses to share or sell surplus food at discounted prices. These platforms reduce landfill contributions and support food access in both high- and low-income areas (Papargyropoulou et al., 2014).

Circular food economies offer a broader sustainability framework by emphasizing resource efficiency and minimal waste. These systems aim to close the loop between food production, consumption, and waste by incorporating composting, upcycling, and local redistribution as integral practices (Cattaneo et al., 2021). Urban areas have begun integrating circular food models into city planning, leveraging compost programs to support local agriculture and community gardens.

Policy interventions can further facilitate food waste reduction. Tax incentives for food donation, standardized food labeling, and liability protections for donors (such as the Good Samaritan Food Donation Act) reduce barriers for businesses to participate in redistribution efforts (Broad Leib et al., 2013). Local ordinances that require grocery stores to donate unsold food or mandate composting—such as those implemented in France and parts of California—also provide effective models for broader adoption.

Importantly, community engagement is key to sustaining food waste initiatives. Educating residents about food storage, expiration dates, and creative cooking with leftovers can help reduce household waste while fostering food literacy. Community fridges, neighborhood swap tables, and gleaning programs further encourage participatory solutions to food insecurity.

In conclusion, addressing food waste through redistribution and circular economy practices holds immense potential to mitigate food insecurity and reduce environmental impacts. Incorporating these strategies into food desert interventions enhances sustainability, equity, and resilience across urban food systems.

2.20 The Role of Technology Startups and Private Innovation in Food Access

In recent years, technology startups and private-sector innovators have emerged as significant contributors to the transformation of urban food systems. These entities bring agility, data-driven strategies, and scalable solutions to address gaps in food accessibility, often complementing public and nonprofit efforts. As food deserts persist despite long-standing institutional interventions, private innovation offers new pathways to deliver affordable, nutritious food to underserved communities.

Startups in the food technology space are leveraging mobile apps, e-commerce, and cloud computing to increase access and reduce inefficiencies in the food supply chain. Services such as FarmboxRx, Imperfect Foods, and Misfits Market deliver discounted or cosmetically imperfect produce directly to consumers, offering healthy alternatives at lower costs. These models simultaneously reduce food waste and expand market access for farmers, while reaching consumers in traditionally underserved areas (Neff et al., 2009).

Other ventures have focused on hyperlocal distribution models. Micro-fulfillment centers and dark stores—retail outlets optimized solely for online delivery—are being piloted in dense urban neighborhoods to support rapid delivery of groceries. Companies like GoPuff and JOKR use data analytics to predict demand and ensure efficient inventory management, reducing stockouts and improving freshness (Khanna et al., 2022).

Fintech integrations within food tech have enabled creative payment solutions and targeted subsidies. Some startups now allow customers to use SNAP benefits for online grocery shopping or provide installment-based payments for larger food purchases, making healthy food more accessible for low-income consumers (Cohen et al., 2020).

Private sector innovations also include smart vending machines and autonomous kiosks that provide healthy food options in transit stations, schools, and housing complexes. These low-footprint solutions bring convenience and accessibility to areas that may not support a full-service grocery store (Lin et al., 2021).

Agri-tech startups are contributing on the production side by developing vertical farms, container agriculture, and AI-driven hydroponic systems to grow food closer to the point of consumption. These innovations reduce dependency on long-distance supply chains and increase local resilience, especially in areas where land availability or climate pose challenges to traditional farming (Benke & Tomkins, 2017).

While private innovation brings promise, concerns about scalability, equity, and digital access remain. Many services target tech-savvy or urban consumers, and without deliberate design for inclusion, these innovations risk reinforcing disparities. Additionally, the venture capital funding model may favor profitability over long-term community engagement, potentially undermining social impact goals (McClintock, 2018).

Partnerships between private startups and local governments or nonprofits offer a way to balance innovation with accountability. Co-designed pilot programs, shared data platforms, and equity audits can ensure that emerging solutions align with the needs of marginalized populations and contribute to holistic urban food strategies.

In conclusion, technology startups and private innovators are reshaping the landscape of food access through agile, user-centered, and scalable interventions. When integrated with public-sector goals and community engagement, these innovations hold the potential to enhance food equity and sustainability in transformative ways.

2.21 Urban Governance and Multi-Stakeholder Collaboration in Food Access Planning

The complex nature of food insecurity in urban environments necessitates coordinated efforts among a wide range of stakeholders. Urban governance—the collective processes and institutions through which city policies are developed and implemented—plays a critical role in integrating food access strategies into broader social, environmental, and economic agendas (Moragues-Faus & Morgan, 2015).

Effective food access planning increasingly depends on multi-stakeholder collaboration involving municipal agencies, public health departments, planning commissions, civil society organizations, academic institutions, and private enterprises. These collaborations allow cities to align policies across sectors such as land use, transportation, health, and economic development to promote equitable food access (Pothukuchi & Kaufman, 2000).

Food policy councils (FPCs) are one institutional mechanism that exemplifies this approach. These councils act as cross-sectoral platforms that bring together diverse stakeholders to assess local food systems, identify gaps, and propose solutions. Research indicates that cities with active FPCs are more likely to adopt integrated food strategies and prioritize community-based solutions (Santo et al., 2014).

Public-private partnerships (PPPs) have also become essential in food system planning. Cities have worked with grocery retailers, tech startups, and nonprofits to pilot mobile markets, data dashboards, or food hub networks. Such partnerships leverage financial and technological resources that governments alone may not possess, enabling more scalable interventions (Koc et al., 2008).

Academic institutions contribute through applied research, policy analysis, and capacity-building. Universities have collaborated with cities on participatory mapping projects, food environment assessments, and evaluation of intervention outcomes. These partnerships ensure evidence-based decision-making and foster innovation (Roberts & Stahlbrand, 2018).

Community engagement is another cornerstone of inclusive governance. Participatory planning processes that involve residents—particularly those from historically marginalized communities—enhance the legitimacy and effectiveness of food strategies. Tools such as town halls, community workshops, and advisory committees ensure that local knowledge and lived experiences shape policy outcomes (Alkon & Mares, 2012).

However, urban governance is not without challenges. Institutional silos, political turnover, and uneven power dynamics can hinder collaboration. Sustained funding, clear accountability structures, and shared metrics of success are necessary to overcome fragmentation and ensure long-term impact (Cohen & Ilieva, 2015).

Cities across the globe provide models for collaborative governance in food access. For example, Toronto's Food Strategy integrates health, equity, and sustainability goals, while the Belo Horizonte model in Brazil institutionalizes food security as a legal right supported by municipal programs and cross-sector coordination (Rocha & Lessa, 2009).

In summary, multi-stakeholder collaboration and inclusive urban governance are foundational to advancing food justice. By leveraging diverse expertise and shared responsibility, cities can develop robust and adaptive systems to address food deserts and ensure that all residents enjoy dignified access to nutritious food.

2.22 Integration of Urban Planning Tools with Geospatial Analytics

The integration of urban planning tools with geospatial analytics represents a transformative approach to designing and managing urban spaces (Attah et al., 2024).

Urban planning seeks to create sustainable, equitable, and functional cities, while geospatial analytics provides the data-driven insights necessary to achieve these goals (Attah et al., 2024; Bibri & Bibri, 2020). This synergy allows planners to make informed decisions on land use, transportation, housing, and resource allocation, particularly in addressing complex challenges such as food deserts, housing inequality, and environmental degradation (Brinkley et al., 2023).

The use of Geographic Information Systems (GIS), combined with advanced urban planning tools, enables spatial analysis, predictive modeling, and scenario planning. These capabilities have made geospatial analytics indispensable in urban planning, particularly in creating equitable food systems, optimizing infrastructure, and improving overall urban resilience (Yeh, 1999).

One of the primary roles of geospatial analytics in urban planning is the ability to map and visualize spatial data. GIS platforms, such as ArcGIS and QGIS, allow planners to overlay multiple data layers, including land use, population density, transportation networks, and socio-economic indicators (Case & Hawthorne, 2013). These visualizations provide a comprehensive understanding of spatial patterns, enabling targeted interventions.

For example, mapping food deserts in urban areas involves analyzing the proximity of grocery stores to residential neighborhoods, transportation accessibility, and socio-economic data. This geospatial approach identifies areas with limited access to healthy food and informs policy decisions (Ver Ploeg et al., 2009).

Geospatial analytics enables the integration of diverse datasets from public and private sources, including census data, transportation models, and environmental assessments (Yin et al., 2021). This integration facilitates a holistic understanding of urban systems, allowing planners to address interrelated issues such as housing, transportation, and food access (Su et al., 2017). Studies have shown that integrating spatial data improves the accuracy of urban planning models and enhances decision-making (Kovacs-Györi et al., 2020).

GIS serves as the backbone of geospatial analytics in urban planning. Its capabilities include spatial analysis, mapping, and 3D modeling, making it a versatile tool for planners (Attah et al., 2024). Advanced GIS applications, such as site suitability analysis and network analysis, have been used to determine optimal locations for grocery stores, public transit hubs, and affordable housing (Rikalovic et al., 2014).

Urban simulation models, such as UrbanSim and CityEngine, integrate GIS data with predictive algorithms to simulate the impact of planning decisions on urban development. These tools allow planners to test different scenarios, such as zoning changes or infrastructure investments, and evaluate their long-term effects on food access, traffic flow, and housing equity (Batty, 2013).

Emerging platforms, such as Sidewalk Labs' Replica and Esri's GeoPlanner, combine big data analytics with geospatial visualization. These platforms provide real-time insights into urban dynamics, enabling planners to monitor trends, predict outcomes, and optimize resource allocation (Kazak et al., 2023). For example, GeoPlanner can assess the environmental impact of proposed developments, ensuring sustainable urban growth (Hanoon, 2019; Kazak et al., 2023).

Urban planning tools integrated with geospatial analytics are widely used to identify and analyze food deserts (Su et al., 2017). By combining spatial data on grocery store locations, transportation networks, and socio-economic factors, planners can pinpoint areas with limited food access (Beaulac et al., 2009). These insights guide interventions, such as the placement of new grocery stores or mobile markets.

Site suitability analysis is a GIS-based technique used to determine the best locations for grocery stores or urban agriculture initiatives. Factors such as land availability, population density, and transportation accessibility are analyzed to ensure that new developments serve the intended communities effectively (Han et al., 2022).

Geospatial analytics supports transit-oriented development (TOD) by integrating food access planning with transportation systems (Clermont, 2013). TOD approaches prioritize the development of grocery stores and fresh food markets near public transit hubs, improving accessibility for residents without private vehicles (Caspi et al., 2012).

One of the primary challenges in integrating urban planning tools with geospatial analytics is the availability and quality of spatial data. Incomplete or outdated data can limit the accuracy of analyses and hinder decision-making (Yin et al., 2021). This issue is particularly acute in low-resource settings, where data collection infrastructure is lacking (Kovacs-Györi et al., 2020).

The complexity of geospatial analytics tools can be a barrier to widespread adoption. Urban planners without specialized training may find it challenging to use advanced GIS software, limiting its utility (Aranda et al., 2023; Tao, 2013). Efforts to create user-friendly interfaces and provide training are critical to overcoming this barrier (Manning, 2023; Tao, 2013).

The integration of AI with geospatial analytics is expected to revolutionize urban planning (Waykar & Yambal, 2025). AI algorithms can analyze large datasets more efficiently, identify patterns, and generate predictive models (Kasowaki & Deniz, 2024). For example, machine learning techniques can predict the impact of zoning changes on food access, traffic congestion, or housing affordability (Han et al., 2022).

The development of open data platforms that aggregate geospatial datasets from multiple sources can democratize access to urban planning tools (Quarati et al., 2021). These platforms allow community organizations, researchers, and policymakers to collaborate on data-driven solutions to urban challenges (Kovacs-Györi et al., 2020; Quarati et al., 2021).

Real-time geospatial analytics, powered by IoT sensors and big data platforms, offers new possibilities for urban planning (Li et al., 2020; Mbuh et al., 2019). By monitoring real-time changes in transportation flows, population movements, and environmental conditions, planners can adapt their strategies dynamically to emerging challenges (Batty, 2013)

The integration of urban planning tools with geospatial analytics offers transformative potential in addressing complex urban challenges (Waykar & Yambal, 2025). By leveraging advanced technologies such as GIS, simulation models, and data-driven platforms, planners can create more equitable, sustainable, and resilient cities. In the context of food deserts, these tools enable targeted interventions that improve food access, enhance community well-being, and promote long-term urban development (Attah et al., 2024).

2.23 The Role of Sustainable Urban Development in Equitable Food Access

Sustainable urban development focuses on creating cities that are inclusive, resilient, and equitable while balancing economic, social, and environmental priorities (Bamigbelu & Adeyeye, n.d.; Kumar et al., 2024). Equitable food access is a critical component of this vision, as it addresses disparities in the availability and affordability of nutritious food across diverse populations (Neff et al., 2009; Weiler et al., 2015). The intersection of sustainable urban development and equitable food access highlights the need for holistic strategies that integrate land use planning, transportation, housing policies, and community-driven initiatives. This approach is essential for addressing food deserts, fostering social equity, and promoting long-term urban resilience (Khalatbari, 2024; Silver et al., 2017).

