Tulsa Undergraduate Research Challenge Student Project

Housing Challenges and Opportunities in the Tulsa Metropolitan Area: Blighted Housing

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Introduction: TURC Housing Policy Project 2025

1.1 Housing Challenges and Opportunities in Tulsa

The United States is currently grappling with an affordable housing crisis that spans across many of its cities and metropolitan areas. This crisis is characterized by a significant disparity between the rising costs of housing and the stagnation of household incomes, resulting in millions of Americans struggling to secure affordable housing. The affordable housing issue not only affects individual families but also has broader implications for economic growth, social stability, and overall quality of life.

In this context, the Tulsa Metropolitan Area faces its own set of housing challenges and opportunities. This paper focuses on the housing landscape of Tulsa, examining various aspects that contribute to its current state and exploring potential solutions. Each chapter delves into a different facet of the housing issue, providing a comprehensive analysis that spans multiple geographic areas and incorporates a comparison with other cities. By analyzing discovered trends and data, we aim to offer valuable insights into Tulsa's affordable housing issues and suggest how the metro might proceed to address these challenges effectively. It is important to note that many of Tulsa's housing issues are not unique; therefore, looking at other cities that have successfully mitigated affordable housing problems can provide valuable examples.

This paper is a collaborative effort, combining chapters written by University of Tulsa undergraduate scholars and junior scholars from local Tulsa high schools. These students spent the summer conducting and writing this research as part of the Tulsa Undergraduate Research Challenge (TURC). This research initiative, in collaboration with the University of Tulsa Center for Real Estate Studies, involved students who worked diligently to understand the challenges and opportunities in Tulsa. They gathered data, reviewed resources, and engaged with local industry professionals and individuals working in Tulsa's metropolitan government sectors related to real estate, housing development, and affordable housing initiatives. The University of Tulsa faculty advisors for this research project were Dr. Meagan McCollum and Dr. Cayman Seagraves.

1.2 Local Housing Factors

The supply and demand dynamics of housing are influenced by various local factors that shape the housing market's landscape. In Tulsa, these factors include economic conditions, population growth, land use policies, and availability of developable land. Understanding these local drivers is crucial for addressing the housing challenges effectively.

Additionally

Economic conditions in Tulsa, such as employment rates and income levels, directly impact the ability of residents to afford housing. Population growth, driven by both natural increase and migration, influences the demand for housing. Additionally, land use policies, including zoning regulations and building codes, play a significant role in determining the type and density of housing that can be developed. The availability of developable land, particularly in urban areas, is another critical factor that affects housing supply. However, existing housing that is in poor condition and considered a "blight" on the neighborhoods where it is found is an underexamined piece of the housing puzzle.

This summer, students selected topics of interest to focus their research on within the broad subject of housing policy in Tulsa. Much of the research this summer is centered around tackling the problem of housing blight in Tulsa, motivated in part by the City's recent strong commitment to focusing on this issue. In February 2025 Mayor Nichols issued an executive order that was aimed at addressing key housing goals in the city including:

- Increasing affordable housing stock by 6,000 units by 2028.
- Reducing blighted (unsafe, unsightly) properties by 60% by 2028.
- Reducing the cost burden taken on by developers to produce more housing.

Additionally, in June 2025 Oklahoma's strategy for handling dilapidated buildings and ensuring public safety got a legislative boost with the enactment of House Bill 2147. This new law grants municipal authorities enhanced powers to enforce building and safety codes, which could have a profound impact on the state's cities and towns.

In an economic environment where building and preserving affordable housing is both desperately needed but extremely challenging, we need to take a closer look at the housing stock that already exists but is not being fully utilized. Cities across the US collectively have hundreds of thousands of properties that are vacant, abandoned, and deteriorated- and millions more that are occupied but are in such poor condition that they do not provide safe, stable, and healthy living conditions for their residents.

What can start with some nuisance complaints to the city about overgrown lawns and junk in the yard can escalate over time to a situation where the property is in such poor condition that the city eventually gains control of the blighted property and demolishes it. Earlier this year, the city of Tulsa announced an ambitious goal to reduce blighted homes by 60% by 2028. This summer, our TURC student project has been focused on research focused on this city policy priority. Our students have been working on collection and analysis of local data to answer questions such as : How can we automate the detection of blighted conditions? What can we do to identify early "warning signs" to help mitigate negative impacts of blight for property owners and nearby neighborhood residents before they become severe? How can we fairly, quickly, and effectively allocate resources to help remediate blight?

The following chapter of the paper provide detailed insights into different aspects of the housing challenges and opportunities in Tulsa:

- **After Blight: Alternative Housing Development in Tulsa**

- **Housing and Blight in Connection to Other Community Amenities**
- **Facilitating Redevelopment of VAD Properties in Tulsa: An AI-Driven Peer City Analysis Tool**
- **VAD Management Program Analysis**
- **Analyzing the Potential Effectiveness of Regression Modeling in Identifying Blight**
- **Facilitating VAD Identification: An AI-Driven Image Classification Tool**
- **Reflections on AI and Its Emerging Role in the Real Estate Industry**
- **AI Workflows**

Through these qualitative and quantitative analyses presented, we hope to provide actionable recommendations that can help Tulsa and similar cities to effectively address their housing challenges, particularly in identifying and remediating blighted housing, fostering sustainable and inclusive growth for all residents.

1.3 Acknowledgments

We gratefully acknowledge the following individuals and organizations who provided valuable insights and assistance to our TURC students this summer: Cat Thomason, Tyler Parette, Jessica Shelton, Phillip Boykin, Vishagan Ratnaswamy, Lisa Copass, Monte Stewart, Austin Chapman, Daniel Jeffries, Travis Hulse, Vicki Jordan, Anthony Faddis, Kathy Portley, Gene Bulmash, Bruce Bolzle, Jonathan Belzley, City of Tulsa, Housing Forward, Green Country Habitat for Humanity, and PartnerTulsa

2 After Blight: Alternative Housing Development in Tulsa

Author: Mori Kurland

2.1 Introduction

Anyone familiar with Tulsa's real estate ecosystem already knows that local housing production is not keeping up with demand, especially when it comes to affordable housing. This is why the overarching focus of our team's research has been expedited and effective blight identification. If blight can be identified and remedied in its early stages before it renders a potentially low-cost home uninhabitable, we can at least ensure stability among existing units. However, preserving what exists is not enough to resolve our housing issues. As such, a secondary question I have investigated is: What construction methods can be used to best add cost-effective housing units to Tulsa?

To begin answering this question, I have taken a multi-pronged approach. Firstly, I have analyzed almost twenty new and emerging alternative housing typologies. In researching these home types, one theme I discovered is that houses with an uncommon or alternative style may have difficulty in the lending and insurance processes. Consequently, the second aspect of my investigation was to survey local homeowners' insurance agents and mortgage lenders to determine their willingness to service unfamiliar housing styles. The last tenet of my research was to analyze Tulsa's zoning rules and housing-related regulatory processes to see if any unreasonable and preventable obstacles to multi-family housing development exist. I also entered thousands of data points that the local government has collected on the 80 Neighborhood Statistical Areas (NSAs) in Tulsa. The data was then graphically analyzed in many ways in an attempt to correlate various factors with different types of housing in Tulsa. Finally, multi-family zoning and NSAs were mapped together to observe potential connections.

Apart from my methods, it is also necessary to disclose my foundational sources in conducting this research. *Blighted: A Story of People, Politics, and an American Housing Miracle*, a memoir written by Margaret Stagmeier to recount her and her colleagues' work renovating a derelict apartment community in Atlanta, Georgia, was particularly meaningful. In reading Ms. Stagmeier's work to acquire background knowledge of the issues I was wading into, I was very inspired by her efforts at community building, as well as by all the businesspeople who made them possible (Stagmeier, 2022). Separately, Sara C. Bronin's book, *Key to the City: How Zoning Shapes our World*, proved very instructive as an overview of the zoning issues different cities around the country face and the innovative solutions they have implemented to overcome them (Bronin, 2024). In other words, it provided perspective on Tulsa's zoning and housing woes. I sincerely hope the research that follows will be similarly useful.

2.2 Alternative Housing Construction Typologies

One of the best conversations I had while journeying into alternative housing research was with a woman named Lisa Copass. Before delving into her insights, it's important to note that for my research purposes, "alternative housing" and "alternative construction" are defined as any method of building a house other than conventional, or "stick-built", construction. Ms. Copass is a housing entrepreneur in the early stages of selling residential Structural Insulated Panel home kits (SIP kits). Her business, CloudHaus Dwellings, is unique in that its products are made of metal in a heavily wood-dominant industry. Ms. Copass's journey into alternative housing began, in her own words, "out of fire." A few years ago, while driving through California, Lisa realized that the only structures to survive recent wildfires were made of metal. From that point forward, according to Lisa, the "genie was out of the bottle" when it came to metal SIPs (Copass, 2025), though frankly this sentiment seems applicable to alternative housing more broadly.

My study of alternative housing typologies consisted of researching the definition, cost, advantages and disadvantages, construction timeline, design limitations, resale value, and example companies for eighteen different types of alternative housing (panelized home kits, modular kits, log cabin kits, SIP kits, timber frame kits, A-frame kits, tiny home kits, manufactured homes, container homes, 3D-printed homes, hybrid prefabricated homes, straw bale homes, earthbag homes, cob homes, rammed earth homes, hempcrete homes, adobe homes, and bamboo homes). This investigation resulted in a detailed review of each alternative housing style (included in A.1). While each style was obviously different and not every piece of information I found was linkable to others, several common themes developed between the individual typologies. These are summarized in Figure 1.

The biggest connection that emerged between the alternative housing styles was environmental benefits. 16 out of the 18 typologies I studied have environmental benefits greater than those provided by conventional construction. One of the most common benefits is energy efficiency. Numerous sources report that alternative construction methods ranging from prefabricated options, like panelized or modular kits, to those based on unusual materials, like rammed earth, offer homeowners temperature regulation and utility efficiency (noa, n.d.d), (noa, n.d.c), (Edmonds, 2008). Sustainability is another common feature. Styles like container homes, earthbag homes, and adobe homes offer homebuyers the chance to repurpose existing materials, potentially including materials they already own, to build a house (Trump, 2017), (Edmonds, 2008), (Anonymous, n.d.), (Park, 2024).

The second most abundant attribute among the alternative construction methods I researched is time savings. According to Angi, a leading residential services website, conventional homes generally take between 7 and 14 months to build (Simms, 2025). Based on that metric, 14 out of the 18 alternative styles are usually constructed faster than a conventional home; in some cases, exponentially faster. Assembling a tiny home kit, for example, can take as little as one day, and the same timeline applies to producing the exterior of a 3D-printed home (Lewis, 2023), (Becher, 2024). Modular homes provide a less drastic example of time savings: a modular home can be ready for occupancy in about 3 months, instead of 7 or more (noa, n.d.c). It is noteworthy, however, that some styles take much longer to build than a stick-built house. An adobe home, for instance, can take 18 months to build, or more than twice as long as its conventional peers (Park, 2024).

Unfortunately, not every trait common to the alternative styles is positive. Approximately two-thirds (11 out of 18) of the styles face resale value uncertainty, which is a much less common problem in conventional construction. Although lack of demand in the resale market is a legitimate cause of this uncertainty for products like tiny home kits (noa, n.d.e) and manufactured homes (K. Hovnanian Homes, 2020), (Vukelich, 2022), a much more common source of the issue is that many alternative housing styles are simply so rare and new that the market has not yet had adequate time or experience to judge their desirability or value. Familiarity with obscure, emerging housing methods, like earthbag and hempcrete, is uncommon, so it follows that their value in the market is proportionally uncertain (noa, n.d.a), (Wesseler, 2024). Of course, as a style establishes itself in an area, uncertainty surrounding it can dissipate. Cob and adobe housing, for example, are accepted styles in England and the American Southwest, respectively, even though they may face more resistance in a new environment, like Tulsa (Marabito, 2021), (Park, 2024).

Speaking more optimistically, the same proportion of alternative styles (11 out of 18) offer homebuyers a cheaper housing option. This is often due to the low cost of materials. Describing an earthbag home, for example, as "dirt-cheap" is not an exaggeration, since a homebuilder can make one with dirt from the lot they already own to put the house on (Edmonds, 2008). Strawbales and bamboo are other examples of building materials that are cheaper than what is normally used (Gromicko, n.d.), (Pritchard, 2022). Factory efficiency can also bring costs down, as is the case with panelized and modular kits (Jacques, 2024), (noa, n.d.c). Although the existence of relative savings is determined here solely based on construction costs, potential savings due to low maintenance requirements in styles like manufactured homes and rammed earth homes are also noteworthy (Vukelich, 2022), (noa, n.d.b).

The final connecting factor between the alternative styles reviewed is that half of them (9 out of 18) are limited in the house designs they can be used for, though a great deal of these limitations are obvious. An A-frame kit, for instance, can only produce a triangular finished product. In other words, an A-frame kit can only be used to build an A-frame house (Kitzmiller, 2022). Another similar example is a tiny home kit. The name of the product should be a clear indicator that space in the finished home will be incredibly limited (noa, n.d.e). Container homes have a less obvious constraint. While shipping containers may seem large, consumers should understand that each container does not actually provide a lot of livable space once it's repurposed. Because container homes are modular based on how many containers are used, and each container provides very limited living space, smaller homes should be the expectation when using this style to build a house (Clayton Homes, 2023), (MasterClass, 2021). Many methods based on alternative materials, including straw bale, earthbag, and hempcrete homes, have style-specific design limits, which are detailed in the relevant appendix.

As demonstrated, the 18 alternative housing typologies explored here are stunningly diverse, with equally varied advantages and disadvantages. Continuing to research these and other new methods of construction is critical as new information emerges. As such, this review should not be taken as comprehensive or final. In fact, one alternative housing style, hybrid natural-prefabricated systems, had to be removed from this report upon final consideration due to lack of information. This, more than anything, illustrates the necessity of further research.

2.3 Mortgage and Home Insurance Accessibility for Alternative Projects

Another linking item between alternative typologies was that many face difficulties receiving home insurance and financing. Because this represents a substantial obstacle to alternative development projects, it warranted its own investigation. The simplest method of learning about this problem seemed to be directly asking those who have the power to either overcome it or perpetuate it, so that's what I did.

Rather than calling homeowners' insurance agents and mortgage lenders without a plan or formula, I decided to make a list of potential research participants in Tulsa and surrounding areas using existing data. The Oklahoma Insurance Department has published information on the top ten homeowners' insurance companies by market share in Oklahoma (see Figure 2), so I researched representatives from the top ten companies listed under "Homeowners Multiple Peril" in the "2017 Licensed Insurance Companies" report, as that was the most current information I could find when this investigation was ongoing (Oklahoma Insurance Department, 2017). Three homeowners' insurance agents or agencies from nine of the top ten companies (United Services Automobile Association (USAA) was excluded because they do not use individual agents) were compiled to create a list of 27 insurance contacts ((State Farm, n.d.; Farmers, n.d.; Google Maps, n.d.; Safeco, n.d.; Liberty Mutual, n.d.; Allstate, n.d.; Shelter, n.d.; Oklahoma Farm Bureau Insurance, n.d.; American Farmers & Ranchers, n.d.)). When insurance companies provided the number of ratings their agents have received and awarded some agents a special designation, both or either indicator (depending on what was available) were used to select agents with the most reviews and/or the higher status designation on the premise that they would most accurately represent their companies' policies and attitudes.

I used a similar strategy to compile a list of mortgage professionals to contact. In the past, the Oklahoma Housing Finance Agency (OHFA) awarded the state's highest-performing lenders the Diamond Award. I used OHFA's most recent (2014) list of Diamond Award-winning lenders to create a new list that just included lenders in Tulsa and directly adjacent counties (noa, n.d.f). The resulting list included 28 lenders, 17 of which were from Bancfirst. No other company populated more than 3 results, so, to make sure Bancfirst did not have an outsized influence on results, I randomly selected 3 Bancfirst lenders, thus creating a final list of 14 lenders to contact.

Once my combined list of 41 insurance agents/agencies and mortgage lenders was finished, I created the survey I would distribute to them. To maximize participation, the survey was made short. It asked five questions, only four of which required a response. The first three required questions, respectively, asked about a participant's familiarity with, past experience(s) with, and negative policies toward each alternative housing typology. The fourth required question asked participants to rate their agreement with statements claiming they are knowledgeable about alternative housing types, they receive encouragement and education about alternative housing, and they would service an alternative housing project if given the chance. The fifth, final, and optional question simply asked participants to provide any additional feedback they have regarding alternative housing in Oklahoma.

My method of distributing this survey was to call every one of the 41 people or agencies identified as an optimal participant. The survey was given once during a phone call; the rest of the responses were collected after emailing the survey to participants who provided an email address while I spoke to them on the phone. At the end of the surveying period, 7 complete responses had been collected, though the first question of the survey (which was about familiarity with alternative housing typologies) received 8 responses. Unfortunately, this represents a 17.07% response rate among those whose participation was requested. Considering that the targeted sample started relatively small, these results are not vigorous enough to draw representative conclusions from.

Anecdotally, the few data that were collected indicate limited familiarity and experience with all included alternative housing typologies aside from manufactured homes and kit homes. However, they also indicate that insurers and lenders do not face substantial regulatory barriers to servicing alternative projects and that they would be open to working with such projects if given the chance. One participant also noted that, because the alternative housing types mentioned in the survey are exceedingly rare in the local environment, a large issue in servicing potential future projects would be insufficient information to perform appraisals due to a lack of relevant comps. In any case, because inadequate evidence was collected to draw conclusions, the necessary next step in this segment of research is to redistribute the survey to a much wider sample of Tulsa's homeowners' insurance and mortgage professionals. This will hopefully allow enough information to emerge to determine what barriers might be stalling the development of alternative housing in Tulsa.

2.4 Multi-family Zoning and Neighborhood Statistical Areas

In researching alternative housing options, it became necessary to review Tulsa's regulatory processes pertaining to housing, as well as city zoning laws. After all, even if a perfect housing type existed, if it couldn't be built in Tulsa, it would not do much good. Since most alternative typologies already reviewed generally produce single-family homes similar (in that regard) to their stick-built counterparts, it follows that single-family zoning applies to both types of home (conventional and alternative). Any drive through Tulsa will show no shortage of single-family development, so attention must turn to more elusive, denser housing styles.

The first step to understanding multi-family housing in Tulsa is to understand where it is, or, more accurately, where it is allowed to be. To do this, I took a GIS (Geographic Information System) shapefile that shows the City of Tulsa divided by zone City of Tulsa, and then I color coordinated the map based on the different allowable, or "by-right", uses of different zone types, as shown in Figure 3. This map yields two major takeaways. The more informative conclusion is that the vast majority of both residential and non-residential land in Tulsa does not allow construction of multi-family housing by-right. The second takeaway, though perhaps obvious given the first, is that although a large amount of Tulsa's land is residentially zoned, the zoning allows only single-family housing.

This raises the question of why multi-family zoning is so minimal in Tulsa. Luckily, city officials have some answers. In speaking with Austin Chapman, AICP; Daniel Jeffries, AICP; and Travis Hulse; Tulsa's Senior Planner, Principal Planner, and Housing Policy Director, respectively, I learned that Tulsa's abundance of single-family residential zoning is largely a holdover from decades ago (Chapman et al., 2025). Sara C. Bronin corroborates this in her book, *Key to the City: How Zoning Shapes our World*, when she describes this phenomenon as common to American cities. According to Bronin, when suburbs began to proliferate in the mid-twentieth century, cities modified their zoning codes to accommodate them. Suburbia was codified, and so it remains today (Bronin, 2024). Considering this, why haven't zoning codes been amended *en masse* once again to allow for more multi-family housing, especially given America's current affordable housing crisis?

In speaking with various members of Tulsa's housing ecosystem about the causes of this issue, I always received the same answer. Housing developers, like Bruce Bolzle and Jonathan Belzley; non-profit housing advocates, like Tyler Parette and Jessica Shelton at Housing Forward; and the city officials named previously all blamed one thing: politics. According to these diverse individuals, the glacial slowness, natural divisiveness, and necessary cooperation of the political process does not allow local zoning to change as quickly as it could to permit the creation of more affordable housing. As the city planning officials I spoke with were quick to point out, this does not mean that local politicians are blameworthy. They simply have a responsibility to honor the wishes of their constituents, some of whom ascribe to a NIMBYist (Not in My Backyard) mentality (Chapman et al., 2025; Bolzle and Jonathan, 2025; Parette, 2025; Shelton, 2025).

By talking with so many people with so much local housing experience, I heard a few solutions to these issues. Regarding political issues with zoning changes, Tulsa's planning staff has taken to recommending smaller changes at once to minimize controversy. And it's working. Whereas rezoning all residential land in Tulsa to allow multi-family housing by-right would have faced formidable obstacles, the city accepted two

Neighborhood Infill Overlays to increase the density of certain Tulsa neighborhoods by allowing many kinds of multi-family housing by-right within them (City of Tulsa, 2015). Hopefully, if these Overlays improve the communities they cover, they can be expanded. Parking is another area in which incremental progress has been made. City officials have decreased minimum parking requirements in Tulsa, resulting in a 50% reduction in some cases. Tulsa officials are also working on a Home Catalog with preapproved plans for single-family homes, duplexes, four-plexes, six-plexes, eight-plexes, ten-plexes, and accessory dwelling units (ADUs). This will allow faster development of diverse housing in Tulsa because some normally burdensome regulatory processes will be able to be bypassed (Chapman et al., 2025).

To complement zoning analysis, I also analyzed Tulsa's neighborhoods to see if there are any connections between their housing compositions and demographics. By compiling all available data from Tulsa's Neighborhood Conditions Index (NCI), I was able to analyze thousands of data points about Tulsa's 80 Neighborhood Statistical Areas (NSAs) (?). This data was plotted in many different ways, but correlations between housing and other data were difficult to establish, as data points were often too dispersed to make conclusions with any statistical confidence, regardless of a trendline's directionality. However, two relatively robust connections emerged. The first is that the population density of, and proportion of multi-family housing in, an NSA increase or decrease together (see Figure 4). The second is that an NSA's proportion of multi-family housing and average family size have an inverse relationship (see Figure 5). While these are certainly not unexpected results, they seem to indicate that Tulsa's housing and zoning patterns may fit its communities better than previously assumed.

After separately considering Tulsa's zoning and NSAs, the final step of this research component was to analyze them together. To that end, I connected with the Tulsa city government again because I needed a copy of the GIS shapefile that divides Tulsa into its 80 NSAs. Once I received it, I used GIS software to overlay multi-family zoning in Tulsa on the NSAs (organized by priority level) (see Figure 6). This was very illuminating.

My first discovery was that the areas of Tulsa with different priority levels are very geographically distinct. Level 1 NSAs need the most improvement, Level 3 need the least improvement, and priority designations were made based on which quartile an NSA's overall score in the Neighborhood Conditions Index fell into. Bottom-quartile NSAs were designated as Level 1, top-quartile NSAs became Level 3, and middle-quartile NSAs received Level 2 status. These designations are presumably updated every two years because that is the frequency with which the NCI is updated (City of Tulsa Planning Office, 2025). Level 1 NSAs are concentrated almost entirely in North Tulsa; Level 3 NSAs are tightly woven in two pockets, one south of downtown and west of the Arkansas river and the other dominating South Tulsa; and Level 2 NSAs fill the rest of the city. While this may come as no surprise to those most familiar with Tulsa, I expected at least slightly more inter-level integration.

The next key observation from this exercise was that huge swaths of different priority level areas have almost no multi-family zoned land. Both the North Tulsa Level 1 region and the Central Tulsa Level 3 region fall into this category, aside from the handful of NSAs that are directly adjacent to downtown. The South Tulsa Level 3 region has considerably more multi-family zoned land due to large tracts of such space in the southeastern corner of Tulsa. No Level 2 region of the city has a plethora of such land, but what is there is arguably more plentiful and scattered. Less downtrodden parts of the city, such as those designated Level 2 or 3, might not be expected to have a great deal of multi-family housing or land because their residents can perhaps afford single-family homes. Therefore, the truly incredible thing revealed here is that the neediest parts of Tulsa have some of the least multi-family zoned land, which is supported by the NSA data analysis discussed earlier. The 20 Level 1 NSAs in Tulsa have, on average, the lowest proportion of multi-family and missing middle housing despite having the lowest median household income by a margin of almost $14,000 (see Figure 7). Obviously, Tulsa's poorest residents need greater, not lesser, access to affordable housing. Such affordable housing usually consists of multi-family developments, so these findings can hopefully prompt Tulsa officials and community members to allocate multi-family zoning solutions where they are most needed.

Ultimately, by researching new housing styles, substantial obstacles their development may face, and where their denser counterparts can go in Tulsa, I have done my best to contribute to the ongoing process of learning how to best help Tulsa serve its residents. My hope is that other researchers will continue to take up this mantle and that those with the power to make change in Tulsa will take my findings seriously in order to develop a more modern, diverse, and accessible housing ecosystem. The discoveries I have made and shared here are by no means comprehensive or final, but I hope they will help make the community that has done so much for me better.

