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Neighborhood transformation in a shrinking city: using multimodal large language models to evaluate housing redevelopment spillover effects in Buffalo, New York

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Across the American Rust Belt, post-industrial "shrinking" cities are characterized by sustained population decline and weakened housing markets in the aftermath of deindustrialization. These conditions have produced deteriorating housing stock and constrained private reinvestment, underscoring the need for alternative planning approaches centered on stabilization rather than growth. This study examines the potential of public-private-nonprofit partnerships (PPNPs) in public housing redevelopment to generate neighborhood-level spillover effects in underdeveloped areas of Buffalo, New York. Understanding these dynamics is critical for informing equitable revitalization strategies in legacy cities where traditional market mechanisms have stalled. This study employs a novel methodological framework using street-level imagery and multimodal large language models. Image data collected at two time points, approximately a decade apart, are analyzed to assess parcel- and street-level changes in residential property conditions surrounding the Perry Homes redevelopment site. This approach enables scalable, temporally comparative analysis while mitigating limitations associated with conventional survey-based methods. The findings indicate that nearly 10 times more properties are categorized as "Improved" than as "Declined," reflecting a strong asymmetry associated with an overall positive shift in neighborhood conditions between 2014 and 2025. This improvement spans a spectrum from minor rehabilitation to substantial upgrades. These patterns suggest that anchor-led PPNP investments can contribute to localized housing stabilization, albeit unevenly. The results demonstrate the utility of generative AI for evaluating urban redevelopment impacts and provide empirical evidence that strategically structured PPNPs can foster incremental neighborhood recovery. This research contributes methodological innovation and policy-relevant insights for stabilizing shrinking cities without reliance on population growth.

KEYWORDS
housing redevelopment spillover effects, multimodal LLM, neighborhood transformation, private investment, shrinking city

1 Introduction

Shrinking cities in the U.S. Rust Belt, such as Buffalo, NY; Detroit, MI; Cleveland, OH; and Pittsburgh, PA, have experienced long-term population decline since deindustrialization began in the mid-twentieth century. This trend has been accompanied by broader economic restructuring and weakening housing markets (Silverman et al., 2013). These dynamics have produced widespread housing vacancy, a deteriorating public housing stock, and fragile private markets that cannot support reinvestment without external intervention (Morckel, 2014; Yin and Silverman, 2015; Yin et al., 2024). These conditions are exemplified in Buffalo's inner-city neighborhoods, which are concentrated on the city's east side. The historically underdeveloped *East Side* neighborhoods have faced decades of compounding challenges, including aging infrastructure, the clustering of public housing, housing disrepair, elevated crime rates, and limited access to essential resources such as affordable food, healthcare, and safe spaces for physical activity (Taylor, 2020; Yin et al., 2022; Yin et al., 2024). These conditions have been attributed to structural inequality and racial segregation that have been produced and reproduced by institutional decisions to the detriment of the East Side of Buffalo (Silverman, 2026). In large part, structural inequality and racial segregation on the East Side of Buffalo mirror conditions identified in other U.S. cities (Safransky, 2018; Hackworth, 2019).

Urban planners and policymakers increasingly recognize shrinkage as a structural condition that calls for stabilization, rather than growth-oriented strategies, and no longer view population decline simply as a temporary setback (Yin and Silverman, 2015; Taylor et al., 2018; Silverman et al., 2019). This perspective has shifted attention away from conventional growth-focused development models toward alternative approaches that emphasize neighborhood stabilization, quality of life, and long-term community wellbeing. These approaches include smart decline, qualitative growth, zero-growth, and degrowth strategies, which prioritize improvements in social, environmental, and physical conditions rather than population or economic expansion alone (Hollander and Nemeth, 2011; Kallis et al., 2012; Patterson et al., 2016; Weiss and Cattaneo, 2017; Hickel and Kallis, 2020; Engler et al., 2024; Cai et al., 2026). Within this context, place-based interventions such as public housing redevelopment may contribute to neighborhood stabilization and improvements in living conditions even in cities that are not experiencing population growth.

One prominent strategy for revitalizing shrinking cities is the use of targeted institutional investments to catalyze redevelopment in surrounding neighborhoods (Attoe and Logan, 1989; van Holm, 2019; Theodos et al., 2024). When intentionally integrated into their surrounding neighborhoods, the catalytic investments can help reverse cycles of disinvestment and reinforce urban stability. Public housing redevelopment projects also play a critical role, especially when implemented through public-private-nonprofit partnerships (PPNPs). In shrinking cities with aging or distressed housing stock, PPNPs enable cities to combine public land, subsidies, and regulatory support with private and nonprofit sector financing, construction expertise, and long-term management.

Public housing redevelopment projects, particularly when anchored by long-term institutions embedded in local neighborhoods, have emerged as a key intervention. Such projects can create spillover effects beyond project boundaries. New or rehabilitated housing, improved streetscapes, and upgraded infrastructure can raise nearby property values, attract small businesses, and encourage additional private investment in surrounding blocks (Silverman et al., 2015). Over the past decade, several major redevelopment initiatives have been completed or are currently underway in this area. One such effort is a PPNP focused on the redevelopment of the Commodore Perry public housing project where Buffalo's East Side and First Ward neighborhoods converge. This PPNP, rebranded as the Perry Homes development project, mobilized capital, shared risk, and enabled large-scale housing investments that would otherwise be financially infeasible. When supported by strong public oversight and meaningful community engagement, PPNPs have the potential to generate positive spillover effects, strengthen neighborhood housing markets, and promote equitable stabilization, without relying on population growth to justify reinvestment.

The examination of the redevelopment of the Commodore Perry public housing project is a critical case study for understanding the neighborhood revitalization and spillover effects of PPNP's. The Commodore Perry public housing project remained vacant and dormant for decades, hampering efforts to catalyze redevelopment in its surrounding neighborhood. The property was unable to secure funding for its stabilization, demolition, and reconstruction until the early 2020s, when funding was secured under the Rental Assistance Demonstration (RAD) program. That funding converted the property from traditional public housing to a project-based Section 8 property called the Perry Homes that is developed and managed through a PPNP. This study uses multimodal large language models (LLMs) to examine images of neighborhoods surrounding the Perry Homes redevelopment site in Buffalo over roughly the past 10 years. It evaluates whether and how the trajectory of surrounding properties has changed in response to this investment.

