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Publication Date

02-05-2025

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Citation for this work (American Psychological Association 7th edition)

Hu, M., Ghorbany, S., Yao, S., Wang, C., & Sisk, M. (2025). *BUILT2AFFORD: Machine-Learning-Driven Passive Retrofits for Affordable Housing* (Version 1). University of Notre Dame. https://doi.org/10.7274/28921238.v1

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BUILT2AFFORD: Machine-Learning-Driven Passive Retrofits for Affordable Housing

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ABSTRACT: The persistent shortage of affordable housing in the United States, coupled with aging infrastructure and rising energy costs, disproportionately impacts low-income households, particularly in historically disinvested communities. Addressing this challenge requires innovative, scalable solutions that balance affordability, energy efficiency, and climate resilience. This study introduces the BUILT2AFFORD dashboard, an integrated tool leveraging machine learning (ML) and Google Street View (GSV) imagery to pre-identify low-cost passive retrofit strategies for preserving and improving affordable housing. The dashboard assesses existing building conditions, evaluates energy retrofit potential, and mitigates heat-related health risks. The research involved on-site audits of single-family homes and Section 8 apartments, combined with continuous monitoring of indoor environmental conditions such as temperature, humidity, and CO2 levels. Preliminary results reveal significant opportunities for energy savings and improved thermal comfort, with scenarios like infiltration reduction and insulation upgrades achieving substantial reductions in energy use. The dashboard's validation through eight testbeds demonstrates its potential to address housing challenges in South Bend, Indiana while advancing carbon-neutral and equity goals. This paper highlights how integrating advanced technologies into retrofit planning can enhance housing quality, reduce displacement risk, and foster climate resilience in vulnerable communities.

KEYWORDS: Google Street View, building information modeling, low-cost solution, energy retrofit

1.0 INTRODUCTION

The shortage of affordable housing in the United States is a persistent and well-documented issue with profound implications for low- and middle-income households (Kang, Jeon, and Airgood-Obrycki 2024;Hinkel and Belman 2022). Affordable housing includes a variety of options, such as single-family homes, units in multi-family buildings, apartments, and mixed-use developments (Hinkel and Belman 2022). However, the demand for such housing continues to outpace supply due to insufficient new construction and the deterioration of existing housing stock (Anacker 2019). This growing deficit is particularly pronounced in the rental market, where a shortfall of 7.3 million affordable and available homes exists for renters with extremely low incomes—those earning at or below the federal poverty guideline or 30% of their area median income, whichever is higher. Alarmingly, for every 100 such households, only 34 affordable and available rental homes are currently accessible (Brown et al. 2020; Drehobl, Ross, and Ayala 2020). This shortage affects every state and major metropolitan area, underscoring the widespread nature of the crisis.

Exacerbating this problem, much of the current affordable housing stock suffers from aging and outdated infrastructure. This not only limits its livability but also burdens residents with disproportionately high utility bills, particularly in historically neglected census tracts populated by low-income and underrepresented communities (National low income housing coaltion 2024). Such financial strain further restricts access to stable housing, amplifying the challenges faced by vulnerable populations. In the State of Indiana, the severity of the affordable housing crisis is evident across all 92 counties, where households earning less than 30% of the county's Area Median Income experience the lowest rates of affordable and available housing. Notably, 22 counties fall below the national average, and cities like South Bend highlight the scale of the issue with an affordable housing gap of 13,510 units (National low income housing coalition 2024;"South Bend Affordable Housing Report Q1 2023" 2023)**.** While constructing new affordable housing units is a slow and expensive process, retrofitting existing buildings has emerged as a more practical and cost-effective solution to address this critical shortage.

Residents of aging affordable housing face additional hardships, such as inadequate or unaffordable mechanical systems (United States Environmental Protection Agency 2011). Energy retrofits present a promising solution to preserve and improve existing housing stock while reducing utility burdens. Research indicates that reducing energy costs by 25% can lower combined rent and utility expenses by approximately 8%, significantly reducing the risk of displacement for low-income households (Wetzstein 2017). However, energy-induced housing insecurity remains pervasive, with 38% of U.S. households—or 46.5 million—spending over 6% of their income on energy costs, and many exceeding 10% (United States Environmental Protection Agency 2011; Drehobl and Ross 2016). These challenges are particularly severe in disinvested communities with older housing stock, where properties are often perceived as too costly or difficult to upgrade, discouraging investments in energy efficiency (Beagon, Boland, and O'Donnell 2018) (Asaee, Ugursal, and Beausoleil-Morrison 2017).

