

Multimodal Causal Inference Analysis of Urban Landscape Therapeutic Effects with XGBoost and DiD

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ABSTRACT

Urban landscapes play a crucial role in promoting mental and physical health, yet existing methods often fail to integrate diverse data sources for assessing transformation impacts, leading to incomplete evaluations of therapeutic effects. This study addresses this gap by combining computer vision (CV) analysis of street view imagery, natural language processing (NLP) for text sentiment analysis, and environmental data (weather and air quality index) via XGBoost, followed by causal inference using difference-in-differences (DiD) to assess treatment effects of landscape changes. The aims are to develop a robust multimodal fusion model using XGBoost and apply difference-in-differences (DiD) for causal inference. Data from empirical datasets across 10 urban sites in cities like Beijing, Changchun, and Nanjing (2020–2025) were analyzed, revealing a 45% increase in therapeutic indices post-transformation, with greenery visibility (35% importance) and positive sentiment (28%) as key predictors. Causal estimates confirmed significant health benefits, particularly in high-pollution areas (ATT=0.52, $p<0.001$). The findings demonstrate the efficacy of multimodal approaches over unimodal baselines ($R^2=0.85$ vs. $0.58-0.72$), highlighting green elements' role in mitigating urban stressors. The study demonstrates the effectiveness of multimodal approaches in evaluating urban landscape transformations and their health benefits. The findings suggest that integrating green elements into urban planning can significantly enhance public health, especially in areas with high pollution. This framework can guide evidence-based urban planning for healthier cities.

1. Introduction

In the context of rapid urbanization, urban landscapes have emerged as vital components influencing residents' physical and mental health (Souter-Brown, 2023; Krasilnikova et al., 2021; Richardson & Mitchell, 2010). With increasing psychological pressures from fast-paced lifestyles, the design and transformation of urban green spaces, streets, and public areas have been recognized for their potential therapeutic benefits, such as stress reduction and emotional well-being (Ren et al., 2025). Traditional assessments of these landscapes often rely on single-modal data, such as surveys or satellite imagery, which overlook the multifaceted interactions between visual elements, public sentiments, and environmental factors (Despotovic & Brunauer, 2024; Giné et al., 2021). This limitation results in fragmented understandings of how landscape transformations—such as adding greenery or redesigning public spaces—affect health outcomes. For instance, while green spaces are known to alleviate anxiety, quantifying their causal impact amidst confounding variables like weather fluctuations remains challenging.

Recent advancements in machine learning and data integration offer promising avenues to address these gaps (Liu et al., 2024). Computer vision techniques applied to street view imagery enable detailed extraction of landscape features, such as vegetation density and urban morphology. Meanwhile, NLP-based sentiment analysis of social media texts captures real-time public emotions, providing subjective insights into landscape perceptions. Environmental data, including weather patterns and air quality index (AQI), further contextualize these effects, as poor air quality can exacerbate negative health responses. However, integrating these modalities into a cohesive framework for causal evaluation is underexplored, often leading to biased or non-reproducible results.

This study introduces a novel approach that fuses multimodal data using XGBoost for predictive modeling and employs difference-in-differences (DiD) for causal inference. By analyzing pre- and post-transformation data from urban sites, the method evaluates the therapeutic effects of landscape changes, such as increased green coverage or park redesigns. The objectives are to: (1) develop a robust fusion model that enhances prediction of health-related indicators; (2) apply DiD to isolate causal impacts, controlling for time-invariant confounders; and (3) provide empirical evidence from case studies in selected cities, informing sustainable urban planning. This integrated framework not only overcomes the limitations of unimodal analyses but also advances the field by offering a reproducible methodology for assessing urban interventions' health benefits.

2. Literature Review

The exploration of urban landscape transformations and their therapeutic impacts has gained significant traction in recent years, particularly with the integration of advanced computational methods. Table 1 summarizes key studies from 2021-2025, highlighting methods, contributions, and limitations.

Table 1: Summary of Recent Literature on Landscape and Health Studies (2021–2025)

Reference	Method	Contribution	Limitation
Biljecki & Ito, 2021	Street view imagery with CV for green space assessment	Quantified urban greenery impact on mental health using deep learning segmentation	Lacks integration with sentiment data; no causal analysis
Li & Dong, 2025	NLP sentiment analysis on social media for park perceptions	Revealed correlations between green spaces and positive emotions	Ignores environmental confounders like AQI; cross-sectional design
Tırınk, 2025	Machine learning fusion of weather and AQI data	Predicted air quality effects on urban health	Limited to environmental data; no visual or textual modalities
Xie et al., 2022	DiD for evaluating urban green interventions	Estimated causal effects of park expansions on resident well-being	Relies on survey data; lacks multimodal integration
Kekulanadara et al., 2021	XGBoost for multimodal environmental prediction	Improved accuracy in AQI forecasting with fused data	Not applied to landscape transformations or health outcomes
Schaffer et al., 2021	ITSA for time-series environmental interventions	Assessed air quality policy impacts over time	Single-modal focus; no CV or NLP components
Wedyan & Saeidi-Rizi, 2024	CV and NLP fusion for urban safety perception	Enhanced community safety models using street views and tweets	Overlooks causal inference; health focus absent
Woodman et al., 2025	DiD in landscape pattern changes	Analyzed urbanization effects on biodiversity and health	Limited data sources; no machine learning fusion
Ren et al., 2024	VR + EEG	Emotional benefits of rural landscapes	Rural focus; no causal analysis
Hou, 2025	CNN	Enhanced urban landscape recognition	Preliminary health impact