The methodology adopted in this analysis to examine neighborhood spillover effects from institutional investment and the revitalization of dormant public housing is an innovative approach that can be replicated. Traditional approaches, such as surveys, remain important in urban policy research but are often time-consuming, costly, and subject to recall bias. In contrast, digital data sources, particularly street-level imagery, provide timely, scalable, and historically comparable insights into neighborhood conditions, including visible indicators of property condition and resident investment. However, analyzing large volumes of visual data consistently requires advanced tools capable of processing multimodal information.

Recent advances in artificial intelligence have made such analysis increasingly feasible (Yin et al., 2026a; Yin and Kim, 2026). This study applies an online multimodal LLM tool[1] that retrieves Google Street View images and employs Gemini, an LLM, to analyze image data collected online at two points in time, the present and approximately a decade earlier, to evaluate street-level and parcel-level changes associated with redevelopment. Overall, the findings demonstrate how multimodal LLMs can support the evaluation of neighborhood change and redevelopment spillover effects, highlighting both progress and persistent gaps. These insights can inform public policy decisions and illustrate the value of GenAI tools for consistent, large-scale analysis of visual data in urban planning and policymaking.

1 www.neighborhoodchange.online

2 Literature review

2.1 Targeted, place-based revitalization efforts

Neighborhoods in many Rust Belt cities, such as Buffalo, particularly its historically underdeveloped neighborhoods, have long faced persistent challenges, including deteriorating housing conditions and aging infrastructure (Silverman et al., 2013; Yin et al., 2023; Yin et al., 2024). Conditions on the East Side of Buffalo have been compounded by historic patterns of racial segregation and the clustering of public housing. Kraus (2000) notes that beginning in the 1940's the Buffalo Municipal Housing Authority (BMHA) sited public housing for African American tenants almost exclusively on the East Side of Buffalo. These clusters were characterized by decades of neglect and disrepair that contributed to neighborhood decline (Silverman et al., 2016). According to Gehl (2020), the Commodore Perry public housing project was one of the most pronounced examples of neglected BMHA properties that impeded neighborhood revitalization efforts in the city. Table 1 summarizes the demographics and socio-economic characteristics of the housing project area, highlighting how this is a highly segregated area.

In this context, major institutional investments are required to reverse the effects of derelict properties on surrounding neighborhoods. These investments are argued to remove blighted properties and catalyze redevelopment in surrounding neighborhoods (Attoe and Logan, 1989; van Holm, 2019; Theodos et al., 2024). The redevelopment of the Commodore Perry public housing project exemplifies this type of institutional investment. This PPNP undertook the demolition of the Commodore Perry project and rebranded its mixed-income replacement housing as the Perry Homes.

Like investments in major transit hubs, convention centers, and new sports arenas, the demolition of public housing and its redevelopment through PPNPs as mixed-income housing projects serve as strategies to catalyze neighborhood revitalization. Rather than merely replacing deteriorated housing with new public housing, contemporary approaches integrate mixed-income development, community services, enhanced public spaces, and higher design standards. By emphasizing mixed-income communities, mixed-use buildings, and strong urban design, these projects are argued to stabilize declining neighborhoods.

PPNPs like the Perry Homes development are intended to produce neighborhood benefits that extend beyond their immediate sites. Investments in housing, infrastructure, and public spaces are intended to catalyze private development, improve neighborhood perceptions, and strengthen local economies in surrounding areas. In shrinking cities, PPNPs can generate positive spillover effects, reinforce neighborhood housing markets, and support equitable stabilization, without relying on population growth to justify reinvestment. When paired with community engagement and safeguards against displacement, these spillovers can promote broader neighborhood stabilization rather than isolated redevelopment. Coordinated efforts with public authorities that lead PPNPs can contribute to long-term revitalization by enhancing residential stability and rebuilding trust in historically marginalized communities.

In Buffalo, neighborhoods where the East Side and the First Ward converge have endured longstanding patterns of disinvestment, poverty, and physical decline. In July 2023, the City of Buffalo approved $260 million for the first phase of the Perry Homes redevelopment project in this area (BMHA in the News, 2024; LaBella, 2025). This public housing redevelopment effort, implemented through a PPNP and led by the BMHA is a targeted, place-based initiative to revitalize the neighborhood. The first phase of the project included the demolition of 27 vacant apartment buildings and the construction of new buildings containing approximately 405 affordable apartment units, along with additional residential development along South Park Avenue and Louisiana Street, all within the area where the East Side and the First Ward converge (BMHA in the News, 2024). Collectively, such cases illustrate how anchor institutions and PPNPs can offer a pragmatic and resilient framework for revitalization in shrinking cities, one that emphasizes long-term commitment, shared risk, and equitable outcomes rather than a return to past population peaks.

2.2 Assessing the impacts of the public housing projects as revitalization engines: challenges and opportunities

Public housing redevelopment has been conceptualized as a catalyst for neighborhood socio-spatial transformation (Turbov, 2006). Redevelopment interventions, such as housing replacement, rehabilitation, and investments in neighborhood amenities, influence neighborhood change through multiple interconnected pathways, including physical environmental improvements, socioeconomic restructuring, demographic change, and housing-market dynamics (Yin et al., 2023). Among these pathways, improvements in the physical environment constitute one of the most direct and observable manifestations of revitalization. By improving housing quality, building maintenance, and the visual appearance of the built environment, redevelopment projects can enhance neighborhood attractiveness, signal investment, and contribute to broader neighborhood transformation. As a result, changes in physical housing and neighborhood conditions have been used as key indicators for evaluating redevelopment outcomes.

However, measuring such changes at the street or property level remains challenging due to the scale, complexity, and spatial heterogeneity of neighborhood transformation processes. Many commonly used indicators of neighborhood change, such as housing quality, vacancy, socioeconomic conditions, and housing-market characteristics, are typically measured and analyzed at aggregate geographic units such as census tracts (Silverman et al., 2015; Taylor et al., 2018; Silverman et al., 2019). While useful for capturing broader patterns, these measures may overlook variations that occur within neighborhoods. Redevelopment impacts often differ substantially across neighborhoods, streets, and individual properties, requiring assessment methods capable of capturing fine-grained spatial variation and changes over time (Yin et al., 2023; Yin et al., 2024). Conventional approaches, including field surveys and resident questionnaires, have long been used to document housing and neighborhood conditions. Although valuable, these methods are often labor-intensive, costly, difficult to scale, and susceptible to reporting bias and human error (Yin et al., 2015; Ki and Lee, 2021).