Climate change further compounds the housing crisis by disproportionately affecting low-income families and vulnerable populations. Increasingly frequent extreme weather events, such as multi-day heatwaves—the leading cause of weather-related mortality in the U.S.—underscore the urgency of addressing this issue (NUSBO 2022). Investments in energy efficiency can provide dual benefits by reducing indoor heat exposure and improving air quality while maintaining stable indoor temperatures. These measures enhance resident comfort, reduce health risks associated with climate extremes, and promote long-term resilience for low-income households. Addressing the intersection of affordable housing, energy efficiency, and climate resilience is not only essential for alleviating economic and environmental burdens but also for ensuring a sustainable and equitable future for vulnerable communities.

This project seeks to address these challenges by co-developing, testing, and validating the BUILT2AFFORD dashboard. This innovative tool integrates machine learning (ML) techniques and Google Street View (GSV) images to pre-identify low-cost passive retrofit strategies for preserving and improving affordable housing. The dashboard incorporates three core functions: assessing existing building conditions, evaluating energy retrofit potential, and mitigating heat-related health risks. These functions will be tested and validated using eight diverse testbeds, providing a scalable solution to address South Bend's housing challenges while advancing the city's carbon-neutral and equity goals.

2.0 WHY LOW-COST PASSIVE SOLUTIONS

The building envelope—which encompasses exterior walls, doors, windows, roofs, and external shading—serves as the primary barrier between indoor and outdoor environments, playing a crucial role in regulating indoor heat exposure and energy use (Ghorbany et al. 2023; Ma et al. 2019;Liu et al. 2023). The materials and design of the building envelope significantly influence its thermal inertia, or the ability to absorb, store, and release heat. This characteristic directly affects indoor temperatures, particularly during extreme heat events (Haines et al. 2009). Low-cost interventions, such as incorporating natural ventilation and high-performance thermal materials, have demonstrated effectiveness in reducing indoor temperatures by 2.2°C, extending thermal comfort by 23%, decreasing cooling loads by 31%, and lowering energy costs by 30% (Liu et al. 2023; Baniassadi, Heusinger, and Sailor 2018; Yu et al. 2010). Despite these promising results, research on implementing passive design strategies at the neighborhood scale remains limited due to a lack of comprehensive, high-quality data on housing conditions across broader geographic areas.

Previous work by the research team and other researchers highlights the potential of passive design strategies to mitigate the impacts of climate change and achieve significant energy efficiency gains (Hu et al. 2023; AIA 2022). These low-cost and low-energy approaches not only reduce carbon emissions by decreasing operational energy demand but also align with sustainable design principles (West et al. 2013; Haines et al. 2009; Remais et al. 2014). Historically, passive design strategies—such as natural ventilation, daylighting, and leveraging thermal mass—were rooted in human-centered and health-conscious design principles. These strategies allowed people to adapt and thrive in harsh climates during pre-industrial times (ArchDaily 2022). Compared to mechanical systems, passive design solutions are not only more affordable but also readily adaptable to buildings of all sizes and budgets.
The Passive Building standard movement, which began in Europe, has gained momentum in the United States. Notably, organizations in New York and Massachusetts are incorporating these principles into the affordable housing sector, demonstrating their viability and scalability (NUSBO 2022; Northeast Sustainable Energy Association 2022).

To evaluate and optimize these strategies, Passive Design Indicators (PDIs) have been developed to measure the effectiveness of building design in achieving energy efficiency and health outcomes. These indicators, listed in Table 1, were identified through a comprehensive process involving (i) a literature review; (ii) resources such as the AIA 2030 Palette; and (iii) sustainable building and neighborhood design evaluation tools, including LEED V4 (Kovats, Hajat, and Wilkinson 2004), LEED for Neighborhood Development (Hajat et al. 2014), the Building Research Establishment Environmental Assessment Method (BREEAM) (Kubba 2012), and the Portland Eco-Districts Toolkit: Assessment (Nguyen et al. 2018). These PDIs serve as critical tools for illustrating the link between design choices, energy performance, and health benefits, enabling a more holistic approach to sustainable building and neighborhood development.