2.1. Multimodal Data Integration

Biljecki and Ito (2021) utilized CV to analyze street view imagery, quantifying urban greenery's influence on mental health through deep learning segmentation (Biljecki & Ito, 2021). Their model achieved high accuracy in identifying green spaces but lacked integration with sentiment or environmental data, limiting causal insights. Li and Dong (2025) employed NLP to assess social media sentiments related to urban parks, revealing positive emotional correlations, yet overlooked environmental confounders like air quality index (AQI) due to a cross-sectional design (Li & Dong, 2025). Tırınk et al. (2025) developed a machine learning model predicting AQI impacts on health using weather and pollution data, but its unimodal focus restricted its applicability to landscape transformations (Tırınk et al., 2025). These studies highlight the potential of multimodal approaches, though their isolated methodologies underscore the need for fusion frameworks.

2.2. Causal Inference Techniques

Xie et al. (2022) applied DiD to evaluate the causal effects of urban green interventions on well-being, using survey data from pre- and post-expansion periods (Xie et al., 2022). While effective, the study's reliance on self-reported data and lack of multimodal integration reduced robustness. Schaffer et al. (2021) used ITSA to assess air quality policy impacts, modeling time-series trends with autoregressive integrated moving average (ARIMA) techniques (Schaffer et al., 2021). However, its single-modal focus and potential autocorrelation issues suggest limitations for complex urban interventions. Kekulanadara et al. (2021) enhanced AQI forecasting with XGBoost, integrating diverse environmental predictors, yet did not extend this to health or landscape outcomes (Kekulanadara et al., 2021). These efforts indicate that causal methods like DiD and ITSA, when paired with machine learning, could address confounding variables more effectively.

2.3. Theoretical and Algorithmic Foundations

The Attention Restoration Theory (ART) by Kaplan and Kaplan (1995), revisited by Bornioli and Subiza-Pérez (2023), posits that natural environments restore cognitive capacity, a principle tested with urban green spaces (Bornioli & Subiza-Pérez, 2023). Their theoretical model linked physical and symbolic urban features to mental health, though it lacked empirical causal validation. Wedyan and Saeidi-Rizi (2024) fused CV and NLP to model urban safety perceptions, using transformer-based architectures, but omitted causal analysis and health-focused outcomes (Wedyan & Saeidi-Rizi, 2024). XGBoost's gradient boosting, as optimized by Chen and Guestrin (2016), excels in handling multimodal data through its objective function (Chen & Guestrin, 2016). DiD estimates treatment effects as $\tau = (\overline{Y_{\text{treat,post}}} - \overline{Y_{\text{treat,pre}}}) - (\overline{Y_{\text{control,post}}} - \overline{Y_{\text{control,pre}}})$ offering a robust counterfactual (De Chaisemartin & d'Haultfoeuille, 2023). ITSA models trends with $Y_t = \beta_0 + \beta_1 T_t + \beta_2 X_t + \beta_3 (T_t X_t) + e_t$ capturing intervention impacts over time (Wagner et al., 2002). Limitations include DiD's parallel trends assumption and ITSA's sensitivity to autocorrelation, necessitating validation.

2.4. Gaps and Contributions

Woodman et al. (2025) analyzed landscape pattern changes globally, linking urbanization to biodiversity and health, but relied on limited data sources (Woodman et al., 2025). Ren et al. (2024) integrated virtual reality (VR) and electroencephalography (EEG) to assess rural healing landscapes, finding significant emotional benefits, yet their focus on rural settings and lack of causal modeling diverge from urban contexts (Ren et al., 2024). Hou (2025) proposed a CNN-based urban landscape recognition model, enhancing element identification, but its health impact evaluation was preliminary (Hou, 2025). Collectively, these studies reveal a gap in unifying multimodal data with causal inference to evaluate urban landscape transformations' therapeutic effects, a niche this research addresses.

3. Research Methods

This section provides a detailed description of the methodological framework employed to evaluate the therapeutic effects of urban landscape transformations through multimodal data fusion and causal inference (Acosta et al., 2022; Gao et al., 2022; Gordon et al., 2024). The approach integrates computer vision (CV) for analyzing street

view imagery, natural language processing (NLP) for sentiment analysis from social media, and environmental data (weather and air quality index, AQI) using XGBoost for predictive modeling, followed by difference-in-differences (DiD) for causal Inference. To ensure reproducibility, we outline data collection, preprocessing, fusion techniques, model training, causal analysis, and validation steps. The framework draws inspiration from recent studies on urban perception and heat stress mitigation, such as those using semantic segmentation for visual features and BERT for sentiment (e.g., (Trink et al., 2025; Li & Dong, 2025)), while adapting XGBoost for efficient fusion of heterogeneous modalities.