At the same time, rapidly advancing digital technologies are transforming how data is collected and analyzed. Emerging data sources, such as social media platforms and Google Street View imagery, provide rich, timely, and fine-grained insights into neighborhood conditions (Yin and Wang, 2016; Ki and Lee, 2021; Crooks and Chen, 2024). For example, images from these platforms can offer visual evidence of how residents maintain their homes and surrounding environments.

TABLE 1 Characteristics of public housing in the study area.

Boundaries	Housing characteristics		Resident characteristics										Census tract characteristics		
	Total units	% Occupied	Average people per occupied unit	% Income from work	% Income from welfare	% Income from social security, SSI, pension or other	% Female headed household	% Female headed household w/children	% of households with a disabled resident	% Minority	% Black	% Hispanic	% Census tract minority	% Census tract below poverty	% of census tract households in single family dwellings
2000															
Commodore Perry Project	623	63	2	34	26	34	75	40	14	95	74	21	96	48	11
Commodore Perry Extension	420	75	1.6	10	6	82	64	15	44	94	76	18	96	48	11
Buffalo-Cheektowaga-Niagara Falls, NY Metro Area	6,533	83	1.9	22	10	65	74	31	25	69	58	11	54	34	22
2009															
Commodore Perry	414	51	2.4	34	3	55	81	48	11	90	73	16	96	48	–
Commodore Perry Extension	393	87	1	19	4	73	63	0	50	79	71	6	96	48	–
Buffalo-Cheektowaga-Niagara Falls, NY Metro Area	6,033	84	1.8	25	5	72	74	30	21	72	60	10	55	33	–
2025															
Commodore Perry [project vacated by 2014]	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
Commodore Perry Extension	381	81	1.1	20	5	74	51	1	40	85	63	22	68	35	25
Buffalo-Cheektowaga-Niagara Falls, NY Metro Area	5,537	4,834	1.7	24	5	64	67	25	26	79	55	32	64	34	33

Source: Picture of Subsidized Households Database, U.S. Department of Housing and Urban Development, https://www.huduser.gov/Portal/datasets/assthsg.html. The Commodore Perry Project is a row house development that was demolished and replaced with the Perry Homes Phase I development in 2025. The Commodore Perry Extension is an 8-story, senior apartment complex located on Perry Street adjacent to the Perry Homes Phase I Project.

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However, effectively analyzing these large and diverse datasets requires advanced technical skills and tools capable of handling multimodal information. Historically, image analysis has depended on specialized expertise in methods with steep learning curves, such as deep learning and other machine learning techniques (Yin et al., 2015; Liu and Song, 2024). These approaches may also require location- or region-specific training data, limiting their scalability and accessibility.

Recent advances in artificial intelligence, particularly large language models (LLMs) and multimodal models, are beginning to address these challenges. AI tools such as ChatGPT and Gemini can process and analyze survey and comment data more quickly and consistently than human analysts, uncovering patterns and insights that might otherwise go unnoticed (Yin et al., 2026b). More importantly, multimodal LLMs can directly interpret visual information from sources such as Google Street View imagery, enabling automated assessments of housing conditions, streetscape quality, and other indicators of physical revitalization through conversational interfaces or application programming interfaces (APIs) (Crooks and Chen, 2024; Akinboyewa et al., 2024; Malekzadeh et al., 2025).

These models extend analytical capabilities beyond text to encompass images and mixed data types, such as maps, where information may be textual, visual, or both (Xu and Tao, 2024; Yin and Kim, 2026). When applied to urban big data (Wang and Yin, 2023), multimodal LLMs enable more comprehensive analyses of the complex relationships between human behavior and the built environment (Akinboyewa et al., 2024; Wang et al., 2024).

In addition, multimodal models can generate structured indicators based on user-defined criteria directly from imagery without requiring task-specific training (Perez and Fusco, 2025; Yin and Kim, 2026). Studies by Malekzadeh et al. (2025) and Jiang (2025) further show that these models can evaluate urban attractiveness from building- or street-level images in ways that closely align with human perception. These emerging capabilities provide new opportunities to measure the physical manifestations of neighborhood transformation associated with public housing redevelopment, while addressing many of the scalability and resource constraints that have traditionally limited impact evaluation.

Although the adoption of new technologies in urban planning and policymaking has historically been slow, largely due to barriers related to cost and technical expertise (Daniel et al., 2023; Yin and Kim, 2026), generative AI and multimodal tools offer a more accessible pathway forward. By reducing reliance on specialized training data and lowering the level of technical expertise required for implementation, these technologies broaden accessibility and facilitate more widespread integration into planning practice (Daniel et al., 2023; Yin and Kim, 2026).

Recent scholarship has also emphasized the importance of value-inclusive design and other participatory planning frameworks in urban revitalization. These approaches recognize that redevelopment outcomes should be evaluated not only through physical, economic, or environmental indicators but also through the values, priorities, and lived experiences of affected communities (Harris et al., 2023; O'Hara et al., 2023; Hampton and O'Hara, 2024). AI-assisted methods for assessing housing and neighborhood physical conditions can complement value-inclusive approaches by providing systematic and scalable evidence on the physical dimensions of neighborhood change. Combined with community perspectives and stakeholder priorities, such evidence can support redevelopment strategies that are both evidence-based and responsive to local needs.

3 Method

This paper applies multimodal LLMs to analyze street-level images of properties within the study area to assess neighborhood change following the workflow illustrated in Figure 1. The process consists of four main stages: (1) study area selection, (2) image data collection and pairing, (3) human review and filtering, and (4) image analysis. Human oversight is incorporated throughout the workflow to ensure image quality, verify image pair matching, and assess the validity of model outputs.