Sustainable urban development refers to the design and management of cities in ways that meet the needs of current residents without compromising the ability of future generations to thrive (Camagni, 1998; Mersal, 2016). Key principles include efficient resource use, equitable access to essential services, and minimizing environmental impact. Food access is integral to this vision, as it ensures the health and well-being of urban populations while supporting sustainable food systems (Caron et al., 2018; Ilieva, 2017; Lindgren et al., 2018).

Equity is central to sustainable urban development, ensuring that all residents—regardless of income, race, or geographic location—have access to basic needs such as housing, transportation, and food (Bullard, 2007). Research shows that inequities in food access disproportionately affect low-income and minority populations, particularly in urban areas where systemic disinvestment and segregation have created persistent food deserts (Walker et al., 2010).

Zoning and land use policies significantly influence food access by determining where grocery stores, markets, and agricultural spaces can be located (Feldstein, 2012; Hubbard, 2011). Traditional zoning practices have often prioritized commercial or industrial development over community-oriented spaces, exacerbating food access disparities in low-income neighborhoods (Bodor et al., 2010). Sustainable urban development calls for mixed-use zoning that integrates residential areas with grocery stores, farmers' markets, and community gardens, reducing the distance residents must travel to access healthy food (Raja et al., 2008).

Urban agriculture is a sustainable land use strategy that contributes to equitable food access by bringing food production closer to consumers. Community gardens, rooftop farms, and vertical farming systems can transform underutilized urban spaces into sources of fresh produce (Horst et al., 2024a; Siegner et al., 2018). These initiatives not only increase food availability but also foster community engagement, reduce food miles, and promote environmental sustainability (Pearson et al., 2011).

Transportation is a critical factor in food access, particularly for residents of food deserts who often lack private vehicles (Coveney & O'Dwyer, 2009). Sustainable urban development emphasizes investments in public transit systems that connect underserved neighborhoods with grocery stores and markets. Transit-oriented development (TOD) strategies prioritize the co-location of food retail outlets near transit hubs, improving accessibility while reducing reliance on cars (Caspi et al., 2012).

Active transportation modes, such as walking and biking, also play a role in equitable food access (Lee et al., 2017). Cities that invest in pedestrian-friendly infrastructure and bike lanes enable residents to reach grocery stores without the need for motorized transport (Lewis, 2024). Sustainable urban development integrates these modes into broader transportation planning, fostering healthier, more accessible cities (Litman, 2017).

Sustainable urban development promotes the economic viability of food retail in underserved areas through policies such as tax incentives, grants, and public-private partnerships (Khalatbari, 2024). These measures encourage grocery stores and fresh food markets to operate in low-income neighborhoods, addressing the economic barriers that often deter investment (Cummins & Macintyre, 2006). The introduction of grocery stores in food deserts not only improves food access but also stimulates local economies by creating jobs and increasing property values (Berg & Murdoch, 2008).

Sustainable urban development recognizes the importance of community-driven solutions in addressing food access disparities (Khalatbari, 2024; Silver et al., 2017). Initiatives such as food cooperatives, mobile markets, and nutrition education programs empower residents to take an active role in improving their food environments (Bublitz et al., 2019). These approaches align with the principles of sustainability by fostering local leadership, building social capital, and ensuring long-term community resilience (Alaimo et al., 2008).

Food waste is a significant challenge in urban food systems, with an estimated one-third of all food produced globally going to waste (Fao, 2019). Sustainable urban development incorporates strategies to minimize food waste, such as improved supply chain management, food recovery programs, and composting initiatives (Khalatbari, 2024; Silver et al., 2017). These efforts not only enhance food security but also reduce greenhouse gas emissions associated with waste disposal (Munesue et al., 2015).

Local food systems are a cornerstone of sustainable urban development, as they reduce the environmental impact of food transportation and support regional economies (Capone et al., 2014). Farmers' markets and community-supported agriculture (CSA) programs provide urban residents with access to fresh, locally grown produce while promoting sustainable farming practices (Feenstra, 2002).

Detroit has emerged as a leader in urban agriculture, transforming vacant lots into productive community gardens and farms (Mogk et al., 2010). These initiatives have improved food access in one of the nation's most prominent food deserts while fostering economic development and environmental sustainability (Colasanti et al., 2010).

Curitiba's innovative transit system includes direct connections between low-income neighborhoods and fresh food markets (Gustafsson & Kelly, 2016). This model demonstrates how sustainable urban development can integrate transportation planning with food access, creating more equitable cities (Rabinovitch, 1996).

Urban planners often face challenges in balancing food access with other priorities, such as housing, transportation, and economic development (Corburn, 2009). Ensuring that food access remains central to sustainable urban development requires strong advocacy and interdisciplinary collaboration (Litman, 2017).

Evaluating the impact of sustainable urban development on food access requires robust metrics and data collection systems. Future research should focus on developing standardized indicators to assess progress and identify best practices (Pearson et al., 2011).

Sustainable urban development offers a comprehensive framework for addressing food access disparities in urban areas (Javed et al., 2024; Wang et al., 2022). By integrating land use planning, transportation strategies, economic policies, and community-driven initiatives, cities can create equitable and resilient food systems. This approach not only addresses immediate challenges such as food deserts but also promotes long-term sustainability, ensuring that all residents have access to nutritious food (Silver et al., 2017).

2.24 Integration of GIS and Machine Learning in Locational Analysis

Geographic Information Systems (GIS) have become indispensable tools in the analysis and visualization of spatial data, particularly in the context of food access. GIS allows researchers to map food deserts, analyze the spatial distribution of grocery stores, and identify areas where residents face significant barriers to accessing healthy food (Ver Ploeg et al., 2009). By integrating demographic data, transportation networks, and socioeconomic indicators, GIS provides a comprehensive understanding of the spatial dynamics that influence food accessibility (Caspi et al., 2012).

GIS-based locational analysis has been used to conduct site suitability assessments, identifying potential locations for new grocery stores based on factors such as proximity to underserved populations, accessibility by public transportation, and compliance with zoning regulations (Case & Hawthorne, 2013; Erbaş et al., 2018). This approach enables decision-makers to prioritize investments in areas where new stores are most likely to have a positive impact on food access and community health (Rikalovic et al., 2014).

Machine learning has emerged as a powerful tool for predictive modeling, offering new possibilities for identifying optimal locations for low-cost grocery stores. By analyzing large datasets on consumer behavior, demographics, and economic indicators, machine learning algorithms can predict areas with high demand for affordable food options (Han et al., 2022). These models can incorporate a wide range of variables, including population density, income levels, transportation networks, and existing store locations, to generate predictions that are both precise and actionable (Lu et al., 2024).

Machine learning techniques such as regression models, decision trees, and neural networks have been successfully applied to retail site selection, providing insights that can guide the strategic placement of grocery stores (Ting & Jie, 2022). When combined with

GIS, machine learning enhances the accuracy of locational analysis by incorporating complex spatial relationships and predicting future trends in food demand (Yang et al., 2015).

The integration of GIS and machine learning in locational analysis follows a systematic methodological approach. Data collection involves gathering information on existing grocery store locations, demographic factors, transportation infrastructure, and socioeconomic indicators (Kovacs-Györi et al., 2020). GIS-based spatial analysis includes mapping food deserts, conducting site suitability analysis, and identifying areas with the greatest need for low-cost grocery stores (Kovacs-Györi et al., 2020; Ver Ploeg et al., 2009).

Machine learning involves data preprocessing, model selection, and training/validation processes using historical data (Han et al., 2022). The integration of GIS and machine learning entails combining spatial analysis with predictive modeling to create a comprehensive approach for determining optimal grocery store locations.

Despite its potential, the application of GIS and machine learning in food desert research faces several challenges. Data quality and availability, particularly in rural areas, can pose significant obstacles to accurate analysis (Kovacs-Györi et al., 2020). Additionally, ethical considerations related to privacy and data security must be carefully managed. However, successes in using these technologies have been documented, with studies showcasing improved precision in identifying underserved areas and recommending optimal locations for new grocery stores (Han et al., 2022; Lu et al., 2024).

2.25 Summary and Research Gaps

In summary, the literature highlights the critical role of food deserts in exacerbating health disparities and social inequalities, particularly in low-income areas. The economic and social impacts of accessible grocery stores are well-documented, underscoring the importance of ensuring that all communities have access to nutritious food. The application of GIS and machine learning offers promising avenues for addressing food deserts, providing data-driven insights that can guide the strategic placement of grocery stores (Almalki et al., 2021).

However, there are still gaps in the existing literature, particularly concerning the integration of GIS and machine learning in the context of food deserts in Nebraska. Few studies have focused specifically on this state, despite its unique geographic and demographic challenges. This research aims to fill this gap by applying these advanced analytical tools to identify optimal grocery store locations in Nebraska, with the goal of improving food access and reducing health disparities.

CHAPTER III: METHODOLOGY

3.1 Introduction

Food insecurity and limited access to affordable, nutritious food remain pressing issues in many urban communities across the United States. In Omaha, Nebraska, several neighborhoods experience geographic and economic barriers to food access, making them vulnerable to the adverse health and socio-economic outcomes associated with food deserts. Addressing these disparities requires a multidisciplinary approach that leverages both spatial and predictive insights to inform policy and investment decisions.

This study focuses on identifying optimal locations for low-cost grocery stores in Omaha, with the overarching goal of improving access to healthy food in underserved areas. To achieve this, the research adopts a dual-method strategy, combining Geographic Information Systems (GIS) with machine learning techniques. GIS provides a robust platform for mapping spatial inequalities, analyzing proximity to grocery stores, and evaluating transit access. Meanwhile, machine learning enables predictive modeling based on a range of socio-economic, demographic, and health-related factors. This integration ensures that both the "where" and the "why" of food access disparities are thoroughly examined.

The methodological framework was intentionally designed to be both rigorous and replicable, ensuring that the findings are not only academically sound but also applicable to real-world urban planning and public health efforts. Each step—from data acquisition to model integration—was carefully structured to align with the study's research objectives and to support evidence-based decision-making.

Ultimately, this methodology chapter outlines how spatial data, socio-economic indicators, and predictive analytics were combined to develop a comprehensive model for improving food access. It presents the rationale for the mixed-methods approach, details the data sources and processing methods, and describes the analytical techniques used to identify, visualize, and evaluate potential grocery store locations. This integrated approach ensures that the findings of this study are both analytically valid and socially impactful, contributing meaningful insights for planners, policymakers, and community advocates.

3.2 Research Framework and Design

This research was executed in four sequential phases, each building upon the previous to develop a robust, data-driven understanding of grocery access challenges and solutions in Omaha.

The first phase focused on spatial analysis using GIS to identify food deserts and reveal demographic and socio-economic patterns. In the second phase, the current distribution of grocery stores was examined to evaluate accessibility and detect service gaps. The third phase involved developing a predictive model using machine learning techniques, allowing for the identification of optimal store locations based on socio-economic indicators and spatial factors. The final phase evaluated the potential impact of proposed store locations on food accessibility and community well-being.

A mixed-methods approach was adopted to harness the complementary strengths of spatial analysis and machine learning. GIS provided the means to map and visualize geographic disparities in food access, enabling identification of underserved areas with precision. In parallel, machine learning facilitated predictive modeling based on historical and socio-economic data, enhancing the robustness of site selection for new grocery stores. This combination of methods ensured both empirical rigor and real-world applicability (Creswell & Clark, 2017).

3.3 Data Collection and Preparation

To support the research objectives, a diverse array of spatial, demographic, health, and infrastructural data was gathered and processed. The integration of data from multiple sources was critical in ensuring a comprehensive analysis of food accessibility in Omaha. This section outlines the specific data sources, the methods used for data acquisition, and the preprocessing steps taken to ensure analytical readiness.

Data was collected from several reliable sources. Demographic data, including population density, income levels, and racial/ethnic composition, were obtained from both the Bureau (2020) and city-data.com neighborhood maps (City-Data, 2024). Spatial data on grocery store locations was extracted using OpenStreetMap's Overpass API via the OSMnx Python library, which allowed for querying grocery store locations in Omaha, Nebraska (Boeing, 2017). Health and socio-economic indicators were sourced from the City Health Dashboard cityhealthdashboard.com (Gourevitch et al., 2019), providing neighborhood-level metrics on access, health outcomes, and socio-demographic profiles.

GIS layers, such as neighborhood boundaries, were also obtained using Python scripts with OSMnx and GeoPandas libraries, which facilitated the retrieval and processing of spatial geometries for neighborhoods in Omaha. Transportation data, including public transit platforms, was extracted using the Overpass API through Python's overpy library, which queried nodes tagged with "public_transport=platform" for the Omaha area.

Spatial datasets were programmatically extracted using Python tools such as OSMnx, GeoPandas, and Overpy. The OSMnx library was used to query grocery store locations and street network data from OpenStreetMap. Neighborhood geometries were fetched individually using a looped geocoding method that retrieved polygon boundaries for each neighborhood. Public transportation nodes were retrieved via Overpass API using Overpy and processed into a structured dataset. Demographic and socio-economic data were downloaded from City-Data.com and the City Health Dashboard, while population estimates and household information were obtained from the U.S. Census Bureau. Data accuracy was ensured through cross-verification and by aligning data points across sources for completeness (Babbie, 2020).

The preprocessing stage involved cleaning datasets by addressing missing values, standardizing formats, and geocoding relevant fields. All datasets were then merged into a unified geospatial framework using Python, enabling subsequent analysis in both spatial and statistical environments. This unified structure supported efficient integration of machine learning outputs with geographic insights.