2.5 FIGURES

Common Themes in Alternative Housing Styles*

Alternative Housing Style	Cost Benefit	Time Benefit	Env. Benefit	Resale Uncertainty	Design Limitations
Panelized Kits	✓	✓	✓	✓	—
Modular Kits	✓	✓	✓	—	—
Log Cabin Kits	✓	✓	—	✓	✓
SIP Kits	—	✓	✓	—	—
Timber Frame Kits	—	—	✓	—	—
A-Frame Kits	✓	✓	✓	✓	✓
Tiny Home Kits	✓	✓	✓	✓	✓
Manufactured Homes	✓	✓	—	✓	✓
Container Homes	—	✓	✓	—	✓
3D-Printed Homes	✓	✓	✓	✓	—
Hybrid Prefab Homes	—	✓	✓	✓	—
Straw Bale Homes	✓	✓	✓	✓	✓
Earthbag Homes	✓	✓	✓	✓	✓
Cob Homes	✓	—	✓	✓	—
Rammed Earth Homes	—	—	✓	—	—
Hempcrete Homes	—	✓	✓	✓	✓
Adobe Homes	—	—	✓	—	✓
Bamboo Homes	✓	✓	✓	—	—

*All information taken from comprehensive review of above alternative housing typologies in the appendix

Figure 1: Alternative Housing Styles Organized by Common Attributes Note: The presence of each variable in an alternative style is determined simply by comparing available information about the stye to conventional construction (i.e. styles cheaper than stick-built housing have a "Cost Benefit")

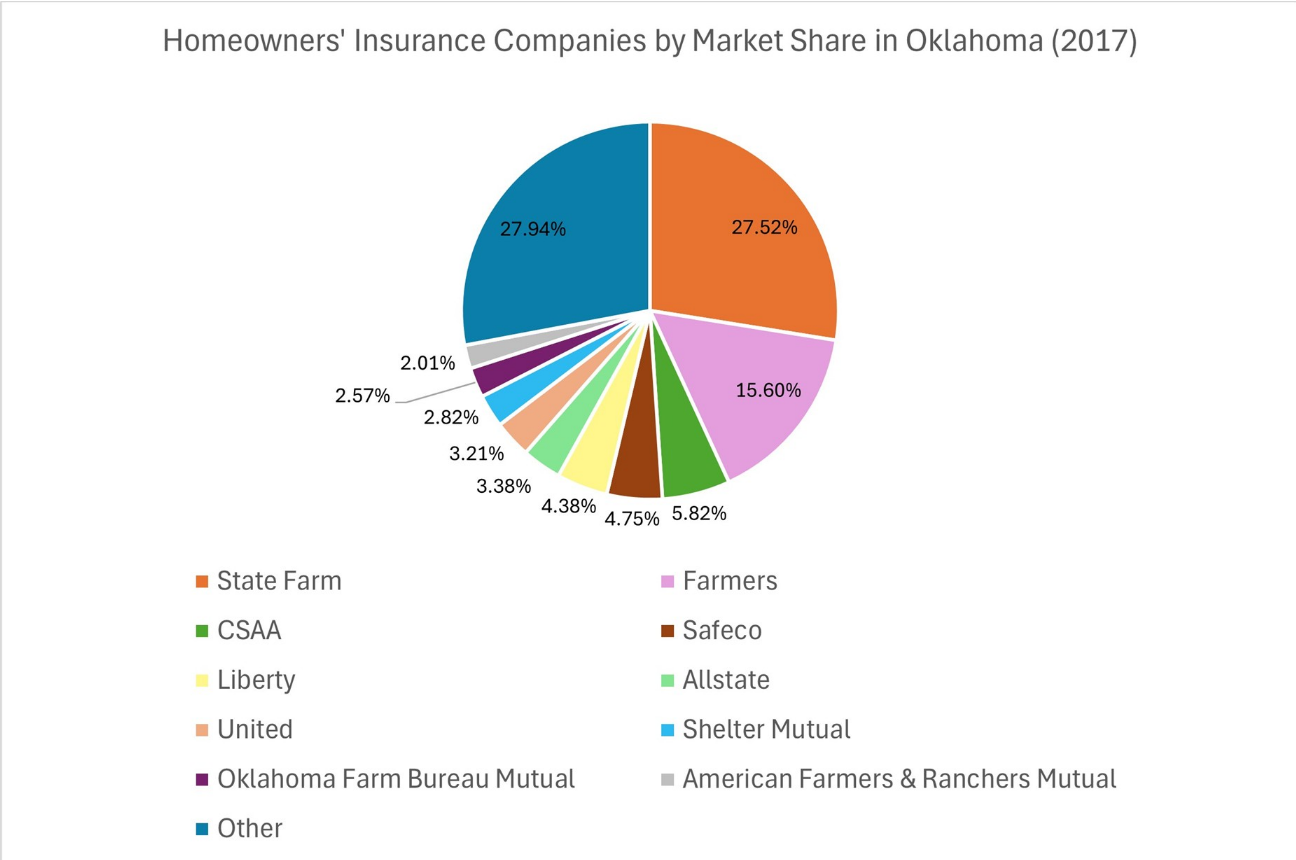

Figure 2: Pie Chart of Homeowners' Insurance Companies' Market Shares in Oklahoma

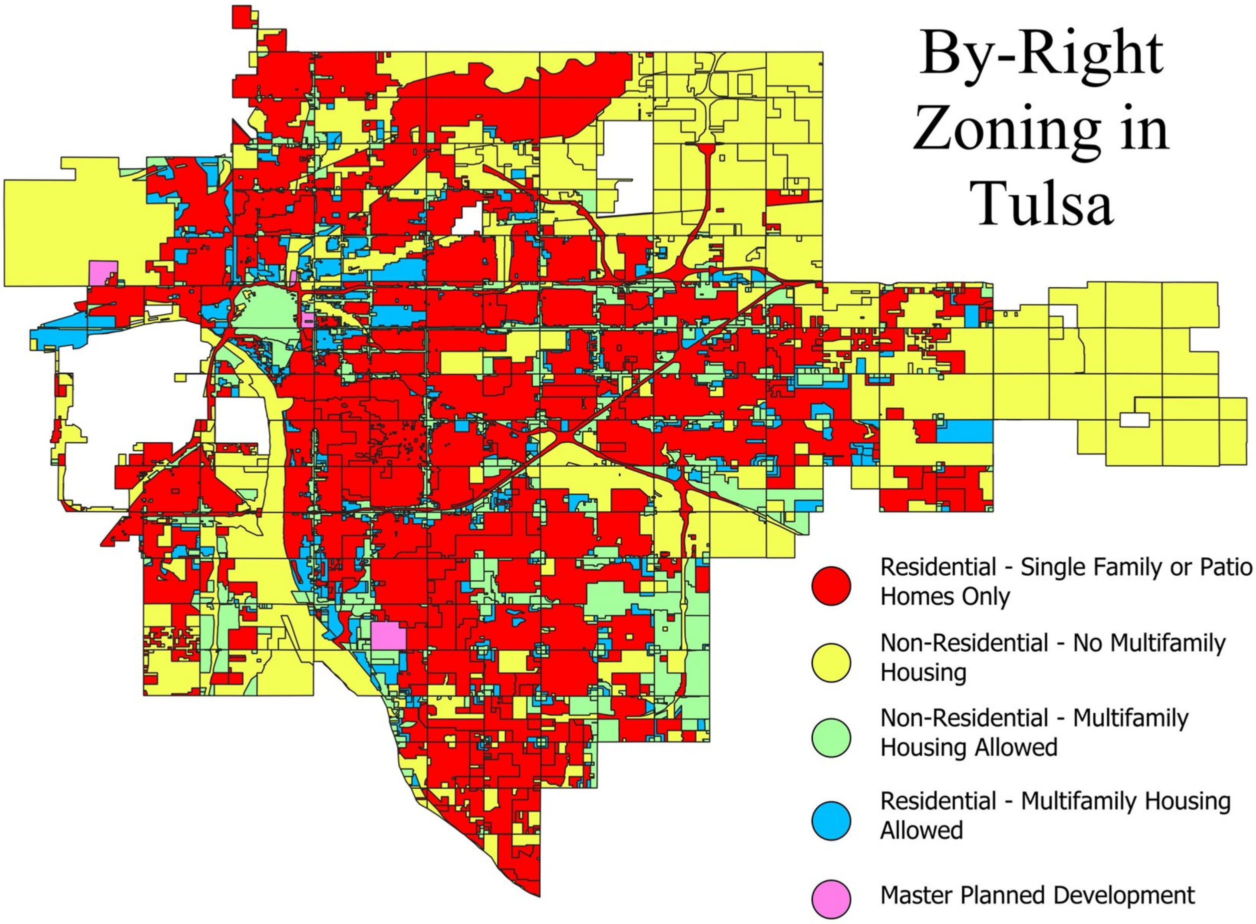

Figure 3: Color-Coded Map of By-Right Zoning in Tulsa

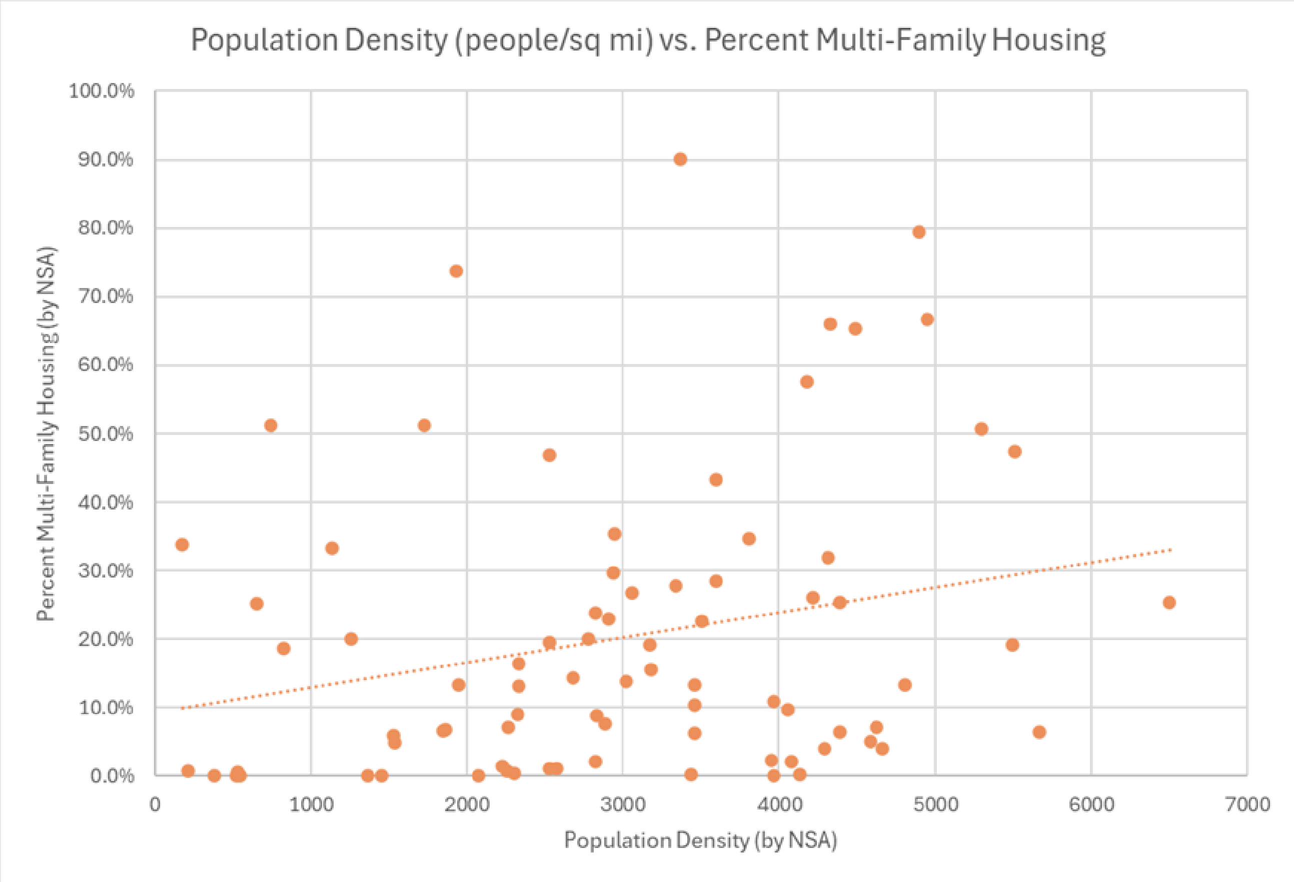

Figure 4: Correlation Between Population Density and Percent Multi-Family Housing (by NSA)

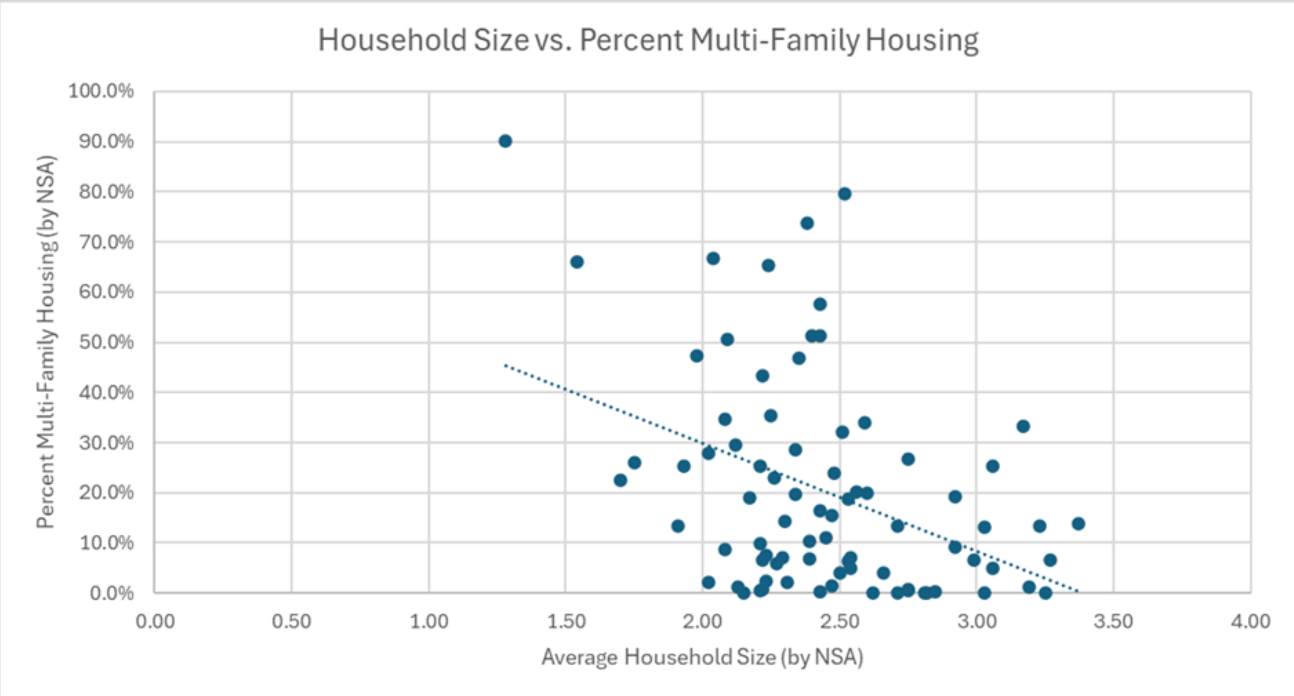

Figure 5: Correlation Between Average Household Size and Percent Multi-Family Housing (by NSA)

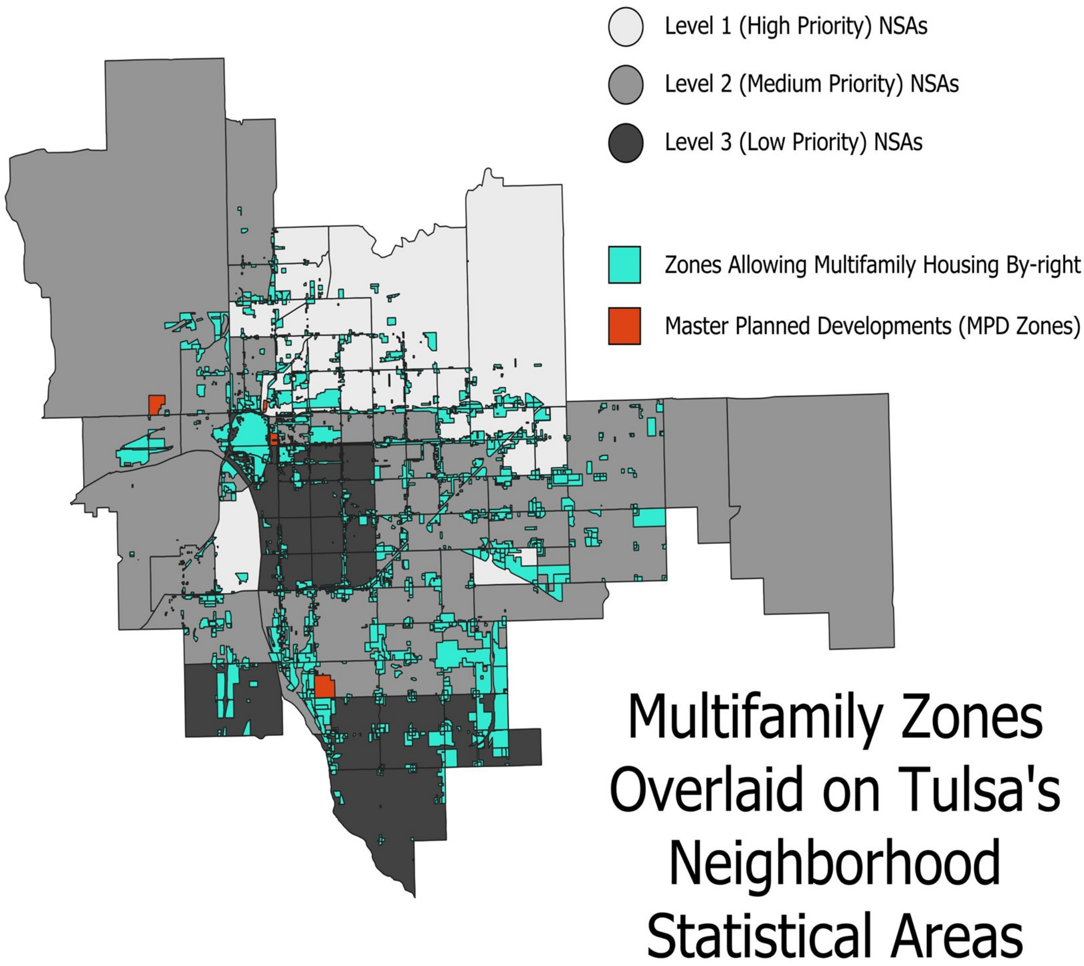

Figure 6: Multi-Family Zoning in Tulsa Overlaid on NSAs Organized by Priority Level

Priority Group	Number of NSAs	Average MHHI	Average % MF	Average % MM	Average % SF
1	20	$34,984.40	12.4%	8.4%	79.2%
2	40	$48,527.50	22.1%	9.0%	68.9%
3	20	$86,017.50	24.1%	8.6%	67.2%

Figure 7: Summary of NSA Statistics by Priority Level Note: MHHI = Median Household Income; MF = Multi-Family Housing; MM = Missing Middle Housing (defined within Tulsa's Comprehensive Plan as "Housing types with densities between detached houses and apartment buildings, such as duplexes, triplexes, quadplexes, and small apartment buildings."22); SF = Single-Family Housing

3

Housing and Blight in Connection to Other Community Amenities

Author: Ella Calvert

3.1 Introduction

Housing, transportation, education, and access to food are all highly connected, necessary components to modern life. While this chapter focuses primarily on the housing aspect, the additional factors of access to public transportation, food, and education are critical, as low-income households are disproportionately affected by blight and more likely to depend on these amenities. For example, low-income households have lower rates of car ownership, making proximity to public transportation essential (Mengedoth, 2023). In Tulsa specifically, the January 2025 City of Tulsa Smart Growth Report, prepared by Smart Growth America, Housing Forward, and The Anne and Henry Zarrow Foundation, outlines various strategies for Tulsa's development and highlights the importance of a place-based approach to urban planning.

From the report: "The SGA (Smart Growth America) team stresses the first issue that permeates through the analysis: Tulsa's planning is minimally place-based. Tulsa needs to implement forward-looking planning strategies that proactively align housing growth, transportation, and infrastructure with a place-based vision for growth and tangible growth targets in housing priority areas." (Smart Growth America, Housing Forward, and The Anne Henry Zarrow Foundation, 2025)

Areas that make up infrastructure include community amenities like transit stops, elementary schools, and grocery stores. These were selected due to their impact on housing stability and neighborhood vitality.

Elementary schools, specifically neighborhood elementary schools, are both geographically and socially linked with the communities around them. Multiple studies have investigated the links between neighborhoods and schools (Rönnberg et al., 2024; Emory et al., 2008). Fewer have explored the specific role of blight in school performance and neighborhood relationships. One significant piece of research that does is Margaret Stagmeier's Blighted, which informed the type of school data collected for this report. In her work, she describes how the Summerdale apartment complex, undergoing renovation, housed as many as 20% of the students at the nearby Brumby Elementary School (Stagmeier, 2024, p. 348).

This chapter documents the collection of geographic data related to residentially zoned areas, public transportation, elementary schools, and grocery store locations in Tulsa. These data are foundational for future analysis and integration into tools like QGIS and Excel. Every map referenced throughout this chapter is of the entire city. Additional versions focused only on the surveyed area in North Tulsa, referenced later in the project, are also available.

3.2 Methodology Overview

The datasets used in this chapter were sourced from the City of Tulsa's Open Data Portal, Tulsa Transit GTFS feeds, the Oklahoma State Department of Education, and the USDA Food Research Atlas(City of Tulsa Geographic Information Systems (GIS), 2025; Metropolitan Tulsa Transit Authority (MTTA), 2025; Oklahoma State Department of Education, 2025; U.S. Department of Agriculture, Economic Research Service, 2025a). GIS tools were used to map these features using latitude and longitude and link them to Census tracts to support future regression analysis between factors and with the data on blight in the Tulsa area.

3.3 Residential Zoning

Zoning data were obtained from the City of Tulsa's Open Data Portal and filtered in QGIS to extract only residential zoning categories (Tulsa Planning Office, 2025). The following table includes definitions adapted from the Tulsa Zoning Code (MetroLink Tulsa Transit, 2025a):

Zone	**Definition**
Agricultural - Residential	A rural residential district that allows limited agriculture and single-family homes on large lots (min. 1 acre), intended for fringe areas or transitions between urban and rural uses.
Residential Duplex	Allows one two-unit residential building (duplex) per lot. Provides a transition between single-family and higher-density multifamily zones.
Residential Estate	A very low-density district allowing detached houses on large lots. It preserves semi-rural residential character within city limits.
Residential Multifamily-O	Permits low-density multifamily housing such as small apartment buildings and townhomes with larger setbacks and less intense use than RM-1.
Residential Multifamily-1	Allows low-density multifamily housing. Typical uses include garden apartments and townhouses. Intended to provide a transition from single-family neighborhoods.
Residential Multifamily-2	A medium-density zone allowing a wider variety of multifamily housing. Intended for more urbanized areas with proximity to transit or commercial centers.
Residential Multifamily-3	High-density multifamily zone intended for stacked apartments and urban townhouse developments with flexible design.
Residential Manufactured House	Designates areas for manufactured home parks, with standards for layout, buffering, and minimum amenities.
RS	The general "Residential Single-family" designation. It includes RS-1 through RS-5 districts with increasing allowable density.

Zone	Definition
Residential Single-1	Large-lot single-family district. Typically suburban-style housing with a low density.
Residential Single-2	Medium-large lots for detached single-family dwellings; more compact than RS-1.
Residential Single-3	Smaller-lot single-family homes. Common in inner-city or older subdivisions with a tighter grid.
Residential Single-4	High-density detached housing on compact lots, allowing more walkable or infill development.
Residential Single-5	Highest-density detached single-family zoning. Minimum lot sizes are smallest in this tier.
Residential Townhouse	Allows attached single-family units (townhouses) on individual lots, usually fronting public streets and separated vertically. Promotes ownership in higher-density formats.

Table 2: Zoning Definitions

These categories include detached single-family, duplex, townhouse, manufactured housing, and various multifamily levels. These zones define where residential development is permitted and are a prerequisite for analyzing proximity to amenities.

A total of 1,354 distinct residentially zoned parcels were identified in the zoning dataset.

3.4 Transportation

In Tulsa, buses serve as the primary form of public transportation. Using data from Tulsa Transit and the General Transit Feed Specification (GTFS) , a spreadsheet of transit stops was created and geocoded to identify their locations by Census Tract and block. Geographic referencing by tract/block is significant because it enables linkage with other demographic variables such as income and race from the U.S. Census for future analysis. To assess transit accessibility, buffer zones were created around each stop at radii of 400, 500, 800, 1000, and 1600 meters. These distances correspond to common walkability standards—approximately 5 to 20 minutes of walking.

There are 1,354 different areas that are zoned residentially. The table Residential Zoning in Tulsa within Specified Distance of a Transit Stop helps interpret and analyze the accessibility of transit stops from residential areas. To interpret the first line of the table, for example: 833 of 1,354 total residentially zoned areas, or approximately 61%, are within 400 meters of a transit stop. Another observation is that approximately 21% of residentially zoned areas are not within 1600 meters of a transit stop, raising accessibility concerns.

Distance (meters)	Distance (degrees)	Residential Zones within distance of a Transit Stop	Decimal	Percentage
400	0.0036	833	0.61521418	61.52141802
500	0.0045	893	0.659527326	65.95273264
800	0.0072	986	0.728212703	72.82127031
1000	0.009	1031	0.761447563	76.14475628
1600	0.0144	1097	0.810192024	81.01920236
>1600	>.01	1354	1	100

Table 4: Residential Zoning in Tulsa within Specified Distance of a Transit Stop

I have also created additional maps and charts to further visualize the coverage of the residential zones as they relate to transit stops. Please see Figures 9, 10, 11, and 12. Please note, QGIS buffer tools rely on geographic degrees, which approximate latitude but can introduce error when used as a direct proxy for distance. The conversion factor used was 1 degree = 111,000 meters (National Ocean Service, NOAA, 2024). Additionally, these buffers are radial and do not account for real-world pedestrian paths, barriers, or sidewalk infrastructure.

Tulsa Transit also operates MicroLink, a demand-responsive service, which may extend practical coverage beyond fixed-route accessibility. From Tulsa Transit: "Micro Transit operates in specific zones, connecting passengers to fixed routes for complete journeys. Users can request rides through various platforms, facilitating convenient and flexible service. Vehicles pick up passengers from their desired location, employing real-time scheduling to optimize routes, reduce wait times, and cater to individual travel needs within defined geographic areas."MetroLink Tulsa Transit (2025b)

3.5 Access to Grocery Stores

Access to affordable, healthy food is a necessity. Grocery store data were obtained by filtering by the Tulsa, OK location and using NAICS code 445110 from the Data Axle U.S. Business Database, via Tulsa City-County Library access (Data Axle Reference Solutions (formerly ReferenceUSA), 2025). Addresses were then geocoded to provide latitude and longitude locations. The USDA defines "low-access" as being more than one mile (urban) or ten miles (rural) from a grocery store for low-income individuals (U.S. Department of Agriculture, Economic Research Service, 2025b). Including this spatial context can help reveal correlations between blighted areas and food insecurity in future research.

In Tulsa, preliminary spatial analysis suggests that:

- The southern part of the city contains more grocery stores, many of which fall outside the reach of the fixed-route transit system.
- Northern neighborhoods exhibit both fewer stores and lower store density.

These observations are visualized in Figure 13, which shows both grocery stores and transit Stops (with 400m Buffer) overlaid on residentially zoned areas.

3.6 Public School Quality

Informed by the book *Blighted* (Stagmeier, 2024), this section explores how neighborhood elementary school quality and housing are interconnected. As Stagmeier notes: "Housing directly impacts school performance, and school performance directly impacts the demand for housing" (p. 348).

School quality was measured using the Oklahoma School Report Card dataset provided by the Oklahoma State Department of Education. From their website:

"Oklahoma's school report cards are measured across multiple indicators, including academic achievement, academic growth, chronic absenteeism, progress in English language proficiency assessments, postsecondary opportunities, and graduation. Measured at different points, indicators work together to provide a snapshot of school performance. Each of these indicators receives a specific point value that translates to a letter grade." (Oklahoma State Department of Education, 2025)

Only neighborhood schools were included in this collection analysis. While Tulsa Public Schools (TPS) operates charter and magnet programs, these schools have limited enrollment capacity, are accessed through a competitive lottery process, and do not serve all students in a given area (Tulsa Public Schools, 2025a). TPS is required to provide schools for all students residing within district boundaries (Oklahoma State Legislature, 1907), which at the elementary level, are neighborhood schools. Although the district allows in-district transfers, transportation is not provided for students outside magnet programs (Tulsa Public Schools, 2025b), making access to higher-performing schools dependent on car ownership or close proximity to Tulsa Transit routes.

Table 3.6 presents information about the academic performance of each Tulsa public neighborhood elementary school performance using Report Card scores and Title I status to help evaluate disparities in educational access by geography.

Tulsa Public Schools Neighborhood Elementary School Performance Table includes:

- School name
- Report card score (out of 85)
- Letter grade
- Title I status
- Decimal/percent score conversion for quantitative analysis

School Name	School Report Card Score (out of 85)	Grade	Title 1 School?	Decimal	Percentage
Anderson	10.79	F	TRUE	0.126941176	12.69411765
Bell	20.25	D	TRUE	0.238235294	23.82352941
Burroughs	10.7	F	TRUE	0.125882353	12.58823529
Carnegie	52.75	C	TRUE	0.620588235	62.05882353
Celia Clinton	8.85	F	TRUE	0.104117647	10.41176471
Clinton West	10.18	F	TRUE	0.119764706	11.97647059
Cooper	13.87	D	TRUE	0.163176471	16.31764706
Council Oak	60.99	B	TRUE	0.717529412	71.75294118
Disney	14.37	D	TRUE	0.169058824	16.90588235
Dolores Huerta	24.57	D	TRUE	0.289058824	28.90588235
Eliot	52.9	C	TRUE	0.622352941	62.23529412
Emerson	22.54	D	TRUE	0.265176471	26.51764706
Eugene Field	22.4	D	TRUE	0.263529412	26.35294118
Greenwood Leadership Academy	17.87	D	TRUE	0.210235294	21.02352941
Grissom	39.28	C	TRUE	0.462117647	46.21176471
Hamilton	23.32	D	TRUE	0.274352941	27.43529412
Hawthorne	13.16	D	TRUE	0.154823529	15.48235294
Hoover	28.27	D	TRUE	0.332588235	33.25882353
John Hope Franklin	5.95	F	TRUE	0.07	7
Kendall-Whittier	30.27	D	TRUE	0.356117647	35.61176471
Kerr	12.66	F	TRUE	0.148941176	14.89411765
Key	24.55	D	TRUE	0.288823529	28.88235294
Lanier	52.55	C	TRUE	0.618235294	61.82352941
Lewis and Clark	23.97	D	TRUE	0.282	28.2
Lindbergh	22.47	D	TRUE	0.264352941	26.43529412
MacArthur	15.02	D	TRUE	0.176705882	17.67058824
Marshall	11.15	F	TRUE	0.131176471	13.11764706
McClure	12.02	F	TRUE	0.141411765	14.14117647
McKinley	18.67	D	TRUE	0.219647059	21.96470588
Mitchell	11.45	F	TRUE	0.134705882	13.47058824
Owen	31.65	D	TRUE	0.372352941	37.23529412

School Name	School Report Card Score (out of 85)	Grade	Title 1 School?	Decimal	Percentage
Patrick Henry	32.72	D	TRUE	0.384941176	38.49411765
Peary	33.29	D	TRUE	0.391647059	39.16470588
Robertson	26.41	D	TRUE	0.310705882	31.07058824
Salk	18.57	D	TRUE	0.218470588	21.84705882
Sequoyah	15.45	D	TRUE	0.181764706	18.17647059
Skelly	17.69	D	TRUE	0.208117647	20.81176471
Springdale	12.84	F	TRUE	0.151058824	15.10588235
Unity Learning Academy	23.31	D	TRUE	0.274235294	27.42352941
Wayman Tisdale Fine Arts Academy	9.98	F	TRUE	0.117411765	11.74117647
Whitman	9.9	F	TRUE	0.116470588	11.64705882

Table 6: Tulsa Public Schools Neighborhood Elementary School Performance Table

The chart reveals that all of their neighborhood elementary schools are Title 1 eligible, which means that using Census Bureau Data, a percentage of the students come from low-income families (National Center for Education Statistics (NCES), 2025). This collected data can be used to tie in USDA Food Research Atlas data and U.S. Census car ownership data to determine the extent of the barrier that transportation and income plays in determining access to better quality schools. Additionally, it also reveals that none of the neighborhood schools in Tulsa Public Schools received an 'A' grade.

While this data is helpful in the form of a chart for those observations, the spatial patterns become clearer when visualized in Figure 14. Preliminary spatial analysis suggests that neighborhood schools in North Tulsa tend to have lower performance scores, while schools located in central and southern areas of the city perform comparatively better. These geographic disparities in school performance appear to correlate with residential zoning types and proximity to grocery stores and transit access, which could warrant further research.

