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Research Article

An Exploratory Spatial–Perceptual Framework for Heritage Revitalization: Mixed-Methods Evidence from Kota Lama Semarang

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Abstract:

Research on urban heritage revitalization faces a critical methodological limitation: the lack of frameworks for statistically testing spatially varying relationships between physical transformation and human perception. This study bridges this gap by developing and validating an integrated Exploratory Spatial–Perceptual Framework (ESPF). The ESPF advances beyond descriptive integration by coupling computational sentiment analysis of geocoded reviews (using a fine-tuned BERT model, F1=0.89) with high-resolution spatial metrics of urban form, and subjecting their relationship to Geographically Weighted Regression (GWR). Applied to Kota Lama Semarang (2003–2024), the ESPF reveals that perceptual outcomes are not uniform but are conditioned by local context. GWR uncovered significant spatial heterogeneity: increased commercial density strongly boosted sentiment in the historic core ($\beta = +0.42$), yet eroded environmental perception in peripheral zones ($\beta = -0.38$). These divergent associations demonstrate a Contextual Tolerance Threshold, empirically validating a core, yet previously untested, principle of the Historic Urban Landscape (HUL) approach. The study's primary contribution is a replicable, evidence-based framework that transforms HUL from a conceptual model into an operational tool for diagnosing the spatially contingent impacts of heritage policy, offering a critical method for equitable revitalization in Global South cities.

1. Introduction

In an era where historic urban districts are increasingly leveraged as catalysts for tourism and economic development, the revitalization of cultural heritage has become a central, yet complex, planning imperative across the Global South [1]. These districts exist at a critical nexus, simultaneously pressured by commercial intensification and climate vulnerabilities while tasked with preserving authenticity and fostering social value [2;3]. While substantial scholarship has developed robust, siloed methodologies for documenting physical transformation through spatial metrics or analyzing heritage perception through surveys, their integration remains methodologically underdeveloped [4]. Pioneering integrative studies, employing techniques such as geovisual overlays or side-by-side juxtaposition, have advanced the field but critically stop short of spatially explicit statistical modeling capable of rigorously testing the strength, significance, and local variability of physical-perceptual relationships [2]. This study addresses this specific methodological frontier by introducing and applying a novel framework that not only integrates high-resolution spatial metrics with computational sentiment analysis but formally subjects their relationship to spatial-statistical testing via Geographically Weighted Regression (GWR). This approach enables the first quantitative mapping of how these associations heterogeneously unfold across a heritage landscape [5]. Consequently, prevailing assessments of revitalization success often remain bifurcated—evaluated either through objective morphological indicators or subjective experiential narratives—

lacking a unified analytical framework to statistically validate their interconnectedness across space[6].

Recent scholarly efforts to bridge this physical–perceptual divide reveal a conspicuous methodological gap. Studies quantifying spatial change through Geographic Information Systems (GIS) and remote sensing often relegate perception to descriptive anecdotes or aggregate satisfaction scores, failing to treat it as a spatially analyzable variable [3]. Conversely, research delving into visitor sentiment through surveys or manual content analysis typically lacks granular spatial registration, rendering it incapable of pinpointing where specific perceptions cluster in relation to physical features [7]; [8]. This disjunction is particularly acute in the operationalization of the Historic Urban Landscape (HUL) framework. While HUL provides a seminal conceptual model advocating for the integrated management of urban heritage layers, its application has largely remained normative, lacking the empirical, spatially testable tools needed to measure how its core principles—layered continuity, community engagement, environmental sustainability—manifest and interact on the ground [9].