Google Street View images were collected, processed, and analyzed through a web-based tool (See footnote 1) that uses the Google API and Gemini to retrieve, pair, and evaluate historical street-view imagery. The assembled image pairs enable the assessment of property conditions over approximately the past decade and facilitate the identification of neighborhood change and potential spillover effects associated with nearby redevelopment projects over time.

3.1 Study area

The Commodore Perry Homes, located where Buffalo's East Side and historic Old First Ward converge, are situated around Perry Street, Louisiana Street, and South Park Avenue, near the upper-left portion of the study area shown in Figure 2. Originally opened in 1939, the development consisted of 27 brick, garden-style apartment buildings ranging from two to three stories. Over time, the site experienced significant disinvestment and deterioration, with many units eventually boarded up, as illustrated in the bottom-left image of Figure 2. A large, multi-phase redevelopment effort has now been underway, illustrated in the middle-left image, with Phase I recently



FIGURE 1
Analysis framework.



FIGURE 2
Study area.

completed and delivering 405 affordable townhouse-style units depicted in the other image in Figure 2.

For this study, we focus on the area east and south of the redevelopment site, bounded by the thick black lines in Figure 2, which contains a high concentration of single-family homes. The study area is defined by Interstate 190 to the north, Louisiana Street to the west, and a railway line to the east, with Republic Street forming the southern boundary along the rail corridor.

3.2 Image data collection and pairing

To apply the proposed framework shown in Figure 1, communities need access to georeferenced street-view imagery covering at least two observation periods within the study area. In the present study, we used images collected approximately ten years apart to capture meaningful changes associated with urban renewal and neighborhood redevelopment. However, the optimal time interval may vary depending on the research objectives and the expected pace of change in the study area. For example, rapidly changing neighborhoods may exhibit substantial physical transformation over a relatively short period, whereas slower-changing areas may require a longer observation window to detect meaningful differences.

At a minimum, the methodology requires street-view imagery from two time periods that provide reasonably comparable views of the same properties or streetscapes. These image pairs support before-and-after comparisons and enable the identification of major changes in property conditions and neighborhood environments. Areas with sparse historical imagery or substantial gaps in coverage may reduce the reliability of neighborhood-level assessments. Therefore, before applying the framework, users should evaluate the availability, quality, and spatial distribution of historical imagery to ensure that a representative sample of properties can be observed throughout the study area.

When additional historical imagery is available, the framework can be extended to support longitudinal analyses of neighborhood change. Multiple observation periods enable researchers to examine not only whether change has occurred, but also its timing, pace, and sequence, thereby providing a richer understanding of neighborhood transformation trajectories.

Ideally, images from different years would be captured from the same location and viewing orientation. In practice, however, historical Street View imagery often varies because camera positions, roadway access, and image acquisition practices change over time. Rather than seeking images with identical viewpoints, we aimed to assemble image pairs that provide sufficiently comparable views of the same property or streetscape across time. This approach enables visible physical changes to be assessed reliably and consistently while ensuring adequate spatial coverage of the properties within the selected study area.

The web-based neighborhood changes tool uses the Google API to retrieve Street View images from capture points located along streets within a user-defined study area. As illustrated in the bottom-right panel of Figure 2, these capture points correspond to locations where Street View panoramas were collected and typically provide dense spatial coverage that includes nearly all properties along the selected streets. Because image locations and viewing perspectives often vary across years, the tool automatically pairs images based on both geographic proximity and camera orientation. When an exact historical match is unavailable, the tool searches nearby capture points and adjusts viewing angles to generate the closest possible view of the same property. A human review process then verifies image-pair quality and removes unsuitable pairs when building visibility, image quality, or viewing perspective is inadequate for reliable comparison.

For each location, the tool retrieved and paired a recent Street View image (2025) with a historical image captured approximately a decade earlier, depending on data availability. When 2014 imagery was unavailable, the closest available image from 2012 was used. The resulting dataset was subsequently screened to retain only image pairs that clearly depicted single-family detached residential properties. Images showing commercial buildings, multi-family housing, vacant lots, or properties with insufficient visibility were excluded from further analysis. In total, more than 350 ($N = 356$) paired images, representing the current period and roughly a decade earlier, were compiled for analysis using Gemini.

3.3 Image assessment: criteria and human evaluations

The visual assessment employed Gemini to evaluate paired images using two sets of criteria: building exterior and landscape and surroundings (Table 2). Each set includes specific components, such as building façades, windows, doors, front yards, fences, and driveways, organized under these two categories. For each component, Gemini was provided with detailed instructions defining the feature and explaining how it should be rated. Most components were scored on a scale from −2 to +2, with 0 indicating the absence of a feature (e.g., no fence). Although the assessment also accounts for design and decorative elements, these factors were assigned lower weights because they are less indicative of private property investment.

The image analysis was conducted by systematically applying the evaluation criteria shown in Table 2. We used the Gemini API to analyze pairs of street-view images captured at different time points. The prompt incorporated all assessment criteria and their associated weights and instructed the model to evaluate each image independently and then compare the image pair. For each image, the model generated three scores: (1) a Composite Score (CS) reflecting overall visual characteristics across all criteria in Table 2, (2) a Building Exterior Score (BS), and (3) a Landscape and Surroundings Score (LSS). The Building Exterior Score (BS) was calculated as the weighted average of all criteria within the Building Exterior category, using the weights presented in Table 2. Similarly, the Landscape and Surroundings Score (LSS) was calculated as the weighted average of all criteria within the Landscape and Surroundings category. The Composite Score (CS) was calculated as the weighted average of all evaluation criteria included in Table 2. For each score, criterion-level scores were multiplied by their respective weights, summed across the relevant criteria, and then standardized by the total weight. This normalization ensured that BS, LSS, and CS all ranged from −2 to +2, allowing direct comparison across images and categories.

To enhance consistency and reproducibility, the prompt explicitly defined the assessment dimensions, scoring rubric, and output structure. For example, the scores were compiled into an Excel file. In addition, the model produced brief descriptive summaries for each component and category to support human interpretation of the assessment results.

Finally, the scores generated for both current and historical images were reviewed and.

validated against human evaluations conducted at both the property and street levels. The evaluators included two researchers, one graduate student, and undergraduate students enrolled in a Spring 2026 course. Two researchers and one graduate student independently reviewed a randomly selected subset of image pairs representing approximately 10% of the total dataset. Each evaluator assessed the image descriptions across the three analytical categories before participating in a consensus discussion. The independent reviews demonstrated over 90% agreement, indicating a high degree of consistency and reliability.