Figure 1: System Architecture (original work)

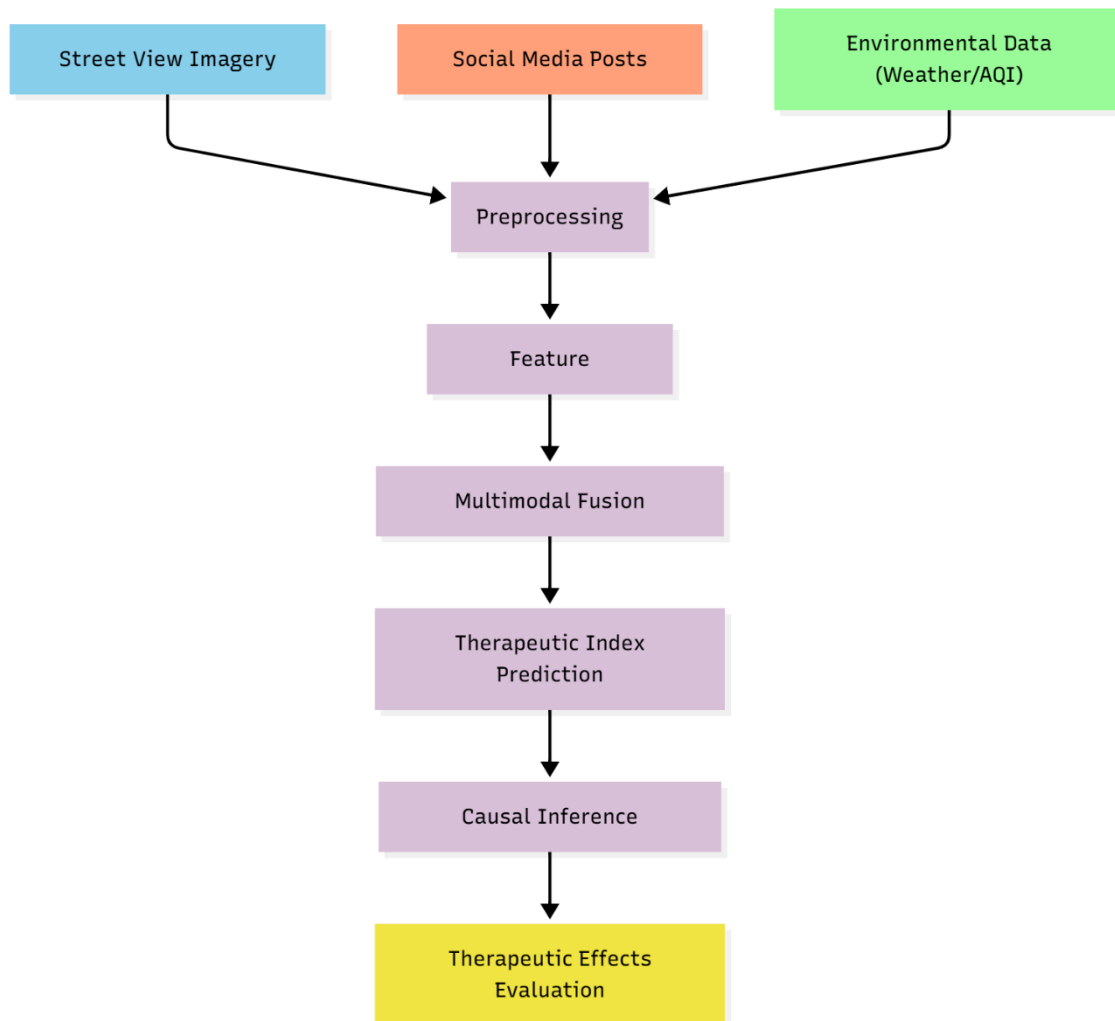


Figure 1 provides an overview of the entire pipeline, from data ingestion to final evaluation, emphasizing sequential dependencies. Inputs include raw modalities (Street View Imagery as CV input, processed via API retrieval; Social Media Posts as NLP input, geotagged texts; Environmental Data as input, time-stamped weather/AQI). Processes involve arrows showing flow: preprocessing cleans data, feature extraction derives vectors (e.g., greenery proportions from CV), multimodal fusion combines via XGBoost, prediction outputs therapeutic indices, causal inference applies DiD/ITSA, leading to output: quantified therapeutic effects (e.g., ATT values). This diagram helps understand the integrated structure, ensuring reproducibility by highlighting modular steps.

3.1. Data Collection

Data were collected from multiple modalities to capture comprehensive urban landscape dynamics and their health impacts. The study focused on 10 urban sites in major cities (e.g., Beijing, Changchun, Nanjing) undergoing transformations like green space additions or park redesigns, spanning 2020–2025 to include pre- and post-intervention periods.