Table 1: Decision-making process for determining wall materials based on responses

Passive Design	Passive design indicators (PDI)		Measurement Unit	Label
Solar Optimization	PDI_1	Window-to-wall ratio	>60% of surface area	Yes/No
	PDI_2	Shading device per window	Count	By count
Natural Ventilation	PDI_3	Operable Window	>20% of Window area	Yes/No
	PDI_4	Exterior materials (brick/wood)	>80% of surface area	Yes/No

Thermal Mass (Insulation)	PDI$_5$	Cool roof (light color)	>80% by surface area	Yes/No

2.0 RESEARCH METHODOLOGY

2.1. Overall Research Flow

This project leverages the long-standing collaboration between the research team and local communities, engaging four key partners: the City of South Bend (CoSB)'s Department of Community Investment, the nonprofit affordable housing developer South Bend Heritage Foundation (SBHF), the for-profit developer OldTown Capital Partners (OldTown), and the Near Northwest Neighborhood (NNN) community group. This research project is divided into two stages, as illustrated in Figure 1. Stage 1 focuses on identifying PDI) using machine learning with Google Street View (GSV) images, housing variables, and weather data while collaborating with civic partners to identify single- and multi-family testbed homes. In Stage 2, teams will retrofit eight testbed buildings, collect physical data, and train residents, followed by calibrating results to finalize the BUILT2AFFORD dashboard. This streamlined process integrates research, community engagement, and implementation to enhance housing energy efficiency and suitability.

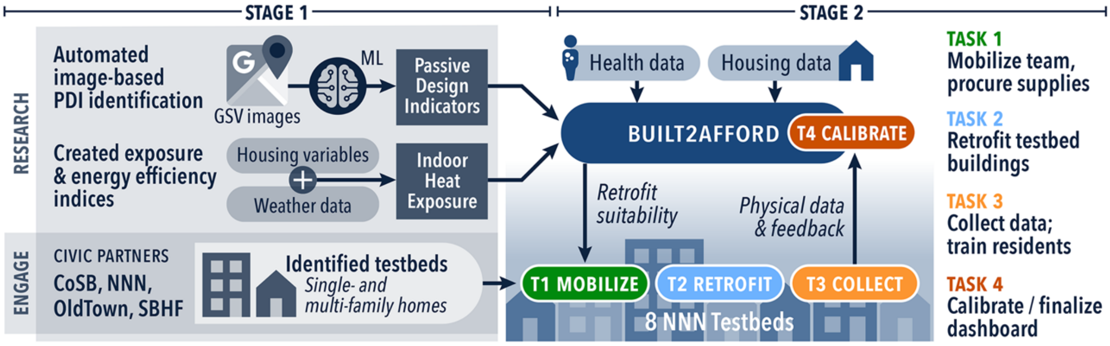


Figure 1: Overview of research flow

Currently, the research team is in the end of stage one. In the following sections, we will describe the methodology and materials of Stage One activities.

2.2. Automated image-based PDI identification

To efficiently identify and classify PDIs in **Error! Reference source not found.**, we developed an ML pipeline that leverages GSV images and satellite data to detect and classify building wall and roof materials and calculate the window-to-wall ratio. This approach achieves high precision without requiring extensive manual labeling, demonstrating significant potential for scalable, automated urban analysis. We utilized GSV's Application Programming Interface (API) to capture 800,000 street-view images in CoSB. Correct labeling or "tagging" of the building PDIs within millions of images cannot be done manually. We developed a zero-shot vision-language ML model that integrates open-set object detection (OSOD) with vision-language models (VLMs) to identify buildings and classify wall/roof materials and windows using GSV and satellite images. Using a two-step approach, we detected wall material types in individual buildings (Figure 2). First, the "building" text input and GSV images were fed into Grounding DINO, a state-of-the-art OSOD model, to accurately identify buildings. Next, BLIP's vision question answering (VQA) features classified wall materials by answering targeted questions about the materials' characteristics (e.g., presence of wood or brick). If BLIP detected multiple materials (e.g., both wood and brick), the wall was classified as a mixed-material structure (Table 2)

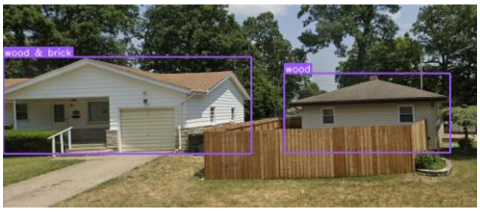


Figure 2: Sample annotated GSV images

Table 2: Decision-making process for determining wall materials based on responses

What Materials	Has Wooden Part?	Has Brick Part?	Class
Wood	Yes/ No	No	Wood
Brick	No	Yes/ No	Brick
Wood	No	Yes	Wood & Brick
Brick	Yes	No	Wood & Brick
Wood/Brick	Yes	Yes	Wood & Brick
Neither	Yes/ No	Yes/ No	Other

To evaluate object detection accuracy, we used mean average precision (mAP), a metric that balances precision and recall across intersection-over-union (IoU) thresholds. Our approach, integrating Grounding DINO and BLIP, outperformed traditional models like Faster R-CNN and YOLO, achieving a mAP of 0.82, with all categories scoring above 0.7 AP. This underscores the robustness of our zero-shot approach, which requires no extensive dataset-specific training and outperforms fully trained alternatives.