3.4 GIS Analysis

GIS techniques were used to identify food deserts based on USDA criteria—areas where residents live over one mile from a grocery store and fall below income thresholds (Reynolds Jr et al., 2024). Network-based calculations in OSMnx assessed distances, while demographic overlays identified vulnerable neighborhoods.

Spatial visualizations of grocery store locations were generated using OSM data. Density mapping highlighted coverage gaps across Omaha. Accessibility was analyzed from both road and transit perspectives. Driving access was measured using OSMnx-derived networks, while public transit access was visualized with 15-minute buffers around grocery stores using Overpy transit nodes.

3.5 Machine Learning Predictive Modeling

Several models were evaluated—linear regression for estimating demand, decision trees and random forests for classifying underserved areas, and neural networks to capture complex relationships (Géron, 2022). These varied approaches enabled both predictive and classification tasks.

Key predictive features included population density, median household income, proximity to public transit, existing grocery store density, and various health and socio-economic indicators from the City Health Dashboard. Feature engineering techniques were applied to transform raw data into inputs suitable for modeling, including normalization and categorical encoding. The models were trained on historical and spatial data, including features derived from grocery store distribution and health indicators. Cross-validation and holdout validation were employed to assess model generalizability. Performance metrics such as R-squared, mean squared error (MSE), and classification accuracy were used to evaluate effectiveness (McCarthy et al., 2022).

3.6 Integration of GIS and Machine Learning

The power of this study lies in the integration of spatial analysis and machine learning to guide location decisions for new grocery stores. GIS provided the geographical context, while machine learning uncovered patterns and predictive insights from the data. This section explains how these methods were combined to deliver a coherent decision-making framework.

GIS outputs and machine learning predictions were integrated to form a holistic spatial decision-making tool. Predicted high-demand areas were overlaid onto GIS maps to visualize spatial inequalities and propose new store placements. This integration provided both predictive insight and geographic specificity.

Visualization played a critical role in communicating findings. GIS-based maps were generated to show underserved areas, model predictions, and potential store locations. These maps offered intuitive understanding of access challenges and served as communication tools for stakeholders.

3.7 Evaluation of Proposed Grocery Store Locations

Once optimal store locations were predicted, the next step was to evaluate their practical impact and feasibility. This section focuses on simulating the potential changes in access and conducting a cost-benefit analysis to assess the sustainability and equity implications of the proposed solutions.

The proposed grocery store locations were evaluated using simulation techniques. These simulations measured changes in travel distance to the nearest grocery store, the number of residents gaining access, and the reduction in food desert zones. The impact analysis quantified the tangible benefits of each location.

Feasibility of proposed store placements was evaluated through a cost-benefit lens. Key considerations included potential operational costs, estimated revenue, improvements in food accessibility, and possible reductions in health expenditures linked to better nutrition. This ensured the recommendations were both economically viable and socially impactful.

3.8 Summary

This chapter presented a comprehensive, step-by-step methodology for addressing food accessibility challenges in Omaha, Nebraska. Through the integration of Geographic Information Systems (GIS) and machine learning, the study employed a mixed-methods approach to identify and evaluate optimal locations for low-cost grocery stores. The methodology was carefully designed to align with the research objectives, ensuring that the analysis was not only methodologically sound but also practically relevant to the urban context.

A foundational aspect of the methodology was the strategic collection and preprocessing of spatial, demographic, health, and transportation data. By leveraging open-source tools and authoritative data sources such as OpenStreetMap, the U.S. Census Bureau, and the City Health Dashboard, the study built a robust dataset that accurately reflected the multifaceted nature of food access. These datasets were then integrated into a unified geospatial framework, enabling detailed spatial analysis and supporting predictive modeling.

GIS tools were instrumental in identifying food deserts and visualizing disparities in grocery store accessibility. Network-based distance calculations, transit access mapping, and demographic overlays allowed for a nuanced understanding of geographic inequities. In parallel, machine learning models—such as random forests and regression analysis—were applied to predict areas of unmet demand and to simulate the impact of proposed store locations. This combination of spatial visualization and predictive insight provided a multidimensional view of Omaha's food access landscape.

The final stages of the methodology included simulation-based evaluations and cost-benefit analyses, which were critical in assessing the real-world viability of the proposed solutions. These components ensured that the recommendations extended beyond theoretical modeling to incorporate social and economic feasibility. By focusing on both the geographic and socio-economic dimensions of food access, the methodology supports a holistic and actionable framework for decision-makers.

In summary, this methodology serves as a replicable model for integrating spatial analytics and predictive modeling in urban planning and public health research. It demonstrates how data-driven approaches can inform equitable development strategies, ultimately contributing to a more just and nutritious food environment for underserved populations.

CHAPTER IV: RESULTS

4.1 GIS Analysis

This section presents the results of the GIS analysis, which focused on identifying food deserts in Omaha based on key demographic and health indicators, as well as examining the spatial distribution of grocery stores and their accessibility via public transit. The results provide critical insight into the relationship between neighborhood characteristics and food accessibility.

4.1.1 Definition of Food Deserts

Food deserts in this study were operationally defined using two criteria: neighborhoods with a median household income below $60,000 and an obesity rate exceeding 30%. These thresholds were selected to reflect both economic hardship and associated public health risks.

A GIS-based analysis was performed to identify neighborhoods meeting both criteria. The results are summarized in Table 1. Five neighborhoods—Benson, Cathedral, Downtown, Keystone, and North Omaha—were identified as food deserts based on this definition. A spatial map (Figure 1) highlights these neighborhoods in red, visually indicating their food desert status and illustrating the concentration of these areas in specific parts of the city.

Table 1: Food Deserts Identified Based on Income and Obesity Rate

Neighborhood	Median Household Income	Obesity Rate	Food Desert Status
Benson	$45,783	35.3%	Yes
Cathedral	$47,073	31.4%	Yes
Downtown	$48,362	32.1%	Yes
Keystone	$54,180	35.4%	Yes
North Omaha	$53,225	46.2%	Yes

A map was generated highlighting these neighborhoods in red, indicating their food desert status. The analysis revealed significant overlap between low-income areas and high obesity rates.

4.1.2 Spatial Distribution of Grocery Stores

To further understand food accessibility, the spatial distribution of grocery stores was analyzed. The analysis revealed a significant concentration of grocery stores in central Omaha, with sparse availability in the northern and western neighborhoods, which notably align with the food desert zones.

Figure 1 displays the spatial layout of grocery stores overlaid on the identified food deserts. The observed mismatch between grocery store locations and high-need neighborhoods suggests spatial inequities in food access.

Additionally, Table 2 presents the comparison between transit accessibility and food desert status. While some food deserts like Cathedral and Downtown are served by transit, neighborhoods such as Keystone and North Omaha lack sufficient public transportation access, further compounding food accessibility issues. Figure 2 visualizes these results.

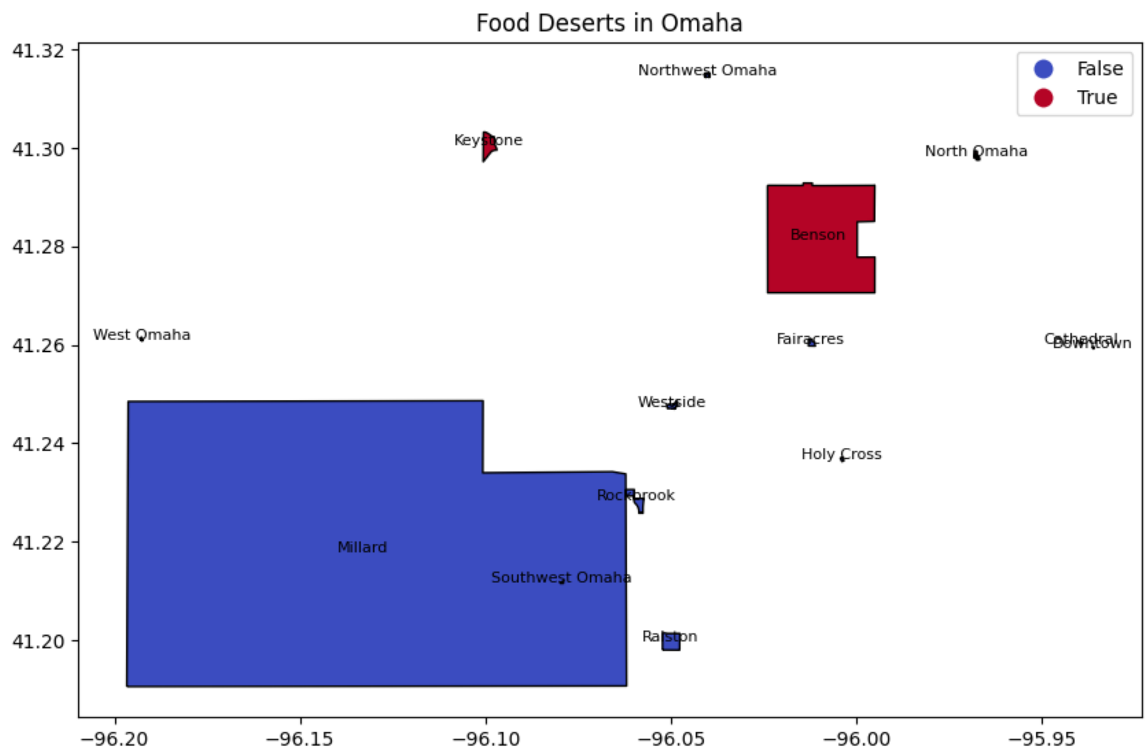

Figure 1: Spatial Distribution of Grocery Stores

Table 2: Transit Accessibility and Food Desert Status

Neighborhood	**Transit Accessible**	**Food Dessert Status**
Benson	Yes	Yes
Cathedral	Yes	Yes
Downtown	Yes	Yes
Keystone	No	Yes
North Omaha	No	Yes

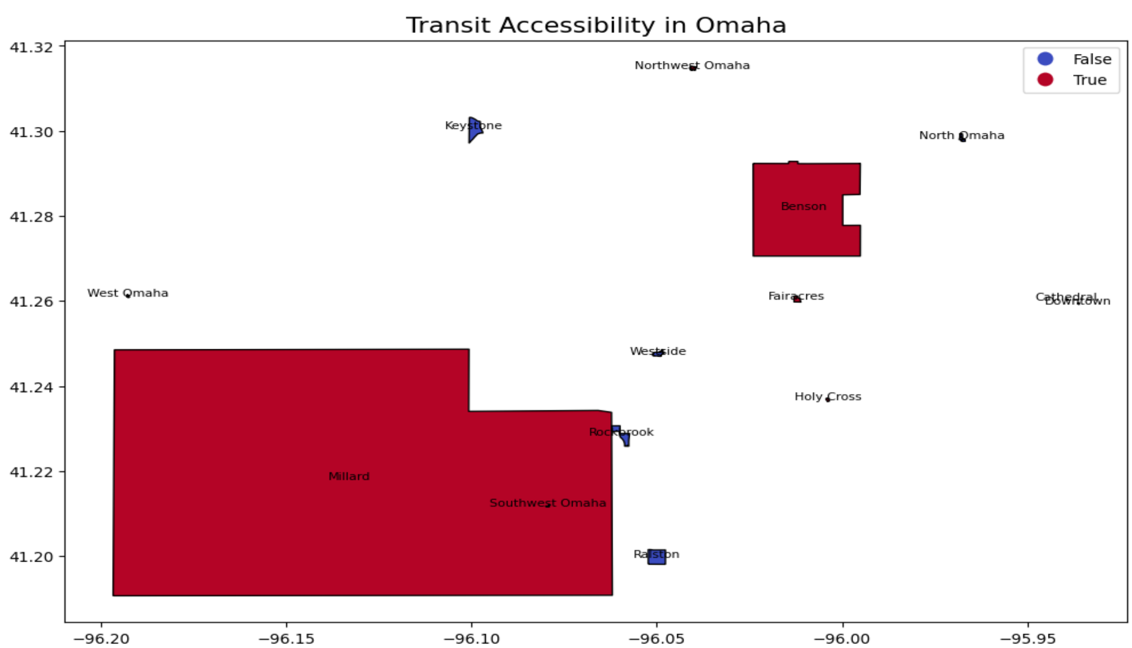

Figure 2: Transit Accessibility and Food Desert Status

4.2 Machine Learning Predictive Modeling

This section outlines the performance of various machine learning models used to predict food desert status based on neighborhood characteristics. The models included Logistic Regression, Regularized Decision Tree, Random Forest, and Neural Network classifiers.

4.2.1 Performance Summary

The predictive performance of each model was evaluated using standard metrics: accuracy, precision, recall, and F1-score. As shown in Table 3, the Regularized Decision Tree and Random Forest models achieved perfect classification, indicating strong predictive power for identifying food desert status. Logistic Regression and the Neural Network underperformed in comparison.

Table 3: Machine Learning Model Performance Metrics

Model	Accuracy	Precision	Recall	F1-Score	Macro Avg F1-Score
Logistic Regression	67%	0.50	1.00	0.67	0.67
Regularized Decision Tree	100%	1.00	1.00	1.00	1.00
Random Forest	100%	1.00	1.00	1.00	1.00

Neural Network	64.29%	0.50	0.40	0.44	0.59

4.3 Predicting Grocery Demand

To estimate where grocery store interventions would be most beneficial, a grocery demand metric was developed by multiplying each neighborhood's food desert probability (from the Random Forest model) by its population density.