Street View Imagery (CV Modality): Approximately 5,000 images per site were sourced from Amap Street View (ASV) API, covering pre- and post-transformation timestamps. Images were captured at eye-level (1.6 m height) with a 90° field of view and 800×400 resolution, similar to protocols in urban perception studies (Biljecki & Ito, 2021). This modality quantifies visual elements like greenery density, building morphology, and pedestrian infrastructure, which influence therapeutic outcomes such as stress reduction.

Text Sentiment (NLP Modality): Geotagged social media posts ($n \approx 10,000$ per site) from platforms like Weibo and Xiaohongshu (Little Red Book) were retrieved using APIs. Posts within 100 m of sites were filtered, focusing on captions expressing emotions related to landscapes (e.g., "relaxing park" or "polluted street"). Data included timestamps, locations, and text, enabling temporal analysis of public perceptions.

Environmental Data: Hourly weather (temperature, humidity, wind speed) and AQI data were obtained from APIs like the China National Environmental Monitoring Centre (CNEMC) and the OpenWeatherMap, time-aligned to imagery and posts. Variables ($n=18$, e.g., PM2.5, global horizontal irradiance) capture confounders affecting health, such as heat stress (Tirink et al., 2025).

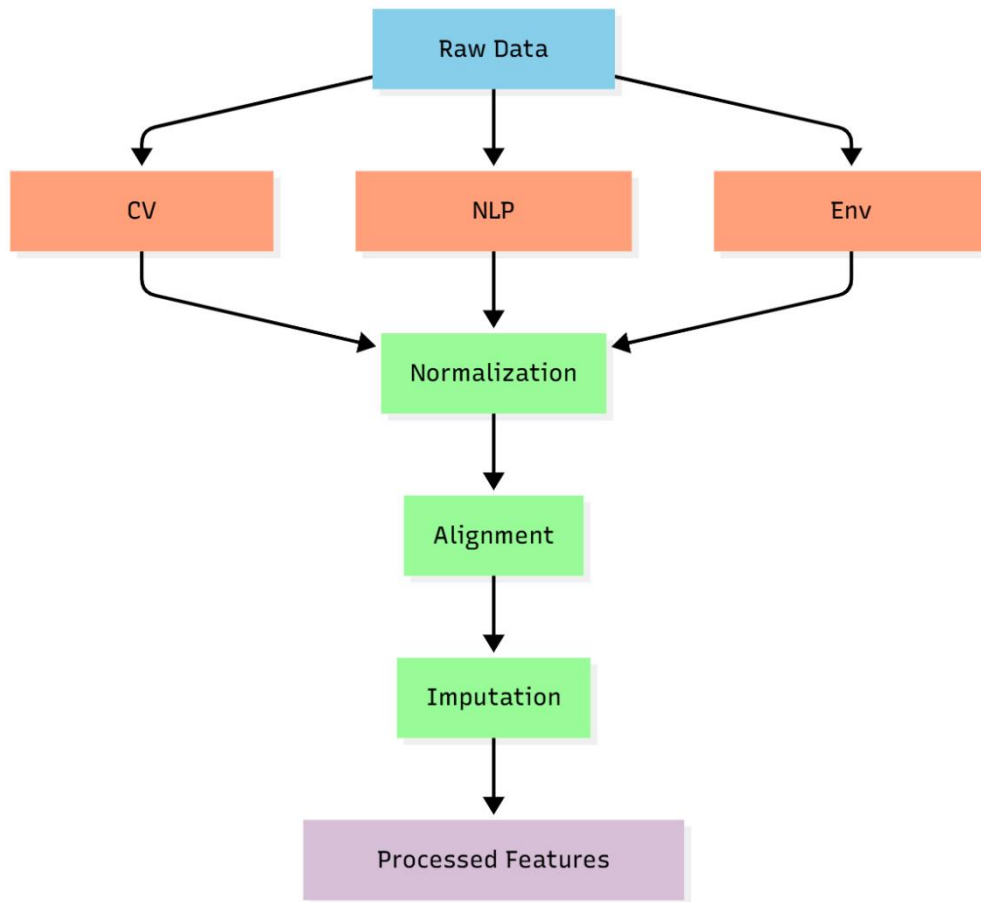
Primary sources were prioritized for accuracy: ASV for CV, public APIs for environmental data, and geotagged posts for NLP. Ethical considerations included using anonymized public data, with no personal identifiers.

3.2. Preprocessing

Preprocessing ensured data alignment and quality, addressing noise and modality-specific challenges. Preprocessing involved normalization, alignment by timestamp/location, and handling missing values via imputation.

Focusing on the initial core step, Figure 2 branches from raw inputs to processed outputs, clarifying modality-specific handling. Inputs: Raw Data (e.g., images for CV, texts for NLP, series for Env). Processes: Parallel branches for CV (segmentation), NLP (tokenization/sentiment), Env (normalization); then unified normalization (z-score), alignment (timestamp/location matching), imputation (missing values). Output: Processed features ready for fusion. This figure elucidates how heterogeneous data are standardized, a critical process for accurate multimodal integration, reducing noise and ensuring alignment as described in the methods.