To refine detection and segmentation accuracy, buildings in GSV were cropped into individual images and processed using Grounding DINO with Segment Anything to generate segmentation masks. Detection classes included "window," "wall," "door," and "roof" to avoid mislabeling (e.g., roofs segmented as walls). Segmentation masks enabled calculation of the window-to-wall ratio, with the window area determined by counting pixels in the "window" segments (purple) and the wall area excluding background (black) and roof (yellow) segments. Our method achieved a superior mAP of 0.82, with all object categories scoring above 0.75 AP.

2.3. Identified testbeds and conducted housing audits

Between July and November 2024, the research team collaborated with the NNN to host four community engagement meetings, reaching over 30 single-family homeowners to introduce the project objectives and explain the benefits and processes of energy retrofits. These meetings aimed to build trust and recruit participants for the on-site assessments. Homeowners who enrolled participated in energy audits of five single-family homes, where the research team evaluated current housing conditions and identified energy efficiency opportunities using pre-determined indicators (PDIs). Simultaneously, the team partnered with SBHF and OldTown to engage Section 8 apartment renters, conducting energy audits of eleven units that included collecting data such as thermal imaging and moisture content.

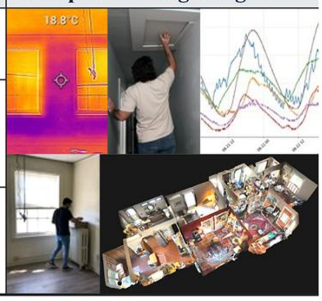
Figure 3: Identified testbeds

The outreach activities secured eight testbeds (see Figure 3 for building conditions) representing dominant housing types in CoSB, including detached single-family homes, small multi-family apartments (2-9 units), and large multi-family apartments (over 50 units). These testbeds were selected to ensure findings are broadly applicable and address Stage One proposal feedback, emphasizing the need for representative housing types to support scalability. The selection of eight testbeds balanced feasibility with diversity, capturing variations in size, building age, and condition. Despite the modest sample size, this carefully curated set provides a robust foundation for developing scalable retrofit strategies that are relevant to CoSB's broader housing stock and similar contexts, ensuring meaningful impact within the Stage 2 one-year implementation period.

Figure 4 Sensors

On-site audits conducted between August and November 2024 allowed the team to evaluate building conditions, identify retrofit opportunities using PDIs, and develop eight prototypes to represent units with similar characteristics across the city. These audits assessed both exterior and interior conditions. Exterior inspections employed visual assessments and thermal imaging to detect thermal leakage, while interior audits evaluated insulation, mechanical systems, moisture levels, physical wear and tear, and conducted 3D scanning (refer to images in Table 3). Following the audits, sensors (see Figure 4) were installed in each unit for 10-14 days to collect continuous data on temperature, humidity, and CO2 levels (refer to recorded data images in Table 3). This combination of on-site and sensor data provided critical insights into building performance, ensuring that the eight testbeds offer meaningful and actionable findings for scaling retrofit strategies across diverse housing types. Additionally, the measured data were used to create indoor heat exposure and energy efficiency indices, which are essential components of the BUILT2AFFORD dashboard.

Table 3: Identified tests

Type		Location	Proposed PDIs	Sample Auditing Images
Single-family Detached Homes	House	806 Leland Ave	Add external shade (removable)	
	House	815 Leland Ave	Add external shade; Add insulation (roof)	
Small Multi-family Apartment Building	Apt, 1 br	SBHF #102	Replace windows; Add insluation	
	Apt, 1 br	SBHF #104	Replace windows; Add insluation	
	Apt, 1 br	SBHF #202	Replace windows; Add insluation	
Large Multi-family Apartment Building	Apt, 1 br	MarMain #122	Replace windows	
	Apt, 1 br	MarMain #315	Replace windows	
	Apt, 1 br	MarMain #322	Replace windows; Add insulation (roof)	