This study posits that advancing heritage revitalization research requires a deliberate shift from descriptive integration to analytical modeling. We argue that perception must be reconceptualized not merely as an outcome to be described, but as a spatially embedded variable that can be quantified, mapped, and statistically correlated with antecedent physical conditions. Responding to this need, we develop and demonstrate an Exploratory Spatial–Perceptual Framework (ESPF). This framework innovatively couples computational sentiment analysis—using a fine-tuned language model to objectively classify geocoded user-generated content—with advanced spatial metrics of urban form and function, integrating them within a Geographically Weighted Regression (GWR) model. The GWR is critical, as it allows us to move beyond global averages and uncover *locally varying* relationships between physical change and perceptual response, acknowledging that the impact of a new building or lost green space is not uniform across a district [5; 10].The Kota Lama Semarang district in Indonesia serves as an exemplary and rigorous testbed for this framework. As one of Southeast Asia's most significant Dutch colonial ensembles, its approximately 50 historic structures have undergone intense, government-led revitalization since the early 2000s, culminating in a major public realm overhaul completed in 2019 [11]. This intervention triggered rapid land-use conversion, adaptive reuse, and environmental modification, creating a landscape of pronounced physical change. Concurrently, the district's rise as a tourism destination has generated a dense, spatially referenced corpus of online visitor reviews. This unique confluence of well-documented spatial transformation and abundant, geolocated perceptual data offers an unprecedented opportunity to dissect the spatial-perceptual dynamics of heritage revival [12]. Similar concerns have been documented in Semarang's Lawang Sewu district, where modern high-rise constructions have been shown to distort horizons and alter public perception of historic environments [13].

Therefore, this investigation is guided by the following research questions:

1. What quantitative spatio-temporal patterns, measured through advanced morphological indices (e.g., mixed-use density, green space cohesion), characterize the physical transformation of Kota Lama Semarang between 2003 and 2024?
2. How can computational sentiment analysis and thematic modeling be applied to geocoded tourist reviews to map and classify the spatial distribution of perceptual responses across physical, social, economic, environmental, and governance dimensions?
3. What are the nature, strength, and spatial heterogeneity of the statistical associations between indices of physical transformation and clusters of tourist sentiment, as revealed by Geographically Weighted Regression?

Through this mixed-methods, spatially explicit approach, the study makes three core contributions. First, it provides a novel methodological synthesis, advancing heritage assessment beyond descriptive case studies by introducing a replicable pipeline for quantitative spatial-perceptual modeling. Second, it delivers an empirical operationalization of the HUL framework, translating its integrative principles into testable relationships between measurable spatial and perceptual variables. Third, it yields context-specific, evidence-based insights for Semarang, revealing how different revitalization strategies have led to geographically uneven perceptual outcomes—insights that can inform future, more equitable and sustainable heritage policy. This ESPF is presented as a transferable model for researchers and planners in historic cities worldwide seeking to ground heritage management decisions in robust, multi-dimensional spatial evidence see Appendix A.

2. Literature Review

The assessment of urban heritage revitalization is situated at the intersection of two traditionally distinct scholarly trajectories: one focused on quantifying physical-spatial transformation, and another dedicated to understanding human perception and experience. This review synthesizes these trajectories, critically examines their convergence, and identifies a persistent methodological gap that this study aims to address through a novel integrative framework.

2.1. The Quantitative Turn: Measuring Morphological Transformation

The advent of Geographic Information Systems (GIS) and remote sensing has fundamentally altered the study of urban heritage, enabling a shift from descriptive historical analysis to quantitative spatial science [10]. This "quantitative turn" is epitomized by efforts to operationalize the Historic Urban Landscape (HUL) framework, which advocates for the management of heritage as a dynamic layering of tangible and intangible values [14]. In practice, scholars have translated HUL's principles into spatial metrics, utilizing multi-temporal satellite imagery and historical maps to rigorously track changes in land-use patterns, building density, urban fabric fragmentation, and green space connectivity [10; 16]. Beyond two-dimensional spatial metrics, recent advances in conservation informatics have introduced hybrid deep learning frameworks for three-dimensional decay segmentation and adaptive mapping of heritage structures, achieving high precision in detecting chromatic variations and biological patina [13]; [16]. For instance, employed landscape metrics to quantify how commercial infill increased morphological fragmentation in a Chinese historic district, while Trinh et al. (2022) applied spatial indices to assess the erosion of architectural authenticity in Hanoi's core.