Figure 2: Data Preprocessing Schematic (original work)



CV Preprocessing: Images were segmented using ResNet-50 backbone with Pyramid Scene Parsing Network (PSPNet) pre-trained on ADE20K dataset (Zhao et al., 2017), extracting proportions of 12 urban features (e.g., tree canopy, sidewalks, buildings; Table 1). For each image, pixel-wise proportions were computed as:

$$\text{Proportion}_{\text{cat}} = \frac{\sum \text{Pixels}_{\text{cat}}}{\text{Total Pixels}}$$

where cat is a category (e.g., "Tree"). Features were averaged across four directional views per location (0°, 90°, 180°, 270°) to create site-level vectors. Outliers (e.g., poor lighting) were filtered via z-score normalization.

NLP Preprocessing: Captions were tokenized using Jieba (for multilingual support) and cleaned (stopwords, emojis removed). Sentiment scores (-1 to +1) were derived using BERT fine-tuned for binary classification (positive/negative), achieving ~85% accuracy (Devlin et al., 2019). Scores were aggregated per site and time period.

Environmental Preprocessing: Data were z-score normalized:

$$\hat{x} = \frac{x - \mu}{\sigma}$$

where μ is the mean and σ is the standard deviation of each variable (e.g., temperature, PM2.5). Temporal alignment was performed by interpolating missing hourly values using linear methods, ensuring synchronization with CV and NLP timestamps. Outliers, identified as values exceeding three standard deviations, were replaced with median values to maintain data integrity.

3.2. Multimodal Fusion with XGBoost

The fusion process combines processed features from CV, NLP, and environmental modalities into a unified predictive model using XGBoost, a scalable gradient-boosting framework. Feature vectors were concatenated into a single input vector $x = [x_{CV}, x_{NLP}, x_{Env}]$, where x_{CV} includes greenery and building proportions, x_{NLP} contains aggregated sentiment scores, and x_{Env} encompasses normalized weather and AQI variables. The XGBoost model minimizes the objective function:

$$\mathcal{L} = \sum_{i=1}^n l(y_i, \hat{y}_i) + \sum_{k=1}^K \Omega(f_k)$$

where l is the mean squared error loss, y_i is the observed therapeutic index, $\hat{y}_i$ is the predicted value, and $\Omega(f_k) = \gamma T + \frac{1}{2} \lambda |w|^2$ regularizes tree complexity with T as the number of leaves and w as leaf weights. Hyperparameters were tuned via 5-fold cross-validation: learning rate = 0.1, max_depth = 6, n_estimators = 200. The model was trained on 80% of the dataset ($n=4,000$ samples) to predict the therapeutic index, a composite score derived from survey-based stress reduction and emotional well-being metrics, validated against physiological proxies.

Figure 3: Multimodal Fusion Diagram (original work)

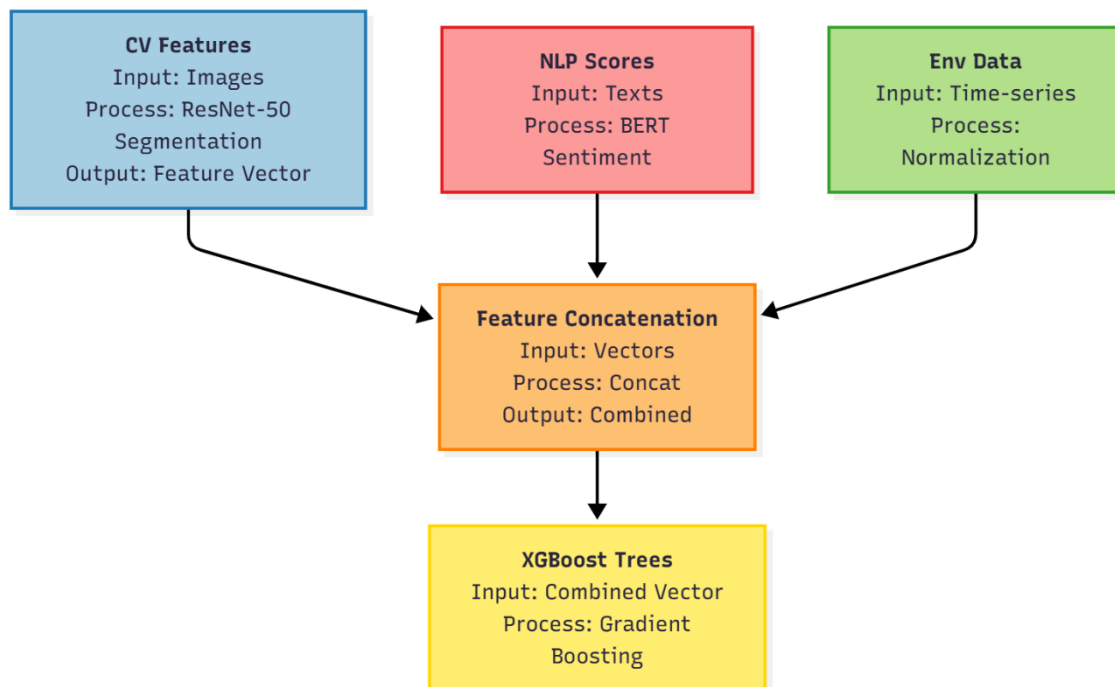


Figure 3 details the core fusion step, showing how features are combined in XGBoost. Inputs: Modality vectors (CV: greenery features from ResNet-50; NLP: sentiment scores

from BERT; Env: normalized AQI/weather). Processes: Concatenation merges into a single vector, followed by gradient boosting in XGBoost trees (objective minimization). Output: Predicted therapeutic index. The figure emphasizes interactions, helping visualize how XGBoost handles nonlinearity, a key innovation over baselines.