3.7 Conclusion

The geographic data collected and presented in this chapter, including residential zoning, transportation stops, grocery store access, and school performance, was next prepared for further analysis and regression modeling later in the project and for future research, and reveals possible correlations between varying access to different amenities, which may be tied to housing blight.

3.8 FIGURES

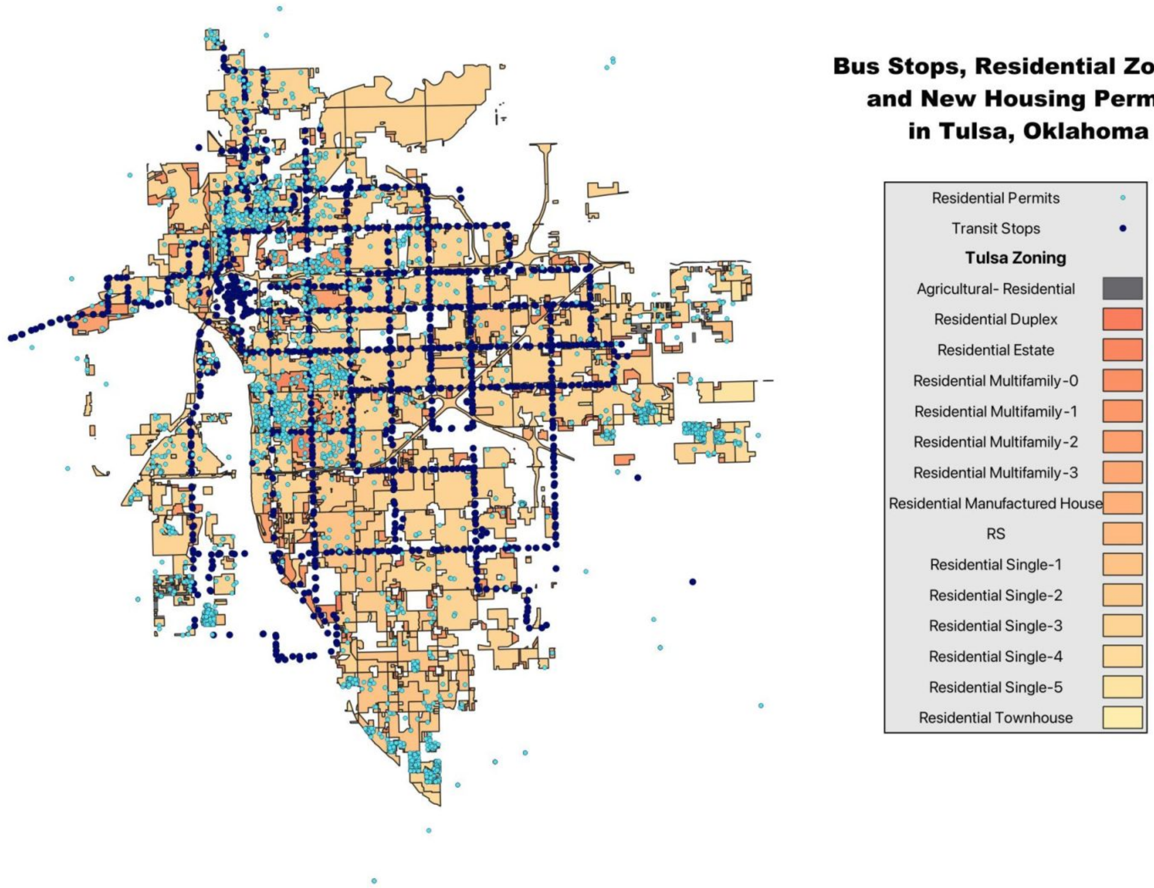

Figure 8

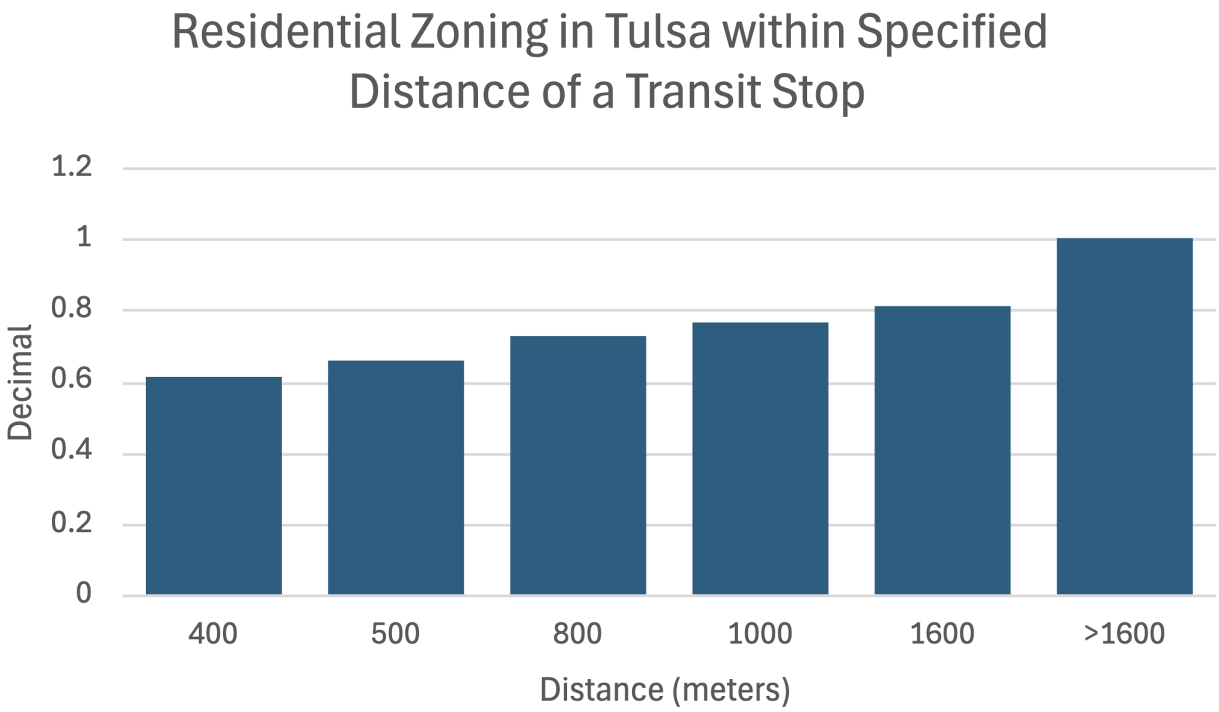
Residential Zoning in Tulsa within Specified Distance of a Transit Stop
1.2
1
0.8
0.6
0.4
0.2
0
Decimal
400
500
800
1000
1600
>1600
Distance (meters)

Figure 9

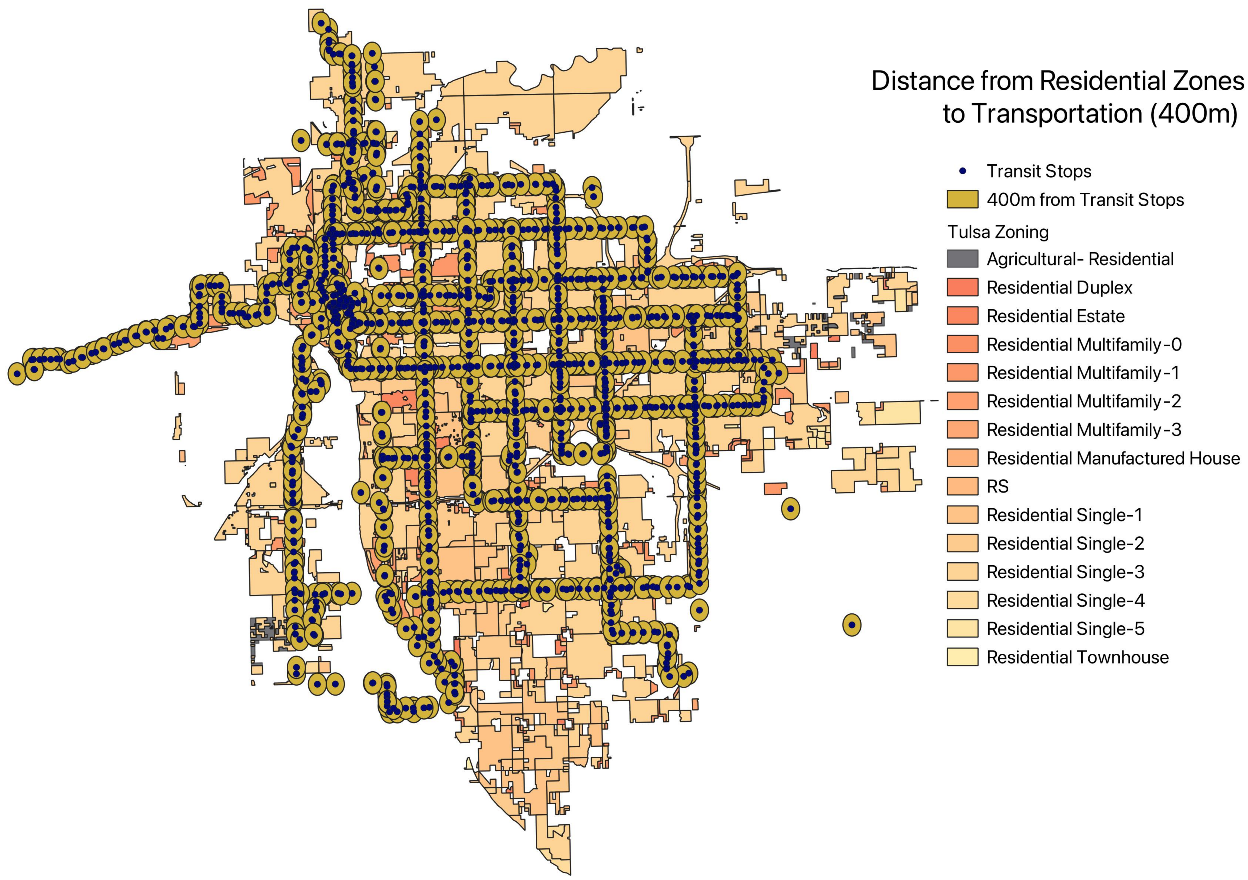
Distance from Residential Zones to Transportation (400m)
Transit Stops
400m from Transit Stops
Tulsa Zoning
Agricultural- Residential
Residential Duplex
Residential Estate
Residential Multifamily-0
Residential Multifamily-1
Residential Multifamily-2
Residential Multifamily-3
Residential Manufactured House
RS
Residential Single-1
Residential Single-2
Residential Single-3
Residential Single-4
Residential Single-5
Residential Townhouse

Figure 10

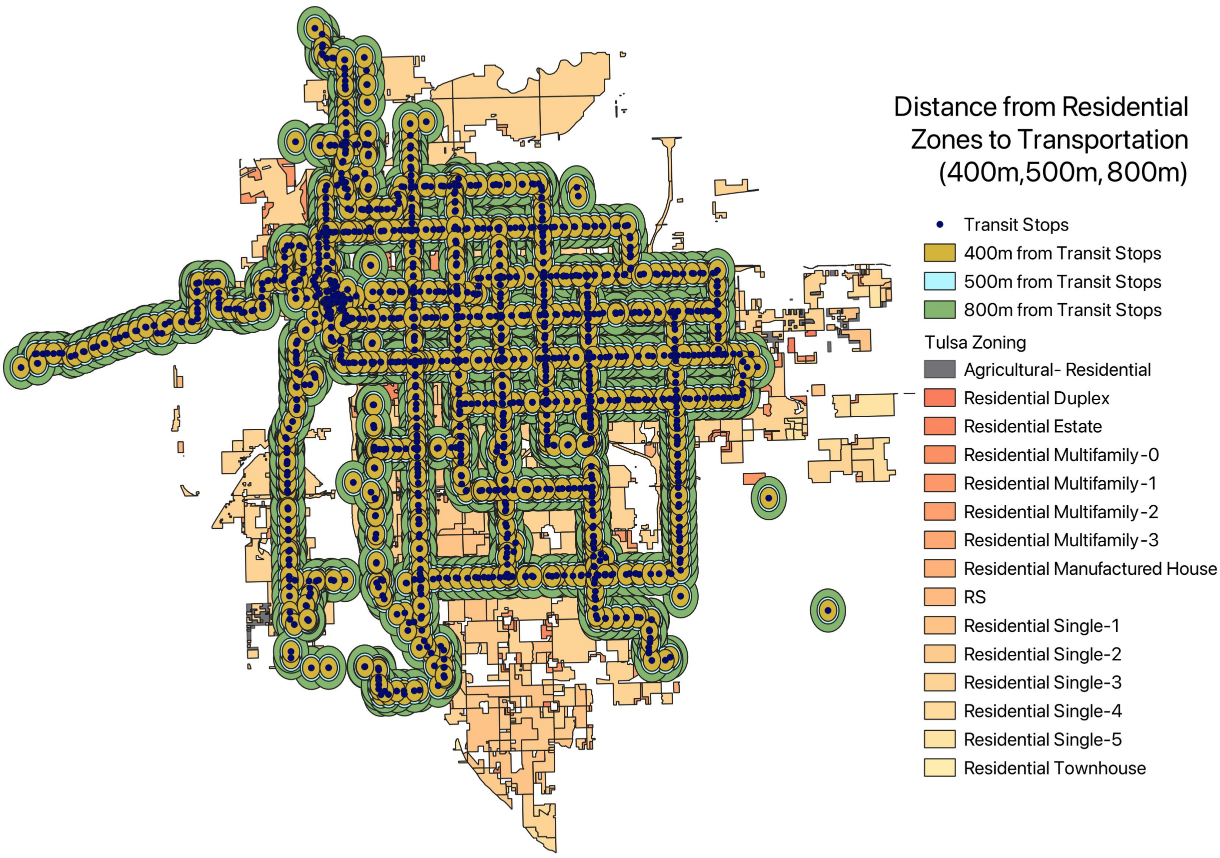
Distance from Residential Zones to Transportation (400m,500m,800m)
Transit Stops
400m from Transit Stops
500m from Transit Stops
800m from Transit Stops
Tulsa Zoning
Agricultural- Residential
Residential Duplex
Residential Estate
Residential Multifamily-0
Residential Multifamily-1
Residential Multifamily-2
Residential Multifamily-3
Residential Manufactured House
RS
Residential Single-1
Residential Single-2
Residential Single-3
Residential Single-4
Residential Single-5
Residential Townhouse

Figure 11

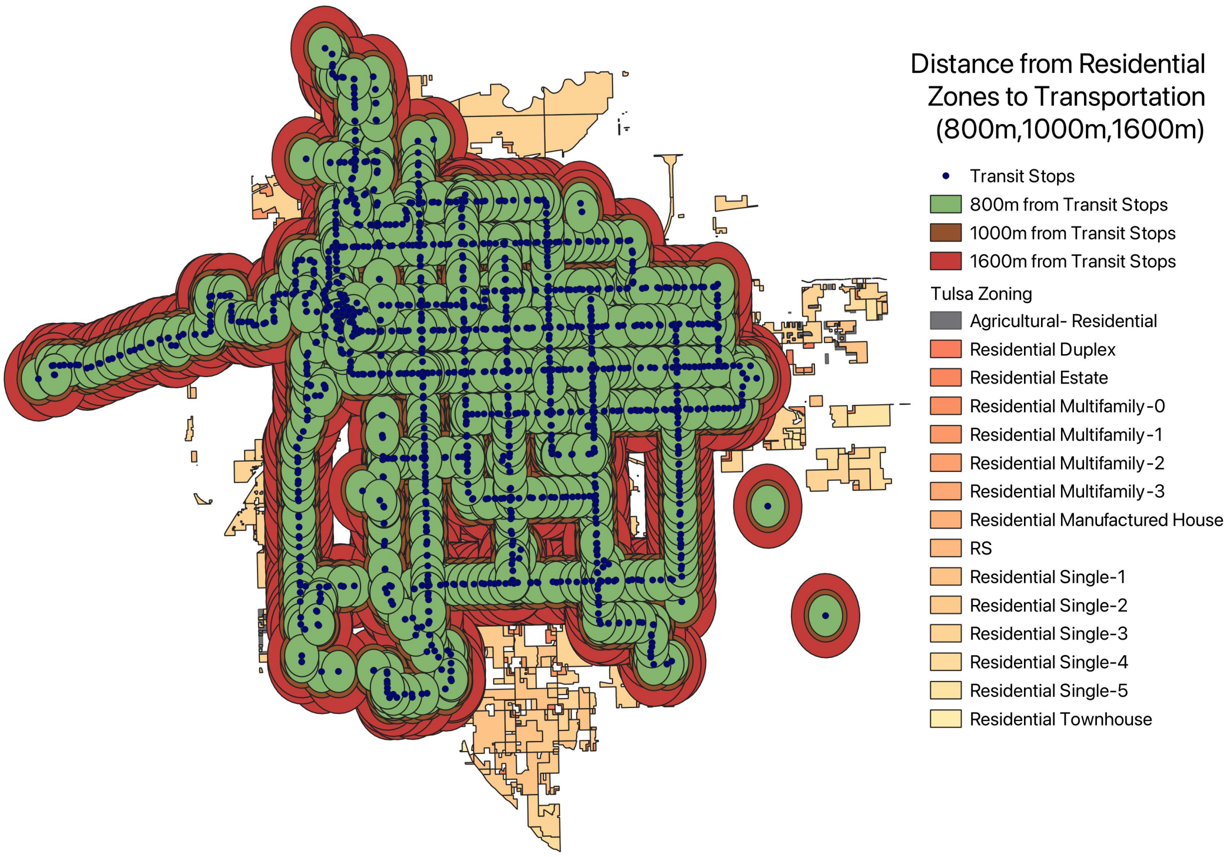
Distance from Residential Zones to Transportation (800m,1000m,1600m)
Transit Stops
800m from Transit Stops
1000m from Transit Stops
1600m from Transit Stops
Tulsa Zoning
Agricultural- Residential
Residential Duplex
Residential Estate
Residential Multifamily-0
Residential Multifamily-1
Residential Multifamily-2
Residential Multifamily-3
Residential Manufactured House
RS
Residential Single-1
Residential Single-2
Residential Single-3
Residential Single-4
Residential Single-5
Residential Townhouse

Figure 12

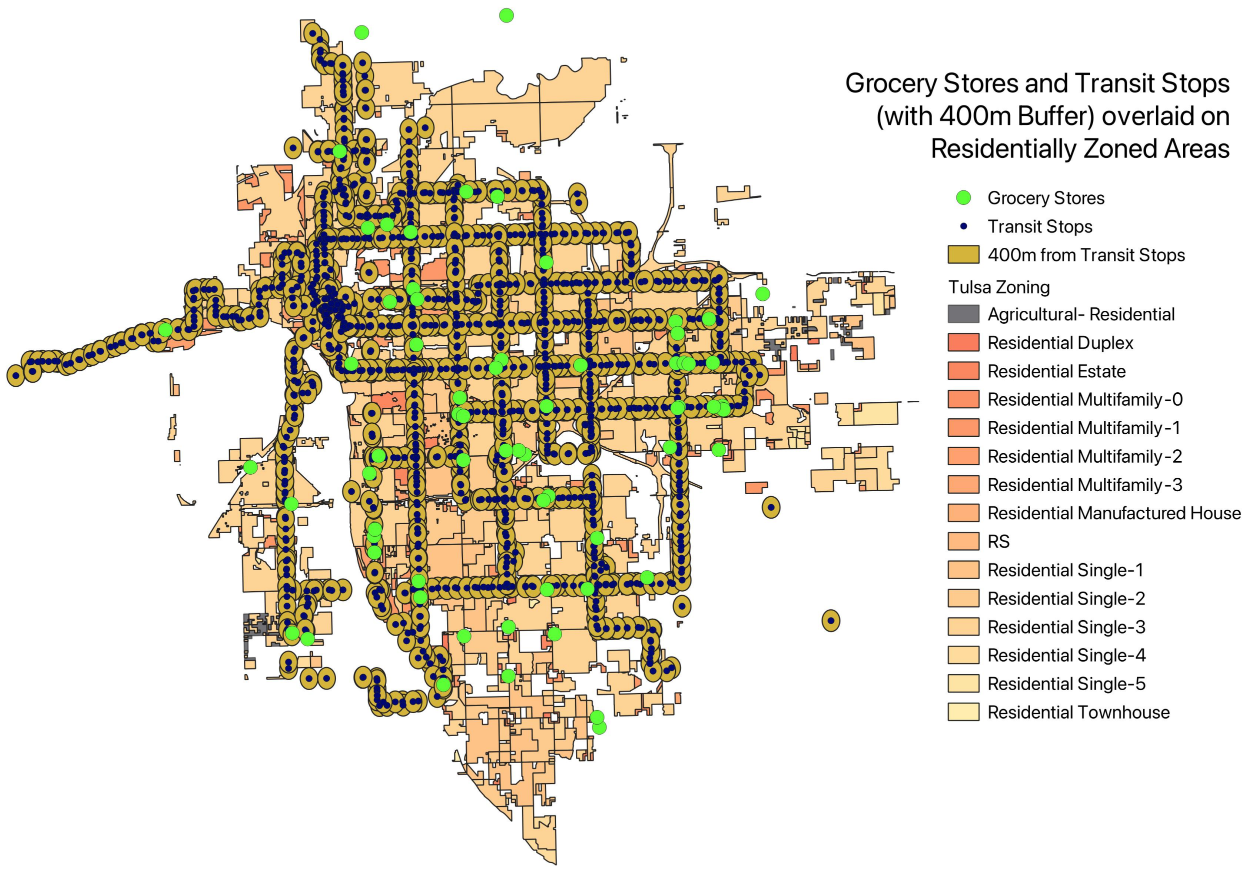
Grocery Stores and Transit Stops
(with 400m Buffer) overlaid on
Residentially Zoned Areas
Grocery Stores
Transit Stops
400m from Transit Stops
Tulsa Zoning
Agricultural- Residential
Residential Duplex
Residential Estate
Residential Multifamily-0
Residential Multifamily-1
Residential Multifamily-2
Residential Multifamily-3
Residential Manufactured House
RS
Residential Single-1
Residential Single-2
Residential Single-3
Residential Single-4
Residential Single-5
Residential Townhouse

Figure 13

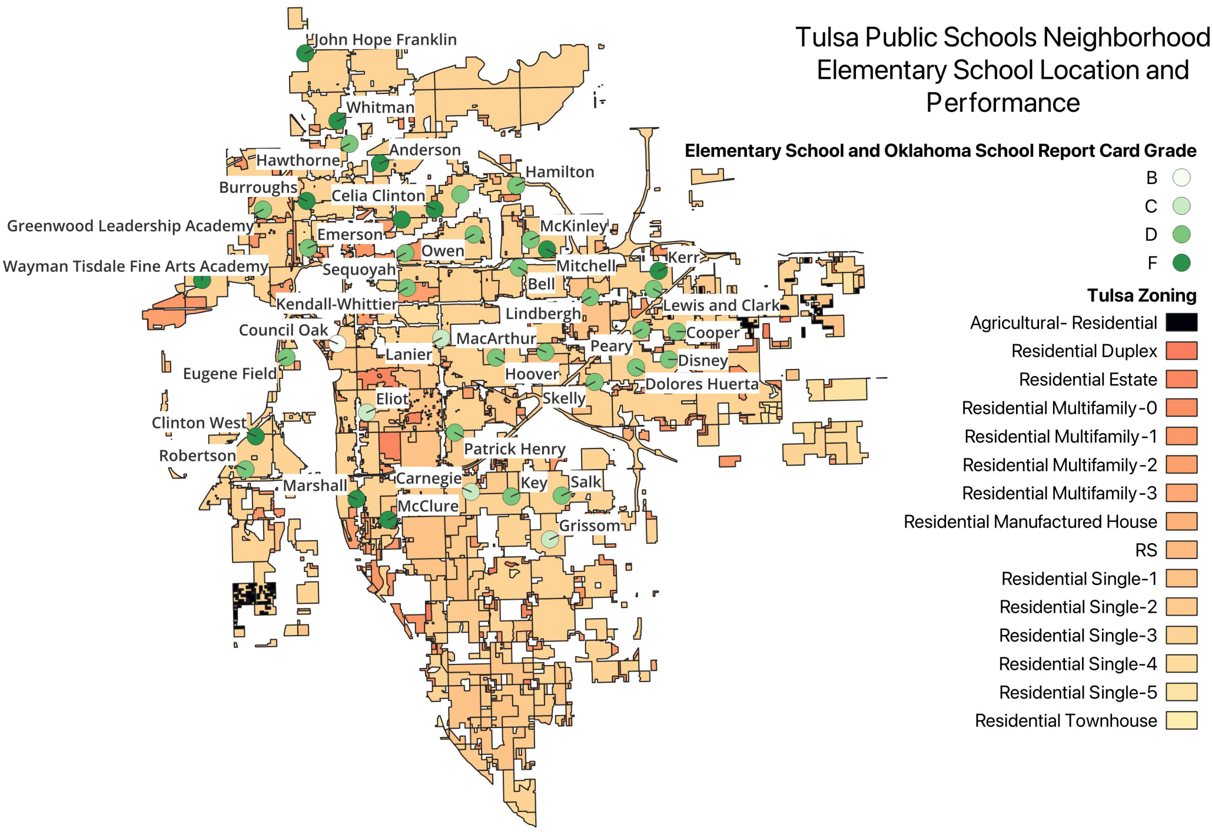
Tulsa Public Schools Neighborhood Elementary School Location and Performance
Elementary School and Oklahoma School Report Card Grade
B
C
D
F
Tulsa Zoning
Agricultural- Residential
Residential Duplex
Residential Estate
Residential Multifamily-0
Residential Multifamily-1
Residential Multifamily-2
Residential Multifamily-3
Residential Manufactured House
RS
Residential Single-1
Residential Single-2
Residential Single-3
Residential Single-4
Residential Single-5
Residential Townhouse
John Hope Franklin
Whitman
Anderson
Hawthorne
Hamilton
Burroughs
Celia Clinton
Greenwood Leadership Academy
McKinley
Emerson
Owen
Wayman Tisdale Fine Arts Academy
Kerr
Sequoyah
Mitchell
Bell
Kendall-Whittier
Lewis and Clark
Lindbergh
Council Oak
Cooper
MacArthur
Peary
Lanier
Disney
Eugene Field
Hoover
Dolores Huerta
Eliot
Skelly
Clinton West
Patrick Henry
Robertson
Carnegie
Key
Salk
Marshall
McClure
Grissom

Figure 14

4

Facilitating Redevelopment of VAD Properties in Tulsa: An AI-Driven Peer City Analysis Tool

Authors: Shawnda M. Henderson & Katrina E. Henderson

4.1 Introduction

Every city must manage vacant, abandoned, and deteriorated (VAD) properties, often referred to as 'blight.' (But because the latter can be a pejorative, misused term, we will try to stick with VAD.[1]) Tulsa is no exception, meaning Tulsan quality of life could improve through better identification of – and then remediation of – VAD conditions, including in residential neighborhoods.

We hope to assist in those efforts by developing two proof-of-concept software tools useful in VAD identification, the first of which is explained in this chapter.[2] Leveraging multiple systems of generative AI, we coded Python solutions to identify Tulsa peer cities.[3] By then researching the VAD management experience of the resulting most relevant peers – what has worked, what has not – we can develop a better plan for Tulsa.

This chapter is accordingly drafted in two parts. The first focuses on the initial step of coding a peer city identifier, while the second examines our teammates' research into the VAD management experiences of identified peers and their application to Tulsa.

4.2 One Goal – Two Models

We have some background in both 'old school' coding and peer city analysis, but for this project we decided to leverage the very significant recent gains in generative AI. And since different algorithms might guide us to different solutions, we decided to use two: Open AI's ChatGPT and Anthropic's Claude. And so our experiences can be helpful to others – especially to others with limited experience coding with generative AI – and so our results can be improved upon as well, we will briefly explain not only our results, but also our process.

4.3 First Peer City Generator – ChatGPT (model GPT-4o)

We began with an initial prompt framing the project goal: helping to reduce residential VAD within Tulsa. ChatGPT responded with a sensible reply, and so we quickly narrowed the discussion to the first task: peer

[1] Center for Community Progress, The Problem with Calling Neighborhoods with Vacant Properties "Blighted" (April 11, 2024), https://communityprogress.org/blog/what-is-blight/.

[2] The second tool, which aims to algorithmically identify VAD conditions from photographs, is explained in a later chapter entitled *Facilitating VAD Identification: An AI-Driven Image-Classification Tool*.

[3] We are of course not the first to develop such a tool (*see*, e.g., the Federal Reserve Bank of Chicago's Peer City Identification Tool), but we hope its particular focus on Tulsa and VAD-identification might provide unique insights for our city.

city identification.

The initial step was to identify variables, or characteristics, on which to base peer city selections. ChatGPT not only provided a sensible list of potentials, but included potential data sources and statistical analysis techniques for gathering and analyzing the same. While we altered aspects of its strategy based on our outside research into peer city analysis, its framework – as described below – played a crucial role in our development of a peer city identification program coded in Python and then modified and run within Google's Colaboratory environment. That framework consisted of several steps: 1) Obtaining a US Census Bureau application programming interface (API) key and then underlying relevant data, 2) standardizing and clustering that data, 3) identifying most relevant peers, 4) visualizing those results, and 5) refining the code based on those results.