A second validation process was conducted through student-led evaluations. Eight undergraduate students participated in a half-semester project focused on assessing neighborhood change within the Old First Ward area. Working in four teams, students independently analyzed different sections of the Old First Ward area using manually collected Street View images from the same two historical points. Students manually paired images for individual properties and used two multimodal LLMs of their choosing to evaluate property conditions, landscape characteristics, and pedestrian and bicycle infrastructure. Student teams independently analyzed image pairs and discussed their findings within and across teams as part of a structured human assessment exercise embedded in a course. The purpose of this activity was not to calculate an exact matching rate with the LLM-generated outputs but to identify and examine instances in which human interpretations diverged from model assessments and to explore the factors contributing to those differences. For example, discussions considered how issues such as image quality, image resolution, or ambiguous visual features might influence interpretation and classification outcomes. These evaluations were conducted independently and in parallel to the present study.

To further assess the robustness of our methodology, randomly selected image pairs from the student-generated dataset were compared with image pairs produced by our web-based tool. Comparisons focused on the suitability of image pairs for change detection, including potential issues such as vegetation or vehicles partially obstructing properties and image blurring.

TABLE 2 Assessment criteria.

Category/item			Description	Rating scale	Weight
Building exterior	Façade	Siding condition	Integrity of exterior siding (damage, missing panels, wear)	−2 (severely damaged) – +2 (excellent/new)	1
		Façade color and paint	Paint quality, presence of peeling, fading, and graffiti	−2 (poor/peeling/graffiti) – +2 (fresh/clean)	1
		Roof condition	Presence of missing shingles, sagging, weathering, or recent replacement	-2 (damaged/aging) – +2 (excellent/new)	1
		Aesthetic appeal	Visual quality, trim, ornamentation, and façade design	−1 (unattractive) – +1 (attractive)	0.5
	Windows	Condition	Whether windows are intact, cracked, broken, or newly installed.	−2 (boarded/broken) – +2 (new/excellent)	1
		Design/shape	Compatibility of design with the structure; architectural appeal.	−1 (inconsistent) – +1 (uniform design)	0.5
	Doors	Condition	Intact, damaged, boarded, or newly replaced.	−2 (boarded/broken) – +2 (new/excellent)	1
		Design/shape	Design quality and architectural consistency.	−1 – +1	0.5
	Signage/building use	Activity	Presence of active use vs. abandonment.	−2 (abandoned/neglected) – +2 (well-maintained/active)	1
		Signage	Clarity and upkeep of signage.	−2 (neglected) – +2 (well-maintained)	0.5
	Structural integrity		Cracks, bulges, foundation issues, sagging.	−2 (major issues visible) – +2 (no visible concerns)	0.5
Landscape and Surroundings	Front yard	Landscape condition	Maintenance of grass, plants, lawn health, and overall care.	−2 (overgrown/abandoned) – +2 (well-maintained)	1
	Fence	Condition	Presence/absence and quality of fencing.	−2 (damaged/unsafe) – 0 (no fence) – +2 (good condition)	1
	Driveway	Surface condition	Smoothness, presence of cracks, potholes, and general integrity.	−2 (poor/severely damaged) – +2 (excellent/new)	1
	Lighting	Condition	Adequacy and presence of fixtures.	−1 (absent) – 0 (visible) – +1 (adequate)	0.1
	Cleanliness	Property cleanliness	Trash, debris, clutter, or visible neglect on the building and immediate surroundings.	−2 (dirty/cluttered) – +2 (clean/well-kept)	1
	Contextual fit and neighborhood condition		Nearby buildings and general upkeep of adjacent properties.	−2 (poor context/neglected surroundings) – +2 (harmonious/well-kept)	1

4 Findings

4.1 Results of the image pair analysis

Positive change scores from 2014 to 2025 indicate neighborhood improvement, whereas negative change scores indicate neighborhood decline. In addition, composite score (CS) thresholds were used to identify two subcategories: substantial improvement and substantial decline. Descriptive statistics for the CS indicate a mean change score of 0.3038, suggesting an overall positive trend in neighborhood conditions during the study period. The median (50th percentile) change score was 0.3000, with a standard deviation of 0.3575. Composite change scores ranged from a minimum of −1.14 to a maximum of 1.39, reflecting considerable variation in neighborhood trajectories. Based on the mean and standard deviation of the composite scores, we established threshold values to identify substantial change: scores of 0.66 and above indicate substantial improvement, while scores of −0.05 and below indicate substantial decline.

Overall, buildings classified as "Improved" substantially outnumbered those classified as "Declining," with the number of improved buildings being nearly 10 times greater than the number of declining buildings. This pattern suggests a strong skew toward positive

neighborhood change during the study period. Notably, this pattern pertains to the broader categories of improvement and decline and should be distinguished from the more specific classifications of substantial improvement and substantial decline.

Figure 3 presents examples of properties that experienced substantial improvement (top panel), minimal or no change (middle panel), and notable decline or deterioration (bottom panel) over the 10-year period. The left column displays images and three associated scores, composite score, building exterior score, and landscape and surroundings score, for approximately 2014, while the middle column presents the corresponding information for 2025. Change scores for building exterior, landscape and surroundings, and the composite measure are reported to the right and beneath each pair of images, along with a brief explanation of the observed changes. Overall, the generated scores and accompanying descriptions align well with property and landscape conditions in both years, as reflected in the images, and are broadly consistent with independently conducted human evaluations.

Figure 4 displays the results of the property-level analysis across the entire study area. Green dots indicate improvement, while red dots indicate decline. These results corroborate the descriptive statistics of the composite change scores, suggesting that most private properties improved between 2014 and 2025, as reflected in the predominance of green markers. Clusters of improvement are evident along all streets; however, these gains are interspersed with declining properties on every street throughout the study area.

Table 3 presents the number and percentage of properties exhibiting substantial improvement, little or no change, or substantial decline, along with brief explanatory summaries for each street in the study area. The results in Table 3 confirm the patterns observed in Figure 3 while also highlighting variation across streets in both the number and proportion of properties falling into each category.