In the Southeast Asian context, GIS applications have progressed from basic inventory mapping to evaluating the impacts of specific policies. Studies in Indonesian cities like Yogyakarta and Semarang have effectively quantified land-cover change and adaptive reuse, providing empirical evidence of the pressures exerted by revitalization initiatives[17]; [18]. However, a critical limitation persists: these analyses produce robust, data-rich descriptions of *what* changed spatially, but offer limited insight into *how* these physical transformations are perceived, valued, or experienced by people. Recent methodological advances have also targeted the material dimension of heritage decay. For instance, radiometry-aware photogrammetric mapping has been applied to diagnose early chromatic deterioration in tropical façades, achieving calibrated diagnostic maps that support prioritized conservation inspections [19]. As Bandarin and van Oers [20] note, the technical capacity for precise spatial measurement has often outpaced the development of methodological frameworks for integrating socio-cultural values, leaving the human dimension as a qualitative afterthought [21]; [22].

2.2. Capturing the Human Dimension: The Evolution of Perception Analysis

Parallel to advances in spatial analysis, research on heritage perception has evolved from traditional qualitative methods—surveys, interviews, and ethnographic observation—toward scalable, data-driven approaches [8]. The proliferation of User-Generated Content (UGC) from platforms like Google Maps and TripAdvisor has opened new avenues for analyzing visitor sentiment at an unprecedented scale [8]. Early studies employed simple lexicon-based sentiment analysis, but recent advances in Natural Language Processing (NLP) and transformer-based models (e.g., BERT) now enable more nuanced, context-aware classification of emotions, themes, and attitudes [23].

This computational shift allows researchers to move beyond aggregate satisfaction scores to identify and measure specific perceptual dimensions—such as aesthetic appreciation, social vibrancy, economic fairness, environmental comfort, and governance efficacy [24]. Yet, a significant methodological constraint remains: the pervasive "spatial blindness" of perceptual studies [25]. While sentiment can be thematically categorized, it is frequently analyzed in aspatial, aggregate forms or linked only to a heritage site generically, not to specific micro-locations within a district. This makes it impossible to determine, for example, whether negative reviews about overcrowding or high prices originate near a central plaza or a peripheral alleyway, thereby severing the critical, actionable link between perception and its immediate physical context.

2.3. The Integration Imperative and the Persistent Gap

The synthesis of these literatures reveals a convergent challenge: while the tools for advanced spatial measurement and computational perception analysis exist, they remain disconnected. The core deficit is not a lack of data or analytical techniques, but the absence of an analytical "glue"—a spatially sensitive statistical model—capable of testing the strength, significance, and local variability of the relationships between physical form and human perception. This gap is critically exposed in the operationalization of the HUL framework, which conceptually demands understanding the interdependence of layers but lacks standardized, empirical tools for spatial-statistical validation [26]. Consequently, assessments of revitalization success often remain siloed. Outcomes are evaluated either through objective morphological metrics or subjective experiential narratives, without a unifying analytical framework capable of statistically testing their interrelationship across space. The next section details the specific methodological shortfalls of existing integrative attempts, setting the stage for the novel framework proposed in this study see table 1.