We first obtained an API key for the US Census Bureau, allowing us (and our code) to access data from the American Community Survey (ACS); this not only provided the data we would need, but it will permit seamless updating as future data is gathered and entered, ensuring the program's ability to remain useful. Utilizing that API in conjunction with Python code, we then compiled the relevant ACS data for all cities in the United States, before culling it based upon designated population cutoffs. Again following ChatGPT's recommendation, we then, in Python code, standardized the data using z-scores and utilized k-means clustering, an unsupervised clustering technique that forms groups or 'clusters' of meaningfully similar data points. After some tinkering, we decided upon seven such clusters.

ChatGPT also assisted – again through articulating initial Python code – in visualizing our results. We used principal component analysis (PCA), a dimension reduction technique, for that visualization, resulting in Figure 15, which shows our seven clusters (numbered 0 to 6) of 'alike' cities and their 'similarity distances.' The nearer two points (cities) are to each other, the more those cities have in common. Tulsa falls within Cluster 3, but it appears on that cluster's edge, suggesting it also shares much in common with cities of neighboring Cluster 2. We thus merged Clusters 3 and 2 and, using that merged cluster, calculated Tulsa's closest peers.

Before discussing those results, we will briefly describe our correlative development experience with Anthropic's Claude.

4.4 Second Peer City Generator – Claude (Sonnet 4)

While we had no particular reason to doubt the model we developed with ChatGPT's assistance, we proceeded to repeat the process with a different generative AI for two reasons. One, we might find a particular tool better suited to the task. Two, if we obtained similar results, it would give us some increased confidence in the same. Indeed, had we more time, we might also have attempted the project with X's Grok, Google's Gemini, and others.

We began Claude with similar prompts, describing both our overall research topic (VAD management in Tulsa) and our particular task (a peer city analysis based on relevant demographic variables). While Claude included k-means clustering among its method options, its preferred take was straight Euclidean distance analysis, and we had no good reason not to try this tweak. So, using Claude as we had ChatGPT, we developed Python code which we then executed in Google's Colaboratory.

Unsurprisingly, this Python program begins much the same as our first: The code first queries the US Census Bureau API to obtain the most recent ACS 5-year estimates of relevant demographic variables for all US cities. It then filters those cities based on population cutoffs, before standardizing the variables using z-scores. Those scaled values are then used to calculate the Euclidean distance between Tulsa and each city in the dataset, where lower distances reflect more similar peers. The program then ranks the cities by Euclidean distance, returning the list of the 'closest' peer candidates.

Because the model again employs multi-variable analysis, it is difficult to visualize in two-dimensional space. So, we again turned to PCA analysis, leveraging Claude to develop the necessary code. The resulting graph (Figure 16) plots Tulsa and its closest identified peers against the first two principal components.

Naturally, the AI-generated code required several rounds of debugging and improvement. As a simple example, an early iteration listed the peer cities using Census API reference codes rather than city names. Similarly, we modified the original PCA graph's format to better match that produced by our first peer city tool, allowing for greater visual consistency.

Overall, we were impressed with the ability of both ChatGPT and Claude to develop Python code, but we would be surprised if a user found the very first instance of such code precisely what was desired. And, at least for us, it was typically easier and more reliable to directly dabble with the Python than to nudge the generative AI. While both ChatGPT and Claude proved quite adept at generating code, both could get confused – or at least could produce rather confused results – when we would ask the AI to tweak only certain portions or aspects thereof.

4.5 Comparison & Analysis

Having developed two peer city generators, we turned to comparing and, ultimately, to combining their results.

We already mentioned the difference in clustering versus straight Euclidean distance. Another divergence was in population cutoffs – not only did the two LLMs set different boundaries to filter the candidate cities, but those boundaries also shifted between code iterations, despite that not being the prompted goal of the particular iteration. This is, of course, simply a result of the algorithms they each run, and such behavior is familiar to anyone working with these tools to develop writing or to generate images – you can ask for a 'duck on the pond' again, and even a much more particular variant, but you won't get the same furry creature on the same body of water. Thus, for example, when we prompted Claude to revise its code to produce more user-friendly output... Claude adjusted its population cutoffs. Ultimately, we manually set the same population boundaries for the two models, thereby helping ensure more consistent results – our point is merely that such behavior is something to watch when using contemporary generative AI to code.

Ultimately, despite the algorithmic differences, there were encouraging similarities in results. For example, both models identified Wichita, Kansas as Tulsa's closest peer. Additionally, several other cities ranked highly on both lists, including Kansas City, Missouri and Tampa, Florida. All three of those peers are mapped in Figure 17.

As a 'spot check,' we manually compared relevant data from those cities in order to verify their status as potential peers, comparing basic metrics like total population, median household income, and poverty rate; the results are shown in Figures 18 - 20.

4.6 Conclusion, Next Steps, & Future Work – Peer City VAD Programs

Having compiled and refined our peer city list, the next step was to investigate those cities' VAD identification and remediation programs, hoping to glean insights from others' experience. Thus, several of our teammates began doing just that, and their results are described in the following sections.

4.7 FIGURES

Figure 15

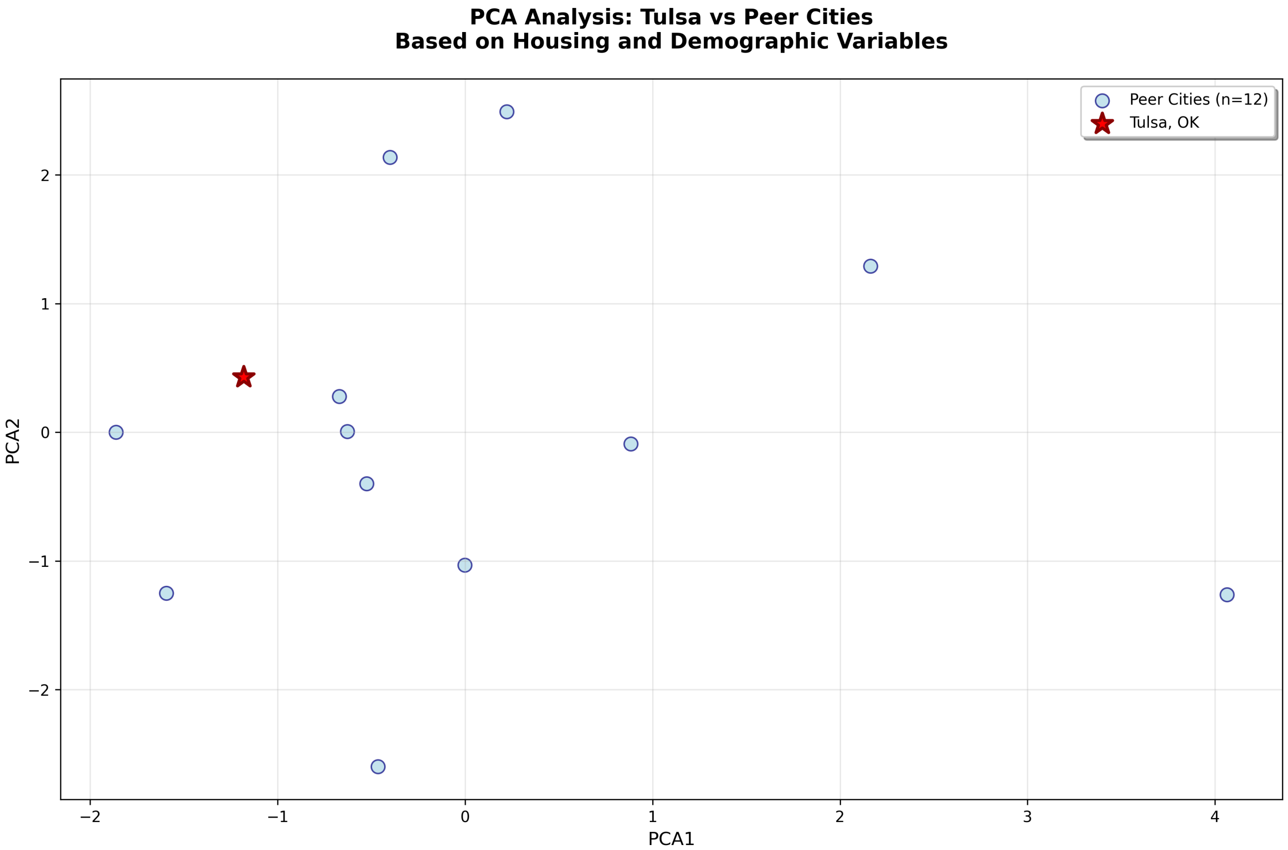

Figure 16

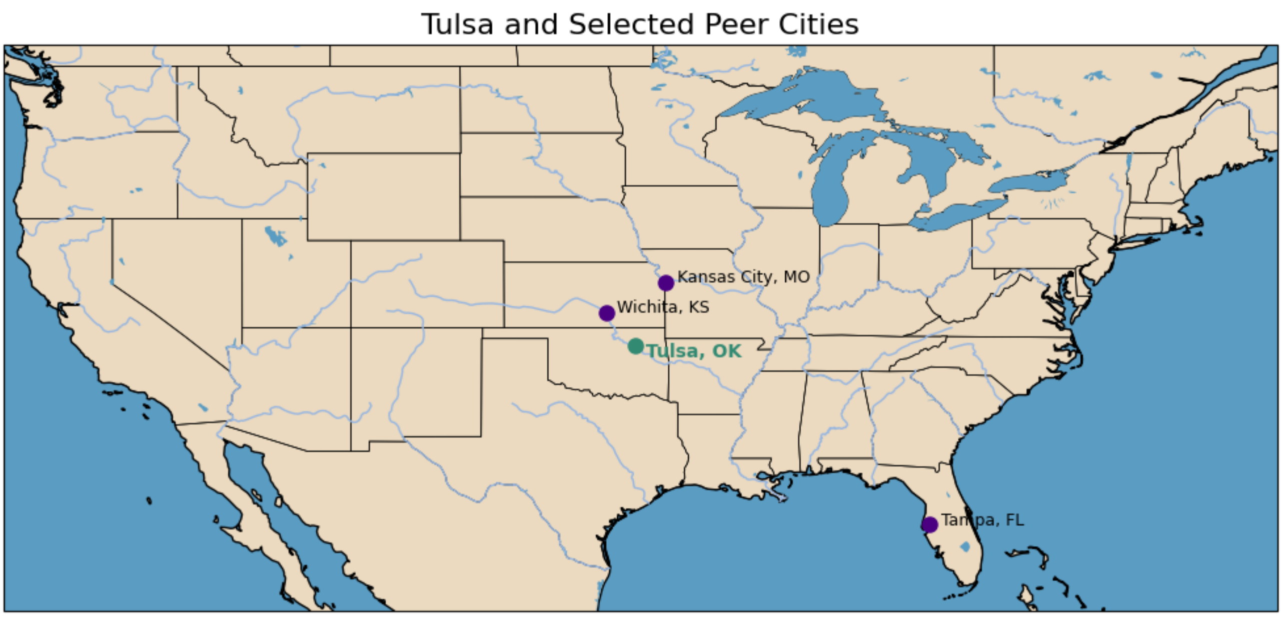

Figure 17

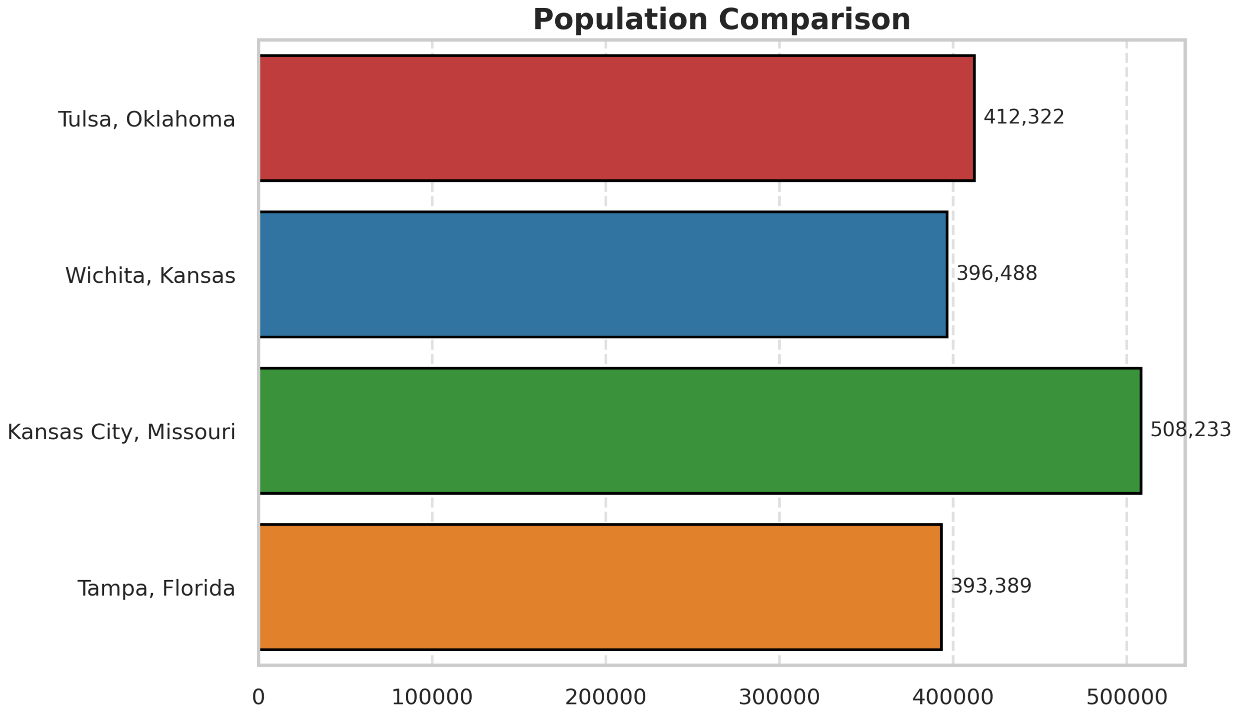

Figure 18

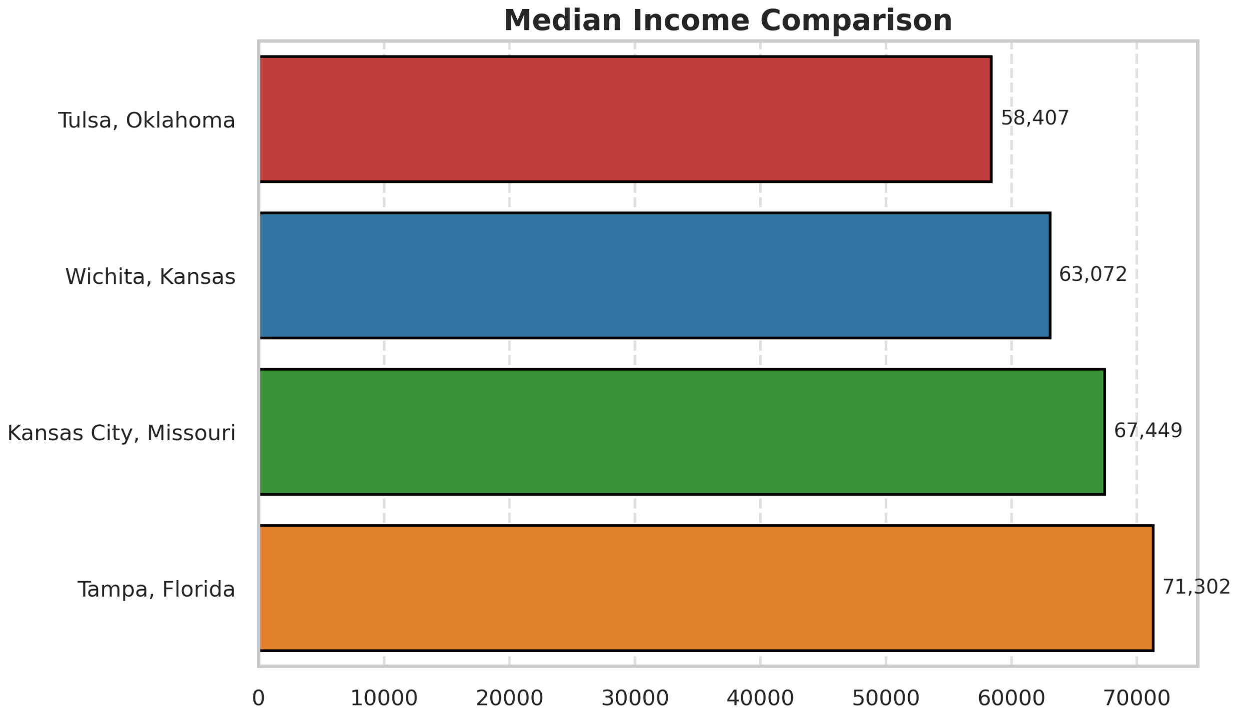

Figure 19

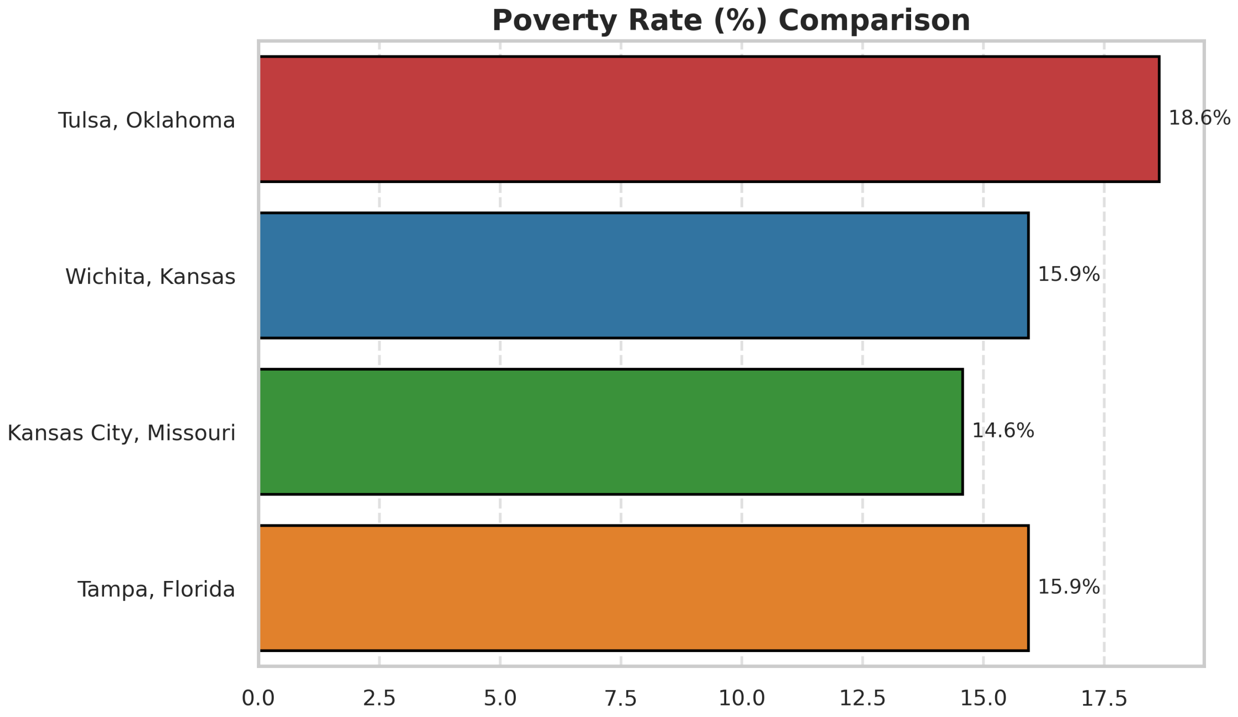
Poverty Rate (%) Comparison
Tulsa, Oklahoma
18.6%
Wichita, Kansas
15.9%
Kansas City, Missouri
14.6%
Tampa, Florida
15.9%
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5

Figure 20

5 VAD Management Program Analysis

Author: Karter Flournoy & Manvi Pinnapareddy

5.1 Peer Cities

5.1.1 Tucson, AZ

Tucson, Arizona utilizes a layered strategy to combat blight, combining targeted home repair, environmental cleanup, and code enforcement with community input and federal funding alignment. Three programs stand out for their sustainability, structure, and replicability: the Tucson Housing Repair Program (THRP), the Brownfields Redevelopment Program, and the city's Code Enforcement and Vacant Property Remediation strategy.

The Tucson Housing Repair Program (THRP), operated through the City's Housing and Community Development Department, delivers critical assistance to low-income, owner-occupied households facing health and safety-related housing repair needs. Although the program does not operate under a single ordinance, it is codified through the city's broader Affordable Housing and Community Development plans and partially funded by federal Community Development Block Grant (CDBG) allocations. Eligible repairs include structural stabilization, roof replacement, plumbing and electrical work, and mold remediation—repairs specifically selected for their potential to prevent vacancy, abandonment, and subsequent neighborhood decline. According to Tucson's 2024–2025 HUD Consolidated Plan, these interventions are geographically prioritized in census tracts with high housing cost burden and aging housing stock (City of Tucson, 2024). The program has been credited with improving habitability in over 300 homes citywide since 2020 (City of Tucson, 2023). Tulsa could benefit from a comparable preventive maintenance model, especially in neighborhoods where owner-occupied homes show early signs of deterioration. However, successful implementation would require establishing a pipeline for licensed contractors and a city-administered intake system to screen applicants and assess project urgency.

Tucson's Brownfields Redevelopment Program plays a complementary role by targeting properties that are already vacant, underutilized, or environmentally hazardous. Administered in partnership with the Arizona Department of Environmental Quality (ADEQ) and the U.S. Environmental Protection Agency (EPA), the program has been active since the late 1990s, leveraging federal funds under Section 104(k) of the Comprehensive Environmental Response, Compensation, and Liability Act (CERCLA). It supports environmental site assessments (Phase I and II), cleanup planning, and, where needed, direct remediation grants or low-interest loans for site rehabilitation. In 2022 alone, the city used these funds to assess 10 brownfield sites—primarily abandoned gas stations and industrial parcels—in the Sugar Hill, Barrio Anita, and Menlo

Park neighborhoods, paving the way for mixed-use redevelopment and affordable housing (Arizona Department of Environmental Quality, 2023). What distinguishes Tucson's approach is its integration with local planning efforts; community stakeholders help shape redevelopment goals, and cleaned parcels are often bundled into broader neighborhood revitalization plans. For Tulsa, a similar brownfields strategy could be particularly impactful in former industrial corridors and North Tulsa neighborhoods with legacy contamination. However, the success of such a program would depend on establishing dedicated grant-writing staff and environmental engineering partnerships to meet EPA criteria.

The city's Code Enforcement and Vacant Property Remediation efforts round out its anti-blight strategy by directly addressing visible signs of property neglect. Managed by the Planning and Development Services Department under Tucson Code Chapter 16 ("Neighborhood Preservation Ordinance"), the program investigates code violations related to overgrown vegetation, unsecured vacant structures, graffiti, trash accumulation, and substandard building conditions. Property owners receive violation notices and timelines for compliance; if they fail to act, the city can abate the issues itself and place a lien on the property to recoup costs. In FY2023, the department responded to over 11,000 code complaints, and 82% were resolved within 60 days (City of Tucson Planning & Development Services, 2023). To encourage community engagement, the city also operates the "Neat Neighbor" initiative, which promotes voluntary compliance through neighborhood education and anonymous reporting. Unlike punitive-only models, Tucson's approach balances enforcement with outreach, reducing recidivism and improving outcomes in historically disinvested areas. For Tulsa, replicating this program would not require legislative overhaul—its foundational elements already exist—but adopting the community-facing tools and investing in mobile inspection capacity could make enforcement more equitable and effective.

Together, these three programs reflect a comprehensive and place-based model for addressing the causes and symptoms of blight. From prevention to enforcement to redevelopment, Tucson's approach offers adaptable frameworks that align with Tulsa's existing infrastructure. Each program could be scaled based on local need, legal framework, and funding capacity. While Tucson still contends with systemic challenges around poverty, vacancy, and aging housing, its coordinated use of federal funding, legal tools, and community engagement strategies makes it a meaningful peer model for Tulsa's own blight remediation efforts.

5.1.2 Tampa, FL

Tampa, Florida, has implemented a multi-pronged approach to address urban blight, with particular focus on the East Tampa neighborhood, an area historically impacted by disinvestment and deteriorating infrastructure (City of Tampa, 2022). Three key initiatives—the East Tampa CRA Action Plan (2022), the East Tampa CRA Infill Development Program (2025), and the citywide Community Development Block Grant (CDBG) Housing Rehabilitation and Clearance Program (2025)—form a comprehensive strategy that combines physical revitalization, affordable housing development, and community engagement (City of Tampa, 2022, n.d.).

The East Tampa CRA Action Plan, adopted in July 2022, serves as a strategic blueprint for revitalizing the East Tampa Community Redevelopment Area (CRA) (City of Tampa, 2022). Under Florida's Community Redevelopment Act (1969), municipalities can designate blighted areas and use tax increment financing (TIF) to fund redevelopment (Trellis Law, n.d.). Tampa leverages this authority to coordinate investments across city departments, focusing on upgrading infrastructure, beautifying neighborhoods, and addressing blight through initiatives such as a year-round youth employment program (City of Tampa, 2022). This employment initiative engages local youth in community projects including parks maintenance and data collection, aiming to build civic participation alongside physical improvements (City of Tampa, 2022). While relatively new, CRAs in Florida have generally contributed to neighborhood stabilization, although displacement remains a concern in the absence of affordability protections (Trellis Law, n.d.). For Tulsa, adopting a similar CRA master plan—particularly in historically disinvested areas like North Tulsa—could help target investments more effectively; however, it would require strong resident engagement and safeguards against displacement to ensure equitable outcomes.

In 2025, Tampa launched the East Tampa CRA Infill Development Program, designed to encourage construction of affordable housing on vacant city-owned lots within the CRA (City of Tampa, 2025). The program offers subsidies of up to $350,000 per affordable unit to incentivize development (City of Tampa, 2025). This initiative aims to reduce blight and boost housing supply by returning underused parcels to active use, using powers granted under Florida's CRA statute to acquire and redevelop land (City of Tampa, 2025). Though early in implementation, the program reflects best practices in blight remediation, particularly when paired with affordability requirements (City of Tampa, 2025). For Tulsa, a similar strategy could be implemented through the Tulsa Land Bank or Tulsa Authority for Economic Opportunity (TAEO), using locally or federally sourced funding to support infill development—though Tulsa would need to ensure transparent selection of developers and robust community input mechanisms to avoid inequities.

The citywide CDBG Housing Rehabilitation and Clearance Program, funded with $400,000 in federal HUD grants for FY2025, aims to preserve affordable housing and demolish blighted structures (City of Tampa, 2025). It sets clear goals: rehabilitating 10 rental units and 5 owner-occupied homes, and demolishing vacant buildings identified by the Metropolitan Area Building and Construction Department (City of Tampa, 2025). This program complements the CRA by targeting smaller-scale blight and housing quality issues that may not be addressed by large-scale redevelopment efforts. For Tulsa, which already receives CDBG funding, establishing a similarly specific housing rehabilitation and clearance program—with quantifiable outcomes and dedicated funding lines—could enhance its ability to address both vacancy and substandard housing in high-need neighborhoods.

Overall, Tampa's integration of CRA tax increment financing, infill housing subsidies, and targeted use of federal CDBG funds creates a coordinated, layered strategy for neighborhood revitalization (City of Tampa, 2022, 2025). However, similar to many redevelopment programs nationwide, these efforts have raised concerns about unintended displacement and gentrification, particularly when affordability safeguards are weak (National Low Income Housing Coalition, 2022). Tampa's youth employment initiative stands out as a socially inclusive element of its CRA, yet there remains a lack of third-party evaluations on its long-term impact (City of Tampa, 2022). Furthermore, the modest scale of CDBG funding may limit the program's immediate impact in distressed neighborhoods (City of Tampa, 2025).

For Tulsa, Tampa's model offers valuable insights. Establishing or reinforcing a CRA-like framework in Tulsa could help consolidate and direct revitalization investments. Implementing a structured infill subsidy program modeled on Tampa's initiative would accelerate reuse of vacant land for affordable housing, especially in North and West Tulsa. Launching a dedicated, outcome-driven CDBG housing rehab and demolition program could improve housing conditions and reduce visible blight. These recommendations would be most effective if Tulsa simultaneously prioritized racial equity, interdepartmental coordination, and continuous public engagement.

While Tampa's approach appears promising, the lack of long-term data and third-party evaluations presents a gap in understanding the sustained impact of these programs on affordability, displacement, and neighborhood resilience (National Low Income Housing Coalition, 2022). Additional research into CRA effectiveness in Florida and HUD-funded initiatives nationwide would further inform Tulsa's adaptation of these models.

5.1.3 Wichita, KS

Wichita, Kansas, has implemented a combination of land policy tools and federally funded redevelopment programs to address urban blight, particularly in historically disinvested neighborhoods. Two of its most central initiatives—the Wichita Land Bank and the 2024–2028 Consolidated Plan and 2024 Annual Action Plan—represent complementary strategies aimed at long-term revitalization and short-term blight reduction. Together, they offer instructive models for cities like Tulsa seeking to blend property intervention with strategic reinvestment.