Hamburg Street, one of the two north–south corridors, shows the highest number of properties with substantial improvements and a relatively high share of such cases. In contrast, Alabama Street, the other north–south corridor, has more than 78% of properties experiencing little or no change. Both east–west streets, South Park Avenue and Mackinaw Street, also exhibit limited substantial change, with over 72% of properties falling into the little or no change category.

Changes across image pairs are primarily reflected in property maintenance, façade remodeling, and landscaping. Substantial improvement scores are typically associated with extensive exterior renovations, most notably the complete replacement or significant repainting of siding and façades. These upgrades often involve shifting from faded or worn appearances to fresh, vibrant, and contemporary color schemes, accompanied by thorough cleaning and surface restoration, resulting in a noticeably cleaner and better-maintained appearance. By contrast, substantial decline is characterized by widespread deterioration of exterior finishes, most commonly evident in increased fading and peeling paint on siding and trim. Many properties show a marked accumulation of dirt and general wear, leading to a duller, dingier, and less vibrant façade over time, occasionally accompanied by missing or damaged siding components, clear indicators of neglect.

5 Discussion

The property-level analysis of building exteriors and landscape and surroundings highlights the potential of multimodal large language models (LLMs) for assessing neighborhood change. The findings suggest that the proposed methodology can serve as an effective diagnostic tool for identifying areas undergoing physical transformation. Multimodal LLMs proved capable of capturing broad patterns of change and detecting shifts in the evolving built environment across the study area. When integrated into user-friendly applications accessible to developers, planning practitioners, local governments, and property owners, these tools could support more informed decision-making related to neighborhood revitalization, stabilization, and investment. At a broader scale, data generated by such tools can also be utilized by academics and researchers to evaluate the outcomes of place-based investments. The effectiveness of these models can be further enhanced as data providers improve the quality of input imagery and expand open-access policies.

However, several limitations should be noted. First, the assessment depends heavily on the quality of the input imagery. Partially obscured façades can limit reliable evaluation; in some cases, façades were obstructed by shadows, trees, shrubs, vehicles, or security-related blurring, further reducing visibility. Additionally, the model may respond to variations in color and lighting that reflect differences in image quality rather than actual physical changes. The viewing angle of Google Street View images may also influence the results.

Second, human evaluation of the results is strongly recommended. In a few cases, declines identified by Gemini may instead reflect improvements or transitional changes, such as the removal of overgrown landscaping or deteriorated features (e.g., awnings, railings, or steps). For example, a house undergoing remodeling, with new windows temporarily installed on support boards, was mistakenly classified as having boarded-up windows. However, the presence of a large pile of construction materials adjacent to the building indicates that the property was, in fact, under renovation.

Third, to ensure accessibility, the data analyzed by professional practitioners and property owners in publicly available applications should be maintained in an open-source environment. In addition to designing user-friendly tools that require limited technical expertise, it is important to recognize that many potential users have limited financial resources. Accordingly, data providers should consider adopting open-access policies and removing paywalls to facilitate use by public-sector practitioners, academic researchers, and small property owners.

Finally, this study did not include formal statistical analyses; however, future research could extend the framework by examining relationships between observed neighborhood change and demographic or socio-economic indicators derived from census and other administrative datasets. While Figure 4 reveals clear spatial concentrations of neighborhood improvement, the current analysis does not directly evaluate how these patterns relate to underlying demographic, economic, or housing conditions. Consequently, the results provide evidence of where socio-spatial transformations have occurred but do not fully explain the processes or factors driving those changes.

Future research could enhance the explanatory power and policy relevance of the framework by integrating demographic and socio-economic data at both neighborhood and citywide scales, including census indicators, housing affordability measures, property values, housing tenure, and population composition. Such integration would allow researchers to examine whether observed improvements disproportionately benefit certain social groups or neighborhoods and whether they are associated with processes such as



FIGURE 3
Selected image pairs with analysis results. CS: composite score. BS: building exterior score. LSS: landscape and surround score.

gentrification, displacement, or increasing socio-spatial inequality. Moreover, combining spatial pattern detection with socio-economic indicators could support more proactive planning and policy interventions by identifying neighborhoods that are likely to experience significant change or are particularly vulnerable to adverse social impacts. In this way, the proposed methodology has the potential to serve not only as a tool for monitoring urban renewal outcomes but also as a decision-support framework that advances more equitable, data-driven, and evidence-based urban planning and policy development.

At the same time, the approach is intended to complement rather than replace participatory and value-inclusive planning