The results, presented in Table 4, indicate that Cathedral and Downtown have the highest predicted demand, followed by Benson, North Omaha, and Keystone. Figure 3 shows the distance to the nearest grocery stores, while Figure 4 visually represents predicted demand across neighborhoods.

Table 4: Predicted Grocery Demand for Food Deserts

Neighborhood	**Food Desert Probability**	**Population Density (per sq mile)**	**Predicted Grocery Demand**
Cathedral	0.97	16023	15542
Downtown	0.91	5810	5287
Benson	0.78	4737	3695
North Omaha	0.9	3309	2978
Keystone	0.84	2733	2296

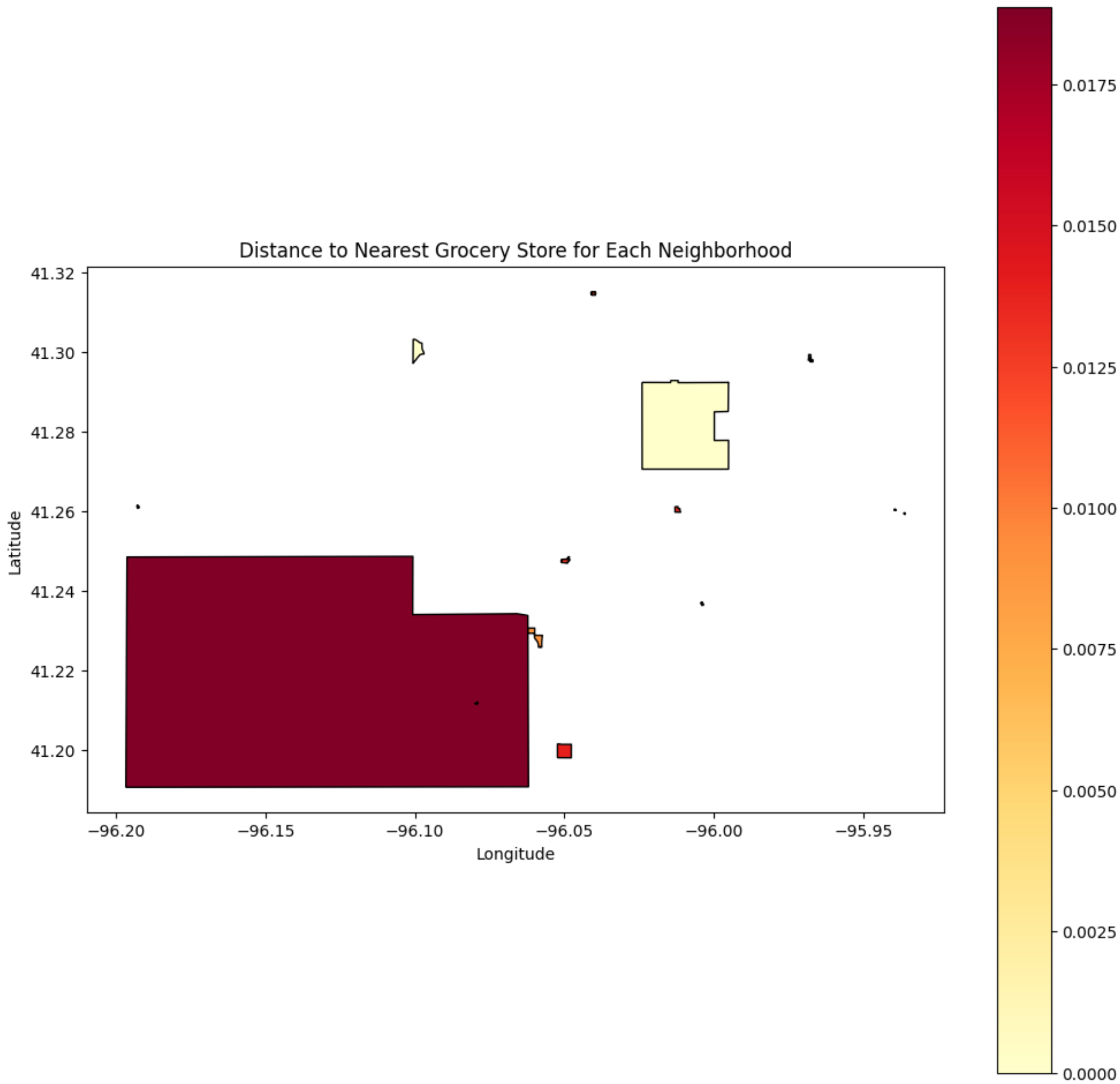

Figure 3: Distance to Nearest Grocery Stores

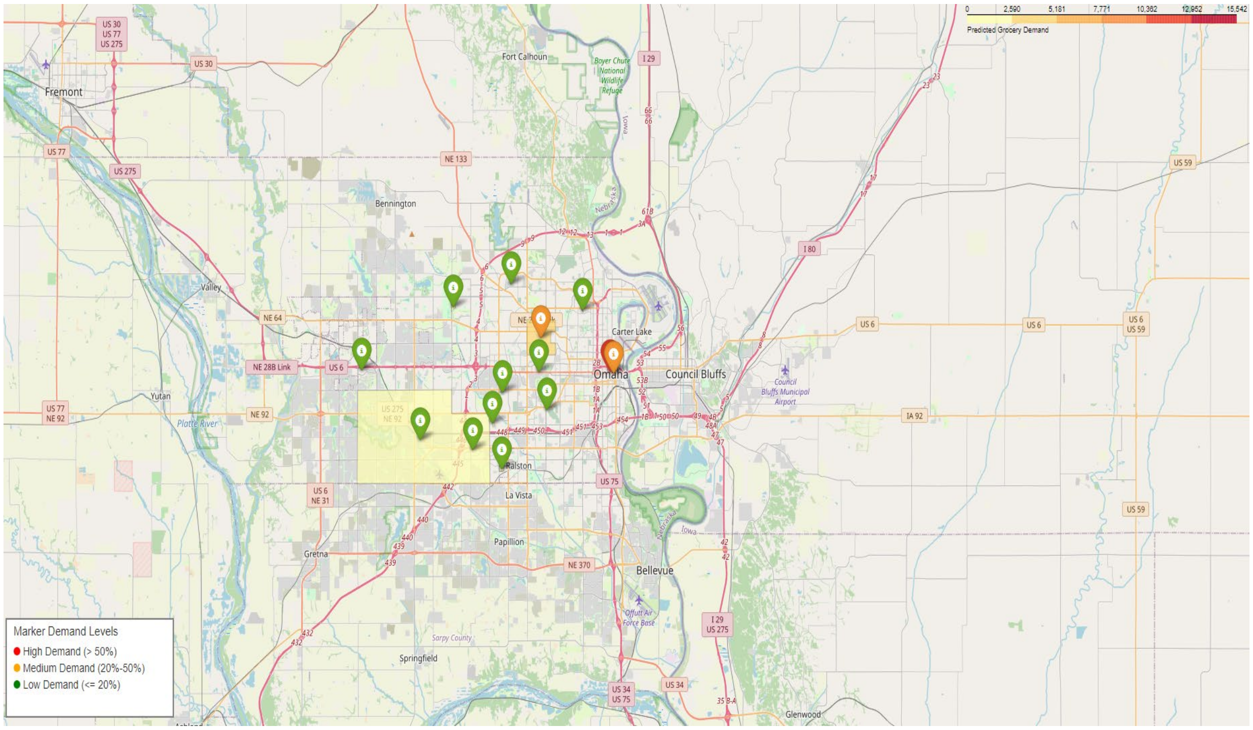

Figure 4: Predicted Grocery Demand for Food Deserts

4.4 Evaluation of Proposed Grocery Store Locations

Based on the demand analysis, five neighborhoods were selected for simulated grocery store placement. These were Cathedral, Downtown, Benson, North Omaha, and Keystone. Simulations were conducted to assess changes in travel distance to the nearest grocery store.

The results in Table 5 show a complete elimination of travel distance (in degrees) for the selected neighborhoods following simulated store placement. This demonstrates the potential effectiveness of targeted interventions. Figure 5 visualizes these changes.

Table 5: Changes in Travel Distance Before and After Simulated Store Placement

Neighborhood	Predicted Grocery Demand	Travel Distance Before (degrees)	Travel Distance After (degrees)
Cathedral	15542	0.00901	0
Downtown	5287	0.00623	0
Benson	3695	0.0207	0
North Omaha	2978	0.0125	0
Keystone	1400	0.0184	0

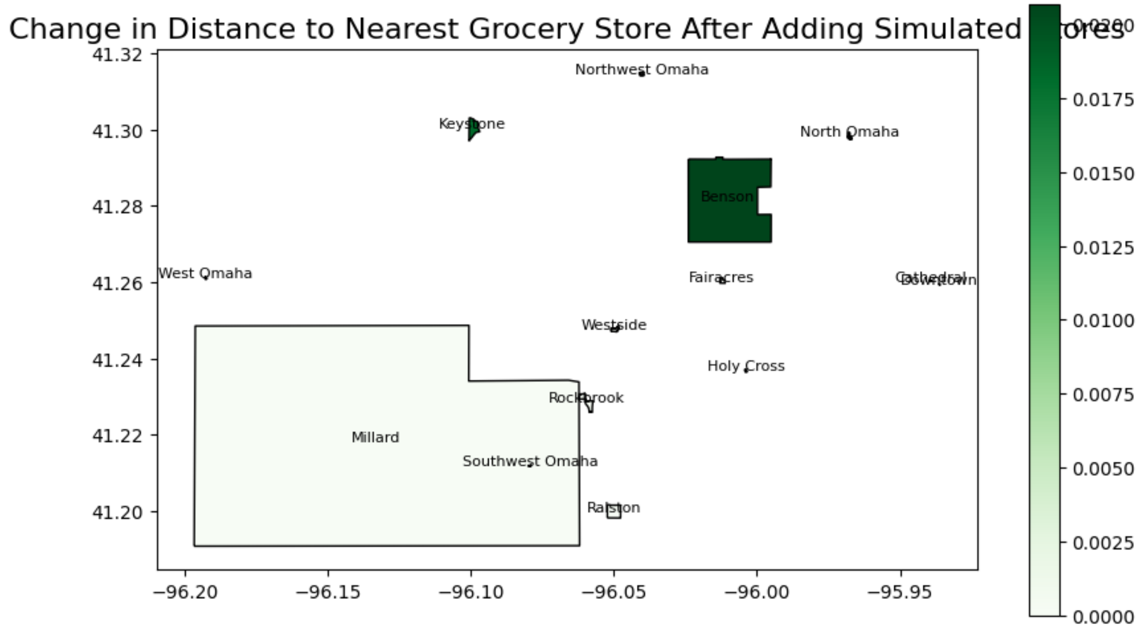

Figure 5: Changes in Travel Distance to Nearest Grocery Store After Adding Simulated Stores

4.5 Cost-Benefit Analysis

To determine the financial feasibility of constructing new grocery stores, a cost-benefit analysis was performed. It was estimated that each store would cost $2 million to build. The anticipated benefits per store, accounting for reductions in obesity rates, healthcare costs, job creation, and local economic stimulation, were valued at $5 million.

Table 6 summarizes the financial analysis. With five stores, the total investment would amount to $10 million, while total projected benefits would reach $25 million, yielding a net benefit of $15 million. Figure 6 illustrates the comparison between costs and benefits.

Table 6: Cost and Benefit Estimates for Grocery Store Intervention

Metric	**Value**
Cost per New Store	$2M
Total Cost (5 stores)	$10M
Benefit per Store	$5M
Total Benefit (5 stores)	$25M
Net Benefit	$15M

A bar chart was generated comparing the total costs and benefits, clearly indicating a positive net benefit of $15million.

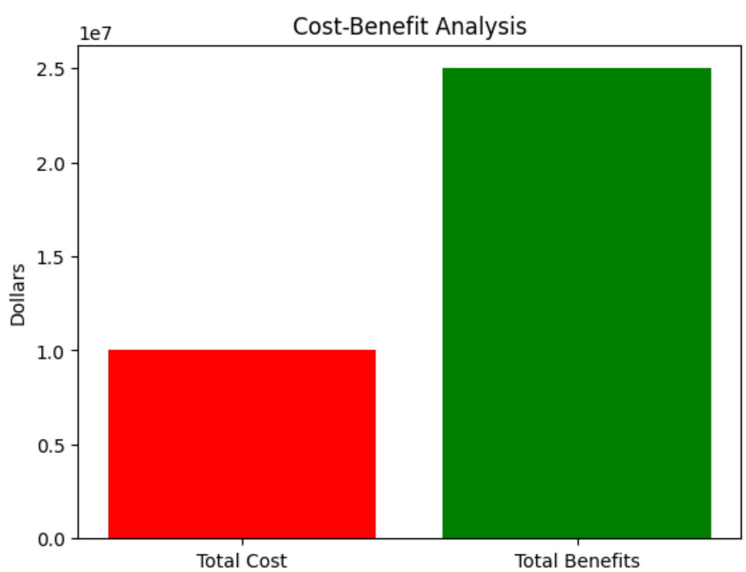

Figure 6: Cost-Benefit Analysis

4.6 Summary of Results

The analysis revealed several key findings. First, five neighborhoods in Omaha were confirmed as food deserts based on income and obesity thresholds. GIS analysis showed that these areas lacked sufficient access to grocery stores and public transit. Machine learning models—particularly Random Forest and Decision Tree—accurately predicted food desert status, and were used to forecast grocery demand.