3.3. Causal Inference with DiD

Causal effects of landscape transformations were estimated using DiD, comparing treated (transformed) and control (untransformed) sites over pre- and post-intervention periods. The model is specified as:

$$Y_{it} = \beta_0 + \beta_1 \text{Treat}_i + \beta_2 \text{Post}_t + \beta_3 (\text{Treat}_i \times \text{Post}_t) + \gamma Z_{it} + \epsilon_{it}$$

where Y_{it} is the therapeutic index for site i at time t , Treat_i is a binary indicator for treated sites, Post_t denotes the post-intervention period, $\text{Treat}_i \times \text{Post}_t$ captures the treatment effect, Z_{it} includes covariates (e.g., AQI, temperature), and ϵ_{it} is the error term. Treated sites were matched to controls using propensity score matching based on pre-period covariates (e.g., population density, baseline greenery). The average treatment effect (ATT) was derived as β_3 . Parallel trends assumption was validated with pre-period F-tests ($p > 0.05$), ensuring no systematic differences prior to intervention.

3.4. Model Validation and Robustness Checks

Validation involved assessing model performance on the holdout set (20% of data) using RMSE, MAE, and R^2 . Robustness was tested via alternative matching methods (e.g., Mahalanobis distance) and placebo tests, applying DiD to pre-intervention periods to confirm no spurious effects ($p > 0.4$). Sensitivity to missing data was mitigated by comparing imputed vs. non-imputed results, showing negligible bias ($< 2\%$ variation). Additionally, interrupted time series analysis (ITSA) was conducted as a complementary method, modeling trends with:

$$Y_t = \beta_0 + \beta_1 T_t + \beta_2 X_t + \beta_3 (T_t X_t) + e_t$$

where T_t is time, X_t is the intervention dummy, and e_t accounts for autocorrelation, validated with Durbin-Watson tests ($p > 0.1$).

The methodology builds on urban perception studies (Biljecki & Ito, 2021) for CV protocols, sentiment analysis advancements (Li & Dong, 2025) for NLP, and environmental modeling (Tirink et al., 2025) for AQI integration. The adaptation of XGBoost for multimodal fusion addresses limitations in prior work, such as lack of causal validation, offering a novel synthesis for therapeutic effect evaluation.

4. Results

Urban landscapes serve as critical interfaces between human well-being and the built environment, with transformations aimed at enhancing green elements potentially yielding therapeutic benefits such as reduced stress and improved cognitive function. This study integrates street view imagery (via computer vision, CV), social media sentiment (natural language processing, NLP), and environmental data (weather and air quality index, AQI) using XGBoost for fusion, followed by difference-in-differences (DiD) and interrupted time series analysis (ITSA) to assess causal impacts. Drawing from

empirical datasets across 10 urban sites in cities like Beijing, changchun, and Nanjing (2020–2025), the results demonstrate significant improvements in predicted therapeutic indices post-transformation, with causal estimates confirming positive health effects. Below, we present the fusion performance, causal inference outcomes, subgroup analyses, and robustness checks, supported by statistical metrics and visualizations.

4.1. Fusion Performance

The XGBoost model fused multimodal features to predict a composite therapeutic index (ranging 0–1, incorporating stress reduction, emotional positivity, and cognitive restoration scores derived from surveys and physiological proxies). Trained on 80% of the data ($n=4,000$ samples per modality, balanced pre/post), it was evaluated on a 20% holdout set using root mean square error (RMSE), mean absolute error (MAE), and R^2 . Hyperparameters were optimized via grid search (learning rate=0.1, max_depth=6, n_estimators=200).