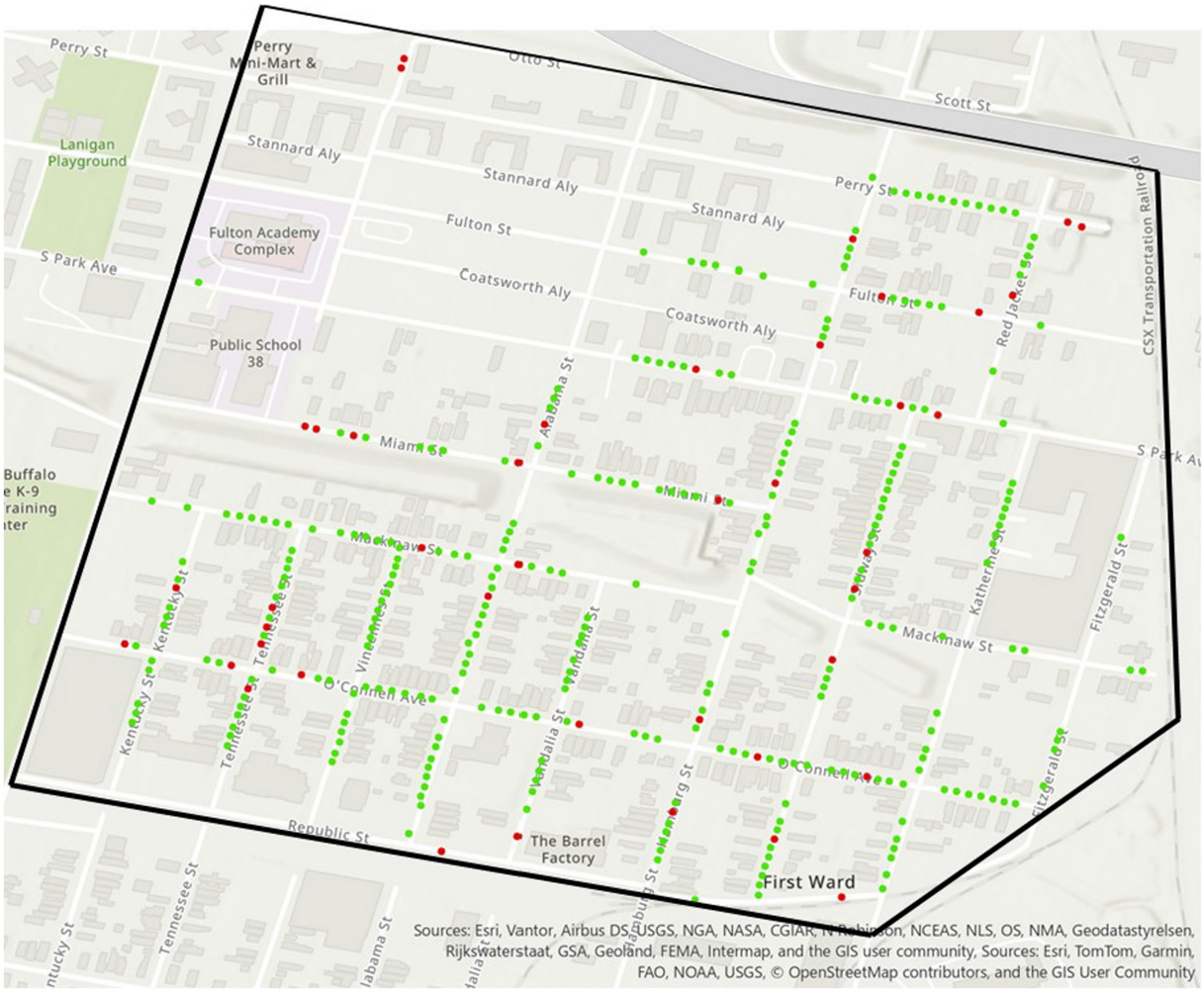


FIGURE 4
Analysis results in the study area.

frameworks. Integrating AI-assisted assessment methods with participatory approaches advocated in value-inclusive design and other meso-level frameworks for sustainable urban development can provide a more comprehensive understanding of neighborhood change by combining systematic physical-condition assessments with community knowledge, stakeholder values, and local priorities (Harris et al., 2023; O'Hara et al., 2023; Hampton and O'Hara, 2024). Such integration may help promote more equitable and context-sensitive urban revitalization strategies for shrinking cities.

6 Conclusion

This study examines the role of PPNPs in housing redevelopment and their potential to generate neighborhood-level spillover effects in an underinvested area of Buffalo, New York, surrounding the Perry Homes redevelopment site. It employs a novel methodological framework that employs street-level imagery with multimodal LLMs, enabling scalable, temporally comparative analysis while addressing limitations associated with conventional survey-based approaches.

The findings indicate that, across the streets in the study area, improved properties outnumber those in decline. In particular, the number of properties identified as "Improved" is nearly 10 times greater than the number classified as "Declined," highlighting a marked imbalance that reflects broadly improving neighborhood conditions from 2014 to 2025. However, these improvements are interspersed with deteriorating properties along all streets in the neighborhood. Spillover effects from the Perry Homes redevelopment appear mixed rather than uniformly positive or negative. Although some streets display clusters of consistent improvement, they also include properties that have remained largely unchanged or even exhibit signs of decline. Improvements are most commonly associated with enhanced building exteriors and landscaping upgrades, whereas properties with declining scores in 2025 typically reflect poorly maintained structures or vegetation.

Consistent with prior studies that have demonstrated the value of street view imagery and AI for measuring built-environment conditions (Yin and Wang, 2016; Naik et al., 2017; Ki and Lee, 2021), our results confirm that street-level visual data can provide meaningful indicators of physical neighborhood change. This study extends the existing literature by demonstrating the strong potential of multimodal LLMs as an alternative and more accessible

TABLE 3 Analysis results by streets.

Street	Substantial improvement			Substantial deterioration			No or minor change		
	#	%	Gemini description of change	#	%	Gemini description of change	#	%	Gemini description of change
Alabama	5	16%	Repainting, enhanced general maintenance, and cleaning	2	6%	Subtle decline, lack of positive development	25	78%	Exterior refreshes, common improvements, upkeep
Fitzgerald	0	0%	–	0	0%	–	5	100%	Superficial exterior improvements
Fulton	5	33%	Significant exterior refreshes: replacement or repainting of siding and facades	2	13%	General wear and degradation of paint, lack of proactive maintenance	8	53%	Signs of improved exterior maintenance
Hamburg	10	24%	Extensive repainting or residing	4	10%	Surface-level degradation: dirt and fading of the exterior	27	66%	Improved maintenance, with facades and siding cleaner and fresher
Katherine	2	10%	Substantial exterior renewal: repainting, or replacement of siding and facades	4	19%	Physical decline and architectural stagnation	15	71%	Superficial aesthetic improvements: repainting
Kentucky	3	27%	Significant exterior renovations: the replacement or repainting of siding	1	9%	Significant fading of facade colors	7	64%	Cleaning, refreshing, or repainting of existing sides and facades
Mackinaw	3	7%	Significant exterior surface upgrades: installing siding, comprehensive repainting	3	7%	Significant fading, peeling paint, and general deterioration	33	85%	Improvements in maintenance: fresher or recently repainted facades and sidings
Miami	2	12%	Significant facade transformations: complete repainting and residing	4	23%	Increased dinginess, fading, and dirt accumulation	11	65%	Enhanced cleanliness, brighter paint, and better-maintained siding
O'Connell	6	12%	Extensive cleaning, repainting, or replacement of siding and facade materials	6	12%	Lack of significant maintenance or improvement	38	76%	Cleaning, repainting, or minor refurbishment of their siding and facades
Perry	0	0%	–	1	7%	Significant weathering, fading, and extensive peeling paint	12	92%	Improvements in general upkeep
Red Jacket	1	17%	Enhanced maintenance: better-maintained siding and facades	1	17%	Often characterized by faded or less clean facade colors	4	67%	Cleaner, brighter, or better-maintained siding and facade colors