2.4 Created indoor heat exposure and energy efficiency indices

We developed digital models for each testbed using 3D scanning images, data collected during auditing, and floor plans provided by civic partners. These models formed the foundation for creating indices, including indoor heat exposure and energy efficiency indices. Directly measuring indoor thermal conditions for individual buildings on a large scale is not feasible with the current method. However, since thermal conditions are primarily determined by a limited set of variables—such as building size, type, thermal properties of materials, and heating and cooling systems —these conditions can be modeled using an energy model. To calculate indoor heat exposure, we modeled hours with dry bulb temperatures exceeding the cooling setpoint of 78.8 °F as "too hot," using Sefaira, a software powered by EnergyPlus. Inputs included PDIs extracted from GSV, audit, and local weather data. Buildings were divided into thermal zones (one per room), and EnergyPlus applied the heat balance method to compute hourly air temperature, humidity, and radiant temperature every 15 minutes over a year. Sefaira filtered EnergyPlus data for operating hours, categorizing hourly Predicted Mean Vote (PMV) results into three groups: "Comfortable," "Too Hot," or "Too Cold," based on "PMV Criteria." The existing conditions served as a baseline for “Too Hot” hours. Low-cost retrofit strategies, such as adding external shading, were modeled to calculate reductions in “Too Hot” hours, generating indoor heat exposure indices. The indices were then used to develop a multivariable regression model to assess health risk mitigation from the retrofit.

For energy efficiency indices, we used utility bills (obtained from testbed owner homers and renters) from the past 12 months as a baseline, averaging summer energy use (June–August) for each testbed. Using EnergyPlus, we modeled energy use (kBTU/ft²/yr) under different retrofit scenarios and calculated reductions from the baseline to create energy efficiency indices. Finally, input variables, modeled energy efficiency, and indoor heat exposure indices were combined with health outcome data to develop a multivariable regression model, forming the foundation of the BUILT2AFFORD dashboard.

3.0 Preliminary Results

3.1. House auditing

The collected data revealed significant findings regarding temperature, humidity, and CO_2 levels during both cooling and heating seasons. A key observation was the presence of mini microclimates within single-family homes, where notable differences in temperature and CO_2 levels occurred across rooms, suggesting non-uniform thermal conditions. These variations appeared to stem from design or layout issues affecting airflow and ventilation efficiency. Further, the assessments highlighted large diurnal temperature and humidity fluctuations exceeding 35°F and 10%, respectively, during the cooling season, which pointed to insufficient insulation and inefficient cooling systems. In the heating season, over 50% of the observed indoor temperatures fell below the ASHRAE-recommended range of 68-72°F (20-22°C), underscoring thermal comfort challenges and potential heating inefficiencies that may be caused by insufficient insulation and inefficient heating systems. Hence, we can hypothesize that improving insulation can solve the problems in both heating and cooling seasons.

Humidity and CO_2 patterns also raised critical concerns. During the cooling season, bedrooms exhibited higher humidity levels exceeding 50%, which can increase bacteria growth by up to 2.8 times, posing health risks. In contrast, humidity levels during the heating season remained within the acceptable ASHRAE range of 30-65%. High CO_2 levels were another consistent issue, with concentrations exceeding 800 ppm in many rooms during both cooling and heating seasons (refer to Figure 5). Some houses recorded levels surpassing the ASHRAE threshold of 1,000 ppm for more than 80% of the time, indicating poor air circulation and potential energy inefficiencies. These findings highlight a need for targeted retrofits to improve insulation, optimize ventilation, and enhance indoor air quality, ensuring homes meet thermal comfort and health standards year-round.