The Wichita Land Bank, formally established by City Ordinance No. 51-614 in May 2021, is designed to acquire underutilized, tax-delinquent, or abandoned properties and facilitate their redevelopment by maintaining them, clearing titles, and transferring them to new owners committed to revitalization. The land bank is governed by a seven-member advisory board and operates within the city's Housing and Community Services Department (City of Wichita, 2021). Unlike some other cities, Kansas law does not give municipal land banks automatic authority to seize properties through tax foreclosure or expedited court transfers, limiting Wichita's ability to acquire inventory efficiently. As a result, the program has struggled: by the end of 2024, the Land Bank had acquired only two properties and spent just $650 in federal funds to maintain vacant lots. These properties were later transferred to Habitat for Humanity, demonstrating the city's intent to partner with nonprofit developers, but the limited scale has raised concerns about its effectiveness. The city has publicly acknowledged the program's challenges and has discussed the possibility of restructuring or discontinuing it unless acquisition volume improves (KWCH, 2025).

Despite these setbacks, the Wichita Land Bank illustrates the potential value of structured, publicly owned land management tools—particularly when paired with strong nonprofit partnerships and supportive state laws. For Tulsa, a similar land bank model could be viable if backed by enabling state legislation that expands acquisition powers and shields land banks from tax liability during property holding. However, Tulsa would need to invest in stronger administrative capacity and establish acquisition partnerships with local tax authorities to avoid the bottlenecks experienced in Wichita.

While the land bank represents a long-term land reuse strategy, the 2024–2028 Consolidated Plan and 2024 Annual Action Plan offers Wichita a more immediate and tactical approach to blight removal. Administered by the Housing & Community Services and Community Investments divisions, this HUD-mandated plan outlines the city's use of federal Community Development Block Grant (CDBG) and HOME Investment Partnerships (HOME) funds. As a CDBG entitlement city, Wichita receives annual formula-based allocations directly from HUD. In 2024, the city allocated $44,780 specifically for the demolition of five vacant residential structures across its neighborhoods. These are typically one- to four-family homes identified by the Metropolitan Area Building and Construction Department (MABCD) as unsafe or severely code-deficient. Another $377,427 was allocated for acquisition and rehabilitation of deteriorated homes in targeted census tracts (City of Wichita, 2024a).

In addition to demolition, the plan supports programs such as emergency home repairs, first-time homebuyer assistance, and vacant property redevelopment. While public engagement is part of the Consolidated Plan's formal process—via hearings and comment periods—the ultimate decisions about fund allocation and project implementation rest with city departments. Public-facing documents note that priority is given to projects that align with Wichita's "Places for People" vision, especially in underserved areas like the South Central and Planeview neighborhoods (City of Wichita, 2024b).

Wichita's approach to CDBG-funded demolition has shown localized success. Reporting by The Beacon noted that code enforcement officers—backed by this funding—successfully stabilized blocks where vacant homes had attracted dumping or criminal activity, particularly in neighborhoods like South Central (Beacon, 2022). However, unlike Kansas City or Minneapolis, Wichita has yet to formally evaluate the long-term neighborhood or economic impact of these demolitions through a third-party study. No impact reports have been published by Wichita State University or planning consultants, representing a gap in transparency and strategic planning.

Gap Note: Wichita lacks independent evaluations of its blight remediation programs. Without third-party assessments—such as longitudinal studies conducted by academic institutions or impact reports from planning consultants—the city cannot determine how demolitions and reinvestment efforts affect neighborhood stability, property values, or resident displacement over time. Future research should include spatial analysis of demolition sites, surveys of resident perception, and post-redevelopment tracking to ensure that interventions lead to equitable and lasting improvements.

Still, Tulsa could adopt several lessons from Wichita's Consolidated Plan implementation. The city could dedicate a greater share of its own CDBG entitlement funds toward demolition and neighborhood stabilization, focusing on smaller-scale projects with high visual or public safety impact. Additionally, Tulsa might benefit from creating a coordinated strategy that links demolition to infill redevelopment or land banking—ensuring that cleared lots are not left vacant indefinitely.

Ultimately, Wichita's experience underscores the importance of program coordination and legal flexibility. The Land Bank's limited success contrasts with the broader reach of CDBG funding, but both initiatives operate in silos. For Tulsa, blending these approaches—while ensuring stronger legal tools, community input, and data evaluation—could provide a more comprehensive and equitable strategy for neighborhood revitalization.

5.1.4 Kansas City, MO

Kansas City, Missouri, has developed several effective strategies to combat urban blight, focusing particularly on neighborhoods with historical disinvestment. Among its initiatives, three programs stand out for their sustainability and potential replicability: the Property Receivership Program, the EPA Brownfields Cleanup and Revolving Loan Fund (RLF), and the ReBuild KC Neighborhood Grants.

The Property Receivership Program, initiated in the early 2020s, operates under Kansas City's municipal ordinance—specifically Article VII of Chapter 56 (Vacant Property Receiver)—which authorizes the city to petition the circuit court to appoint a receiver for vacant nuisance properties when owners fail to remedy code violations or pay fines after nine months. This legal mechanism, rooted in Kansas City Code of Ordinances §56-620 to §56-800, is a city-level policy rather than a state law, and it allows the court to transfer limited control to nonprofits or redevelopment entities to stabilize and rehabilitate blighted properties. While there have been isolated procedural delays and objections during implementation, no legal challenges have overturned the ordinance or restricted its authority (Kansas City Code of Ordinances, 2024). This legal intervention aims to stabilize neighborhoods by accelerating rehabilitation and preventing long-term vacancy. Receivers are empowered to secure funding for repairs, manage properties, and either sell or return them to owners, which helps to reduce blight and restore community safety. Although comprehensive data on the program's outcomes in Kansas City is limited, national research identifies receivership as a critical tool in vacant property management and neighborhood revitalization (Alexander and Powell, 2022). Regional planning agencies have reported positive effects in neighborhoods where receivership was employed (Mid-America Regional Council, 2023). For Tulsa, adopting a similar receivership framework could effectively address vacancy and abandonment issues prevalent in some areas, though legal frameworks and partnerships would need development. Further research is required to understand the program's long-term impacts on housing affordability and community stability.

Since 1995, Kansas City has leveraged the U.S. Environmental Protection Agency's (EPA) Brownfields Program, specifically through competitive federal grants and a Revolving Loan Fund (RLF), to remediate environmentally contaminated properties and return them to productive use (Environmental Protection Agency, 2023). The program provides federally funded, project-specific grants and loans to eligible entities, including local governments, nonprofits, and quasi-public redevelopment agencies. These are not block grants; rather, funding is awarded directly by the EPA through a national application process. Grant recipients must submit proposals detailing cleanup plans and intended community benefits, and if awarded, the city is responsible for administering the funds in accordance with EPA guidelines (Environmental Protection Agency, 2022). In Kansas City, the Brownfields RLF is managed by the Economic Development Corporation (EDC), which oversees disbursement to qualifying local projects. To date, this initiative has facilitated the remediation of over 130 brownfield sites, with significant redevelopment impacts in neighborhoods such as the 18th & Vine Historic District. Research from the University of Missouri–Kansas City (2022) found that these projects contributed to localized economic growth, increased land values, and improved community health indicators. Tulsa could replicate this approach by expanding its EPA grant applications and establishing its own RLF, ideally prioritizing underserved areas and requiring community partnership in redevelopment decisions. Sustained oversight would be essential to prevent displacement and ensure equitable benefits.

Launched in 2022 and expanded in 2023, the ReBuild KC Neighborhood Grants program is funded through the American Rescue Plan Act (ARPA) and administered by Kansas City's Housing & Community Development Department. The program has allocated approximately $20 million in ARPA funds over two rounds, with $15 million distributed in 2022 across over 210 neighborhood-led projects and $4.4 million awarded in 2023 to 69 initiatives focused on blight removal, infrastructure repair, affordable housing, and beautification. Funding is reimbursable and requires quarterly reporting, with final approval and oversight handled at the city level. Though the grants originate from federal dollars, local entities determine project selection, allowing for direct community impact while ensuring alignment with city equity goals. By awarding grants to neighborhood associations and community organizations, the program decentralizes blight remediation, empowering residents to set priorities and implement local improvements such as lot clearing and sidewalk repairs. Early reports indicate high levels of community engagement and successful project completions, with positive feedback from residents and city officials (KCUR, 2023). Tulsa could benefit from a comparable grant program, particularly in historically underserved neighborhoods, provided it invests in capacity building and technical assistance to support local organizations. Given its recent launch, ongoing evaluation will be critical to measure long-term neighborhood improvements.

Overall, Kansas City's multifaceted approach to blight remediation offers valuable models that Tulsa can adapt. The combination of legal intervention, environmental cleanup funding, and grassroots empowerment addresses blight comprehensively. However, each program's scalability will depend on local legal frameworks, funding availability, and community capacity. Further empirical research, particularly longitudinal studies, is needed to fully understand the sustained impacts of these initiatives.

5.1.5 Winston-Salem, NC

Winston-Salem, North Carolina, employs a multi-faceted approach to address urban blight and revitalize its neighborhoods. The city focuses on targeted building rehabilitation, homeowner assistance, and proactive demolition efforts. Three programs stand out for their sustainability, scope, and community impact: the Neighborhood Revitalization Strategy Area (NRSA) Building Rehabilitation Program, the Neighborhood Services Rehabilitation Program (TURN), and the Demolition Program.

The Neighborhood Revitalization Strategy Area (NRSA) Building Rehabilitation Program has been active since the 1990s and is designed to encourage private investment within designated distressed areas through financial assistance for commercial and industrial property rehabilitation. Funded primarily through Community Development Block Grant (CDBG) dollars and administered by Winston-Salem's Community and Business Development Department, NRSA provides grants and loans to property owners to improve their buildings and stimulate economic activity. Although specific annual funding figures are not publicly available, the program has successfully rehabilitated numerous properties, such as the notable redevelopment of 410 Waughtown Street, which has contributed to increased property values and neighborhood stabilization. This program demonstrates the effectiveness of incentivizing private sector engagement to complement public revitalization efforts. Tulsa could benefit from adopting a similar program to encourage investment in its underserved commercial corridors, though local stakeholder collaboration and funding mechanisms would need to be developed to ensure equitable impact (City of Winston-Salem Community and Business Development, 2023).

Launched in 2014, the Neighborhood Services Rehabilitation Program (TURN) targets low- and moderate-income homeowners by providing up to $65,000 in forgivable loans for home repairs aimed at improving safety, accessibility, and energy efficiency. Funded through a mix of federal CDBG and HOME Investment Partnership Program funds, TURN prioritizes neighborhoods experiencing economic decline and high vacancy rates. Administered by the Neighborhood Services Department, the program has improved housing stock and increased homeownership retention, contributing significantly to neighborhood stability. For example, in the 2023-2024 program year, TURN facilitated numerous home rehabilitations that enhanced residents' quality of life. This homeowner-focused model could be highly effective in Tulsa, where aging housing stock and affordability are pressing concerns; however, scaling would require increased funding and administrative resources to match Tulsa's size (City of Winston-Salem Neighborhood Services Department, 2022).

Complementing these rehabilitation efforts is Winston-Salem's Demolition Program, which addresses the removal of vacant, dilapidated, and unsafe structures posing hazards to the community. Administered by the Code Enforcement Division and funded primarily through CDBG allocations, the program prioritizes demolitions based on safety risks such as structural instability and fire damage. Although precise demolition numbers are unavailable, the program has played a crucial role in eliminating blighted structures, improving neighborhood aesthetics, and opening sites for redevelopment. The city's approach pairs demolition with rehabilitation and affordable housing initiatives to mitigate displacement concerns. Tulsa could adopt a similar demolition strategy, but should ensure robust community engagement and affordable housing replacement to maintain neighborhood diversity and prevent gentrification pressures (City of Winston-Salem Neighborhood Services Department, 2023).

Together, these programs showcase a comprehensive strategy combining private investment incentives, direct homeowner assistance, and strategic property clearance to tackle blight in Winston-Salem. For Tulsa, these initiatives offer valuable models that balance revitalization goals with equity and sustainability. Further research and local adaptation would be needed to navigate Tulsa's specific legal and funding landscapes and to maximize community benefits.

5.2 Leading National Programs

5.2.1 Detroit, MI

Detroit, Michigan, has faced decades of profound urban decline marked by widespread property abandonment and speculative investment. In response, the Detroit Land Bank Authority (DLBA), established in 2008 as one of the largest land banks in the nation, has implemented innovative policies to curb speculation and ensure meaningful property rehabilitation (Detroit Land Bank Authority, 2021). A central initiative launched in 2021 is the Anti-Speculation Disposition Policy, designed to prevent the rapid resale and neglect of vacant properties by requiring buyers to demonstrate concrete plans for rehabilitation or occupancy within defined timelines (Detroit Land Bank Authority, 2021)).

Under this policy, prospective purchasers of vacant homes and lots must submit detailed development plans and commit to specific milestones, including occupancy or substantial rehabilitation within 12 to 24 months post-sale (Detroit Land Bank Authority, 2021). Failure to meet these conditions can result in forfeiture of the property back to the DLBA, ensuring that ownership translates into tangible neighborhood improvements rather than financial speculation (Detroit Land Bank Authority, 2021). Additionally, the policy prioritizes sales to adjacent property owners and nonprofit developers to foster local stewardship and community-oriented redevelopment (Detroit Land Bank Authority, 2021). Properties not claimed through this preference are then offered on the open market, but remain subject to the rehabilitation requirements (Detroit Land Bank Authority, 2021).

This approach addresses two critical challenges Detroit has faced: the proliferation of speculative purchases that left homes vacant and deteriorating, and the difficulty in re-engaging residents and trusted entities in neighborhood rebuilding (Detroit Neighborhood Partnership, 2022). Independent evaluations by the University of Michigan's Taubman College of Architecture and Urban Planning highlight that since the policy's enactment, properties sold under these constraints exhibit significantly higher rehabilitation completion rates compared to previous disposition methods, contributing to improved neighborhood stability and reductions in vacancy-related crime (Taubman College of Architecture and Urban Planning, University of Michigan, 2023). Moreover, local community groups report increased resident confidence and investment, viewing the policy as a safeguard against destabilizing absentee ownership (Detroit Neighborhood Partnership, 2022).

For Tulsa, adopting a similar anti-speculation disposition policy could effectively mitigate risks of property flipping and abandonment, which have been persistent issues in several neighborhoods. By requiring purchasers to demonstrate actionable redevelopment plans and imposing enforceable timelines, Tulsa could better ensure that vacant properties transition into productive use that benefits residents directly. Prioritizing adjacent homeowners and nonprofit developers could also enhance community control and continuity. However, implementing such a policy would necessitate legal authority to enforce forfeiture provisions and robust administrative oversight to monitor compliance and adjudicate disputes. Tulsa would also need to establish clear criteria for plan approval and develop mechanisms to support capacity-building for local buyers unfamiliar with property redevelopment.

While Detroit's policy has shown promising early results, continued monitoring is essential to assess long-term impacts on housing affordability and displacement risk (Taubman College of Architecture and Urban Planning, University of Michigan, 2023). Tulsa should integrate comprehensive data collection and community feedback processes to tailor the policy's enforcement in ways that maximize equity and neighborhood resilience (Detroit Neighborhood Partnership, 2022).

5.2.2 Cleveland, OH

Cleveland, Ohio, has established one of the nation's most effective land reutilization systems to combat urban blight and promote neighborhood stabilization. Central to its approach is the Cuyahoga County Land Reutilization Corporation—commonly referred to as the Cuyahoga Land Bank—established in 2009 under

Ohio Senate Bill 353. The Land Bank's statutory authority allows it to acquire tax-delinquent, abandoned, or foreclosed properties through an expedited tax foreclosure process and subsequently transfer these properties for redevelopment or demolition (Ohio Revised Code Chapter 5722, 2024). This program operates in partnership with numerous nonprofit developers and community groups to return vacant parcels to productive use, prioritizing affordability and neighborhood revitalization.

One of the Land Bank's most notable initiatives is the Side Yard Expansion Program, which permits adjacent homeowners to purchase vacant, city-owned side lots for a nominal fee—often as low as $100—subject to requirements for property maintenance and improvement within a defined timeframe (Cuyahoga Land Bank, 2023). This program significantly reduces municipal costs related to property maintenance and illegal dumping while simultaneously increasing resident ownership and community stewardship. Since its inception, the Side Yard program has facilitated the transfer of hundreds of parcels in neighborhoods with persistent vacancy, such as Slavic Village and Glenville, contributing to localized improvements in property conditions and neighborhood cohesion (Cuyahoga Land Bank, 2023).

Economic impact assessments conducted by Cleveland State University's Levin College of Urban Affairs underscore the Land Bank's substantial contribution to neighborhood revitalization. Over a 15-year period, the Land Bank has overseen the demolition of approximately 9,000 blighted structures and the rehabilitation of over 2,100 homes, generating an estimated $1.43 billion in direct economic activity, including increased property values, new private investments exceeding $395 million, and restored property tax revenue amounting to over $48 million (Levin College of Urban Affairs, Cleveland State University, 2023). These figures reflect the program's capacity to catalyze both market recovery and improved public safety in historically disinvested neighborhoods.

For Tulsa, adopting a model akin to Cleveland's Land Bank and Side Yard Expansion Program could provide multiple advantages. First, enabling adjacent homeowners to acquire and improve vacant lots at minimal cost would promote resident-driven neighborhood stabilization and reduce the city's maintenance burden. Second, the legal framework supporting expedited acquisition and disposition of tax-delinquent properties could accelerate interventions in Tulsa's areas affected by vacancy and abandonment. However, such adoption would require legislative authorization at the municipal or state level to establish land bank authority, along with allocation of administrative resources to manage acquisition, disposition, and compliance monitoring. Further, Tulsa would need to develop clear eligibility criteria and enforcement mechanisms to ensure that property improvements meet community standards and prevent speculative misuse.

Notwithstanding the demonstrated economic benefits of Cleveland's program, data on social equity outcomes, such as displacement rates and resident satisfaction, remain limited. Consequently, Tulsa's implementation should incorporate comprehensive evaluation metrics—including community engagement feedback, housing affordability impacts, and long-term neighborhood vitality—to assess and adjust the program's effectiveness in promoting equitable revitalization.

5.2.3 Baltimore, MD

Baltimore, Maryland, has confronted persistent challenges related to widespread vacancy, disinvestment, and deteriorating housing stock across numerous neighborhoods (Baltimore Department of Housing & Community Development, 2020). In 2010, the city launched the Vacants to Value (V2V) initiative, a data-driven, multifaceted strategy designed to accelerate the remediation and productive reuse of vacant properties through targeted demolition, rehabilitation incentives, and enhanced code enforcement (Baltimore Department of Housing & Community Development, 2020).

The V2V program employs geographic information system (GIS) mapping and vacancy data to identify priority clusters of blighted buildings, enabling the city to focus resources where they can have the greatest neighborhood impact (Baltimore Department of Housing & Community Development, 2020). This data-driven targeting facilitates coordinated action, combining proactive demolition of irreparable structures with incentives to encourage private-sector rehabilitation of salvageable properties (Baltimore Department of Housing & Community Development, 2020). Key elements include streamlining of the permitting process to reduce redevelopment delays and offering tax credits to developers investing in residential rehab projects (Baltimore Department of Housing & Community Development, 2022).

An important legal tool under V2V is the use of receivership, which allows the city or court-appointed entities to take control of vacant properties when owners fail to maintain them or address code violations (Baltimore Department of Housing & Community Development, 2022). This tool expedites the transfer of properties to responsible developers or community organizations capable of rehabilitation or redevelopment (Baltimore Department of Housing & Community Development, 2022). Additionally, V2V has pioneered bulk property sales, packaging clusters of vacant homes for sale to developers with proven track records in affordable housing and community revitalization (Baltimore Department of Housing & Community Development, 2020). By 2020, the program reported over 4,000 properties either demolished or rehabilitated, reflecting significant progress in reducing vacancy and stabilizing neighborhoods (Baltimore Department of Housing & Community Development, 2020).

Evaluations by the Abell Foundation and Johns Hopkins University's Urban Health Institute highlight that V2V's comprehensive approach has contributed to measurable improvements in property values, reduced crime rates in targeted areas, and increased homeownership opportunities, particularly in historically disinvested communities (Abell Foundation, 2022; Johns Hopkins Urban Health Institute, 2021). However, challenges remain around ensuring long-term affordability and preventing displacement as neighborhoods recover, necessitating ongoing policy refinement and community engagement (Abell Foundation, 2022; Johns Hopkins Urban Health Institute, 2021).

For Tulsa, replicating Baltimore's Vacants to Value initiative could provide a robust framework for integrating data-driven targeting with legal and financial tools to accelerate blight remediation (Baltimore Department of Housing & Community Development, 2020). Tulsa could benefit from implementing or enhancing GIS-based vacancy tracking to better allocate resources and monitor progress (Baltimore Department of Housing & Community Development, 2020). Streamlining permitting processes and incentivizing private rehabilitation through targeted tax credits or grants would also align with Tulsa's goals to revitalize neighborhoods without extensive displacement (Baltimore Department of Housing & Community Development, 2022). Employing receivership mechanisms and considering bulk sales of clustered properties could improve efficiency in transferring vacant properties to committed developers (Baltimore Department of Housing & Community Development, 2020). Successful adoption would require Tulsa to develop local ordinances authorizing receivership and build partnerships with nonprofit and private developers experienced in equitable redevelopment (Abell Foundation, 2022).

Ongoing evaluation and transparent community involvement will be critical to ensuring that Tulsa's adaptation of V2V prioritizes equitable outcomes and preserves affordable housing (Johns Hopkins Urban Health Institute, 2021). Lessons from Baltimore emphasize that comprehensive strategies combining demolition, rehab, and legal enforcement—when grounded in data and community collaboration—can effectively address entrenched urban blight (Baltimore Department of Housing & Community Development, 2020; Abell Foundation, 2022).

5.3 Conclusion: Policy Implications for Tulsa

The comparative analysis of peer cities and nationally recognized best practices, summarized in Figures **??** and 22, underscores that effective urban blight remediation necessitates a comprehensive, multi-jurisdictional approach integrating legal frameworks, strategic resource allocation, and sustained community engagement. Across varied municipal contexts, cities have deployed a combination of regulatory enforcement mechanisms, innovative property disposition tools, and targeted financial incentives to curtail vacancy, stabilize neighborhoods, and promote equitable redevelopment.

Legal interventions such as property receivership and anti-speculation disposition policies have emerged as critical instruments for addressing the pernicious effects of property abandonment and speculative landholding. These mechanisms impose enforceable obligations on property owners, enabling local governments or designated entities to intervene where owners fail to maintain or rehabilitate blighted properties within prescribed timelines. By instituting legal accountability, these policies mitigate prolonged vacancy and accelerate the return of distressed properties to productive use, thereby enhancing neighborhood safety and market stability.

Land banking institutions, particularly those with robust acquisition powers and clear statutory authority, facilitate the aggregation and reutilization of tax-delinquent and abandoned properties. Programs like Cleveland's Side Yard Expansion demonstrate how transferring ownership to adjacent homeowners can reduce municipal maintenance burdens, deter illegal dumping, and foster localized stewardship. When paired with complementary strategies such as data-driven targeted demolition, green reuse initiatives, and coordinated code enforcement—as exemplified by Baltimore's Vacants to Value program—these approaches provide a holistic framework for neighborhood revitalization while addressing concerns of displacement and equitable access.

A recurring theme in the examined programs is the imperative for meaningful resident participation and transparent governance. Inclusive community engagement not only legitimizes policy interventions but also ensures that redevelopment efforts are responsive to local priorities and socio-economic realities. Concurrently, rigorous monitoring and evaluation frameworks are essential to assess program efficacy, identify unintended consequences, and recalibrate interventions to optimize outcomes.

For Tulsa, these findings translate into several actionable policy imperatives. Strengthening the city's land bank through enhanced statutory authority—particularly regarding expedited property acquisition, title clearance, and liability protections—is foundational to expanding its operational capacity. Implementing homeowner rehabilitation initiatives, supported by forgivable loan programs and targeted subsidies, can address housing stock deterioration while promoting affordability and homeownership stability. Integrating demolition activities with coordinated infill development and green infrastructure investments will maximize land reutilization and mitigate risks associated with protracted vacancies. Enacting anti-speculation measures with enforceable compliance benchmarks will deter opportunistic property holding and incentivize timely reinvestment. Crucially, embedding robust community engagement protocols and data-driven oversight mechanisms will underpin equitable and sustainable revitalization efforts, fostering long-term neighborhood resilience.

In sum, Tulsa's strategic response to urban blight should be predicated on a synthesis of proven peer city methodologies and nationally validated practices, adapted within a rigorous legal and administrative framework. By harmonizing enforceable legal tools, targeted funding strategies, participatory governance, and empirical evaluation, Tulsa can effectively transform blighted assets into catalysts for inclusive economic growth, enhanced public safety, and community stability. This integrated, evidence-based, and community-centered policy paradigm offers the optimal pathway to sustainable neighborhood revitalization and improved urban quality of life.

5.4 Figures

Figure 21: Summary of all peer-city programs, part 1

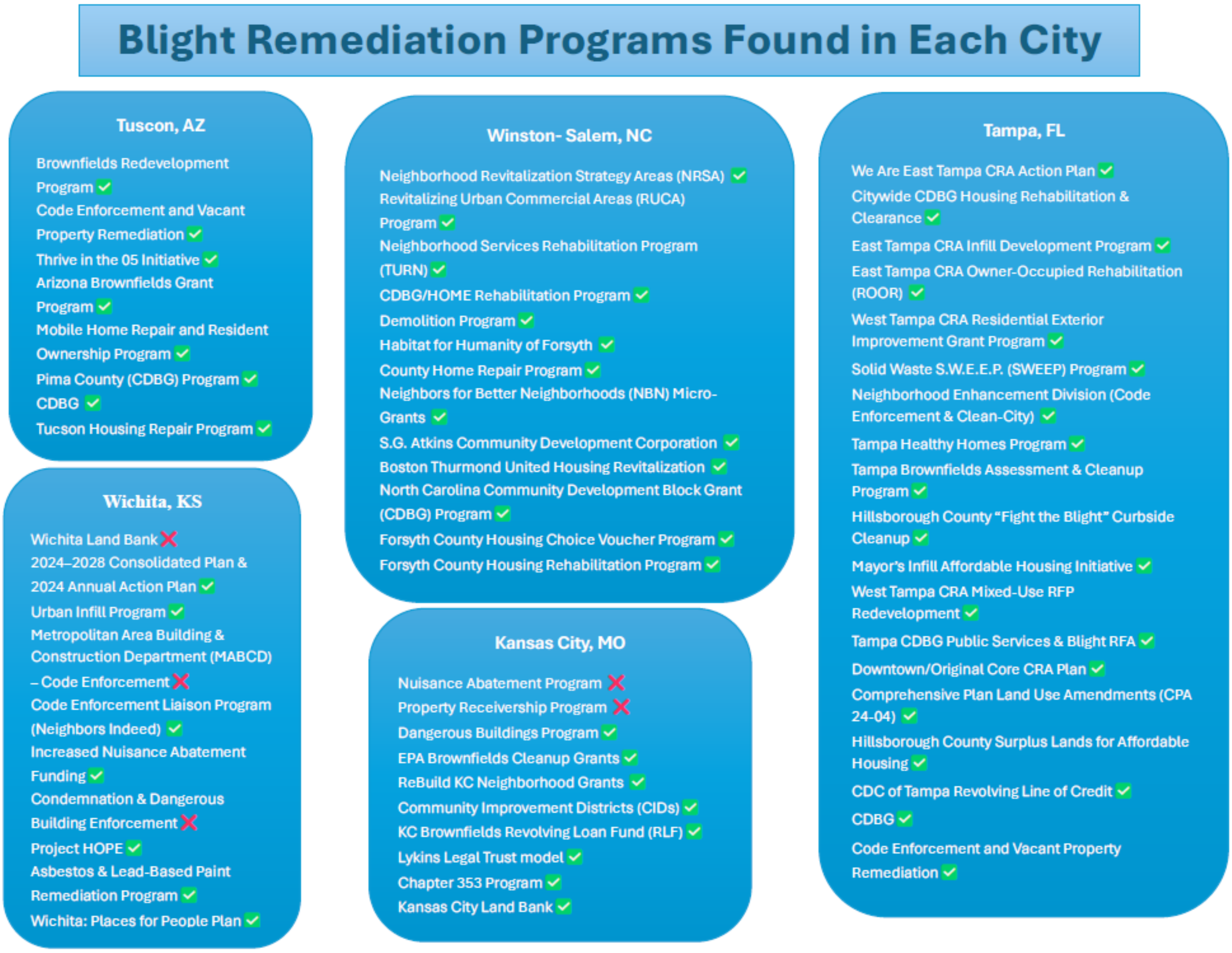

Figure 22: Summary of all peer-city programs, part 2

6 Analyzing the Potential Effectiveness of Regression Modeling in Identifying Blight

Author: Anna Hart

6.1 Introduction

The identification of blighted housing is a difficult process that often relies on in person investigations of properties. Building a regression model that can predict the likelihood that a property is blighted based on publicly available data could be useful in streamlining the process of identifying and addressing blight in Tulsa. Nondemographic data such as the incidences of nuisance, property maintenance, and demolition cases associated with a property were included in the model to hopefully increase its accuracy. The inspiration for the inclusion of these variables came from Blighted: A Story of People, Politics, and an American Housing Miracle by Margaret Stagmeier. The book details the challenges Stagmeier experienced while rehabilitating a blighted apartment complex. The idea of including nondemographic variables came from the desire to find a way to represent the characteristics of blight Stagmeier describes in her book (Stagmeier, 2024). This chapter focuses on four different negative binomial and logistical regression models and the insights these models provide into how the likelihood of a property becoming blighted can be predicted using common statistical methods.