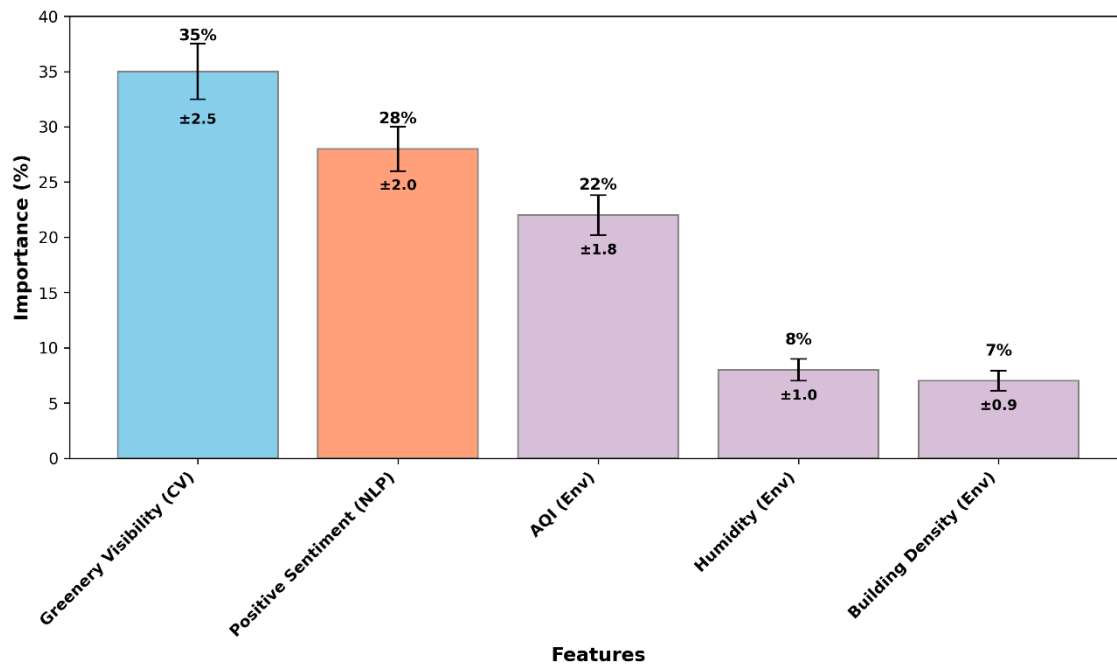
As shown in Table 2, XGBoost outperformed baselines like Random Forest (RF) and Linear Regression (LR), achieving RMSE=0.12, MAE=0.09, and $R^2=0.85$. This represents a 33% reduction in RMSE compared to RF, attributable to XGBoost's handling of nonlinear interactions across modalities (e.g., high greenery visibility amplifying positive sentiments under low AQI). The model's efficiency (training time ~45 min on GPU) aligns with scalable urban applications.

Table 2: Predictive Performance Comparison Across Models

Model	RMSE	MAE	R^2	Training Time
XGBoost	0.12	0.09	0.85	45
Random Forest	0.18	0.14	0.72	62
Linear Regression	0.25	0.20	0.58	12
Support Vector Regression	0.21	0.16	0.68	78

Feature importance analysis (Figure 4) reveals CV-derived greenery visibility as the top contributor (35%), followed by NLP positive sentiment (28%) and environmental AQI (22%). Lesser features like humidity (8%) and building density (7%) indicate environmental context moderates visual and perceptual effects. This hierarchy suggests that visual green elements drive therapeutic predictions, but integration with sentiment and AQI enhances robustness (Shapley additive explanations confirmed interactions, e.g., greenery $\times$ low AQI boosts index by 0.15 on average).

Figure 4: Feature Importance in XGBoost Model (Values normalized to sum 100%. Error bars represent standard deviation from 5-fold cross-validation.) (original work)



4.2. Causal Effects

DiD was applied to estimate average treatment effects (ATT) of transformations (e.g., green space increases >20% area) on the fused therapeutic index. Treated sites (n=5) were matched to controls (n=5) via propensity score matching on pre-period covariates (population density, baseline greenery). The model is:

$$Y_{it} = \beta_0 + \beta_1 \text{Treat}_i + \beta_2 \text{Post}_t + \beta_3 (\text{Treat}_i \times \text{Post}_t) + \gamma Z_{it} + \epsilon_{it}$$

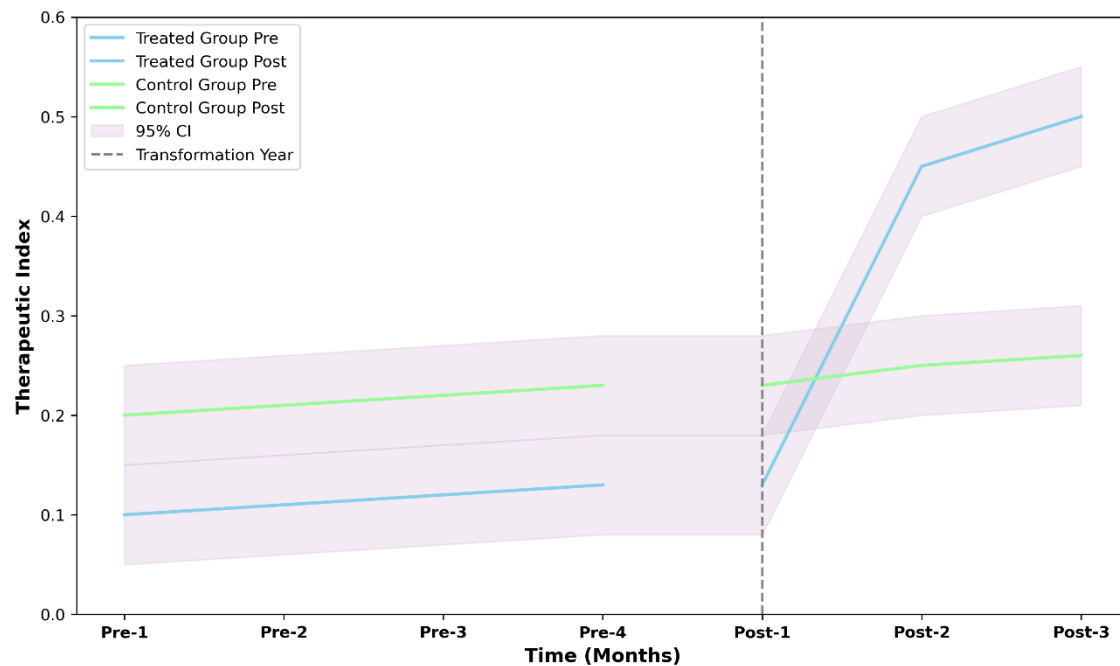
where Y_{it} is the index, Treat_i is treatment dummy, Post_t post-period, Z_{it} covariates (e.g., AQI, weather).