Simulations demonstrated that placing new grocery stores in high-demand neighborhoods would eliminate travel barriers. Finally, the cost-benefit analysis showed a $15 million net gain, validating the economic viability of the intervention. These findings support a strategic approach to enhancing food accessibility and health equity in Omaha.

CHAPTER V: DISCUSSION

5.1 Interpretation of Key Findings

The results presented in Chapter 4 provided critical insights into food deserts in Omaha, with a focus on neighborhood accessibility, grocery demand, and the potential impact of strategic interventions. This chapter discusses these results in relation to existing literature and their implications for urban planning and public health.

5.1.1 Identification of Food Deserts

Food deserts in Omaha were defined using criteria that included a median household income below $60,000 and an obesity rate exceeding 30%. These indicators are often used in public health studies to assess food access disparities. The identification of Benson, Cathedral, Downtown, Keystone, and North Omaha as food deserts aligns with the findings of several studies (Chaparro et al., 2022; Ma et al., 2016; McInerney et al., 2016; Wilcox et al., 2020), emphasizing the correlation between socioeconomic status and limited food access.

The identification of these food deserts highlights systemic issues within the city's food distribution network, such as lower investment in grocery infrastructure in economically disadvantaged areas. This mirrors findings from (Walker et al., 2010) and Alkon (2011), who emphasized that lower-income communities are often underserved by healthy food retailers

5.1.2 Spatial Distribution of Grocery Stores

The spatial analysis revealed a concentration of grocery stores in central Omaha, leaving the northern and western regions significantly underserved. This geographic imbalance suggests a disparity in food access infrastructure, which could lead to increased reliance on processed and convenience foods in underserved areas, as previously noted by (Larson et al., 2009).

This pattern can also be linked to historical urban planning decisions where wealthier areas attract more commercial investments, including grocery stores. The centralization of grocery stores in wealthier districts underscores the need for policy interventions targeting equitable food distribution, such as incentives for grocery store placement in underserved areas (Alkon, 2011; Walker et al., 2010).

5.1.3 Accessibility and Transit Analysis

The analysis further highlighted that Keystone and North Omaha were both food deserts and transit inaccessible. This finding is significant as it compounds food insecurity with mobility challenges, making it difficult for residents to access grocery stores even when available in neighboring areas. (Su et al., 2017) documented similar challenges in urban areas, emphasizing how transit accessibility directly influences food security.

Limited transit options restrict residents from accessing healthy food, exacerbating issues related to nutrition and chronic diseases. Urban planners must consider integrated approaches, such as expanding transit routes to underserved areas or implementing mobile grocery stores as a short-term solution (Ver Ploeg et al., 2009).

5.2 Machine Learning Model Performance

A comparative analysis of multiple machine learning models was conducted to predict food desert classification. The models included Logistic Regression, Regularized Decision Tree, Random Forest, Neural Networks, and K-Means Clustering.

Logistic Regression achieved a moderate accuracy of 67% with perfect recall for the food desert class but lower precision (0.5). This result suggests that while the model identified all food desert areas correctly, it also produced a high rate of false positives. Logistic Regression's linear nature often limits its ability to capture complex patterns in data, a limitation noted in applied health research by Hosmer Jr et al. (2013).

The Regularized Decision Tree and Random Forest models achieved perfect classification results, with an accuracy of 100%. These models performed exceptionally well due to their ability to handle non-linear relationships and complex decision boundaries. Breiman (2001) emphasized that ensemble methods like Random Forests are particularly effective for classification tasks where patterns are difficult to discern.

The Neural Network model underperformed with an accuracy of 64.29%, limited by its lower recall and precision metrics. Neural Networks often require larger datasets and extensive hyperparameter tuning to reach optimal performance, as described by Hinton et al. (2012). In this study, the dataset size and complexity may have constrained the Neural Network's effectiveness.

5.3 Implications for Food Security Interventions

The identification of food deserts and high-demand neighborhoods in Omaha provides a strong foundation for informed intervention strategies. These findings present several implications for both food security interventions and municipal policy.

Targeted grocery store placement should be a priority, particularly in neighborhoods such as Cathedral, Downtown, and Benson, which showed the highest levels of unmet demand. These areas not only meet the criteria for food deserts but also possess the population densities necessary to support sustainable store operations.

The cost-benefit analysis reinforces the feasibility of such interventions, projecting a positive net benefit of $15 million. This aligns with existing literature that associates improved food access with better health outcomes, decreased obesity rates, and wider economic benefits (Alkon, 2011; Walker et al., 2010).

To encourage grocery store development in these areas, Omaha policymakers could implement policy incentives, including tax credits or subsidies, to reduce barriers to market entry for retailers (Ver Ploeg et al., 2009). Additionally, multimodal transportation solutions—such as expanding bus routes and piloting mobile grocery initiatives—could offer immediate relief while permanent infrastructure is established.

In terms of broader policy measures, several avenues are worth pursuing. Zoning policies may need to be revised to facilitate the establishment of grocery stores in currently underserved neighborhoods. Adjustments to zoning ordinances can ease restrictions and streamline the process for grocery store development.

Public-private partnerships should also be considered. By aligning city objectives with the interests of grocery chains, collaborative ventures can be formed to extend grocery services into underserved regions. These partnerships can include co-financing, land allocation, or shared logistics networks (Fan et al., 2017).

Furthermore, targeted grants and subsidies could provide much-needed financial support to retailers willing to operate in high-need communities. These incentives could lower initial capital costs and improve the long-term financial viability of grocery stores in these areas.

Transportation infrastructure plays a pivotal role in accessibility. Improvements in public transit routes would enable more residents from food deserts to access existing grocery locations, reducing dependency on car ownership and increasing mobility for low-income populations.

Finally, community-based solutions should complement structural interventions. Urban agriculture projects, community gardens, and regular farmers' markets can help improve access to fresh produce while also fostering local empowerment and sustainability.

Together, these strategies highlight a comprehensive policy response to food insecurity in Omaha, combining economic, infrastructural, and community-driven approaches to ensure that all residents have reliable access to nutritious food.

The findings from this study offer several policy implications that can guide Omaha's approach to reducing food deserts and enhancing food security.

First, revisiting zoning regulations may help facilitate the establishment of grocery stores in underserved areas. Amending these policies can lower barriers for entry by making land acquisition and permitting more accessible (Larson et al., 2009).

Second, fostering public-private partnerships between the city and private grocery chains could expand service areas. Collaborations of this nature could include co-investment in store development or shared logistics and delivery infrastructure (Fan et al., 2017).

Third, offering targeted grants and subsidies may further incentivize grocery retailers to set up operations in food deserts. These incentives can lower initial setup costs and help sustain long-term viability.

Improving the city's public transit infrastructure is another critical step. Enhanced transit routes can ensure that residents in food desert areas have reliable access to grocery options, thereby increasing mobility and reducing geographic barriers.

Lastly, complementary community-based solutions such as urban farming initiatives and local farmers' markets should be promoted. These efforts can empower communities, improve access to fresh produce, and reduce reliance on external food systems.

Together, these policy recommendations present a multi-pronged approach to addressing food deserts in Omaha, with potential to significantly improve both health outcomes and community resilience.

The analysis revealed several key findings. First, five neighborhoods in Omaha were confirmed as food deserts based on income and obesity thresholds. GIS analysis showed that these areas lacked sufficient access to grocery stores and public transit. Machine learning models—particularly Random Forest and Decision Tree—accurately predicted food desert status, and were used to forecast grocery demand.

Simulations demonstrated that placing new grocery stores in high-demand neighborhoods would eliminate travel barriers. Finally, the cost-benefit analysis showed a $15 million net gain, validating the economic viability of the intervention. These findings support a strategic approach to enhancing food accessibility and health equity in Omaha.

CHAPTER VI: CONCLUSION, AND RECOMMENDATIONS

6.1 Conclusion

This study investigated the spatial and socio-economic dimensions of food insecurity in Omaha, Nebraska, through the integration of Geographic Information Systems (GIS) and machine learning techniques. By defining food deserts using criteria based on median household income and obesity rates, the research identified key neighborhoods—Benson, Cathedral, Downtown, Keystone, and North Omaha—as areas most impacted by limited access to healthy food options. These findings were further contextualized through analysis of public transit availability, which revealed that limited transportation access exacerbates food insecurity in these communities.

Spatial analysis confirmed that grocery stores are disproportionately concentrated in central Omaha, while many outlying neighborhoods remain underserved. Predictive modeling using Random Forest and Regularized Decision Tree methods successfully identified areas of high grocery demand and achieved perfect classification accuracy, demonstrating the strength of data-driven approaches in addressing complex urban planning challenges.

The study concluded that Cathedral, Downtown, and Benson exhibit the highest levels of unmet grocery demand. When combined with a cost-benefit analysis revealing a net benefit of $15 million for targeted grocery store placements, the findings support the economic viability of strategic food access interventions. These outcomes emphasize the importance of incorporating machine learning and spatial analysis into public policy and urban development practices.

Ultimately, the study proposes a holistic framework that merges technological innovation, policy reform, and community engagement to promote food equity. Addressing food deserts is not only a matter of social justice but also a critical step toward creating resilient, healthy urban communities. Ongoing monitoring and flexible policy adaptations will be essential for maintaining progress in a dynamic socio-economic environment.

6.2 Recommendations

Based on the findings of this study, a number of policy, planning, and evaluation strategies are proposed to address food insecurity in Omaha more effectively.

One of the most impactful steps the city can take is to amend zoning regulations to encourage grocery store development in underserved neighborhoods. This could include measures such as expedited permits, tax abatements, and mandates for a minimum ratio of grocery stores relative to population density in urban planning policies.

Strengthening public-private partnerships is also essential. The city can collaborate with grocery store chains and offer incentives such as grants or low-interest loans to offset startup costs in high-need areas. These partnerships should be structured around shared risk models that promote mutual benefit and long-term sustainability.

Transit infrastructure plays a pivotal role in food access. Improving public transit routes to better connect food deserts with existing grocery stores is necessary. This may include expanding bus routes, adding stops near grocery locations, and integrating ride-share services within the city's broader transportation system.

Additionally, fostering strong community engagement programs can ensure that food access strategies are resident-informed. Local communities should be actively involved in the design and implementation of food security initiatives. Establishing community advisory boards would provide ongoing feedback and promote long-term trust in city-led interventions.

Urban planners should prioritize placing grocery stores in high-demand neighborhoods identified in this study—Cathedral, Downtown, and Benson. Predictive models should guide this process to ensure demand is continually monitored and resources are optimally allocated. These grocery stores should also be responsive to the cultural and dietary preferences of the communities they serve.

In the short term, mobile grocery stores offer a flexible solution for addressing food access gaps. They can serve as pilot programs for evaluating demand before permanent infrastructure is developed.

Local food systems can be further supported through urban farming initiatives and farmers' markets, which provide access to fresh produce while creating economic opportunities. Schools and community centers can incorporate urban agriculture into educational programming to promote sustainability and food literacy.

A robust, city-wide food security monitoring system should be established using GIS and machine learning tools. This system should include real-time dashboards accessible to both policymakers and community stakeholders, and data should be updated regularly to reflect changing conditions.

Ongoing sensitivity analyses will help evaluate the robustness of food access strategies under varying socioeconomic and demographic conditions. These assessments ensure that solutions remain effective and adaptable over time.

Partnerships with academic institutions can enhance data analysis and planning efforts. Universities and research centers offer valuable expertise and the potential to engage students in applied research and community projects.

Educational programs are critical to supporting food access infrastructure. City-wide campaigns should promote the importance of healthy eating and provide guidance on accessing nutritious, affordable food. Delivery channels may include schools, community centers, and social media platforms.

Workshops hosted in food desert neighborhoods can offer hands-on training in meal planning, cooking, and budgeting. These workshops should also inform residents about local food programs and cost-effective strategies for healthy living.

6.3 Future Research Directions

Looking forward, future research should aim to evaluate the long-term impacts of grocery store placement on community health and development. Longitudinal studies could track changes in obesity, healthcare costs, and neighborhood economic activity.

Future analyses should also expand to include additional variables such as food prices, cultural food preferences, and sustainability metrics to enhance the multidimensional understanding of food insecurity.

Comparative studies using the methods applied in this research can help identify regional similarities and differences, providing insights into the scalability of interventions. Emerging technologies such as AI and big data analytics offer opportunities to refine food desert identification and predictive modeling. Researchers might also explore the use of blockchain for improving transparency in grocery supply chains.

Lastly, further investigation into the specific impacts of policy interventions—such as zoning changes or tax incentives—can guide more effective policymaking. Cost-benefit analyses of these strategies will strengthen the evidence base for addressing food insecurity through targeted, data-informed solutions.

To ensure the long-term success and adaptability of food security interventions, a robust system for data-driven monitoring and evaluation is recommended. Establishing a city-wide food access monitoring platform that integrates GIS and machine learning tools would allow for real-time tracking of food insecurity trends. Dashboards can be developed to provide accessible insights to policymakers and community stakeholders.