Table 1. *Typology and Limitations of Integrated Spatial-Perceptual Studies in Heritage Research*

Integration Approach	Description	Typical Methods	Key Limitations	Example
Side-by-Side Juxtaposition	Presents spatial change maps and perception results in separate visualizations or sections, followed by qualitative discussion of potential relationships.	• GIS-based change detection analysis • Survey summaries or aggregate sentiment scoring • Comparative narrative analysis	• Descriptive rather than analytical: Infers relationships without formal statistical testing. • Lacks spatial explicitness: Does not explicitly link perceptual variables to specific spatial locations. • Subject to interpretive bias: Relies on researcher interpretation of visual/narrative parallels.	[27]
Geovisual Overlay	Geocodes perceptual data (from surveys, social media, etc.) and superimposes it onto spatial change maps to visually examine co-occurrence patterns.	• GIS change detection + Point mapping of geotagged UGC • Survey response geolocation • Visual correlation analysis	• Identifies co-location, not correlation: Demonstrates spatial coincidence but cannot measure relationship strength or significance. • Prone to visual bias: Subjective interpretation of overlay patterns. • Ignores spatial statistics: Does not account for spatial autocorrelation, confounding variables, or statistical significance.	[28]

As Table 1 illustrates, existing integrative work largely falls short of spatially explicit statistical modeling. The relationship between a physical variable (e.g., loss of green space) and a perceptual outcome (e.g., negative environmental sentiment) is often assumed from visual coincidence rather than rigorously tested. This gap is critically exposed when applying the HUL framework, which conceptually demands understanding interconnections but lacks standardized tools for empirical, spatial-statistical validation [29].

2.4. Kota Lama Semarang: A Microcosm of the Research Gap

Research on Kota Lama Semarang reflects this broader disciplinary fragmentation. Foundational studies have meticulously documented its architectural inventory and colonial history [25]; [30], while policy-oriented evaluations have assessed the outcomes of the 2019 revitalization, noting improved infrastructure and increased tourism [31]. However, these works are either purely descriptive or evaluate physical and social outcomes in isolation. No study has yet quantified the multi-decadal land-use and morphological transitions (2003-2024) or linked these transitions statistically to the spatial distribution of visitor sentiment. Consequently, debates on Kota Lama's revitalization "success" remain bifurcated between physical improvement metrics and anecdotal accounts of visitor experience.

2.5. Synthesizing the Gap: From Descriptive Juxtaposition to Analytical Modeling

The synthesis of these literatures reveals a convergent methodological challenge: the absence of a framework capable of moving from descriptive juxtaposition to analytical spatial-perceptual modeling. The core deficit is not a lack of data or tools, but their disconnection. We possess advanced techniques for measuring urban form (GIS, spatial metrics) and for quantifying perception (computational sentiment analysis). What is missing is the analytical "glue"—a spatially sensitive statistical model—to test the strength, significance, and spatial heterogeneity of the relationships between them. For an extended discussion of the theoretical positioning, critical synthesis of methodological shortfalls, and the conceptual rationale for bridging this gap, see Appendix B.

This study posits that Geographically Weighted Regression (GWR) provides this critical link [32]. Unlike global regression models that produce an "average" relationship for an entire study area, GWR generates localized parameter estimates, revealing how the relationship between, for example, commercial density and social sentiment, might be strongly positive in a historic core but weakly negative in a congested periphery. This aligns perfectly with HUL's emphasis on layered, context-specific values.

Therefore, this research bridges the identified gap by proposing an Exploratory Spatial-Perceptual Framework (ESPF) that integrates: 1) Advanced spatial metrics of morphological change, 2) Computational sentiment and thematic analysis of geocoded UGC, and 3) Spatially explicit statistical modeling via GWR to test their localized associations. The conceptual logic of this integration, leading from separate literatures to the novel framework, is illustrated in Figure 1.