6.2 Data Collection

6.2.1 Extracting Data from the City of Tulsa Self-Service Portal

The City of Tulsa makes information on housing related issues available to the public through its self-service permitting portal. This portal is difficult to extract information from, as the built-in export option only allows a user to export either 100 results at a time or the first 1,000 results. The portal is a web application that relies on an application programming interface (API) to retrieve the records relevant to a user's search. Specifically, the API operates using the JSON-RPC protocol. JSON-RPC is a type of request-response protocol. When performing a search on the self-service portal, this portal sends your request for information to the City of Tulsa's internal servers using a remote procedure call and then receives the response in a JSON format. Since the portal restricts the size of the requests you can make, a different API needed to be used to send the request. The popular API development platform, Postman, was used to send the request.

To access the sever where the housing related records were stored, the request sent from Postman needed to have the same response body and associated authorization tokens as the requests being sent by the self-service portal. This information, as well as the request URL, can be found using the developer tools menu while performing a search on the self-service portal. The request for the data relevant to this project was contained within the Fetch/XHR request named search. The authorizations tokens needed to perform the request were located under cookies in the application tab in developer tools. To expand the search beyond the limitations of the portal, the value of PageSize was manually changed to 10,000. PageSize could not be increased beyond 10,000 because 10,000 is the default maximum query size of most APIs. Performing a request larger than 10,000 returned an error.

After obtaining the relevant information needed to perform the request, Postman was able to retrieve the raw JSON response file that the self-service portal reads from to display information about individual cases and the addresses associated with them. This raw JSON code was then saved as a new JSON file. To analyze and clean the data, the raw JSON file was converted into a .csv file. This process was repeated for three different code case types: nuisance, property maintenance, and demolition.

6.2.2 Merging Datasets

Additional data included in the dataset used in this regression analysis came from three main sources: other members of the research group, the U.S. Census Bureau, and data collected by Jessica Shelton, the Director of Research and Development at Housing Forward. Shelton's data contains the results of in-person inspections of a few thousand homes in Tulsa. Shelton performed these observations for one of their projects and was kind enough to share the data with our research group. Census data about a variety of demographic characteristics is publicly available on the U.S. Census Bureau website. The census does not report data for each individual household, rather, totals and averages are reported for each census tract. Additionally, variables in the datasets created by my colleagues Ella Calvert and Nathan Exum were included in the dataset used to perform logistic regression analysis. The variables included from these datasets were the average score of the schools within a census tract on the 2024 Oklahoma Schools Report Card and the number of sewer plugs issued in each census tract since 2018.

To accurately analyze what factors, influence the likelihood of a property becoming blighted, the properties included in the dataset must be the same for every variable. Datasets are often merged by linking a common attribute between the two. The data obtained from the self-service portal and the data provided by Housing Forward both contain parcel numbers for each observation. Some parcel numbers were associated with multiple code cases of the same type. To handle this, the data for nuisance, property maintenance, and demolition cases were subset to only include reports where the parcel number associated with the report was also part of the dataset from Housing Forward. Then, each dataset was converted from long to wide format using Power Query in Excel. A count variable was created for each dataset whose value was equal to the number of reports associated with each parcel number. A Boolean variable was also created for each code case type that would be set to one when a parcel has at least one report of the variable's type.

The census data, report card scores, and sewer plug data did not contain any common variables with the other datasets, so a spatial join would need to be performed using QGIS, a type of geographic information system. By plotting instances of sewer plugs being issued and the locations of local schools within the area surveyed by Jessica Shelton, each observation could be assigned a census tract number based on where it intersected a map of census tract boundaries in Oklahoma. Shapefiles of all the census tracts are made publicly available by the U.S. Census Bureau, and these can easily be imported as a vector layer in QGIS. Each of the datasets are imported as delimited text layers. After generating a spatial index for each layer, the values contained within the datasets can be merged into the census tract dataset using the join attributes by location function. In this instance, the common attribute between the datasets is the name of the census tract. The dataset containing the data from Housing Forward and the code case data was then matched with a census tract using the same spatial join method. Each parcel number had an associated census tract number, which allowed for the census tract data to be merged many-to-one using the statistical software package Stata.

6.3 Methodology

The explanatory variables included in the model were chosen based on key attributes of blighted properties repeatedly mentioned across the literature read by the team at the beginning of the research process. In particular, Blighted: A Story of People, Politics, and an American Housing Miracle written by Margaret Stagmeier, Stagmeier recalls the challenges that came with working on rehabilitating a blighted apartment complex. Some of the issues encountered involved criminal activity, poorly maintained communal spaces, and abandoned units in a state of disrepair. Nuisance, property maintenance, and demolition cases were chosen because of their similarities to the problems identified by Stagmeier.

Additional explanatory variables were added to improve the accuracy of the model. The demographic variables obtained from the census data were chosen based on their perceived relation to the financial status of a homeowner. Detailed information on the relevance of education quality and instances of sewer plugs being issued to the identification of blight can be found in other chapters in this report. Descriptions of each variable are presented in Figure 23 and summary statistics for each numeric variable are presented in Figure 24.

6.3.1 Negative Binomial Regression Models

The dependent variable *blightcount* is a count variable that can only take on whole number values and represents the frequency of instances of blight for a specific parcel. Count data tends to follow a negative binomial or Poisson distribution. From the summary statistics provided in Figure 2, we can see that the data exhibits overdispersion, since the variance of multiple explanatory variables is greater than the mean. Therefore, negative regression is the most appropriate model for evaluating this dataset with a continuous dependent variable. The negative binomial distribution has the generic form:

$$log(\mu) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_m X_m$$

where μ is the expected count and β_i is the parameter for all $i = 0, 1, 2, \ldots m$ where m is the number of explanatory variables. Two variations of the negative binomial regression model will be used to determine the expected count of signs of blight, expressed as the value of *blightcount*. One will use the Boolean variables *nuis*, *demo*, and *pm* and the other will use the count variables *nuiscount*, *democount*, and *pmcount* as regressors.

6.3.2 Logistic Regression Models

The variable *blighted* is a Boolean variable, which has only two possible outcomes, true or false. A blighted property is defined within the dataset as a property that when assessed, had at least one sign of blight. For blighted properties, the variable *blighted = 1*; otherwise *blighted = 0*. Since the dependent variable is binary and the model includes both continuous and discrete regressors, logistic regression is the most appropriate model. A logistic regression model has the generic form:

$$\mu = \frac{1}{1 + e^{-}(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_m X_m)}$$

where μ is the probability of success and β_i is the parameter for all $i = 0, 1, 2, \ldots m$ where m is the number of explanatory variables. In this case, the probability of success is the probability that a property is blighted. Two different logistic regression models will be used to estimate blighted, one using Boolean variables *nuis*, *pm*, and *demo* to represent nuisance, property maintenance, and demolition cases, and the other using count variables *nuiscount*, *pmcount*, and *democount*.

6.4 Results

After estimating the regression models using Stata, it was found that the variables *sewerplugcount* and *educscore* exhibited multicollinearity and thus were excluded from the model. This may be due to the lack of variation in the sample. These attributes were merged with the rest of the data at the census tract level. Since there were only a few different census tracts within the sample, a good estimation of the relationship between *educscore* and *sewerplugcount* could not be found. After excluding these variables, the four regression models were estimated using the remaining independnent varaibles. The results of the four regression models are presented in Figures 25, 26, 27, and 28.

6.5 Hypothesis Testing

6.5.1 Negative Binomial Regression Model

For reference, the negative binomial regression model that uses the explanatory variables *nuis*, *pm*, and *demo* was presented in Figure 25 (model 1). The other negative binomial regression model was presented in Figure 26 (model 2). The Wald test is the best method for determining the significance of the model. If the p-value generated for each model by the Wald test is less than 0.05, then the coefficients of predictors are not simultaneously equal to zero and these predictors are statistically significant. The individual p-values reported for each explanatory variable after performing the initial negative binomial regression are also an indicator of if a regressor is statistically significance.

For the first binominal model, the results of the Wald test are shown in Figure 29. What we can learn from this test, as well as the individual p-values of each explanatory variable, is that the model is statistically significant. The p-value associated with the chi-squared value of 254.71 with seven degrees of freedom is less than 0.05, so we reject the null hypothesis. However, the individual p-value of variable *nuis* is 0.113, which means that it may not be statistically significant and not worth including in the model. But since the sample size of the data is only a few thousand homes, it is worth keeping *nuis* in the model for further investigation.

The results of hypothesis testing for the second binominal model are similar to the results the first The results of the Wald test are presented in Figure 30 In this model, *nuiscount* has a p-value greater than 0.05, which means it is not individually statistically significant to the model. But since the results of the Wald test show that the p-value associated with a chi-squared value of 241.85 with seven degrees of freedom, we can reject the null hypothesis and the model is statistically significant, the variable has been left in. A screenshot of a computer

6.5.2 Logistic Regression Model

The logistic model using Boolean variables to represent nuisance, property maintenance, and demolition cases was presented in Figure 27 (model 3) and the logistic model using count variables was presented in Figure 28 (model 4). The Wald test will also be used to test the significance of the models. Figure 31 shows the results of the Wald test for model 3. From these results, we can reject the null hypothesis and conclude that the coefficients of the predictors of the model are statistically different from zero. But the individual p-values for the regressors *nuis*, *demo*, and *pm* shown in Figure 27 means that they are not individually statistically significant. Since the p-value associated with the chi-squared value of 354.15 with seven degrees of freedom is less than 0.05, we reject the null hypothesis.

Figure 32 shows the results of the Wald test for model 4. The results are similar to model 3, we can reject the null hypothesis based on the significance of the whole model. But the variables *nuiscount, pmcount*, and *democount* do not appear to be individually statistically significant because their p-values exceed 0.05. Since the p-value associated with the chi-squared value of 351.07 with seven degrees of freedom is less than 0.05, we reject the null hypothesis. However, it should be noted that individual p-values for *nuis* in model 3 and *nuiscount* in model 4 exceed 0.05 and may not be individually statistically significant

6.6 CONCLUSION

The results of the hypothesis tests show that all four models are statistically significant. When interpreting the effects of individuals variables on whether a property is blighted or not, only the effects of variables with p-values less than 0.05 will be taken into consideration since the effects of a variable that is not individually statistically significant cannot be interpreted reliably. The interpretations of the values of individual explanatory variables are summarized Figure 33.

The variables representing property maintenance and demolition cases were significant when used in the negative binomial regression models to predict the dependent variable *blightcount*. However, these variables were not as statistically significant when evaluating blight as a binary variable. Demolition was statistically significant in model 3 but had a negative correlation that implies that having at least one demolition case makes a property less likely to be blighted. This might be a result of having a sample where a higher proportion of properties are blighted because of the surveying being done in neighborhoods identified as at risk of blight. There is not enough variation in the data to accurately predict the likelihood of a property being blighted using code case data. More data that includes more non-blighted properties from a more diverse set of neighborhoods would be needed to produce an accurate model. This is also the likely reason that the code case variables were not significant in the logistic regression models. The larger range of the *blightcount* variable makes it easier to fit a model to the data with a limited sample size.

The statistical significance of property maintenance and demolition cases to the number of blighted items identified on a property is promising. This result suggests that non-demographic factors can be used to increase the accuracy of models that aim to predict the likelihood of a property becoming blighted. Further investigation and more extensive data collection will need to be done before an accurate model can be created and used in various real-world applications.

6.7 FIGURES

Variable	Type	Definition
nuis	Boolean	If there exists a nuisance case associated with the parcel number, nuis = 1. Otherwise, nuis = 0.
nuiscount	Numeric	Number of nuisance cases associated with a parcel number.
demo	Boolean	If there exists a demolition case associated with the parcel number, demo = 1. Otherwise, demo = 0.
democount	Numeric	Number of demolition cases associated with a parcel number.
pm	Boolean	If there exists a property maintenance case associated with the parcel number, pm = 1. Otherwise, pm = 0.
pmcount	Numeric	Number of property maintenance cases associated with a parcel number.
medianhouseholdinc	Numeric	Median household income of the census tract a parcel is in as reported in the 2023 American Community Survey.
lfrate	Numeric	Labor force participation rate for the census tract a parcel in located in. Calculated using data from the 2023 American Community Survey.
gradrate	Numeric	Rate of high school graduation within the census tract a parcel is located in. Calculated using data from the 2023 American Community Survey.
renterocc	Boolean	If the property is renter owned, renterocc = 1. If not, renterocc = 0.
educscore	Numeric	Average score of the schools within a census tract on the 2024 Oklahoma Schools Report Card.
sewerplugcount	Numeric	Number of sewer plugs issued within a census tract since 2018.

Figure 23: Variable Descriptions

Variable	Obs	Mean	Std. dev.	Min	Max
nuiscount	6,363	.0276599	.2124437	0	7
pmcount	6,363	.1026245	.3827436	0	9
democount	6,363	.019802	.1512314	0	3
medianhous~c	6,363	36675.41	6600.21	23750	49313
educscore	5,346	9.631032	2.858199	5.95	13.16
sewerplugc~t	5,429	2.90606	1.22008	2	10
lfrate	6,363	.5702209	.0392553	.4755784	.6500872
gradrate	6,363	.5808672	.0669026	.4815643	.6776777

Figure 24: Summary Statistics

Negative binomial regression

Number of obs = 6,363
LR chi2(7) = 251.13
Prob > chi2 = 0.0000
Pseudo R2 = 0.0112

Dispersion: mean
Log likelihood = -11064.859

blightcount	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
nuis	.1000907	.0630905	1.59	0.113	-.0235645	.2237458
demo	.2089092	.0646433	3.23	0.001	.0822107	.3356077
pm	.213183	.0326965	6.52	0.000	.1490991	.277267
medianhouseholdinc	.0000146	2.66e-06	5.48	0.000	9.37e-06	.0000198
lfrate	-4.338983	.3983155	-10.89	0.000	-5.119667	-3.558299
gradrate	-.8483509	.1647391	-5.15	0.000	-1.171234	-.5254681
renterocc	-.0692831	.019109	-3.63	0.000	-.1067361	-.0318301
_cons	3.092315	.1958636	15.79	0.000	2.708429	3.4762
/lnalpha	-2.920954	.211089			-3.334681	-2.507227
alpha	.0538822	.0113739			.035626	.0814939

LR test of alpha=0: chibar2(01) = 26.49 Prob >= chibar2 = 0.000

Figure 25: Results of negative binomial regression with dependent variable blightcount and Boolean explanatory variables nuis, demo, and pm

```
Negative binomial regression                     Number of obs =  6,363
                                                  LR chi2(7)    = 238.07
Dispersion: mean                                  Prob > chi2   = 0.0000
Log likelihood = -11071.394                       Pseudo R2     = 0.0106
```

blightcount	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
nuiscount	.0553931	.0405389	1.37	0.172	-.0240616	.1348478
democount	.2054179	.0559489	3.67	0.000	.09576	.3150758
pmcount	.1196696	.0229177	5.22	0.000	.0747517	.1645875
medianhouseholdinc	.0000148	2.66e-06	5.55	0.000	9.57e-06	.00002
lfrate	-4.386716	.3981353	-11.02	0.000	-5.167046	-3.606385
gradrate	-.8647779	.1644896	-5.26	0.000	-1.187172	-.5423843
renterocc	-.0636505	.0190948	-3.33	0.001	-.1010756	-.0262254
_cons	3.125482	.195503	15.99	0.000	2.742303	3.508661
/lnalpha	-2.895073	.206449			-3.299706	-2.490441
alpha	.055295	.0114156			.036894	.0828734

```
LR test of alpha=0: chibar2(01) = 27.79           Prob >= chibar2 = 0.000
```

Figure 26: Results of negative binomial regression with dependent variable blightcount and explanatory variables nuiscount, democount, and pmcount.

```
Logistic regression                               Number of obs =  6,363
                                                  LR chi2(7)    = 377.99
                                                  Prob > chi2   = 0.0000
Log likelihood = -3514.2864                       Pseudo R2     = 0.0510
```

blighted	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
nuis	.3607452	.2067036	1.75	0.081	-.0443864	.7658769
demo	-.4382448	.2114504	-2.07	0.038	-.8526799	-.0238096
pm	.1879461	.1136363	1.65	0.098	-.034777	.4106692
medianhouseholdinc	.000069	7.61e-06	9.06	0.000	.0000541	.0000839
lfrate	-18.50825	1.253003	-14.77	0.000	-20.96409	-16.05241
gradrate	-2.815083	.548214	-5.14	0.000	-3.889563	-1.740603
renterocc	-.4662439	.0598507	-7.79	0.000	-.583549	-.3489387
_cons	10.97163	.5917663	18.54	0.000	9.811788	12.13147

Figure 27: Results of logistic regression with dependent variable blighted and explanatory variables nuis, demo, and pm.

```
Logistic regression                                     Number of obs =  6,363
                                                        LR chi2(7)    = 374.40
                                                        Prob > chi2   = 0.0000
Log likelihood = -3516.085                              Pseudo R2     = 0.0505
```

blighted	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
nuiscount	.2070769	.1537428	1.35	0.178	-.0942535	.5084073
democount	-.3393215	.1890934	-1.79	0.073	-.7099377	.0312947
pmcount	.0871987	.0828115	1.05	0.292	-.0751089	.2495063
medianhouseholdinc	.0000687	7.61e-06	9.03	0.000	.0000538	.0000836
lfrate	-18.46547	1.251135	-14.76	0.000	-20.91765	-16.01329
gradrate	-2.801872	.5476545	-5.12	0.000	-3.875255	-1.728489
renterocc	-.463729	.0597638	-7.76	0.000	-.5808639	-.346594
_cons	10.95692	.5903958	18.56	0.000	9.799766	12.11407

Figure 28: Results of logistic regression with dependent variable blighted and explanatory variables nuiscount, democount, and pmcount.

```
. test nuis demo pm medianhouseholdinc lfrate gradrate renterocc

 ( 1)  [blightcount]nuis = 0
 ( 2)  [blightcount]demo = 0
 ( 3)  [blightcount]pm = 0
 ( 4)  [blightcount]medianhouseholdinc = 0
 ( 5)  [blightcount]lfrate = 0
 ( 6)  [blightcount]gradrate = 0
 ( 7)  [blightcount]renterocc = 0

           chi2(  7) =  254.71
         Prob > chi2 =    0.0000
```

Figure 29: Results of Wald Test for first binomial model (Model 1)

```
. test nuiscount democount pmcount medianhouseholdinc lfrate gradrate renterocc

 ( 1)  [blightcount]nuiscount = 0
 ( 2)  [blightcount]democount = 0
 ( 3)  [blightcount]pmcount = 0
 ( 4)  [blightcount]medianhouseholdinc = 0
 ( 5)  [blightcount]lfrate = 0
 ( 6)  [blightcount]gradrate = 0
 ( 7)  [blightcount]renterocc = 0

           chi2(  7) =  241.85
         Prob > chi2 =    0.0000
```

Figure 30: Results of Wald Test of second binomial model (Model 2)

```
.  test nuis demo pm medianhouseholdinc lfrate gradrate renterocc

 ( 1)  [blighted]nuis = 0
 ( 2)  [blighted]demo = 0
 ( 3)  [blighted]pm = 0
 ( 4)  [blighted]medianhouseholdinc = 0
 ( 5)  [blighted]lfrate = 0
 ( 6)  [blighted]gradrate = 0
 ( 7)  [blighted]renterocc = 0

           chi2(  7) =  354.15
         Prob > chi2 =    0.0000
```

Figure 31: Results of Wald Test for first logistic model (Model 3)

```
. test nuiscount democount pmcount medianhouseholdinc lfrate gradrate renterocc

 ( 1)  [blighted]nuiscount = 0
 ( 2)  [blighted]democount = 0
 ( 3)  [blighted]pmcount = 0
 ( 4)  [blighted]medianhouseholdinc = 0
 ( 5)  [blighted]lfrate = 0
 ( 6)  [blighted]gradrate = 0
 ( 7)  [blighted]renterocc = 0

           chi2(  7) =  351.07
         Prob > chi2 =    0.0000
```

Figure 32: Results of Wald Test for second logistic model (Model 4)

Model	Explanatory Variable	Coefficient	Interpretation
Model 1: Negative binomial regression with dependent variable *blightcount* and Boolean explanatory variables *nuis*, *demo*, and *pm*	*nuis*	0.1000907	P-value exceeds 0.05, cannot reliably interpret the effects of *nuis* on *blightcount*
	demo	0.2089092	Having at least one demolition case associated with a parcel increases the expected count of blighted items by approximately 1.232.
	pm	0.213183	Having at least one property maintenance case associated with a parcel increases the expected count of blighted items by 1.238.
Model 2: Negative binomial regression with dependent variable *blightcount* and explanatory variables *nuiscount*, *democount*, and *pmcount*	nuiscount	0.0553931	P-value exceeds 0.05, cannot reliably interpret the effects of *nuiscount* on *blightcount*
	democount	0.2054179	For each demolition case a parcel has associated with it, the expected count of blighted items increases by 1.228.
	pmcount	0.1196696	For each property maintenance case a parcel has associated with it, the expected count of blighted items increases by 1.127.
Model 3: Logistic regression with dependent variable *blighted* and explanatory variables *nuis*, *demo*, and *pm*	nuis	0.3607452	P-value exceeds 0.05, cannot reliably interpret the effects of *nuis* on *blightcount*
	demo	-0.4382448	When a property has at least one demolition case associated with it, the odds of the property being blighted are 0.645 times the normal odds.
	pm	0.1879461	P-value exceeds 0.05, cannot reliably interpret the effects of *pm* on *blighted*
Model 4: Logistic regression with dependent variable *blighted* and explanatory variables *nuiscount*, *democount*, and *pmcount*	nuiscount	0.20270769	P-value exceeds 0.05, cannot reliably interpret the effects of *nuiscount* on *blighted*
	democount	-0.3393215	P-value exceeds 0.05, cannot reliably interpret the effects of *democount* on *blighted*
	pmcount	0.0871987	P-value exceeds 0.05, cannot reliably interpret the effects of *pmcount* on *blighted*

Figure 33: Interpretations of Key Explanatory Variables

7

Facilitating VAD Identification: An AI-Driven Image Classification Tool

Authors: Katrina E. Henderson & Shawnda M. Henderson

7.1 Introduction

As introduced in our previous chapter (Chapter 4), our work this summer consisted of developing two distinct software tools. Having described the first – a peer city generator – we now turn to the second: a Python-based machine-learning program that identifies residential VAD from street-based photographs of home exteriors.

More specifically, and again leveraging generative AI, we developed a tool that utilizes a convolutional neural network (CNN) to classify photographs as VAD or non-VAD properties. Of course, that is an oversimplified, binary designation for a nuanced issue; there is not, and cannot be, any single definition for what constitutes VAD,[4] an issue which we address later in this report. Ultimately, for this and other reasons that we also describe herein, our model is a proof of concept. Our purpose – which we achieved – was to illustrate such a tool as an intriguing possibility, and to learn through that experience what a practical tool might require, thereby offering a potential avenue for further work.

The chapter thus proceeds as follows. First, we provide a basic description of both neural networks and CNNs, after which we summarize our particular model. Then we turn to the model's limitations, some of which seem inherent to any VAD identification, but which might prove especially tricky for photographic or videographic identification. But to the extent those can be overcome, such a tool could be useful in a city's toolkit to address problematic residential properties and groupings thereof.

7.2 Neural Networks

As for the coding of our peer city generator, we leveraged generative AI – in this case, Google's Gemini. In our initial prompts, we outlined our overall goal: developing Python code to classify VAD properties based upon photographs of homes. In response, it recommended we utilize a convolutional neural network, or CNN.

Neural networks are used in machine learning applications, designed to learn patterns in data without explicit instruction. Their structure is very roughly based on that of the human brain: layers of interconnected nodes, or 'neurons,' receive, transform, and pass data to one another. In 'dense' neural networks, each neuron is connected to every other neuron in the previous layer. Connections between neurons are assigned different

[4] *See*, e.g., The Vacant Properties Research Network, *Charting the Multiple Meanings of Blight* (May 20, 2015), available at https://keeplouisianabeautiful.org/wp-content/uploads/2019/08/Charting_the_Multiple_Meanings_of_Blight_FINAL_REPORT.pdf.

'weights,' which represent the relative strength or importance of the connection. As described more below, these weights enable the model to 'learn': after each training cycle, the model adjusts its parameters based on performance.

Most neural networks have three types of layers: an input layer, hidden layers, and an output layer. Data first enters the input layer, with each input neuron accepting a portion thereof. The data then flows into the hidden layers, where the bulk of the data transformation takes place. Specifically, each neuron takes the output from the previous layer's neurons and performs a mathematical operation thereon. This is often a weighted sum, applying the weight from the relevant connection. The sum is then passed through a so-called 'activation function,' which allows the model to recognize more complex patterns. The results then flow into the next hidden layer, where it is similarly transformed. This process repeats, with the data propagating forward until it reaches the output layer. This layer produces the final result – in our case, a classification as 'VAD' or 'not VAD.'

A model is trained in stages of forward and back propagation. After producing an initial result, the model evaluates its performance by calculating the error, or 'loss,' using a so-called 'loss function.' The details of those functions – like all details of such networks – are beyond our scope, but this step essentially describes how 'wrong' the prediction was. The model then begins the process of 'back propagation,' adjusting its weights based on the computed loss. Once the weights are updated, the system starts the process over again. This cycle of forward and back propagation is repeated a predetermined number of times, with each full cycle constituting an 'epoch.'

For this model training, available data is split into at least two – often three – portions: a training set, a validation set, and an optional test set.[5] The model uses the training set to learn; each epoch is one pass through the training set. After each epoch, the model tests itself using the validation set. Unlike the training results, the validation performance is *not* used to update the weights. Instead, this is used to identify potential 'overfitting,' which describes when the model has learned the training data *too* well. In other words, the model has learned the patterns unique to this training set, which may include noise and details that do not generalize to unseen inputs. Thus, after each epoch, the model calculates the loss from both the training and validation sets. The training loss is used to optimize the model, while the validation loss is used to detect potential overfitting.

7.3 CONVOLUTIONAL NEURAL NETWORKS

A convolutional neural network (CNN) is a type of neural network designed for processing grid-like or spatially-connected data, such as an image. While a datum's 'location' can often be irrelevant to a problem

[5] The test set is put aside during the training process, and is used to evaluate the resulting model, just like any newly obtained data would be used once the model is ready. As later described, we set aside 20 photos in a test set.

– for example, perhaps a row or column number within a spreadsheet – datum location is crucial for processing images: determining whether pixels combine to form a dog, a car, or a house requires knowing where those pixels lie within an image. Likewise, classifying our home photographs as VAD or non-VAD properties requires the same, and thus, we used a CNN for our model.

Like any neural network, a CNN can only classify an image once it 'learns' its target. Say, for example, a CNN is intended to classify whether an image contains a dog. The network has no initial conception of what a dog is or 'looks like'; so, in order to identify one in a photograph, the network will need to learn the patterns or features that combine to form a dog: two ears, a nose, a tail, etcetera. However, the CNN also has no conception of ears, noses, or tails. Thus, during training, the network memorizes the patterns of pixel intensities that form features consistently present in the user-tagged training data. These patterns are stored in matrices called filters, and, during prediction, they are applied to detect the presence of those features in new images.

Now that the CNN knows what *features* to look for, it needs to understand how they combine to form the relevant object. In the previous example, this is equivalent to asking, how many of those 'learned' features are needed to form a dog? In other words, what if the CNN detects two ears but no tail? What about two ears, a tail, but no nose? To make this final classification – 'dog' or 'not a dog' – the network uses a dense or fully connected layer. Along with its classification, it provides a probability, which provides the CNN's level of confidence in its determination. During the training phase, the CNN uses this classification and probability to 'learn' and become more accurate. After training, this classification determines whether a photograph is sorted into the 'dog' or 'not a dog' category.

Equipped with this basic understanding of convolutional neural networks, we now turn to our particular VAD classification model.

7.4 Model

The success of any neural network critically depends upon its training data, and our data was unfortunately – though understandably – very constrained. We more thoroughly describe those limitations in a later section; here, we will explain what we used.

Our dataset consists of 436 photographs of homes, 110 of which have been human-classified as containing VAD properties. These photographs were gathered by our teammates and therefore feature actual Tulsa homes, a process that requires considerable legwork. Indeed, given the time-intensive collection process, our teammates were obliged to resort to videography, from which we then manually captured still-frame images for our dataset. This approach was a consequence of our time and monetary constraints, and – as outlined in Section X – it creates very significant limitations in our model's results. Still, our current dataset allows us to run the model, illustrating proof of concept.

After collecting the photographs, we turned to data preparation. Many CNN architectures require a consistent input size, and the Python libraries we used to build our model are no exception. Thus, before training, we had to pad each image, establishing a consistent square aspect ratio for each photograph. In order to efficiently resize the entire dataset, we wrote separate Python code in Google's Colaboratory.