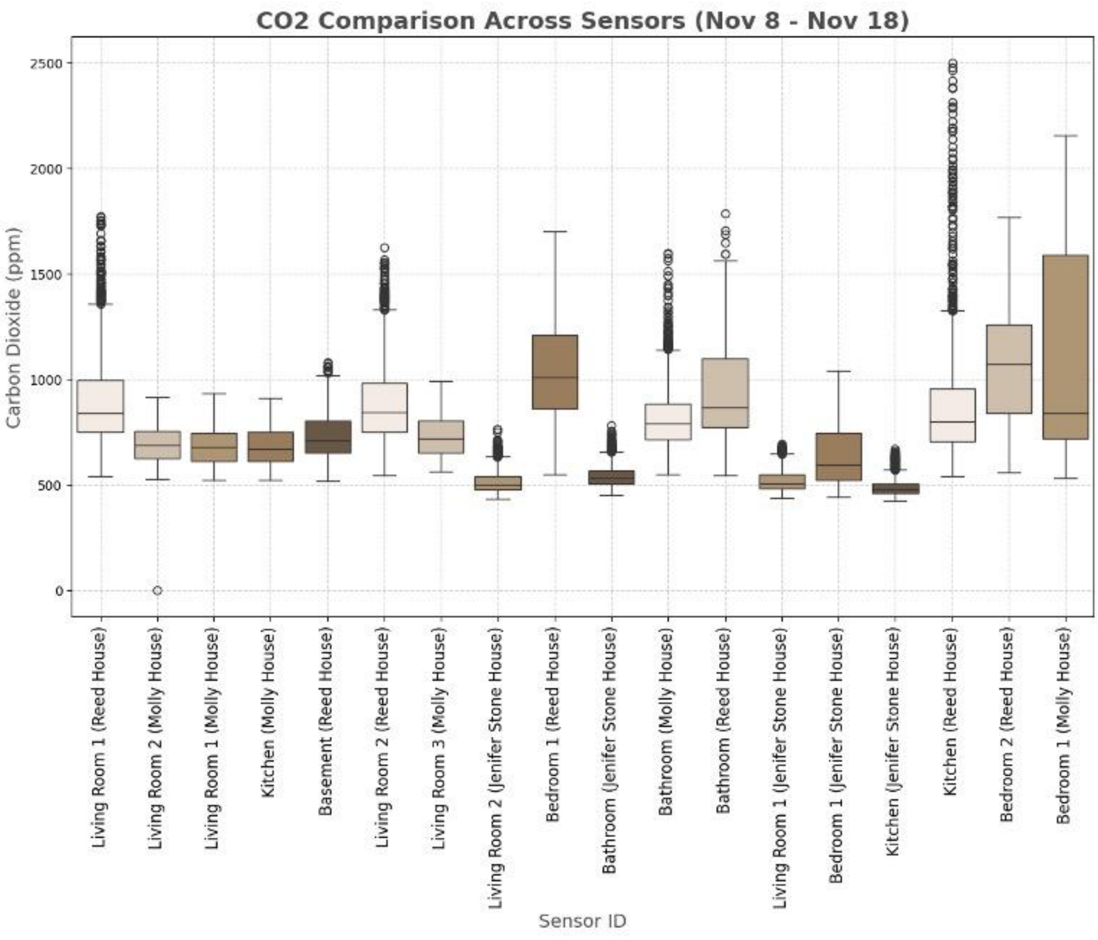


Figure 5: CO_2 level data collected from sensors

In contrast to the single-family houses, the apartment units demonstrated more consistent environmental performance across both large and small buildings. The environmental metrics—including temperature, humidity, and CO2 levels—were nearly identical within spaces of the same unit, with only minor statistical differences observed. This uniformity suggests that the apartments generally benefit from more stable thermal and air quality conditions compared to single-family homes, likely due to more centralized systems and shared building infrastructure. Overall, the apartment units exhibited comfortable environmental conditions during the assessment period. Average temperatures ranged from 65.3°F to 73.4°F (18.5°C to 23°C), while humidity levels remained within the recommended range of 38-45%, aligning well with ASHRAE standards. However, temperature emerged as the primary area of concern, as values below the comfort threshold can drive increased heating demand, highlighting a potential opportunity for targeted energy retrofits to optimize thermal performance.

3.2. Predicted energy efficiency indices from PDI

Fifteen different retrofit scenarios using various PDI combinations were simulated in Sefaira. The analysis reveals that Infiltration - Best Practice (0.27 cfm/ft² at 50 Pascals pressure) consistently outperforms all other measures in reducing energy consumption and fan energy use. For comparison, the most stringent standard, the Passive House standard, requires an infiltration rate of 0.06 cfm/ft² of envelope area at 50 Pa. For the existing orientation (E-S), this strategy reduces total energy use from the baseline of 2,985 kWh to 1,685 kWh, a 43.5% improvement, while fan energy decreases from 1,367 kWh to 108 kWh, a 92.1% improvement. These results underscore the effectiveness of sealing air leaks and optimizing ventilation systems in minimizing HVAC loads and improving indoor thermal conditions, making it the most impactful and cost-efficient retrofit option.