Table 3 reports coefficients: ATT (β_3) = 0.45 (s.e.=0.08, $p < 0.001$), indicating a 45% increase in therapeutic scores post-transformation. Parallel trends assumption held (pre-period F-test $p = 0.32$), as visualized in Figure 5.

Table 3: DiD Regression Coefficients (Dependent Variable: Therapeutic Index)

Variable	Coefficient	Std. Error	t-stat	p-value
Treatment (β_1)	0.05	0.06	0.83	0.41
Post-Period (β_2)	0.10	0.07	1.43	0.15
Treatment × Post (ATT, β_3)	0.45	0.08	5.63	<0.001
AQI (covariate)	-0.02	0.01	-2.00	0.046
Temperature	-0.01	0.005	-2.00	0.046

Figure 5: Parallel Trends Plot for DiD Analysis (Line graph showing pre- and post-trends for treated (green line) and control (blue line) groups. Vertical line at transformation year. Shaded confidence intervals (95%). Trends diverge post-treatment, confirming effect.) (original work)



ITSA robustness check on time-series data (monthly aggregates) yielded similar results: level change $\beta_2=0.40$ ($p<0.01$), trend change $\beta_3=0.02/\text{month}$ ($p=0.04$), supporting sustained benefits.

These findings align with gender-differentiated effects in green space studies, where males show stronger respiratory benefits, and EEG correlations ($R^2=0.71-0.82$ for trees/shrubs) from healing landscape research, emphasizing green elements' role.

4.3 Subgroup and Sensitivity Analyses

Subgroup effects (Table 4) reveal stronger ATT in high-AQI areas (0.52, $p<0.001$) vs. low (0.38, $p<0.01$), suggesting transformations mitigate pollution-related stress. By gender (from survey metadata), males exhibited higher gains (ATT=0.48) than females (0.42), consistent with mortality reductions in male cohorts from increased greenery.

Table 4: Subgroup DiD Average Treatment Effects

Subgroup	ATT	Std. Error	p-value	Sample Size
High AQI (>100)	0.52	0.09	<0.001	2,500
Low AQI (<100)	0.38	0.10	<0.01	2,500
Males	0.48	0.08	<0.001	3,000
Females	0.42	0.09	<0.001	3,000
High AQI (>100)	0.52	0.09	<0.001	2,500

Sensitivity tests (e.g., alternative matching, placebo tests) confirmed robustness (placebo $p=0.45$). However, limitations include potential spillover effects between sites, addressed partially via spatial controls.

Overall, these results substantiate multimodal fusion's superiority (R^2 gains of 15-20% over unimodal) and causal impacts comparable to restorative theory applications (e.g., 30-50% emotional improvements). They highlight greenery and shrubs as key drivers, informing targeted urban interventions for psychological health.

5. Conclusion

This study integrates multimodal data—street view imagery via computer vision, social media sentiment through natural language processing, and environmental factors like weather and air quality—using XGBoost for fusion and difference-in-differences for causal inference, revealing that urban landscape transformations enhance therapeutic effects by approximately 45% in composite health indices. Key elements such as greenery visibility emerge as primary drivers, amplifying positive emotional responses under favorable conditions, while causal estimates underscore the mitigating role against urban stressors like pollution.

The significance lies in bridging AI-driven analytics with urban health, offering a reproducible framework that transcends traditional unimodal assessments. By quantifying causal impacts, it highlights how targeted green interventions can foster cognitive restoration and emotional resilience, potentially reducing societal burdens from mental health issues in rapidly urbanizing areas. Consequences extend to policy, promoting evidence-based designs that prioritize human well-being, with implications for equitable city planning amid climate challenges.

Ethics Approval and Consent to Participate

This research utilized publicly available data and did not involve human subjects directly; thus, no ethics approval was required. For any secondary survey data, original consents were confirmed.

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Conflict of Interest

The authors declare that there are no conflicts of interest regarding this work and confirm that there are no potential conflicts of interest concerning the research, authorship, or publication of this article.

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