With the data so prepared, we started in on model development. Once again, we leveraged AI – specifically Google's Gemini – to develop Python code. The resulting code utilizes the TensorFlow software library and its high-level application programming interface, Keras, to build a standard CNN model. After loading the data and configuring the proper directories within Google's Colaboratory, training could begin, and it operates as follows.

First, the program separates the data into training and validation sets, leaving aside 20 photographs for testing.[6] It then begins the formal training phase, performing several epochs, or iterations through the training photographs. As explained above, during a single epoch the model iterates through each image in the training set, classifies it as 'contains VAD' or 'does not contain VAD,' and adjusts its algorithm based on its performance. After 'learning' from the training set, the model of the current epoch is applied to images in the validation set. Its performance is then evaluated by calculating its accuracy – the proportion of images it classified correctly – and its loss – the average amount by which the model's predicted outputs differ from the actual classification.

Once the training phase was complete, the trained model was applied to a new set of images – the test set. As expected given our data limitations, the resulting output is unimpressive: the model performs slightly better than a random classifier. We can now address those limitations in detail, with an eye to paving the way forward.

7.5 LIMITATIONS & FURTHER WORK

Despite many hours of collection and sorting, our data remains too limited in both quantity and quality.

First, quantity: we simply lack enough photographs to train the CNN. While required numbers may be particular to this project – we made no attempt at any such mathematics or algorithm – recommendations typically range in the thousands of images. As previously explained, our dataset contains fewer than 500 photographs; so, even were every image useable (and, in a moment we will explain why they were not), that number is just too small. Thus, any practically useful model would require much more training data, which will require greater efficiencies in collection and processing.

Second, quality: our dataset exhibits at least two significant quality limitations. First, the photographs lack *consistency*: homes naturally vary greatly in size and typology, and we surely have too few of each 'type.'

[6] This test set is evenly split between the two categories of 'contains VAD' and 'does not contain VAD,' with that dichotomy being a human observer classification.

Moreover, even photographs of the same *type* of house differ widely in perspective, angle, and lighting conditions – some videography was conducted in early evening, for example, and therefore the resulting stills either have drastic shadowing or, on the other side of the street, dramatic lens flare that obscures much of the image. Finally, each image contains different combinations of non-house objects, such as vehicles, animals, people, and vegetation. Often, these objects obstruct appreciable portions of the home, further complicating model training.

Critically, these complications don't just hinder the computer model – and this point is fundamental to this work, and must be seriously considered moving forward: the model is of course dependent upon human-classified photographs, either 'contains VAD' or 'no VAD.' Any such visual classification is highly subjective, and, in our case given project constraints, the classification had to be made rather quickly. It is a classification that might not only be wrong by particular objective assessments, but it is a classification that can be value laden and pushed by both known and unknown biases. There is not – and seemingly cannot be – any single definition of what constitutes VAD. So, not only may the determination vary from person to person, but – and this is huge – even a single human 'judge' may offer rather wildly inconsistent judgments, despite all honest attempts and good intentions. If so, as for the neural network, it's garbage in, garbage out.

Think on it like this: if one wishes to train a CNN to identify photographs 'containing a dog' and 'not containing a dog,' there will be little debate whether each photograph in fact contains one of those furry companions – and, when there *is* any such debate, that photograph can be tossed. That is hardly the case when it comes to VAD homes, for, without much more, deterioration is in the eye of the beholder.

So, moving forward, a practical classification effort will require a well-articulated definition of VAD, establishing – to every extent possible – objective, consistent visual criteria. And those criteria, and hence which persons are best suited to apply them, will critically depend upon the precise goal of the project. In other words, what does one aim to *do* with resulting classifications? For example, one might aim to identify structural issues that are problematic but could be helped by a 'stitch in time,' in order to best deploy funds for repair. Or, one might aim to identify issues so severe that the property is a good legal candidate for condemnation proceedings, then requiring the specifics of that local law. Or, one might simply aim to identify homes that a particular viewer personally considers unsightly or undesirable – as for use in some sort of real estate home search. With a different goal comes different project design, including whether the human classifier needs to be (or include) a contractor, a lawyer, or a member of a particular citizenry, or even perhaps ought to consist of a diverse citizen 'jury' of richly differing demographics and life experiences.

In short, VAD management is well known to be incredibly complex, and while a neural network might help – and then either a network using visual imagery like our own or one basing judgments on various numerical designations – much good work remains.

8 Reflections on AI and Its Emerging Role in the Real Estate Industry

Author: Nathan Exum

8.1 Brief Introduction to AI Agents

An AI agent is a software component which will often observe data, and reasoning about objectives, and make autonomous actions to achieve specified goals. Unlike traditional rule-based scripting programs, AI agents are able to handle ambiguity, adapt to new information and scenarios, and can integrate multiple tools or workflows into a single system. For real estate, AI enables faster data integration, smarter decision support for property management, and proactive identification of issues- transforming how cities like Tulsa allocate resources and respond to blight.

8.1.1 n8n: A Platform for Building Agents

n8n is an open-source, node-based workflow automation tool. Each "node" performs an action—calling an API, running code, or writing to a database—and nodes are linked to form reliable pipelines. When combined with an AI "Agent" node, n8n can dynamically choose next steps, loop over data, and invoke multiple workflows, making it ideal for deploying real-world AI agents without extensive engineering overhead. Advantages of n8n include:

- Visual design: No-code and low-code development makes n8n more accessible and user friendly.
- Flexibility: Custom JavaScript/Python logic via function nodes makes n8n a viable choice for experienced users.
- Extensibility: Integrates with hundreds of already existing and future APIs and self-hosted instances.
- Auditability: Full execution logs and retry mechanisms make troubleshooting a breeze.

Types of AI Agents in Real Estate There are many types of AI Agents which can help for an unlimited amount of usage cases, but there are four which are the most notable:

1. Assistive (Copilot) Agents which guide users through data queries or forms, where humans remain in control.
2. Workflow Agents, which automate end-to-end tasks such as sending reports, updating records, triggering notifications, or sending emails.
3. Domain-Specific autonomous agents, which are very customizable for real estate tasks, e.g., permit tracking or risk scoring with minimal human input.

4. Finally, multi-agent systems, these allow for agents to be combined into a team specializing in data ingestion, analysis, and intervention recommendations, collaborating like city departments.

8.2 Example Workflows

Not all agents have to be inherently complex, sometimes very simple agents which can automate mundane tasks are some of the most useful. A great example of this is a simple AI Chat Agent which I created that can lookup pre-determined parameters about any address. For example, I fed my own address into this agent and it returned my parcel ID "36540-94-02-16230", my neighborhood "Rose Dew" it found that it was last sold on 1/29/2008, it also found that no renovations or permits of any kind have been issued for my home within the last 5 years. I also created a mapping agent for blight visualization, this will allow me to input a list of addresses e.g. my list of residential sewer plug data, and it can geocode all addresses, compute density by region, neighborhood, and ZIP code, and finally with the right data generate a heat map highlighting blight clusters.

8.2.1 Sewer plug data research and how Agents served useful

Earlier in the summer I also analyzed Tulsa GIS Records and did research on permanent sewer plug permits (2018- 2025)(City of Tulsa Public Works, 2025). I found that while it was a very strong indicator of blight, most properties in the dataset I compiled required less than $10,000 in repairs each, making many units viable candidates for intervention. The yearly trends show that permits peaked in 2023 but began a downward slope in early 2025; this trend often precedes visible blight as it's not something easily observable to outsiders looking in on the situation. My mapping agent found that north Tulsa and midtown saw the highest density of permits, which correlates with lower property values and aging infrastructure.

8.2.2 Blight Detection Workflow System

This is a multi part system that was primarily developed by Gijs who built a blight-risk scoring agent, and Nat who created a blight early warning system. (See Section 9 for more details.) I created a third agent which aggregates their data and compiles it into a portfolio where it can be sorted and tracked over time. By integrating this agent into Nat's, we are able to identify high and medium-risk properties and then segment them into batches of manageable sets of data for inspections or outreach. We can also autonomously assign blight interventions by assigning inspections for high-risk properties and outreach letters for medium risk properties, we can then estimate the impact or the likelihood of blight prevention from the intervention. Finally, we can also track the history of the various addresses by optionally logging the interventions in a supabase table. To show how these workflows operate we can feed data such as the images which we took around neighborhoods primarily in North Tulsa which were found very likely to contain blight, and see how the workflows sort through the data and act accordingly.

8.3 Insights Discovered Through Work With IQLand

Over the summer I also worked as an intern for IQLand primarily under CTO Vishigan Ratnaswamy. There I worked with and discovered many ways how more complex AI techniques can play a role in detecting blight. Computer Vision Vision language models can be used to detect property condition signs from street-level imagery. NeRFs (Neural Radiance Fields) can generate 3D reconstructions of building exteriors from multiple 2D images to allow for a more accurate deterioration assessment. Finally, machine learning pipelines can be used to train models to predict blight progression based on combined tabular and visual data.

8.4 Conclusion

AI agents, especially when built on flexible platforms such as n8n, are revolutionizing real estate analytics and city planning without many even noticing. By automating some of the aforementioned tasks like data aggregation, risk scoring, visualization, and intervention matching, these agents help cities move from reactive blight management to proactive, data-driven preventative strategies.

9 AI Workflows

Authors: Gijs Hovius and Natalie Maldonado

9.1 Understanding AI Agents

An AI agent is "a software component that has the agency to act on behalf of a user or a system to perform tasks" (Anthropic PBC, 2024). While the term "AI agent" can sometimes feel overused or buzzword-heavy, at its core, it simply means a system that can observe what's happening, make decisions, and act—all, ideally, to help us work smarter, not harder (Bawcom et al., 2025).

AI agents are different from the simple "automations" or rule-based programs that have been around for decades. Instead of following a rigid script, agents are built to handle ambiguity and make informed choices in dynamic settings. In Tulsa, as in cities across the country, leaders are looking for practical ways to leverage these advances to address long-standing civic challenges like neighborhood blight, data bottlenecks, and the ever-increasing complexity of city planning.

9.1.1 Core Characteristics of AI Agents

Borrowing from McKinsey and Anthropic's research, the best way to understand an AI agent is as a digital colleague-one that observes, reasons, acts, and improves:

- Observation: AI agents take in information from databases, documents, or even live sensors (Anthropic PBC, 2024).
- Reasoning: Using advanced models (like ChatGPT or Claude), the agent analyzes context, interprets goals, and decides what should happen next (Bawcom et al., 2025).
- Action: Rather than just recommending a step, the agent can actually do something—update records, send a report, launch a process, or ask a follow-up question (Bawcom et al., 2025).
- Feedback and Learning: Agents can adapt over time, learning from successes and mistakes (Anthropic PBC, 2024).
- This combination of abilities makes agents powerful in fields that demand speed, accuracy, and flexibility—like city planning, business operations, and customer support (Bawcom et al., 2025).

9.1.2 Types of AI Agents

AI agents come in a variety of forms, each suited for different roles:

- Copilot or Assistive Agents: Think Microsoft Copilot or ChatGPT in its "helper" mode—these agents help individuals get more done but always keep a human in the driver's seat (Anthropic PBC, 2024).
- Workflow-Oriented Agents: These orchestrate and automate sets of tasks—like sending weekly reports, updating records, or handling requests from start to finish (Bawcom et al., 2025).
- Domain-Specific Autonomous Agents: These are specialized agents, often custom-built for a field, like city permitting or real estate, and can handle more complexity with less human oversight (Anthropic PBC, 2024).
- Multi-Agent Systems: Teams of agents work together, each with a specific role, collaborating much like city departments on a large project (Silfverski"old, 2025).
- Collaborative Agents (Flows): These agents strike a balance—doing much of the heavy lifting but bringing in a human for approvals, tricky decisions, or quality checks (Bawcom et al., 2025).

9.2 When Are Agents Useful?

Research by Anthropic and McKinsey emphasizes a critical point: AI agents are most valuable when a task is too big or complex for a simple script, or when the path from A to B isn't always the same (Anthropic PBC, 2024; Bawcom et al., 2025). For example, when handling unpredictable public requests, combining data from different sources, or flagging exceptions that need a trained eye. On the other hand, for very predictable, repetitive tasks, simpler automations (without "agentic" features) are usually faster and more reliable (Anthropic PBC, 2024).

From Anthropic's practical guide:

- Use an agent when the path to a goal is unknown or varies
- Avoid agents for predictable, short tasks where simple workflows or single LLM calls will suffice

Agents are powerful when you need: access to multiple tools and sources, flexibility to replan mid-task, and human–AI collaboration (Anthropic PBC, 2024).

9.2.1 Common Agent Architectures

- Multi-Agent: Multiple agents, each with a clear responsibility, working together on more sophisticated tasks (Silfverski"old, 2025).
- Evaluator-Optimizer Loop: One agent produces an answer; another reviews, critiques, or improves it—much like a supervisor reviews an employee's work (Bawcom et al., 2025).
- Orchestrator-Worker Model: A central "manager" agent assigns tasks to "worker" agents and collects results—mirroring how city project leads might delegate assignments (Bawcom et al., 2025).
- Single-Agent: One agent with many tools. Great for straightforward processes but can become overwhelmed in complex environments (Silfverski"old, 2025).

9.3 Objective

The City of Tulsa faces a daunting challenge: reduce the number of blighted and nuisance properties by 2028. Blight doesn't just affect property values; it impacts public safety, quality of life, and the city's overall economic health. The scope—tens of thousands of records, multiple data sources, evolving policies—demands more than human effort alone.

Our approach to this problem is pragmatic, and people centered. We wanted a system that could:

1. Process large volumes of property and nuisance data automatically
2. Surface urgent cases for city staff to review and act on
3. Provide leaders with clear, up-to-date dashboards for decision-making

At every step, we've kept humans "in the loop"—not replacing jobs but making the tough jobs easier and more impactful (Windsurf, 2025).

9.4 What is n8n?

n8n ("node-node") is an open-source platform for workflow automation. If you've ever built a LEGO set, you already get the idea: each "node" in n8n is like a block, performing a specific action read a spreadsheet, call a city database, send an email, or run an AI model. By linking nodes together, you build powerful digital assembly lines

We chose n8n because it allowed fast prototyping with both no-code and full-code capabilities, could be hosted locally (important for data control and privacy), it integrates well with external APIs and services, and it supports custom logic via "Function" nodes using JavaScript.

9.4.1 What Are Workflows and How Did We Use Them?

While AI agents perform intelligent tasks, they require a structured system to feed them information and capture their outputs. These systems are called workflows.

A workflow is a repeatable sequence of steps, often automated, that moves data from one stage to the next like an assembly line for digital tasks. For example, a workflow might retrieve records from a database, clean and reformat the entries, and send them to an AI agent. It ensures the entire process happens reliably, quickly, and without manual intervention.

Workflows matter because:

- They scale: You can process large volumes of data automatically.
- They reduce errors: Automation minimizes inconsistencies and manual effort.
- They connect systems: Workflows can pull from APIs, spreadsheets, and databases and merge it all into one usable format.
- They keep things transparent: Every step in a workflow can be audited, logged, and updated over time.

To build and run workflows, we used n8n, a visual workflow automation tool. It's open source, highly customizable, and designed to integrate with both structured data sources and generative AI tools.

9.5 Workflow 1: Blight Risk Scoring Workflow

Purpose: Agent 1 takes raw property data and turns it into a single blight risk score, along with an explanation of why that score was given. Even though city datasets include lots of information like code violations and ownership, they don't say how likely a property is to be blighted. This workflow fills that gap by making the risk clear and easy to understand.

Why It's Useful:

- Transforms Data into Insights: Converts complex property data into a single, interpretable risk score, moving beyond mere lists of violations or historical records.
- Objective and Consistent: Applies standardized scoring logic to all properties, removing subjective judgment and ensuring every property is evaluated equally.

- Transparent Explanations: Each risk score is paired with an explanation, highlighting the specific factors influencing the risk level.
- Prioritization Support: Provides estimated repair costs with each risk score, making it easier to focus on properties where repairs are most urgent or will have the biggest impact.
- Reliable Identification: Uses a unique property id to accurately track properties across datasets, even when addresses are missing or inconsistent.

Key nodes used are summarized below and presented visually in Figure 34.

- Trigger Node: Initiates the workflow, either on-demand or via scheduled automation.
- Supabase Node: Retrieves property records from the master dataset.
- Function Node (Data Preparation): Cleans and formats data fields to ensure consistency for downstream processing.
- Function Node (Risk Scoring): Implements the scoring logic, aggregating indicators into a total risk score.
- AI Agent Node: Analyzes the structured property data, generates a risk explanation, and estimates repair costs.
- Function Node (Output Parser): Converts AI-generated text into structured JSON fields for reliable storage.
- Supabase Node (Results Update): Writes the final risk scores, explanations, and repair estimates back to the database for reporting and analysis.

9.6 Workflow 2: AI Monitoring, Tracking, & Email Report

Purpose: Workflow 2 establishes a comprehensive, intelligent monitoring and notification system specifically designed to tackle the challenges currently facing Tulsa's property inspection and management process. Presently, Tulsa city staff manage property cases primarily based on public submissions, which are handled without a structured system to prioritize severity or urgency. The absence of a centralized tracking database makes it nearly impossible to monitor the progression of blight conditions over time, often resulting in delayed interventions and wasted resources on less urgent cases.

This workflow directly addresses these critical gaps. By continuously monitoring properties classified with moderate (50%) to severe (80%) blight risk scores, the AI system automates prioritization, ensuring immediate visibility of high-risk properties to city staff. Regularly scheduled email reports—customizable based on user preference—highlight only the most critical properties (80%), providing clear, concise, and actionable information. Staff can then quickly validate and confirm properties, which are automatically saved to a secure, structured, and timestamped database for ongoing tracking and collaborative management.

Why It's Useful (and Transformative): The implementation of this workflow represents a significant advancement in property management practices for Tulsa, transforming a traditionally reactive and manual process into a proactive, data-driven system.

Its benefits include:

- Automated Prioritization: Ensures limited staff focus on the most critical cases by risk category. Currently, the city lacks an objective method to evaluate the severity of reported blight cases. This workflow introduces an AI-powered risk classification system, automatically assessing and categorizing each property based on clearly defined severity thresholds.
- Historical Tracking and Analysis:Previously, no systematic method existed for tracking the progression of blight conditions. The automated and secure database implemented by this workflow allows the city to maintain a historical record, enabling staff to identify trends, monitor deterioration rates, and predict when moderate-risk properties might escalate to severe cases.
- Regular and Structured Monitoring: Instead of relying on sporadic public submissions or random inspections, the workflow provides ongoing, regular assessments of property conditions, enabling proactive interventions. This consistent monitoring reduces the likelihood of properties deteriorating unnoticed, ultimately decreasing long-term remediation costs and preserving neighborhood stability.
- Enhanced Collaboration and Accountability:With an organized database that timestamps each property's evaluation and tracks ongoing staff notes, the system significantly enhances transparency, accountability, and collaboration among city staff. It facilitates informed decision-making and effective communication among teams, significantly reducing the likelihood of cases falling through the cracks.

Key nodes used in Workflow 2 are summarized below and presented visually in Figure 35.

- Spreadsheet Node & Supabase: Efficiently updates, imports and exports property datasets.
- Function Node: Cleans and standardizes textual data, ensuring consistency and accuracy in property records.
- AI Node: Applies natural language processing to accurately categorize blight severity, greatly enhancing the city's ability to objectively assess property risks.
- Notification Node: Automatically generates timely email alerts, directing staff attention immediately to critical properties needing intervention.

By introducing an AI-driven monitoring and notification system, this workflow marks a transformative leap forward in Tulsa's ability to manage property blight. It addresses longstanding systemic gaps by prioritizing critical interventions, establishing a clear, historical record of property conditions, and enabling the city to transition from a reactionary approach to proactive and strategic property management. This innovation not only maximizes the efficiency of limited city resources but also significantly enhances the effectiveness and responsiveness of blight management efforts citywide.

9.7 Workflow 3: Multi-Source Data Aggregation & Portfolio Tracking

Purpose: Workflow 3 (Figure 36 systematically integrates property data from diverse city sources into a centralized master dataset, laying the groundwork for targeted property interventions. By aggregating essential information such as city code violations, property tax and ownership records, and publicly reported property issues, this workflow provides a comprehensive, unified view of property conditions across Tulsa. This unified dataset seamlessly connects to the Portfolio Tracking workflow, which strategically manages and tracks interventions. This workflow would also be building on Workflow 2's identification and initial triage of properties with blight risk scores 50% (medium) and 80% (high).

How It Works: Data Aggregation and Cleaning

Workflow 3 continuously pulls property data from multiple city databases, including, but not limited to:

- City code enforcement records
- Property tax and ownership databases
- Citizen-submitted reports and public complaints

The workflow meticulously cleans, standardizes, and merges these datasets into a master dataset, removing duplicates and resolving data inconsistencies to ensure accuracy and reliability.

Portfolio Tracking and Intervention Assignment: Once data aggregation is complete, the Portfolio Tracking workflow is triggered to:

- Identify High-Risk Properties:Automatically retrieves properties marked as high-risk (50% blight risk scores).
- Batch Management: Divides the high-risk property list into manageable, actionable groups for city staff.
- Assign Targeted Interventions:Determines interventions based on specific risk thresholds:
- Properties with a risk score 80%are scheduled for site inspections.
- Properties with scores <80% and >50% receive proactive outreach letters.
- Calculate Potential Impact: Determines the estimated numeric upside potential from interventions.
- Historical Data Tracking: Updates intervention details (plan, date, and calculated impact) back into the master dataset and inserts structured records into an "Interventions" database table, tracking each property's status over time (e.g., Pending, Complete, Incomplete).

Why It's Transformative

Unified Intelligence: Merges previously siloed data into a comprehensive view, empowering strategic, citywide planning.

Quantified Impact: The metric translates risk scores into actionable upside estimates, guiding resource allocation and developer engagement.

Full Auditability:Text fields and interventions records provide a transparent history of agent decisions, enhancing accountability and enabling continuous process improvement.

Reflection Workflow 3 is a foundational structure of our AI-powered property management system, transforming previously fragmented and reactive processes into a streamlined, proactive, and accountable approach.

9.8 Limitations and Considerations

Despite their power, AI agents are still emerging and carry trade-offs:

- Latency: Agents often take longer to complete tasks due to their iterative nature
- Cost: Each tool call or model run has a cost, especially in long agentic loops.
- Control and Debugging: Agents need clear tool interfaces and strong logging to avoid compounding errors.
- Trust and Adoption: Users must understand and trust what the agent is doing a key point McKinsey highlights in enterprise deployments.

Human Thoughts Along the Way: As Windsurf's 2025 industry review notes, much of the hype about "AI agents" misses a crucial truth: human oversight and collaboration remain essential for building trust and ensuring real-world value. We've found the best results come when city staff and digital agents work hand-in-hand—automation handling the repetitive grind, humans guiding, correcting, and interpreting the results.

Quoting McKinsey's experts: "The companies that derive the most value from AI will be those that create trust with their customers, employees, and stakeholders. People must trust AI enough to hand over tasks. Companies' ethical decisions must be rooted in the values unique to each organization and the values of a society that places humans at the center of the AI ecosystem."

9.9 Conclusion and Next Steps

AI agents represent a new way of thinking about automation: not just doing things faster but doing them smarter. They turn models from content generators into decision-makers that can plan, act, and learn. They also blur lines between software and collaboration: agents don't just replace tasks — they change workflows. As adoption grows, it will be important to balance innovation with safety, transparency, and human oversight. In summary, what we've built is not just a technical solution, but a foundation for smarter, more responsive city management:

- Cleaner, richer data: Reliable records enable better analysis and action.
- Faster response: Staff are freed from manual drudgery to focus on meaningful work.
- Smarter decisions: Dashboards and AI triage put real-time insights at leaders' fingertips.

- Scalability: These workflows can grow as Tulsa's needs grow—incorporating new data, new tools, and new challenges

The progress described here relies on partnerships—between city staff, IT professionals, outside experts, and the citizens of Tulsa. More (and better) data leads to better outcomes; but more importantly, it takes ongoing teamwork and transparency to build the trust and habits needed for lasting change.

AI agents represent the next step in digital transformation—helping cities like Tulsa serve their citizens more effectively, make better use of resources, and rise to meet new challenges. Drawing on best practices from industry leaders like Anthropic, McKinsey, and Windsurf, we've built a set of workflows and tools that combine the strengths of automation and human judgment.

As our research progresses, future enhancements will further elevate Tulsa's blight management approach. Planned research directions include:

- Enhanced User Interface & Dashboards: Developing intuitive dashboards and interactive visualizations for city stakeholders to efficiently monitor and respond to evolving property conditions.
- Expanded Geospatial Analysis: Employing advanced spatial analytics to visualize blight patterns, enabling more precise targeting of interventions at the neighborhood and citywide levels.
- Refining our Workflows: We believe it's important to continue refining and improving our workflows as we receive more feedback from real estate professionals.

9.10 FIGURES

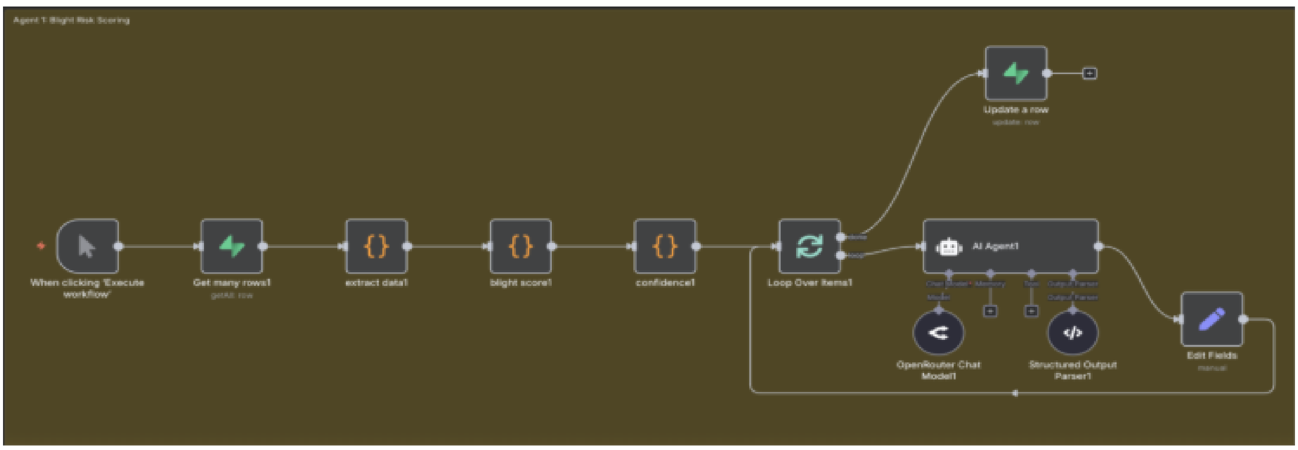

Figure 34: Blight Risk Scoring Workflow

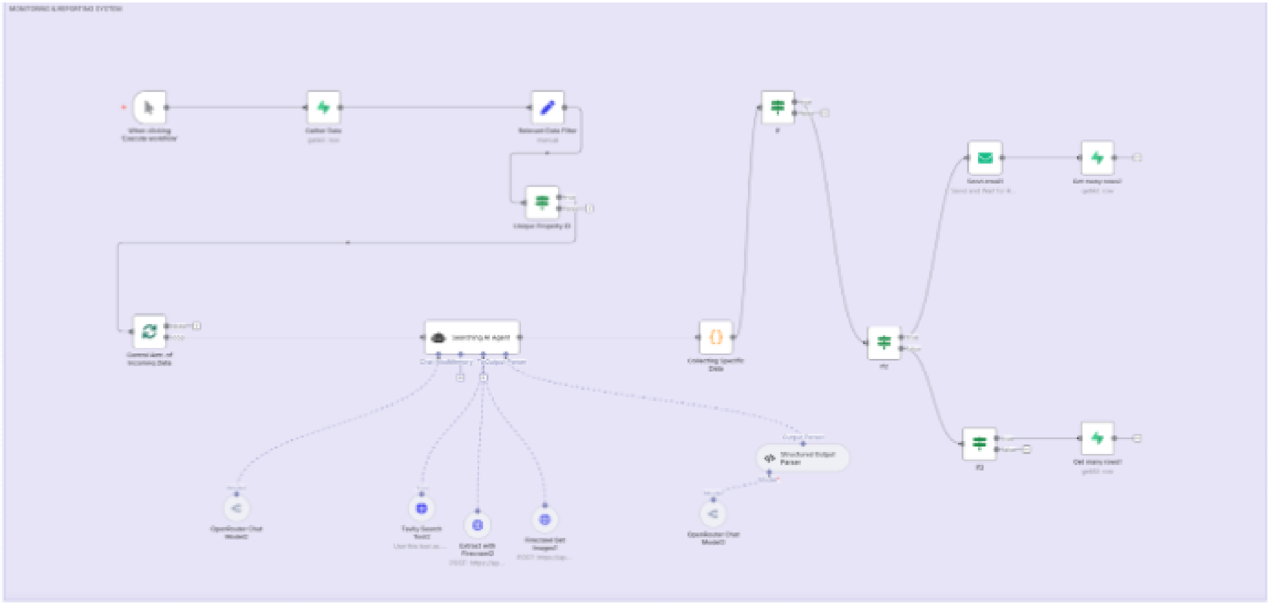

Figure 35: AI Monitoring, Tracking, & Email Report

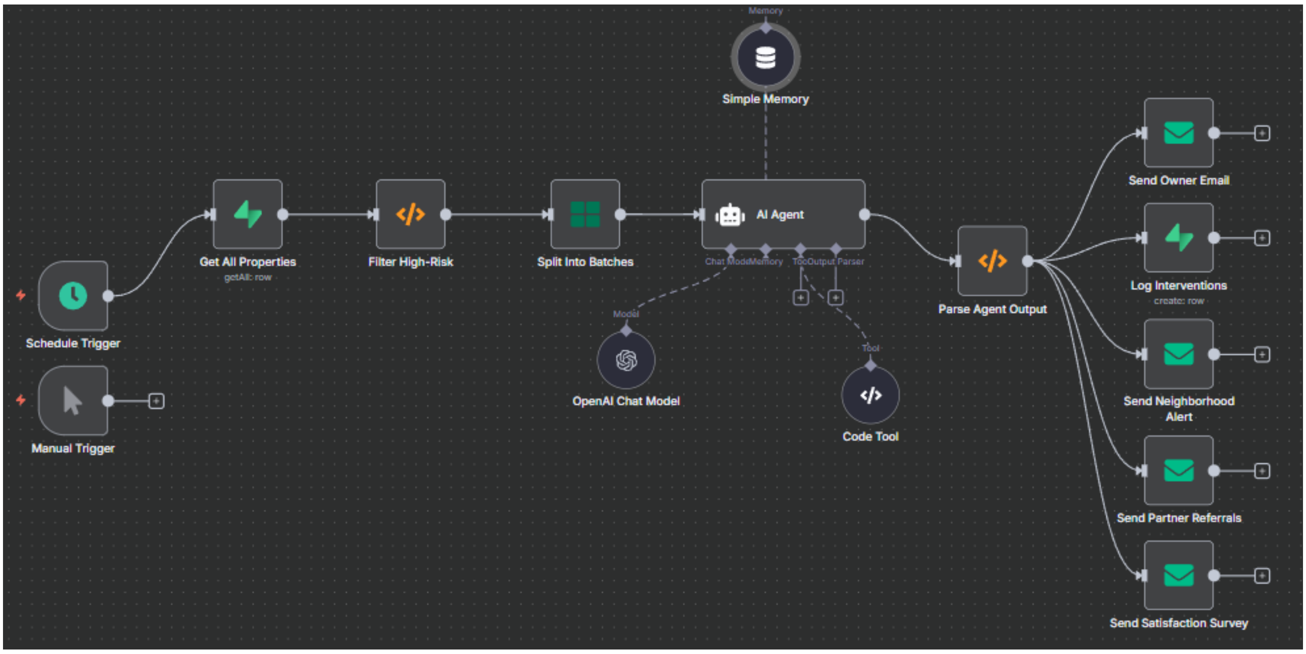

Figure 36: Multi-Source Data Aggregation & Portfolio Tracking

10

Conclusion

The comprehensive analysis of housing challenges and opportunities in the Tulsa Metropolitan Area provides critical insights into the multifaceted issue of affordable housing. This collaborative effort by University of Tulsa undergraduate scholars and local high school junior scholars, under the guidance of Dr. Meagan McCollum and Dr. Cayman Seagraves, has yielded valuable findings and strategic recommendations for addressing Tulsa's housing needs.