The second most effective strategy is Insulation (Roof + Wall), which achieves significant reductions in total energy use by enhancing thermal resistance across the building envelope. For the E-W orientation, this scenario reduces total energy from the baseline 2,985 kWh to 1,796 kWh, a 39.8% improvement, and fan energy from 1,367 kWh to 145 kWh, an 89.4% improvement. For the N-S orientation, total energy decreases further to 1,779 kWh, a 40.4% improvement, while fan energy drops to 142 kWh, an 89.6% improvement. These improvements demonstrate the critical role of comprehensive insulation in stabilizing indoor temperatures and mitigating heat transfer, particularly in poorly insulated buildings.

Moderate energy savings are observed with Insulation (Roof + Shade), which is particularly effective in addressing solar heat gain. For the original orientation, total energy use is reduced from 2,985 kWh to 2,308 kWh, a 22.7% improvement, while fan energy decreases from 1,367 kWh to 126 kWh, a 90.8% improvement. Similarly, the N-S orientation achieves reductions to 2,275 kWh in total energy, a 23.7% improvement, and 121 kWh in fan energy, a 91.1% improvement. Although less impactful than infiltration or wall insulation measures, this strategy offers balanced improvements, especially in climates with high solar exposure.

Window Replacement and Shade-Only Retrofits provide modest energy savings and are less effective compared to comprehensive measures. In both orientations, total energy use remains above 2,300 kWh, with reductions limited to approximately 22.9% for total energy and around 90.9% for fan energy, depending on the scenario. While these measures can complement primary retrofits, their standalone impact is relatively minor and best suited for addressing specific localized issues.

In summary, the results confirm that Infiltration - Best Practice and Insulation (Roof + Wall) deliver the most significant reductions in energy consumption and operational costs, making them the preferred retrofit strategies. Supplementary measures, such as Insulation (Roof + Shade) or Window Replacement, can be considered for additional improvements but are less effective when implemented alone. These findings emphasize the importance of targeting air leakage and thermal performance to achieve optimal energy efficiency and thermal comfort.

3.3. BUILT2AFFORD dashboard

As illustrated in Figure 6, the proposed BUILT2AFFORD dashboard is an interactive tool designed to empower stakeholders to assess affordable housing conditions, identify cost-effective passive retrofit strategies, and address health risks related to extreme heat. The BUILT2AFFORD dashboard features an intuitive and user-friendly interface divided into three distinct sections: the left pane, the center map, and the right pane, each serving a unique function to support housing retrofit decisions. In the left pane, users can input personalized information to customize their retrofit assessment. Fields include *address entry*, *income level selection* (e.g., low income), and *health risk categories* such as mental health, asthma, heat stroke, or heart risks. Users can also select specific retrofit solutions, such as "*Add Shading*" or "*Add Insulation*," along with shading options like "*External Shading*." This section acts as a control panel, enabling users to filter and refine recommendations based on individual or household needs.

The center map serves as the dashboard's core visualization component, displaying a detailed geographic layout of South Bend's housing stock. Overlaid with multiple data layers, the map provides insights into housing conditions, energy burdens, and health risks across neighborhoods. It allows users to spatially analyze housing characteristics, identify priority areas, and evaluate retrofit opportunities within specific locations. The right pane focuses on summarizing the *Solutions and Benefits* of the selected retrofits and their associated *Estimated Costs*. A benefits bar graph quantifies outcomes such as cost savings (e.g., 30%), energy savings (45%), and heat-related health risk mitigation (up to 80%). Below this, an *Estimated Cost* graph illustrates the price range of retrofits (e.g., \$100/ft to \$300/ft) and highlights potential funding sources, including city, state, federal, and contractor resources. This pane translates technical insights into actionable, easy-to-understand results, helping stakeholders balance costs and benefits effectively. Together, these three sections—interactive inputs, spatial mapping, and quantitative benefits analysis—create a cohesive and accessible platform for users to identify cost-effective retrofit strategies, address heat-related health risks, and contribute to South Bend's equity and carbon-neutral goals