(Continued)

TABLE 3 (Continued)

Street	Substantial improvement			Substantial deterioration			No or minor change		
	#	%	Gemini description of change	#	%	Gemini description of change	#	%	Gemini description of change
Sidway	3	9%	Extensive cleaning, repainting, or complete replacement of siding and facade materials	4	12%	Consistent stability and good maintenance	26	79%	Enhanced curb appeal through routine maintenance
South Park Avenue	4	22%	Significant exterior renovations: installing new siding, fresh paint, and the replacement of worn facade elements	1	6%	No significant visible damage or deterioration	13	72%	Refreshed paint, cleaner siding, and brighter facades, through routine maintenance
Tennessee	3	21%	Significant exterior facade renovations: replacement or refreshing of siding	2	14%	Decline in aesthetic appeal and general upkeep	9	64%	Aesthetic improvements: cleaning, repainting, or minor updates to siding
Vandalia	1	7%	Significant visible modifications to elements like siding or paint	3	21%	Buildings registered minor negative changes in their physical condition	10	71%	Evidence of general upkeep: cleaning or repainting of siding and facades
Vincennes	1	7%	Significant visible modifications to elements like siding or paint	3	21%	Negative change in their overall physical state	10	71%	Evidence of general upkeep: cleaning or repainting of siding and facades
Vincennes	0	0%	–	1	7%	Subtle but measurable decline	12	92%	Cosmetic enhancements and routine maintenance

approach for assessing street-level housing and neighborhood conditions at scale, underscoring their value for urban planning research.

The findings have important implications for shrinking cities, where neighborhood stabilization and improvements in quality of life are increasingly viewed as more attainable policy objectives than population growth. In these contexts, public housing redevelopment and other place-based interventions are often implemented to address physical decline and improve neighborhood conditions. Understanding the property- and street-level dynamics is critical for informing equitable revitalization strategies in legacy cities where traditional market mechanisms have struggled to deliver investment. This project demonstrates that generative AI-assisted approaches offer a scalable and cost-effective tool for monitoring these physical changes at a level of spatial detail that is difficult to achieve through conventional approaches. By enabling systematic evaluation of housing and neighborhood conditions over time, the methodology can help planners and policymakers identify areas of improvement, target resources more effectively, and assess whether redevelopment investments contribute to broader goals of neighborhood stabilization.

The study therefore advances current methodological discussions by highlighting how emerging foundation models can complement or potentially expand existing approaches to assessing the physical impacts of public housing redevelopment and neighborhood transformation. However, human oversight remains essential to ensure accuracy and interpretability. In particular, multimodal LLMs proved effective in evaluating façade, landscape, and surroundings conditions, especially when their outputs were validated and refined through human review.

6.1 Methodological implications: comparison and integration of multimodal LLM and traditional approaches

The findings of this study highlight the methodological value of combining Multimodal Large Language Models (Multimodal LLMs) with urban big data to examine socio-spatial transformations associated with urban renewal in shrinking cities. Compared with traditional research approaches, such as field observations, household surveys, interviews, archival analysis, and GIS-based spatial analysis, this approach offers several distinct advantages. First, Multimodal LLMs can efficiently process and integrate heterogeneous data sources collected over extended periods, including street-view imagery, planning documents, and other textual and visual materials. This

capability enables large-scale, multidimensional, and longitudinal analyses of neighborhood change. By automating data processing and coding tasks, Multimodal LLMs significantly reduce the time and labor required for analysis while facilitating the identification of complex spatial and social patterns that may be difficult to detect through manual methods. As a result, they are particularly valuable for exploratory research, large-scale monitoring, and rapid assessments of urban transformation across multiple neighborhoods or cities.

At the same time, the analytical strengths of Multimodal LLMs are best understood in conjunction with the complementary advantages of traditional research methods. Qualitative approaches, such as interviews, focus groups, and ethnographic observations, remain indispensable for capturing residents' lived experiences, perceptions of displacement, community attachment, and other nuanced social dynamics that are often not directly observable in visual or textual datasets (Silverman et al., 2015, 2019). Future studies can further enhance Multimodal LLM-based analyses by incorporating a wider range of data sources generated through conventional research methods, including planning documents, interview transcripts, focus group discussions, survey responses, and social media content. Such integration would provide richer contextual information and enable a more comprehensive understanding of neighborhood transformation processes.

Similarly, traditional quantitative approaches, including surveys, econometric analysis, and statistical modeling, offer greater transparency, replicability, and inferential rigor when examining causal relationships between urban renewal interventions and socio-spatial outcomes. In contrast, Multimodal LLMs may be affected by biases embedded in the input data, limitations in model interpretability, and potential inaccuracies in context-specific reasoning, particularly in rapidly changing urban environments or culturally specific settings. Consequently, conventional quantitative methods remain essential when robust causal inference and statistical validation are required.

Rather than viewing Multimodal LLMs and traditional approaches as competing alternatives, future research should pursue their integration within a mixed-method framework. Insights derived from qualitative and quantitative studies can be used to refine prompts, evaluation criteria, and domain-specific knowledge structures that guide Multimodal LLM analyses. Conversely, Multimodal LLMs can be employed to identify patterns, generate preliminary interpretations, and detect areas requiring further investigation, thereby informing subsequent fieldwork, surveys, and stakeholder engagement activities.

Such a human-in-the-loop approach combines the scalability, efficiency, and multimodal analytical capabilities of Multimodal LLMs with the contextual depth, interpretive richness, and methodological rigor of established urban research methods. Through this integration, researchers can develop a more comprehensive understanding of the socio-spatial impacts of urban renewal while improving the reliability, validity, and interpretability of research outcomes. Future studies should therefore advance integrated analytical frameworks that combine Multimodal LLM-based analysis with fieldwork, surveys, interviews, and spatial statistical techniques. Such methodological integration has considerable potential to enhance both the efficiency and robustness of urban renewal assessment and contribute to a more holistic understanding of neighborhood change.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

LY: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. RS: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Visualization, Writing – original draft, Writing – review & editing.

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The author(s) declared that Generative AI was used in the creation of this manuscript. The use of AI was explained in detail in the method section.

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