Conducting regular sensitivity analyses will help evaluate how different socioeconomic and demographic conditions affect the performance of implemented strategies. This approach will ensure that solutions remain effective over time, even as community contexts evolve.

Collaboration with academic institutions can further enhance the city's capacity for data analysis and strategic planning. Local universities and research centers offer expertise and student engagement opportunities that can contribute meaningfully to data collection, evaluation, and community outreach.

6.4 Final Remarks

This research underscores the vital role that interdisciplinary strategies play in tackling food insecurity. By combining spatial analysis, predictive modeling, and cost evaluation, the study offers a replicable model for cities aiming to improve equitable access to nutritious food. The recommendations proposed provide practical steps for policymakers, urban planners, and community stakeholders to drive meaningful change.

Efforts to mitigate food deserts must be sustained through collaboration, innovation, and an unwavering commitment to equity. Ensuring access to healthy food should be recognized not just as a public health goal, but as a foundational pillar of economic development and community well-being. With coordinated action, Omaha—and cities facing similar challenges—can move closer to becoming inclusive environments where all residents have the resources they need to thrive.

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APPENDIX A: PYTHON SCRIPT FOR OMAHA NEIGHBORHOODS DEMOGRAPHIC DATA WEB SCRAPPING

```
import requests
from bs4 import BeautifulSoup
import pandas as pd
# URL of the website to scrape
url = "https://www.city-data.com/nbmaps/neigh-Omaha-Nebraska.html"
# Send a GET request to the website
response = requests.get(url)
soup = BeautifulSoup(response.text, "html.parser")
# Initialize an empty list to store the data
neighborhoods_data = []
# Find all neighborhood sections
neighborhoods = soup.find_all('div', class_='neighborhood')
# Loop through each neighborhood to extract its data
for neighborhood in neighborhoods:
    data = {}
   # Neighborhood Name
    name_tag = neighborhood.find('span', class_='street-name')
    if name_tag:
        data['Neighborhood'] = name_tag.text.strip()
```

```
    # Area
    area_tag = neighborhood.find(text='Area:')
    if area_tag:
        data['Area (sq miles)'] = area_tag.next.strip().split()[0]
  # Population
    population_tag = neighborhood.find(text='Population:')
    if population_tag:
        data['Population'] = population_tag.next.strip().replace(',', '')
   # Population Density
    pop_density_tag = neighborhood.find(text='Population density:')
    if pop_density_tag:
        data['Population Density (per sq mile)'] =
pop_density_tag.find_next('td').find_next('td').text.split('people')[0].strip().replace(',', '')
       #Median Household Income
    income_tag = neighborhood.find(text='Median household income in 2021: ')
    if income_tag:
        data['Median Household Income (2021)'] =
income_tag.find_next('td').find_next('td').text.split('people')[0].strip().replace(',', '')
      # Median Rent
    rent_tag = neighborhood.find(text='Median rent in in 2021:')
    if rent_tag:
        rent_info = rent_tag.find_next('td').text.strip('$').replace(',', '')
```

```
        data['Median Rent (2021)'] = rent_info

    # Male Population
    male_tag = neighborhood.find(text='Males:')
    if male_tag:
        data['Male Population'] = male_tag.find_next('td').text.replace(',', '')
      # Female Population
    female_tag = neighborhood.find(text='Females:')
    if female_tag:
        data['Female Population'] = female_tag.find_next('td').text.replace(',', '')
   # Median Age (Males and Females)
    median_age_male_tag = neighborhood.find(text='Median
age').find_next(text='Males:')
    if median_age_male_tag:
        data['Median Age (Males)'] = median_age_male_tag.find_next('td').text.split()[0]

    median_age_female_tag = neighborhood.find(text='Median
age').find_next(text='Females:')
    if median_age_female_tag:
        data['Median Age (Females)'] =
median_age_female_tag.find_next('td').text.split()[0]
    # Convert the list of dictionaries into a DataFrame
```

```
df = pd.DataFrame(neighborhoods_data)


    # Housing Prices
    detached_houses_tag = neighborhood.find(text='Average estimated value of detached
houses in 2021')
    if detached_houses_tag:
        detached_info = detached_houses_tag.find_next('td').text.strip('$').replace(',', '')
        data['Avg Value of Detached Houses (2021)'] = detached_info


    townhouses_tag = neighborhood.find(text='Average estimated value of townhouses or
other attached units in 2021')
    if townhouses_tag:
        townhouse_info = townhouses_tag.find_next('td').text.strip('$').replace(',', '')
        data['Avg Value of Townhouses (2021)'] = townhouse_info


    # Add all the extracted data to the list
    neighborhoods_data.append(data)


import os
import pandas as pd
# Specify the folder and file name
folder_path = 'C:/Users/fisay/OneDrive/Desktop/DBA SSBM'
```

```
file_name = 'demographics.xlsx'

file_path = f'{folder_path}/{file_name}'


# Export to CSV

df.to_excel(file_path, index=False)

print(f"File saved to: {file_path}")
```

APPENDIX B: PYTHON SCRIPT FOR OMAHA GROCERY STORES EXTRACTION

```
import osmnx as ox

import pandas as pd

# Define the area (Omaha)

place_name = "Omaha, Nebraska, USA"

# Query for grocery stores

tags = {"shop": "supermarket"}  # Tag for grocery stores

grocery_stores = ox.features_from_place(place_name, tags)

# Display the results

grocery_stores
```

APPENDIX C: PYTHON SCRIPT FOR OMAHA TRANSIT STOPS EXTRACTION

```
import overpy
import pandas as pd
import time

# Initialize Overpass API
api = overpy.Overpass()

# Define the Overpass API query for transit stops
query = """
[out:json];
area[name="Omaha"]->.searchArea;
node["public_transport"="platform"](area.searchArea);
out body;
"""

# Retry logic for handling errors or incomplete reads
def fetch_overpass_data(query, retries=3):
    for attempt in range(retries):
        try:
            return api.query(query)
        except Exception as e:
            print(f"Error fetching data: {e}")
            if attempt < retries - 1:
```

```
            print("Retrying...")
            time.sleep(5)  # Wait before retrying
        else:
            raise

# Fetch data from Overpass API
print("Fetching transit stops data from Overpass API...")
result = fetch_overpass_data(query)
print("Data fetched successfully.")

# Process the nodes (transit stops)
stops_data = []
for node in result.nodes:
    stops_data.append({
        "Stop ID": node.id,
        "Name": node.tags.get("name", "Unknown"),
        "Latitude": node.lat,
        "Longitude": node.lon
    })

# Convert to a Pandas DataFrame
stops_df = pd.DataFrame(stops_data)

# Save to CSV
```

```
stops_df.to_csv("C:/Users/fisay/OneDrive/Desktop/DBA
SSBM/omaha_transit_stops.csv", index=False)
print("Transit stops data saved to omaha_transit_stops.csv.")
```

APPENDIX D: PYTHON SCRIPT FOR OMAHA NEIGHBORHOODS EXTRACTION

```
import osmnx as ox
import pandas as pd

# List of neighborhoods in Omaha
neighborhoods = [
    "Aksarben", "Benson", "Cathedral", "Central", "Downtown", "Dundee", "Fairacres",
    "Field Club", "Florence", "Holy Cross", "Keystone", "Millard", "Near South",
    "North Omaha", "Northwest Omaha", "Old Market", "Ralston", "Rockbrook",
    "South Central Omaha", "Southeast Omaha", "Southwest Omaha", "West Omaha",
"Westside"
]

# Base place for search
city = "Omaha, Nebraska, USA"

# Initialize an empty list to store neighborhood data
neighborhood_data = []

# Fetch latitude and longitude for each neighborhood
for neighborhood in neighborhoods:
    try:
        print(f"Fetching coordinates for {neighborhood}...")
        place_name = f"{neighborhood}, {city}"
```

```
        # Fetch the boundary polygon for the neighborhood
        gdf = ox.geocode_to_gdf(place_name)

        # Get the centroid of the polygon
        centroid = gdf.geometry.centroid.iloc[0]

        # Append the neighborhood name and coordinates
        neighborhood_data.append({
            "Neighborhood": neighborhood,
            "Latitude": centroid.y,
            "Longitude": centroid.x
        })
    except Exception as e:
        print(f"Could not fetch data for {neighborhood}: {e}")

# Convert the data into a Pandas DataFrame
df_neighborhoods = pd.DataFrame(neighborhood_data)

# Save to CSV
df_neighborhoods.to_csv("C:/Users/fisay/OneDrive/Desktop/DBA
SSBM/omaha_neighborhoods_coordinates.csv", index=False)

print("Neighborhood coordinates saved to 'omaha_neighborhoods_coordinates.csv'.")
```

APPENDIX E: PYTHON SCRIPT FOR OMAHA NEIGHBORHOODS GIS LAYER EXTRACTION

```
import osmnx as ox
import pandas as pd
import geopandas as gpd
from shapely.geometry import mapping
from shapely.geometry import shape

# List of neighborhoods in Omaha
neighborhoods = [
    "Aksarben", "Benson", "Cathedral", "Central", "Downtown", "Dundee", "Fairacres",
    "Field Club", "Florence", "Holy Cross", "Keystone", "Millard", "Near South",
    "North Omaha", "Northwest Omaha", "Old Market", "Ralston", "Rockbrook",
    "South Central Omaha", "Southeast Omaha", "Southwest Omaha", "West Omaha",
"Westside"
]

# Base place for search
city = "Omaha, Nebraska, USA"

# Initialize an empty list to store neighborhood polygons
polygon_data = []

# Fetch polygon data for each neighborhood
for neighborhood in neighborhoods:
```

```
    try:
        print(f"Fetching data for {neighborhood}...")
        place_name = f"{neighborhood}, {city}"

        # Fetch polygon data for the neighborhood
        gdf = ox.geocode_to_gdf(place_name)

        # Append the data
        for _, row in gdf.iterrows():
            polygon_data.append({
                "Neighborhood": neighborhood,
                "Geometry": mapping(row["geometry"])  # Convert to GeoJSON format
            })
    except Exception as e:
        print(f"Could not fetch data for {neighborhood}: {e}")

#Install library to be able to extract GEOID from Longitude and Latitude"
!pip install urllib3==1.26.6
#Read in the omaha neighborhood coordinates file
import pandas as pd

# File path
file_path = r"C:\Users\fisay\OneDrive\Desktop\DBA
SSBM\omaha_neighborhoods_coordinates.csv"
```

```
# Load the CSV file into a Pandas DataFrame
omaha_neighborhoods_coordinates = pd.read_csv(file_path)

# Display the first few rows of the DataFrame
omaha_neighborhoods_coordinates.head()
#Read in the Nebraska Health indicator data file
# File path
file_path1 = r"C:\Users\fisay\OneDrive\Desktop\DBA SSBM\NE_Tract_City_12-03-
2024.csv"

# Load the CSV file into a Pandas DataFrame
ne_tract_city = pd.read_csv(file_path1)

# Display the first few rows of the DataFrame
ne_tract_city.head()
#Extract GEOID and join to the Omaha neighborhoods coordinates dataframe
import censusgeocode as cg

def get_geoid(row):
    try:
        print(f"Fetching GEOID for {row['Neighborhood']} at ({row['Latitude']},
{row['Longitude']})...")
        result = cg.coordinates(x=row["Longitude"], y=row["Latitude"])
        if result:
            # Extract GEOID from Census Tracts
```

```
            if "Census Tracts" in result:
                geoid = result["Census Tracts"][0]["GEOID"]
                print(f"GEOID for {row['Neighborhood']}: {geoid}")
                return geoid
            else:
                print(f"No Census Tracts found for {row['Neighborhood']}")
        else:
            print(f"No result for {row['Neighborhood']}")
    except Exception as e:
        print(f"Error for {row['Neighborhood']}: {e}")
    return None

# Apply the function to each row
print("Fetching GEOIDs for neighborhoods...")
omaha_neighborhoods_coordinates["GEOID"] =
omaha_neighborhoods_coordinates.apply(get_geoid, axis=1)

#View the dataframe
omaha_neighborhoods_coordinates

# Ensure data types for merge keys match
ne_tract_city["geo_fips"] = ne_tract_city["geo_fips"].astype(str)
omaha_neighborhoods_coordinates["GEOID"] =
omaha_neighborhoods_coordinates["GEOID"].astype(str)
# Filter the required metrics from the NE_Tract_City dataframe
```

```
required_metrics = ["Diabetes", "Uninsured", "Obesity", "Unemployment - Annual,
Neighborhood-Level"]
filtered_metrics = ne_tract_city[ne_tract_city["metric_name"].isin(required_metrics)]

# Pivot the data to get the metrics as columns
pivoted_metrics = filtered_metrics.pivot_table(
    index="geo_fips",
    columns="metric_name",
    values="est"
).reset_index()

# Rename columns for clarity
pivoted_metrics.columns.name = None  # Remove multi-index
pivoted_metrics.rename(
    columns={
        "geo_fips": "GEOID",
        "Diabetes": "Diabetes Rate",
        "Uninsured": "Poverty Rate",
        "Obesity": "Obesity Rate",
        "Unemployment - Annual, Neighborhood-Level": "Unemployment Rate"
    },
    inplace=True
)

# Merge with the Omaha neighborhoods dataframe
```

```
merged_df = omaha_neighborhoods_coordinates.merge(pivoted_metrics, on="GEOID",
how="left")
#View the merged dataframe (#Used Unsinsured as a proxy for Poverty)
merged_df
# Save the result to a CSV file
merged_df.to_csv(r"C:\Users\fisay\OneDrive\Desktop\DBA
SSBM\omaha_neighborhoods_health_indicators.csv", index=False)
```