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A Appendix

A.1 Appendix

A.1.1 Home Building Kits

Panelized Kits

Definition[1,2]:	Panels comprising the roof, floor, and (exterior) walls of a house are constructed in a factory and then delivered to a construction site for assembly into a house
Cost Comparison:	Panelized Home Kit: $40-$60/sqft[2] Money can be saved via: shorter building times[1,3], fewer delays while building[1], economies of scale make panels cheaper to produce[3], pre-made plans and designs[3] Money can be lost via: transportation costs[3], unexpected carpentry costs[3]
Advantages:	Cheaper and faster than stick-built, fully customizable[1], quality/materials can be chosen (very high quality is possible)[1,3], environmentally friendly (ICC 700 National Green Building Standard-recognized)[1,2,4], factory production minimizes elemental exposure[1,3], precise measurements[3,4], reduced waste[1,2,4], cheaper heating and cooling costs[1]
Disadvantages:	Logistical challenges (large trucks, cranes, rescheduling, etc.)[3], high quality is not a guarantee[3], potential assembly issues[2,3]
Timeline[1,3]:	Panelized structure (equivalent to stick-built structure) can be assembled in days or weeks, instead of months, but every other aspect of construction takes just as long (foundation, interior walls, housing finishes, etc.)
Design Limitations[1,3]:	None. Any style of house design can be panelized using software, though pre-planned designs provide the most savings
Resale Value[4]:	Uncertain currently as market is still emerging and maturing, but appreciation, given adequate maintenance and upgrades over time, is a reasonable expectation
Example Companies:	Redstone Engineered Home Systems, Inc.[5] and Green-R-Panel[7]

Table 7: Panelized Kits

Modular Kits

Definition8:	Large sections of a home are built in a factory. Once complete, they are transported to a construction site where they are brought together and attached to a foundation to make a finished home
Cost Comparison10:	Unit-only Cost: $50-$100/sqft Total Cost: $80-$160/sqft Notes: "Modular home building costs 10 to 20 percent less than stick-built homes"
Advantages8:	Environmentally friendly (ICC 700 National Green Building Standard & reduced waste), lower heating and cooling costs, "weather delays, missing materials and subcontractor no-shows are all but eliminated, saving time and money", "Prefabricated homes in an off-site factory setting allows for more consistent quality due to uniform construction processes, training techniques and inspections. All system-built homes are inspected by an independent, third-party home inspection agency before leaving the factory. Once on site, they are again inspected, this time by a local building inspector. This modular housing meets and often exceeds all requirements of locally-adopted building and fire codes."
Disadvantages9:	"Local zoning restrictions dictate where modular homes can go, and passing this hurdle is often the hardest part of the whole process for many people." "Size is arguably the most critical limiting factor of any modular home...each section can't exceed the dimensions that are safe on the road"
Timeline:	"A typical modular house can be move-in ready in about three months"8 "Modular home[s] are built 30% to 60% faster [than stick-built homes]"10
Design Limitations8:	None. "While most manufacturers have a portfolio of home plans to choose from, computer-assisted design (CAD) allows limitless possibilities and customization when planning a new modular home."
Resale Value10:	"[Modular homes] appreciate in value like site-built homes"
Example Companies:	Clayton Manufacturing9, Champion10, Pratt10, Kent10, Huntington10

Table 8: Modular Kits

Log Cabin Kits

Definition:	"Log home kits are log packages that contain everything that you need to erect your log home right from the get-go. However, it's important to note that a kit only helps you build the basic skeleton of your house and not the overall finished home. You will have to spend additional resource[s]...and money to get the flooring, cabinetry, and other finishing elements done."11 "Based on most log home kits they typically include log wall systems, a roofing system, windows and doors."11 "Kits vary from an unfinished shell to a fully-assembled cabin"12
Cost Comparison:	"Building a log home using a kit might cost you 1/3rd of the price of buying a finished home, depending on the package."11 Three Types12 • Shell-Only (exterior and uncovered floors): $50-$80/sqft • Dry-In (exterior and basic interior structure): $70-$130/sqft • Turnkey (move-in ready cabin, including some built-in furniture): $120-$200/sqft
Advantages11: quick assembly (days)	Potential for construction experience
Disadvantages:	"One major disadvantage of a...house built with a kit is its [sic] not finished. Installing the flooring, electrical materials, plumbing, etc. will eventually add up and take your costs higher then you may have initially planned for,"11, difficulties faced by inexperienced craftsmen11, lots of maintenance14
Timeline11:	The elements of the kit could be assembled in days (this timeframe does not include installing all of the additional elements necessary to upgrade a log cabin kit into a livable home)
Design Limitations11:	"Depending on the design and customization that you are looking for with your log home you may be limited to the design options. Many companies have set plans and designs for you to choose from and don't allow for some customizations in their log home kit packages."
Resale Value13:	While valid "comps" are hard to find, making appraisals of log cabins difficult, log cabins often include many features deemed upgrades compared to regular stick-built housing, creating potential for increased demand among certain buyer pools
Example Companies:	Amish Built Cabins6, Southland Log Homes15, LogHome Mart16, Honest Abe Log Homes17

Table 9: Log Cabin Kits

SIP Kits

Definition:	"SIP panel home kits consist of Structural Insulated Panels (SIPs), an advanced building material that synergizes insulation with two structural facings, typically made of engineered oriented strand board (OSB)."[20] In addition to exterior, roof, and floor panels, SIP kits can include interior framing[19]
Cost Comparison[23]:	Innova Panel home costs used as an example: $65-$105/sqft
Advantages:	"Key advantages of SIP panel home kits include their superior insulation, speed of assembly, and environmental benefits"[20], "The advantages of SIP panel home kits are multifold, emphasizing energy efficiency, lower heating and cooling costs, and a reduced carbon footprint"[20,21], better air quality and less necessary labor[18,21], "SIP panel walls are proved to be stronger than 2×4 and 2×6 framed homes,"[22], "A SIP panel home uses LESS wood and helps preserve natural resources,"[22]
Disadvantages[20]:	Upfront cost, alterations after construction are difficult, specialized labor, limited availability
Timeline[20]:	Quicker than stick-built (see above)
Design Limitations[18]:	None. Panels can be adapted to fit any building design, even some commercial ones
Resale Value[24]:	"Energy-efficient homes with superior indoor comfort and durability often have a higher resale value. SIP homes are increasingly attractive to buyers looking for sustainable, cost-effective housing, making them a strong investment."
Example Companies:	Innova Panel[23], My Barndo Plans (Barndominiums)[19], CloudHaus[88]

Table 10: SIP Kits

Timber Frame Kits

Definition25:	"A timber home is a kind of house that uses a frame structure of large posts and beams that are joined with pegs or by other types of decorative joinery. Almost always, the walls of the structure are positioned on the outside of the timber frame, leaving the timbers exposed for visual effect."
Cost Comparison:	"Timber frames can be as much as 15% more costly when compared to traditional buildings."27 "...the main thing to consider about cost is your chosen materials."27 "Timber frame homes are generally more expensive to build than stick-built homes."28
Advantages:	No load bearing walls necessary25, durable25, fire-resistant25, energy efficient26
Disadvantages27:	High maintenance and potentially more costly than stick-built homes
Timeline27:	"Timber frames can also require more lead time or 8-12 weeks from placing the order to delivery"
Design Limitations25:	Timber is usually exposed, so a rustic exterior should be the expectation, although coverings are possible. Because no load bearing walls are necessary, extremely open floor plans are possible
Resale Value28:	"Timber frame homes appear to be growing in popularity with each passing year. This is the type of home that, if properly cared for, can turn into an excellent investment for most owners. The lifespan of the modern timber-frame house is impressive and the resale value of timber-framed houses is often quite high."
Example Companies:	Woodhouse26 and Hamill Creek Timber Homes28

Table 11: Timber Frame Kits

A-Frame Kits

Definition29:	"An A-frame house is a type of home that is easily identified by its triangular, "A" shaped structure. It has a steep, pitched roof that stretches to the ground on either side of the home."
Cost Comparison30:	Total cost: 100–300/sqft Generally cheaper than stick-built homes because A-Frames are smaller
Advantages29:	"...they may only work best as a vacation home...given their size and other limitations, like lack of storage space,", costly maintenance (especially on the roof), limited space and privacy, sloped walls
Disadvantages29:	"...they may only work best as a vacation home...given their size and other limitations, like lack of storage space,", costly maintenance (especially on the roof), limited space and privacy, sloped walls
Timeline30:	Complete building time is 4-8 months
Design Limitations29:	The following are common, or possibly essential, features of an A-Frame home, or the kit that one can use to build one • "Large windows: A-frame houses often have floor to ceiling windows on the front and back walls. This compensates for the long roof that covers both sides of the home. The best part? The large windows provide a lot of natural light. • Loft-style interior: Since A-frames are triangle-shaped, they typically have a bottom floor and a partial second floor. The size of the second floor is constrained by the steep roof, so it's typically a small, loft-style room. • Steep, triangular roof: The hallmark of an A-frame house is its sloping, triangular roof. • Wood exterior and details: Most A-frame homes have wooden, cabin-like exteriors. This aesthetic is often carried to the interior with exposed wooden beams and wood walls and floors."
Resale Value29:	"Location is an important factor if you plan to sell or rent the property. Resale values vary widely depending on the location. For example, since A-frames are smaller and lack privacy, it will be more difficult to resell the property if you build it in a residential, family neighborhood instead of a remote vacation destination."
Example Companies30:	Nolla, DEN, Lushna, Avrame

Table 12: A-Frame Kits

Tiny Home Kits

Definition:	A package that includes all elements necessary to construct the exterior of a tiny home as a DIY project or by hiring labor31 "Any home that is 400 square feet or less is usually known as a tiny home; most tiny homes sit in the 100-250 sq ft range."32
Cost Comparison31:	"In 2023, a tiny home will run you about $50,000, give or take. That's substantially less than the cost of a regular home at about $298,000, and that is typically when it is fully built." "Buying a kit can save you thousands and cost only $6,000 to $8,000."
Advantages:	Mobility (if on wheels)31, potential to be a temporary solution31, environmentally friendly32, ADU potential33, utility-efficient33, ADU potential32
Disadvantages:	Legal limitations exist as to where and how tiny homes can be used31, difficult to get a mortgage32, no permanent foundation32, dangerous in extreme weather32, very limited space and storage32, no returns; Limited refunds33, kits do not include interior finishing, only the exterior frame33
Timeline33:	Assembly could take a day to a week
Design Limitations32:	Size is finite and incredibly limited. Different and creative aesthetic options exist for both the exterior and interior of tiny homes to maximize space in these small dwellings
Resale Value32:	Low cost to custom order and personalize makes reselling an existing tiny home difficult, though market conditions could change as tiny homes become more popular
Example Companies:	Worldwide Steel Buildings34 and Home Depot35

Table 13: Tiny Home Kits

A.2 Prefabricated Homes

Manufactured Homes

Definition:	Factory-built homes built after June 15th, 1976 that are transported and affixed to a home site after construction36,37 "Modern manufactured homes come in one of three general floor plans: • Single-wide: This is a home built in one long section. • Double-wide: A model that's popular with first-time home buyers, a double-wide features two sections joined together to make a larger home. • Triple-wide: The least common of the three manufactured home models, a triple-wide has three sections joined together to create a larger, more spacious home."38
Cost Comparison:	An average new manufactured home is about 1/3 the cost of an average detached single-family home39 "The average price of a new-construction house in January 2022 was nearly $500,000, according to the U.S. Census Bureau...The average sale price of a manufactured home, as of February 2022, was $128,000, according to the U.S. Census Bureau (exclusive of land cost or other expenses)."37
Advantages:	Minimal construction delays36 and simple maintenance37
Disadvantages:	Stigma36, financing is harder to get. Mortgages are not always an option37 (without land to put the home on, prospective buyers will have to get a personal loan, which comes with a higher interest rate37,39), location restrictions37
Timeline36,37:	Much faster than stick-built homes
Design Limitations36,37,39:	Many aesthetic options exist with a limited variety of interior options, though space is limited
Resale Value36,37:	Appreciation in a manufactured home's value is uncertain, while depreciation is more likely than with stick-built homes
Example Companies:	Oak Creek Homes40, Freedom Homes41, Lifeway Homes42

Table 14: Manufactured Homes

Kit Homes (SEE ABOVE)

- Panelized Kits
- Modular Kits
- Log Cabin Kits
- SIP Kits
- Timber Frame Kits -Frame Kits
- Tiny Home Kits

Container Homes

Definition44:	"A shipping container home is...a living space constructed from a standard shipping container or containers...that is modified to have most of the things you'd find in a traditional house."
Cost Comparison46:	"Shipping container houses vary in cost. For a single container model, average costs are between $25,000 to $80,000. If you choose to use multiple containers in your build, the price goes up, with most multi-container homes costing between $80,000 to $$250,000 to build.[sic]" "factors that can raise the cost include: Deep-cleaning services if buying used containers, Mandatory insulation installation, Maintaining structural integrity if you cut it open, Electrical and plumbing installation, Transporting the box once you buy it, Costs for the land where you'll put your container home"
Advantages:	Recycling potential43, durable and strong44, mobility45
Disadvantages44:	Limited supply, limited space, potentially high temperatures, health hazard potential, zoning/permit uncertainties
Timeline 44,45,46,47:	Container homes are faster to build than stick-built homes
Design Limitations45,47:	Because container homes are modular based on how many containers are used, space comes in small increments, and the lifestyle of residents should match smaller available spaces. The exterior of container homes can mask their industrial nature, but an industrial aesthetic should still be the expectation. Interior spaces can be cordoned off, but because containers are so small, space-saving solutions like those found in tiny homes can be employed.
Resale Value46,48:	Depending on location, container homes can be successful as rental properties, though they also generally retain their value and can even appreciate over time
Example Companies:	Clayton Homes of Grand Rapids45, Bob's Containers49, Backcountry Containers50

Table 15: Container Homes

3D Printed Homes

Definition51:	Huge 3D printers are used to build a house layer by layer with a cement mix
Cost Comparison:	Developers have reported cost savings of up to 30% by using 3D printing tech to build houses51 Non-profits in Austin, TX are already working to build affordable housing using 3D printing for a cost of $99,00 or less per unit52
Advantages:	Sustainable and resilient52, high density and individuality can be achieved52, incredibly low construction times51
Disadvantages51:	Potential for job loss in construction
Timeline51:	The 3D printed shell of a house can be produced in as little as 12-24 hours, though installing utilities and finishing the home will take longer
Design Limitations52:	None. 3D printing technology allows for extensive creativity, modularity, and individuality.
Resale Value:	Too early to tell
Example Companies51:	Citizen Robotics, ICON, COBOD, Kamp C

Table 16: 3D Printed Homes

Hybrid Prefab Homes

Definition 53,54:	A home whose building process combines one or more prefab methods of construction
Cost Comparison:	Cost efficiency is very possible, depending on the specific techniques that are hybridized. It stands to reason that generally cheaper methods will generally produce more economical houses compared to stick-built housing.
Advantages:	Highly customizable, more easily buildable at higher altitudes53, environmentally friendly54, potentially fire-resistant, depending on materials54
Disadvantages:	Complexity, potential transportation issues if modules are incorporated53, minimal time savings if panels are incorporated53
Timeline53:	Assembly of a home's basic structure could happen in as little as a day, but site preparation and interior finishing take longer
Design Limitations:	None. Because prefab options offer so many options and customizations, logic dictates that using these same methods with each other would only offer more options and customizations.
Resale Value:	Resale expectations can reasonably be tied to the individual methods used to build a hybrid home.
Example Companies:	Impresa Modular53, Sander Architects54

Table 17: Hybrid Prefab Homes

A.3 Alternative Materials

Straw Bale Houses

Definition55:	"A straw bale house is made using straw as either a main structural element, insulation, or both. The buildings are constructed by stacking rows of compact straw bales on a strong foundation before sealing with a moisture barrier and outer plaster layer."
Cost Comparison:	"One paper found that straw bale buildings save 40% of construction costs when compared to traditional homes."55 "per square foot, building a straw bale house costs about the same as a similar house made of more common materials."56 "a few green builders are developing straw bale wall systems that are prefabricated, to cut down on costs and labor."56 "Constructing a home out of straw bales: is relatively inexpensive because of the low cost of the raw material"57
Advantages:	Energy efficient55; cheap building material55; low-waste, eco-friendly, renewable, biodegradable construction55; natural disaster resistant55,56
Disadvantages:	Potential permitting difficulties (building codes for straw bale houses may not even exist in some places)55, prone to moisture issues55, no studs in the walls to hang things on55, pest issues55, high maintenance55, financing and insurance can be difficult to get57
Timeline57:	"Constructing a home out of straw bales: tends to go rapidly because the building blocks are simple and large, and require less expertise than conventional building practices"
Design Limitations57:	"Straw bale is used in two basic styles of construction: "Nebraska"-style structures, which resemble Southwestern adobe-style architecture and use the straw for structural support; and post-and-beam construction, with straw-bale infill for insulation. Some structures incorporate both of these styles"
Resale Value57:	Stigma around strawbale homes makes homebuyers hesitant to trust them; the market for strawbale homes is weaker than that of traditional homes
Example Companies:	PSE Consulting Engineers, Inc58 and The Salamander Company59

Table 18: Straw Bale Houses

Earthbag Homes

Definition60:	"Earthbag homes are exactly what they sound like – bags filled with earthen materials stacked to make a house." Superadobe is a subset of Earthbag homes: very long fabric tubes instead of individual bags are filled with soil and coiled to build a house
Cost Comparison60:	"Earthbag homes are inexpensive, with many builders able to use the soil that's on-site to build the home. Bags are usually low-priced in bulk, particularly misprinted bags that companies sell at reduced rates."
Advantages:	Sustainable60,61, exceeds natural disaster resistance requirements60, temperature-regulating60, incredibly environmentally friendly and low-carbon61
Disadvantages60:	Labor-intensive; financing, insurance, and building permits can be more difficult to get than with traditional houses
Timeline63:	"Generally, it can take between 1-8 weeks to complete an earthbag building project, with most projects taking around two weeks."
Design Limitations60:	Earthbag homes often take a hive-like shape when finished, but that isn't always the case. Space is also limited because earthbag homes are only structurally sound up to certain dimensions
Resale Value65:	As an emerging technology, the resale value of earthbag homes is currently unclear, though it may be similar to adobe homes
Example Companies:	BE Structural61 and PSE Consulting Engineers, Inc.62

Table 19: Earthbag Homes

Cob Houses

Definition64:	"A cob house is an earthen structure constructed out of a mixture of clay, sand, and straw."
Cost Comparison64:	"a cob house can save homeowners about 25% compared to the cost of building conventional walls. Implementing reclaimed or secondhand materials can also bring the cost down. Self-building your cob house can save on labor but end up costing you more time, potentially."
Advantages64:	Economical, environmentally friendly, light and accessible materials, DIY potential (lower labor costs), natural disaster resistance (fire and earthquake)
Disadvantages64:	Can't be used for more than one-story without wooden supports, relevant building codes are uncommon in the United States, needs lots of time and labor, potential water issues, permitting difficulties
Timeline64:	"Due to the drying time, it will take around 15 months to complete a cob house."
Design Limitations64:	"They [cob houses] can be shaped into curves or other designs making them very artistically flexible. Cob houses are usually curved with arches and organic shapes...This structure is highly customizable and usually takes on very artistic and unusual shapes. The walls must be arranged to evenly distribute any weight...The placement of windows and doors must be planned out while the walls are being constructed...Traditionally, the roof of a cob house is thatched and made out of natural materials."
Resale Value65:	While this is an emerging technology in the U.S., cob's similarity to methods like adobe could indicate similar resale potential
Example Companies:	PSE Consulting Engineers, Inc.67 and This Cob House66

Table 20: Cob Houses

Rammed Earth Homes

Definition68:	"Rammed earth homes are like building sand castles...the form of the home, which is usually a plywood structure that provides the outline of a wall, is already in place. A cross-grade, or mix, of soils is rammed into the walls, either by hand or machine. When everything is packed tightly, the forms are removed, and what's left is a solid, stable rammed earth wall. Builders ram and repeat until the entire house is built."
Cost Comparison68:	"Rammed earth builder David Easton estimates that a wall system in a rammed earth home can cost about 30 percent to 50 percent more than a conventional wood-frame house, which means the entire home might cost about 5 percent to 15 percent more"
Advantages:	Temperature regulated68, fire resistant68, best in desert environments68, noise reduction69, low maintenance69, pest resistant69
Disadvantages68:	High labor costs, challenges in rainy climates, potential difficulties with permitting, financing, and insurance, especially outside the American Southwest
Timeline70:	"The average sized house (200m2) can have the earth walls completed in around six months, after the concrete slab has gone down. The rest of the build (roof, interior finishing, etc) is comparable to a conventional build. Therefore an average sized rammed earth home may be completed in around four months from the time the plans come out of council."
Design Limitations69:	Rammed earth buildings can be used for residential or commercial purposes in many styles and designs; it is a very versatile method
Resale Value72,73:	A rammed earth home has the potential for higher resale value than a conventional home due to its environmental benefits
Example Companies:	Modern Earth Homes71 and Rammed Earth Constructions69

Table 21: Rammed Earth Homes

Hempcrete Homes

Definition:	"hempcrete...[is] an insulation product that can replace products like fiberglass, rockwool, and foam. Hempcrete is created by combining the hemp plant's stalk...with water and lime"74 "Our unique material is lightweight fibre-reinforced concrete made from industrial hemp fibre and chips. We use material that is proven as a cost-effective and sustainable construction method"75 "To construct a hemp masonry wall, wet hemp mix is placed directly into a timber frame."76
Cost Comparison74:	"although the average hempcrete home is still more expensive than a business-as-usual equivalent, a hempcrete building program at the Lower Sioux Community in Minnesota has shown that it's possible to achieve notable cost savings with the material"
Advantages:	Nontoxic and biodegradable74; fire, pest, and mold resistant74; temperature and humidity regulating74; carbon storage74; climatic versatility76; eco-friendly77; potential for local sourcing77
Disadvantages76:	Labor-intensive; longer construction time; material scarcity; low strength (timber needed to undergird many structures)
Timeline76:	Hemp masonry takes a week to dry and three months to cure
Design Limitations76:	Due to its weakness, hempcrete has limited structural uses, therefore housing designs will need to factor in the need for a load-bearing timber frame
Resale Value:	As of February 2024, the United States was home to less than 100 hempcrete homes.74 It is too early to determine resale value patterns of these homes, though it stands to reason that it would be similar to other alternative building methods.
Example Companies:	Hempcrete Natural Building Ltd75 and youarethecity74

Table 22: Hempcrete Homes

Adobe Houses

Definition78:	"Adobe isn't the name of a specific architectural style, but rather a descriptor for structures constructed using a unique building technique and a specific material—namely adobe bricks, or blocks."
Cost Comparison78:	"The biggest obstacle for many is the cost. Though materials are, on paper, free if you own the land, the lack of qualified adobe construction specialists mean you pay a labor premium to build adobe homes. In Albuquerque...a 2,000-square-foot home might cost $250,000 to build. An adobe home of the same size, built by a contractor who knows what they're doing, would cost $350,000 to $400,000." "Don't be surprised if labor takes up half or more of your project budget or if your costs run four times or more what a stick-frame would cost you. Furthermore, you have to factor in the fact that adobe buildings can take four times or longer to complete, adding to your costs."
Advantages78:	Pest resistant, fire resistant, environmentally friendly, temperature regulating, low-cost materials, more flexible than concrete (better in earthquakes)
Disadvantages78:	Not suitable in wet environments without extra precautions, interior material considerations (wood chunks might have to be integrated to allow for hanging paintings and the like), specialized and expensive labor
Timeline78:	Up to 18 months (6-9 times longer than stick-built)
Design Limitations79:	"On the exterior of Adobe- or Pueblo-style homes, you'll notice an earthy exterior hue (often some iterations of cream, tan, yellow or pink), with a flat roof and rounded edges. It's also common for many of these homes to put an emphasis on the outdoors...Inside, Adobe-style homes focus on a meld of form and function, trading fancier finishes like molding and trim for simplicity and natural elements meant to patina beautifully over time. Wood, tile, brick, and other natural finishes are common, with square windows that are set deep into clay or plaster-covered walls, creating a ledge."
Resale Value80:	Potentially higher than conventional homes
Example Companies:	Sun and Earth Construction LLC80 and Zachary and Sons Custom Homes81

Table 23: Adobe Houses

Bamboo Homes

Definition82:	"Bamboo is green engineering and building at its best. If you prefer wood, but want increased sustainability, bamboo is a green home design material that is not only environmentally friendly but also easy on your wallet. Bamboo homes are attractive and offer many benefits to homeowners."
Cost Comparison85:	Bamboo is a cheaper building material than what is used in conventional houses, however higher maintenance costs can cut into whatever savings are found
Advantages:	Pollution-absorbing82; produces more oxygenated air82; erosion-resistant (works well on the coast)82; flexible82; sustainable82; earthquake, tornado, and hurricane resistant82; fast growing82,83; stronger than steel by weight83
Disadvantages:	Funding difficulties84, potential moisture and heat issues84, no national building standards84, formaldehyde used in treating bamboo84, deforestation used to grow bamboo84, high maintenance costs85
Timeline86:	Constructing a small house will take 3-6 months
Design Limitations:	"Bamboo is flexible so you can bend it without fear of splintering or breaking. It can also be grown into different shapes using boxes or molds. This makes it versatile enough to work for walls, roofs, floors, concrete reinforcement, piping, and even scaffolding."82 Many projects look tropical83
Resale Value85:	"Investing in a house built with bamboo guarantees you a durable and eco-friendly house that's pocket friendly. Although the maintenance cost is high, it pays off in the long run with its unique design and sustainable building materials."
Example Companies83:	Bamboo Living83

Table 24: Bamboo Homes

Timeline for Stick-Built Homes: 7-14 months87