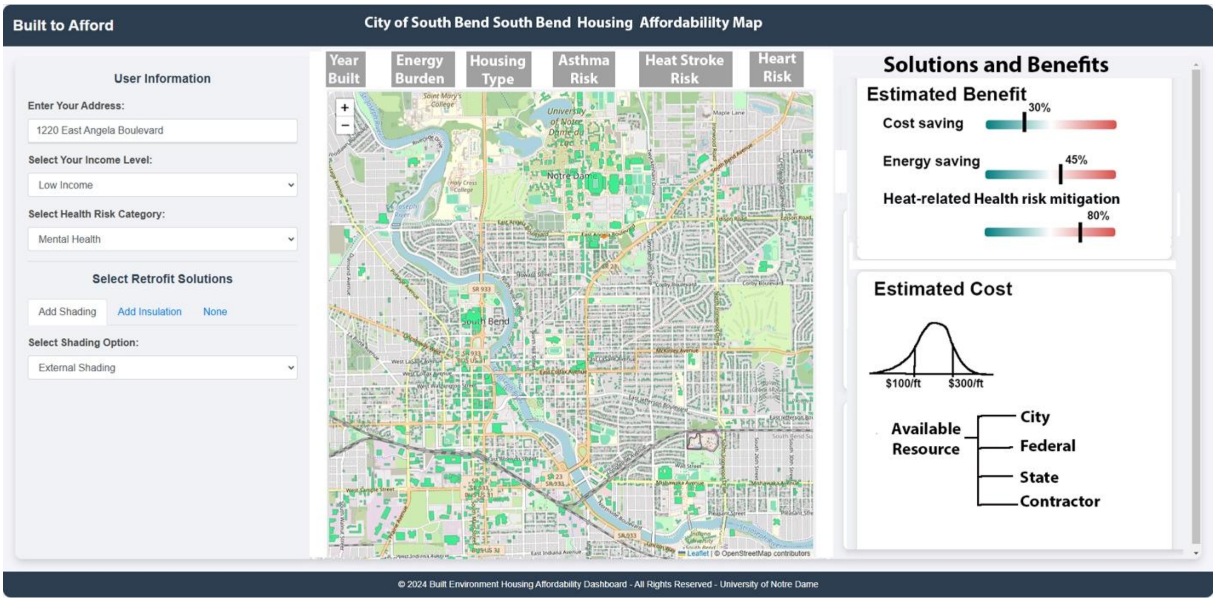


Figure 6: Proposed BUILT2AFFORD dashboard

4.0 CONCLUSION

The U.S. faces a severe shortage of affordable housing; only 34 affordable and available rental homes exist for every 100 extremely low-income renter households, creating a gap that exists across every state and major metropolitan area (National low income housing coaltion 2024). Outdated housing infrastructure exacerbates this crisis by imposing high energy burdens through steep utility bills, disproportionately affecting residents in historically neglected neighborhoods, many of whom are low-income and from underrepresented populations (Brown et al. 2020; Drehobl, Ross, and Ayala 2020).

The BUILT2AFFORD project addresses critical challenges at the intersection of affordable housing, energy efficiency, and climate resilience. Through a combination of machine learning, Google Street View imagery, and on-site audits, the project develops scalable and cost-effective strategies for improving housing conditions while reducing energy burdens on vulnerable populations. This work highlights the potential of integrating advanced technologies and community engagement to transform outdated housing stock into sustainable, energy-efficient homes.

Key achievements include the development of the BUILT2AFFORD dashboard, a tool designed to assess building conditions, evaluate energy retrofit potential, and mitigate heat-related health risks. This tool leverages innovative zero-shot vision-language models to identify passive design indicators (PDIs) from vast datasets, enabling a streamlined and scalable approach to retrofit analysis. On-site audits and continuous environmental monitoring across eight diverse testbeds provided critical insights into building performance, validating the dashboard's capacity to generate actionable recommendations for various housing types.

Preliminary results demonstrate substantial energy savings and improved indoor comfort through targeted retrofit strategies such as infiltration reduction and insulation upgrades. For instance, infiltration reduction achieved up to a 43.5% reduction in total energy use and a 92.1% reduction in fan energy consumption, underscoring the effectiveness of sealing air leaks and optimizing ventilation systems. Similarly, roof and wall insulation retrofits stabilized indoor temperatures and reduced heat transfer, enhancing thermal comfort and energy efficiency.

Looking forward, the BUILT2AFFORD dashboard offers a replicable framework for addressing housing challenges in other regions. By combining advanced technology with localized community engagement, this project paves the way for the broader adoption of passive design strategies in the affordable housing sector. The findings emphasize the importance of scalable, data-driven solutions in achieving equity-focused, sustainable development, aligning with broader goals of carbon neutrality and climate resilience. Through continued collaboration and refinement, BUILT2AFFORD has the potential to significantly enhance housing quality and reduce environmental and economic disparities nationwide.

ACKNOWLEDGEMENTS

This research was supported by National Science Foundation #2317971, National Science Foundation #2430623, and in part by the Intramural Research Program of the NIH.

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