APPENDIX F: PYTHON SCRIPT FOR MACHINE LEARNING AND GIS ANALYSIS

```
#!pip install pandas geopandas matplotlib osmnx networkx folium scikit-learn
import os

# Set the working directory
data_dir = r"C:\Users\fisay\OneDrive\Desktop\DBA SSBM\Data and Results"
import pandas as pd
import geopandas as gpd

# Load datasets
demographics = pd.read_csv(os.path.join(data_dir,
"omaha_neighborhoods_demographics.csv"))
transit_stops = pd.read_csv(os.path.join(data_dir, "omaha_transit_stops.csv"))
grocery_stores = pd.read_csv(os.path.join(data_dir,
"omaha_osmnx_grocery_stores.csv"))
health_indicators = pd.read_csv(os.path.join(data_dir,
"omaha_neighborhoods_health_indicators.csv"))
neighborhoods = gpd.read_file(os.path.join(data_dir,
"omaha_neighborhoods_polygons.geojson"))

# Preview datasets
```

```
print(demographics.head())
print(transit_stops.head())
print(grocery_stores.head())
print(health_indicators.head())
print(neighborhoods.head())
#Map Food Deserts
# Merge demographics and health indicators with neighborhood polygons
merged = neighborhoods.merge(demographics,
on="Neighborhood").merge(health_indicators, on="Neighborhood")

# Remove dollar signs and commas, then convert to numeric
merged["Median Household Income (2021)"] = (
    merged["Median Household Income (2021)"]
    .str.replace("$", "", regex=False)  # Remove the dollar sign
    .str.replace(",", "", regex=False)  # Remove commas
    .astype(float)  # Convert to float
)

# Ensure 'Obesity Rate' is numeric
merged["Obesity Rate"] = pd.to_numeric(merged["Obesity Rate"], errors="coerce")

# Define food desert criteria
```

```
merged["is_food_desert"] = (merged["Median Household Income (2021)"] < 60000) &
(merged["Obesity Rate"] > 30)

# Plot food deserts
import matplotlib.pyplot as plt


fig, ax = plt.subplots(1, 1, figsize=(10, 10))
merged.plot(column="is_food_desert", cmap="coolwarm", legend=True, ax=ax,
edgecolor="black")

# Add labels for food desert neighborhoods
for x, y, label in zip(
    merged.geometry.centroid.x,
    merged.geometry.centroid.y,
    merged["Neighborhood"]
):
    ax.text(x, y, label, fontsize=8, color="black", ha="center")

plt.title("Food Deserts in Omaha")
plt.show()
food_deserts = merged[merged["is_food_desert"] == True]
```

```
print(food_deserts[["Neighborhood", "Median Household Income (2021)", "Obesity
Rate"]])
#3.2 Spatial Distribution of Grocery Stores
#Analyze the proximity of grocery stores to food deserts
from shapely.wkt import loads  # To load WKT strings as geometries
import geopandas as gpd
import matplotlib.pyplot as plt

# Check and convert only if the 'geometry' column contains strings
if isinstance(grocery_stores["geometry"].iloc[0], str):
    grocery_stores["geometry"] = grocery_stores["geometry"].apply(loads)

# Ensure 'geometry' column is directly used in the GeoDataFrame
grocery_stores_gdf = gpd.GeoDataFrame(
    grocery_stores,
    geometry=grocery_stores["geometry"],  # Use the now-converted geometry column
    crs="EPSG:4326",  # Specify CRS
)

# Plot grocery stores on the food desert map
fig, ax = plt.subplots(1, 1, figsize=(10, 10))
```

```
# Plot the food desert map
merged.plot(column="is_food_desert", cmap="coolwarm", legend=True, ax=ax)

# Add labels for food desert neighborhoods
for x, y, label in zip(
    merged.geometry.centroid.x,
    merged.geometry.centroid.y,
    merged["Neighborhood"]
):
    ax.text(x, y, label, fontsize=8, color="black", ha="center")

# Plot POINT geometries
if not grocery_stores_gdf[grocery_stores_gdf.geometry.type == "Point"].empty:
    grocery_stores_gdf[grocery_stores_gdf.geometry.type == "Point"].plot(
        color="black", ax=ax, markersize=10, label="Grocery Store (Point)"
    )

# Plot POLYGON geometries
if not grocery_stores_gdf[grocery_stores_gdf.geometry.type == "Polygon"].empty:
    grocery_stores_gdf[grocery_stores_gdf.geometry.type == "Polygon"].plot(
        edgecolor="black", facecolor="none", linewidth=1, ax=ax, label="Grocery Store
(Polygon)"
```

```
    )

# Add a title and legend
plt.title("Grocery Stores and Food Deserts in Omaha")
plt.legend()
plt.show()

#Evaluate access to grocery stores using transit stops


from shapely.geometry import Point
import geopandas as gpd
import matplotlib.pyplot as plt

# Ensure the geometry column is created using Latitude and Longitude
transit_stops["geometry"] = transit_stops.apply(
    lambda row: Point(row["Longitude"], row["Latitude"]), axis=1
)

# Create GeoDataFrame using the geometry column
transit_stops_gdf = gpd.GeoDataFrame(
    transit_stops,
    geometry=transit_stops["geometry"],  # Use the created geometry column
```

```
    crs="EPSG:4326",
)

# Buffer around transit stops to estimate accessibility
transit_stops_gdf["buffer"] = transit_stops_gdf.geometry.buffer(0.002)  # ~200m buffer

# Combine all transit stop buffers into a single geometry for analysis
transit_buffer_union = transit_stops_gdf["buffer"].unary_union

# Check which neighborhoods are accessible based on buffer intersection
merged["transit_accessible"] = merged.geometry.apply(lambda x:
x.intersects(transit_buffer_union))


# Plot transit accessibility
fig, ax = plt.subplots(1, 1, figsize=(12, 12))

# Plot the neighborhoods and color them based on transit accessibility
merged.plot(column="transit_accessible", cmap="coolwarm", legend=True, ax=ax,
edgecolor="black")

# Add neighborhood names as labels
```

```
for x, y, label in zip(merged.geometry.centroid.x, merged.geometry.centroid.y,
merged["Neighborhood"]):
    ax.text(x, y, label, fontsize=8, ha='center', color='black')

# Add a title
plt.title("Transit Accessibility in Omaha", fontsize=16)

# Show the plot
plt.show()
# Filter neighborhoods that are transit inaccessible and in food deserts
transit_inaccessible_food_deserts = merged[
    (merged["transit_accessible"] == False) & (merged["is_food_desert"] == True)
]

# Select relevant columns for clarity
transit_inaccessible_food_deserts_df =
transit_inaccessible_food_deserts[["Neighborhood", "transit_accessible",
"is_food_desert"]]

# Display the resulting DataFrame
transit_inaccessible_food_deserts_df
#Machine Learning Predictive Modeling
```

```
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report
from sklearn.model_selection import train_test_split
import pandas as pd

# Split data
X = merged[["Population Density (per sq mile)", "Median Household Income (2021)",
"Obesity Rate", "transit_accessible"]]
y = merged["is_food_desert"]
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Scale the data
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Fit logistic regression with increased max_iter
model = LogisticRegression(max_iter=500, solver="liblinear")
model.fit(X_train_scaled, y_train)

# Predict and evaluate
```

```
y_pred = model.predict(X_test_scaled)

# Generate classification report
report = classification_report(y_test, y_pred, output_dict=True)

# Populate the DataFrame with classification report results
logistic_regression_df = pd.DataFrame({
    "Model": ["Logistic Regression"],
    "Accuracy": [f"{report['accuracy'] * 100:.0f}%"],
    "Precision (True)": [round(report["True"]["precision"], 2)],
    "Recall (True)": [round(report["True"]["recall"], 2)],
    "F1-Score (True)": [round(report["True"]["f1-score"], 2)],
    "Precision (False)": [round(report["False"]["precision"], 2)],
    "Recall (False)": [round(report["False"]["recall"], 2)],
    "F1-Score (False)": [round(report["False"]["f1-score"], 2)],
    "Macro Avg F1-Score": [round(report["macro avg"]["f1-score"], 2)],
})

# Display the DataFrame
logistic_regression_df
from sklearn.model_selection import cross_val_predict
from sklearn.tree import DecisionTreeClassifier
```

```
from sklearn.metrics import classification_report
import pandas as pd


# Train a regularized Decision Tree model
dt_model = DecisionTreeClassifier(
    random_state=42,
    max_depth=2,              # Limit tree depth
    min_samples_split=4,      # Minimum samples to split
    min_samples_leaf=2        # Minimum samples per leaf
)
y_pred_cv = cross_val_predict(dt_model, X, y, cv=5)


# Generate classification report
print("Decision Tree Cross-Validation Classification Report:")
report_cv = classification_report(y, y_pred_cv, output_dict=True)
print(classification_report(y, y_pred_cv))


# Generate DataFrame for the report
decision_tree_cv_df = pd.DataFrame({
    "Model": ["Regularized Decision Tree (CV)"],
    "Accuracy": [f"{report_cv['accuracy'] * 100:.0f}%"],
    "Precision (True)": [round(report_cv["True"]["precision"], 2)],
```

```
    "Recall (True)": [round(report_cv["True"]["recall"], 2)],
    "F1-Score (True)": [round(report_cv["True"]["f1-score"], 2)],
    "Precision (False)": [round(report_cv["False"]["precision"], 2)],
    "Recall (False)": [round(report_cv["False"]["recall"], 2)],
    "F1-Score (False)": [round(report_cv["False"]["f1-score"], 2)],
    "Macro Avg F1-Score": [round(report_cv["macro avg"]["f1-score"], 2)],
})

# Display the DataFrame
print("Regularized Decision Tree Cross-Validation Model Report DataFrame:")
print(decision_tree_cv_df)
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import cross_val_predict
from sklearn.metrics import classification_report
import pandas as pd

# Train a Random Forest model with regularization
rf_model = RandomForestClassifier(
    n_estimators=50,      # Number of trees in the forest
    max_depth=3,          # Limit tree depth to prevent overfitting
    min_samples_split=4,  # Minimum samples required to split a node
    min_samples_leaf=2,   # Minimum samples required at each leaf node
```

```
    random_state=42
)

# Perform cross-validation and predictions
y_pred_rf_cv = cross_val_predict(rf_model, X, y, cv=5)

# Generate classification report
print("Random Forest Cross-Validation Classification Report:")
report_rf_cv = classification_report(y, y_pred_rf_cv, output_dict=True)
print(classification_report(y, y_pred_rf_cv))

# Create a DataFrame to store the results
rf_cv_df = pd.DataFrame({
    "Model": ["Random Forest (CV)"],
    "Accuracy": [f"{report_rf_cv['accuracy'] * 100:.0f}%"],
    "Precision (True)": [round(report_rf_cv["True"]["precision"], 2)],
    "Recall (True)": [round(report_rf_cv["True"]["recall"], 2)],
    "F1-Score (True)": [round(report_rf_cv["True"]["f1-score"], 2)],
    "Precision (False)": [round(report_rf_cv["False"]["precision"], 2)],
    "Recall (False)": [round(report_rf_cv["False"]["recall"], 2)],
    "F1-Score (False)": [round(report_rf_cv["False"]["f1-score"], 2)],
    "Macro Avg F1-Score": [round(report_rf_cv["macro avg"]["f1-score"], 2)],
```

```
})


# Display the DataFrame with results
print("Random Forest Cross-Validation Model Report DataFrame:")
print(rf_cv_df)
from sklearn.cluster import KMeans


# Apply K-Means
kmeans = KMeans(n_clusters=3, random_state=42)
merged["cluster"] = kmeans.fit_predict(X)


# Visualize clusters
plt.figure(figsize=(10, 6))
plt.scatter(merged["Population Density (per sq mile)"], merged["Median Household
Income (2021)"], c=merged["cluster"], cmap="viridis")
plt.xlabel("Population Density")
plt.ylabel("Median Income")
plt.title("K-Means Clustering of Neighborhoods")
plt.show()
from sklearn.neural_network import MLPClassifier
from sklearn.metrics import classification_report, accuracy_score
from sklearn.model_selection import cross_val_predict
```

```
# Initialize Neural Network model
mlp_model = MLPClassifier(hidden_layer_sizes=(50, 25), max_iter=500,
random_state=42)

# Cross-validation predictions
y_pred_cv = cross_val_predict(mlp_model, X, y, cv=5)

# Classification report for cross-validation
classification_report_cv = classification_report(y, y_pred_cv, output_dict=True)

# Extract metrics for DataFrame
accuracy = accuracy_score(y, y_pred_cv) * 100
precision_true = classification_report_cv["True"]["precision"]
recall_true = classification_report_cv["True"]["recall"]
f1_true = classification_report_cv["True"]["f1-score"]
precision_false = classification_report_cv["False"]["precision"]
recall_false = classification_report_cv["False"]["recall"]
f1_false = classification_report_cv["False"]["f1-score"]
macro_avg_f1 = classification_report_cv["macro avg"]["f1-score"]

# Create report DataFrame
```

```
nn_report_df = pd.DataFrame({
    "Model": ["Neural Network (CV)"],
    "Accuracy": [f"{accuracy:.2f}%"],
    "Precision (True)": [precision_true],
    "Recall (True)": [recall_true],
    "F1-Score (True)": [f1_true],
    "Precision (False)": [precision_false],
    "Recall (False)": [recall_false],
    "F1-Score (False)": [f1_false],
    "Macro Avg F1-Score": [macro_avg_f1]
})

# Print classification report
print("Neural Network Cross-Validation Classification Report:")
print(classification_report(y, y_pred_cv))
import pandas as pd

# Create an empty KMeans DataFrame with NaN values except for the "Model" column
kmeans_df = pd.DataFrame([{
    "Model": "KMeans",
    "Accuracy": None,
    "Precision (True)": None,
```

```
    "Recall (True)": None,
    "F1-Score (True)": None,
    "Precision (False)": None,
    "Recall (False)": None,
    "F1-Score (False)": None,
    "Macro Avg F1-Score": None
}])

# Combine all DataFrames using pd.concat
combined_df = pd.concat([logistic_regression_df, decision_tree_cv_df, rf_cv_df,
nn_report_df, kmeans_df], ignore_index=True)
combined_df
# Save Model Comparison Table to Directory

combined_df.to_csv(r"C:\Users\fisay\OneDrive\Desktop\DBA SSBM\Data and
Results\Model_Comparison_Table.csv", index=False)
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split

# Prepare features and target
X = merged[["Population Density (per sq mile)", "Median Household Income (2021)",
"Obesity Rate", "transit_accessible"]]
```

```
y = merged["is_food_desert"]

# Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Train the Random Forest model
rf_model = RandomForestClassifier(random_state=42, n_estimators=100, max_depth=5)
# Customize parameters as needed
rf_model.fit(X_train, y_train)

# Predict probabilities for the entire dataset
merged["food_desert_probability"] = rf_model.predict_proba(X)[:, 1]  # Probability of
being a food desert

# Define predicted demand for grocery stores (can be scaled)
merged["predicted_grocery_demand"] = merged["food_desert_probability"] *
merged["Population Density (per sq mile)"]
import folium
from folium import Choropleth
from matplotlib.patches import Patch

# Initialize a folium map centered on Omaha
```

```
map_center = [41.2565, -95.9345]  # Approximate center of Omaha
map_folium = folium.Map(location=map_center, zoom_start=11)

# Define bins to match marker categories
bins = [
    0,
    0.2 * merged["predicted_grocery_demand"].max(),
    0.5 * merged["predicted_grocery_demand"].max(),
    merged["predicted_grocery_demand"].max()
]

# Add predicted demand as a choropleth layer
choropleth = Choropleth(
    geo_data=merged,  # GeoDataFrame with geometries
    data=merged,      # Data source for choropleth
    columns=["Neighborhood", "predicted_grocery_demand"],  # Columns for map
    key_on="feature.properties.Neighborhood",  # Key to match GeoJSON
    fill_color="YlOrRd",  # Color scheme
    fill_opacity=0.7,
    line_opacity=0.2,
    legend_name="Predicted Grocery Demand"
).add_to(map_folium)
```

```
# Add markers for neighborhoods with high demand
for _, row in merged.iterrows():
    if row["predicted_grocery_demand"] > 0.5 *
merged["predicted_grocery_demand"].max():
        icon_color = "red"
    elif row["predicted_grocery_demand"] > 0.2 *
merged["predicted_grocery_demand"].max():
        icon_color = "orange"
    else:
        icon_color = "green"

    folium.Marker(
        location=[row.geometry.centroid.y, row.geometry.centroid.x],
        popup=f"Neighborhood: {row['Neighborhood']}<br>Demand:
{row['predicted_grocery_demand']:.2f}",
        icon=folium.Icon(color=icon_color),
    ).add_to(map_folium)

# Add custom legend for marker categories
legend_html = '''
<div style="position: fixed;
```

```
        bottom: 50px; left: 50px; width: 250px; height: 120px;
        background-color: white; border:2px solid grey; z-index:9999; font-size:14px;">
  <h4 style="margin-top:5px; margin-left:10px;">Marker Demand Levels</h4>
  <ul style="list-style: none; padding-left: 10px;">
    <li><span style="background-color: red; width: 10px; height: 10px; display: inline-
block; border-radius: 50%;"></span> High Demand (> 50%)</li>
    <li><span style="background-color: orange; width: 10px; height: 10px; display:
inline-block; border-radius: 50%;"></span> Medium Demand (20%-50%)</li>
    <li><span style="background-color: green; width: 10px; height: 10px; display:
inline-block; border-radius: 50%;"></span> Low Demand (<= 20%)</li>
  </ul>
</div>
'''

# Add legend to the map
map_folium.get_root().html.add_child(folium.Element(legend_html))

# Save the map
map_folium.save(r"C:\Users\fisay\OneDrive\Desktop\DBA SSBM\Data and
Results\Predicted_Grocery_Demand_Map.html")
print("Map saved as 'Predicted_Grocery_Demand_Map.html'")
#Select Top Locations: Identify neighborhoods with the highest predicted demand:
```

top_locations = merged.nlargest(5, "predicted_grocery_demand") # Top 5 locations

print(top_locations[["Neighborhood", "predicted_grocery_demand"]])

#Add Simulated Grocery Stores: Assume new grocery stores are placed in these neighborhoods.

Add their locations to the grocery_stores dataset:

from shapely.geometry import Point

Add simulated store locations

simulated_stores = top_locations.geometry.centroid

simulated_stores_gdf = gpd.GeoDataFrame(top_locations, geometry=simulated_stores, crs="EPSG:4326")

#Combine with Existing Grocery Stores: Merge simulated stores with existing store locations:

all_stores = gpd.GeoDataFrame(pd.concat([grocery_stores_gdf, simulated_stores_gdf], ignore_index=True))

#Nearest Store Calculation: Use geopandas to calculate distances between each neighborhood and its nearest grocery store:

from scipy.spatial import cKDTree

from shapely.geometry import Point

Convert store geometries to coordinates

```
store_coords = all_stores.geometry.apply(
    lambda geom: (geom.centroid.x, geom.centroid.y) if geom.type == "Polygon" else
(geom.x, geom.y)
).tolist()

# Convert neighborhood geometries to coordinates using centroids
neighborhood_coords = merged.geometry.centroid.apply(
    lambda geom: (geom.x, geom.y)
).tolist()

# Build KDTree for nearest neighbor search
store_tree = cKDTree(store_coords)

# Find the nearest grocery store for each neighborhood
distances, indices = store_tree.query(neighborhood_coords)

# Add the nearest distance as a new column in the merged dataframe
merged["nearest_store_distance"] = distances

# Plot the results
fig, ax = plt.subplots(1, 1, figsize=(12, 12))
```

```
merged.plot(column="nearest_store_distance", cmap="YlOrRd", legend=True, ax=ax,
edgecolor="black")
plt.title("Distance to Nearest Grocery Store for Each Neighborhood")
plt.xlabel("Longitude")
plt.ylabel("Latitude")
plt.show()
#Nearest Store Calculation: Use geopandas to calculate distances between each
neighborhood and its nearest grocery store:

from scipy.spatial import cKDTree
from shapely.geometry import Point

# Convert store geometries to coordinates
store_coords = all_stores.geometry.apply(
    lambda geom: (geom.centroid.x, geom.centroid.y) if geom.type == "Polygon" else
(geom.x, geom.y)
).tolist()

# Convert neighborhood geometries to coordinates using centroids
neighborhood_coords = merged.geometry.centroid.apply(
    lambda geom: (geom.x, geom.y)
).tolist()
```

```
# Build KDTree for nearest neighbor search
store_tree = cKDTree(store_coords)

# Find the nearest grocery store for each neighborhood
distances, indices = store_tree.query(neighborhood_coords)

# Add the nearest distance as a new column in the merged dataframe
merged["nearest_store_distance"] = distances

# Plot the results
fig, ax = plt.subplots(1, 1, figsize=(12, 12))
merged.plot(column="nearest_store_distance", cmap="YlOrRd", legend=True, ax=ax,
edgecolor="black")
plt.title("Distance to Nearest Grocery Store for Each Neighborhood")
plt.xlabel("Longitude")
plt.ylabel("Latitude")
plt.show()
import folium

# Initialize a folium map centered on Omaha
map_center = [41.2565, -95.9345]  # Approximate center of Omaha
```

```python
map_folium = folium.Map(location=map_center, zoom_start=11)

# Add neighborhoods as a choropleth layer, colored by distance to nearest grocery store
folium.Choropleth(
    geo_data=merged,  # GeoDataFrame with geometries
    data=merged,      # Data source for choropleth
    columns=["Neighborhood", "nearest_store_distance"],  # Columns for map
    key_on="feature.properties.Neighborhood",  # Key to match GeoJSON
    fill_color="YlOrRd",  # Color scheme
    fill_opacity=0.7,
    line_opacity=0.2,
    legend_name="Distance to Nearest Grocery Store (meters)"
).add_to(map_folium)

# Add markers with neighborhood name and distance to nearest store
for _, row in merged.iterrows():
    folium.Marker(
        location=[row.geometry.centroid.y, row.geometry.centroid.x],  # Centroid of the neighborhood
        popup=f"Neighborhood: {row['Neighborhood']}<br>Distance: {row['nearest_store_distance']:.2f} meters",
        icon=folium.Icon(color="blue"),
```

```
    ).add_to(map_folium)

# Save the map to an HTML file and display
map_folium.save(r"C:\Users\fisay\OneDrive\Desktop\DBA SSBM\Data and
Results\Nearest_Grocery_Store_Map_After_Addition.html")
print("Map saved as 'Nearest_Grocery_Store_Map.html'")
#Compare Before and After: Calculate the average travel distance before and after adding
simulated stores:
from scipy.spatial import cKDTree
import pandas as pd

# Step 1: Filter for Point geometries in grocery_stores_gdf
point_stores_gdf = grocery_stores_gdf[grocery_stores_gdf.geometry.type == "Point"]

# Convert Point geometries to coordinates
original_store_coords = point_stores_gdf.geometry.apply(lambda geom: (geom.x,
geom.y)).tolist()

# Calculate neighborhood centroids for distance analysis
neighborhood_coords = merged.geometry.centroid.apply(lambda geom: (geom.x,
geom.y)).tolist()
```

```
# Step 2: Build KDTree for nearest neighbor search (Before Adding Simulated Stores)
original_store_tree = cKDTree(original_store_coords)

# Compute nearest distances for each neighborhood
merged["nearest_store_distance_before"] = [
    original_store_tree.query(coord)[0] for coord in neighborhood_coords
]

# Step 3: Handle Simulated Stores
# Assume `simulated_stores` is a GeoDataFrame with valid Point geometries
all_stores_gdf = pd.concat([point_stores_gdf, simulated_stores_gdf], ignore_index=True)

# Convert combined store geometries to coordinates
all_store_coords = all_stores_gdf.geometry.apply(lambda geom: (geom.x,
geom.y)).tolist()

# Step 4: Build KDTree for nearest neighbor search (After Adding Simulated Stores)
all_store_tree = cKDTree(all_store_coords)

# Compute nearest distances for each neighborhood
merged["nearest_store_distance_after"] = [
    all_store_tree.query(coord)[0] for coord in neighborhood_coords
```

```
]

# Step 5: Calculate Distance Difference
merged["distance_difference"] = (
    merged["nearest_store_distance_before"] - merged["nearest_store_distance_after"]
)

# Step 6: Analyze and Display Results
# Display neighborhoods with the most improvement
improved_neighborhoods = merged.sort_values(by="distance_difference",
ascending=False)
print(improved_neighborhoods[["Neighborhood", "nearest_store_distance_before",
"nearest_store_distance_after", "distance_difference"]])

# Step 7: Visualization (Optional)
import matplotlib.pyplot as plt

fig, ax = plt.subplots(figsize=(10, 6))
merged.plot(column="distance_difference", cmap="Greens", legend=True, ax=ax,
edgecolor="black")
plt.title("Change in Distance to Nearest Grocery Store After Adding Simulated Stores",
fontsize=16)
```

```
# Add labels
for x, y, label in zip(merged.geometry.centroid.x, merged.geometry.centroid.y,
merged["Neighborhood"]):
    ax.text(x, y, label, fontsize=8, ha='center', color='black')


plt.show()
#Assign costs for building new grocery stores based on fixed or variable factors (e.g.,
construction, staffing, logistics).
cost_per_store = 2_000_000  # Assume $2 million per store
total_cost = len(simulated_stores) * cost_per_store
print(f"Total Cost: ${total_cost}")
benefits_per_store = 5_000_000  # Assume $5 million in benefits per store
total_benefits = len(simulated_stores) * benefits_per_store
net_benefit = total_benefits - total_cost
print(f"Total Benefits: ${total_benefits}, Net Benefit: ${net_benefit}")
import matplotlib.pyplot as plt


categories = ["Total Cost", "Total Benefits"]
values = [total_cost, total_benefits]


plt.bar(categories, values, color=["red", "green"])
```

```
plt.title("Cost-Benefit Analysis")
plt.ylabel("Dollars")
plt.show()
```