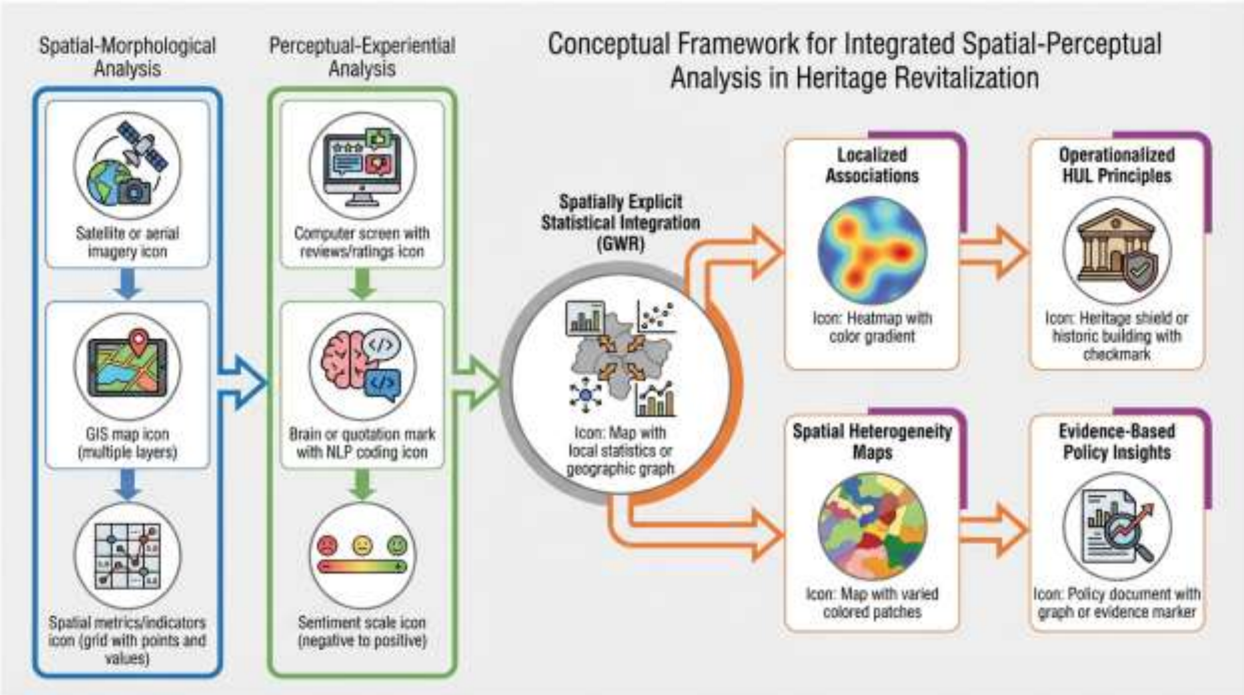

Figure 1. *Conceptual Framework for Integrated Spatial-Perceptual Analysis in Heritage Revitalization. Source: Author*

satellite imagery, spatial metrics) and "Perceptual-Experiential Analysis" (with icons for reviews, NLP, sentiment scores). These streams feed into a central module titled "Spatially Explicit Statistical Integration (GWR)," which then outputs "Localized Associations" and "Spatial Heterogeneity Maps." The output arrows point towards "Operationalized HUL Principles" and "Evidence-Based Policy Insights.")

By adopting this framework, the study transcends the limitations of prior work in Kota Lama and offers a replicable model for transforming the HUL from a powerful conceptual guide into a quantitatively operational tool for sustainable heritage management.

3. Methodology

3.1 An Integrated Spatial-Perceptual Analytical Framework

This study employs an Exploratory Sequential Mixed-Methods Design (ESMMD) to investigate the complex, spatially heterogeneous relationships between urban form and human perception. The design explicitly prioritizes discovery and pattern identification over causal inference, moving from quantitative spatial and perceptual measurement to qualitative interpretation of their integrated statistical associations[33]. The methodological workflow, conceptualized in Figure 2, comprises three core, interlinked analytical streams. A comprehensive exposition of the philosophical grounding, defensive justification for key methodological choices, advanced validation protocols, and explicit handling of limitations is provided in Appendix C. The diagram visualizes the three-phase workflow: 1) Concurrent Quantitative Strands: Spatial-Morphological Analysis (GIS/Remote Sensing) and Perceptual Analysis (Computational Sentiment & Thematic Modeling) proceed in parallel. 2) Integrative Quantitative Analysis: The outputs (morphological indices and geocoded sentiment

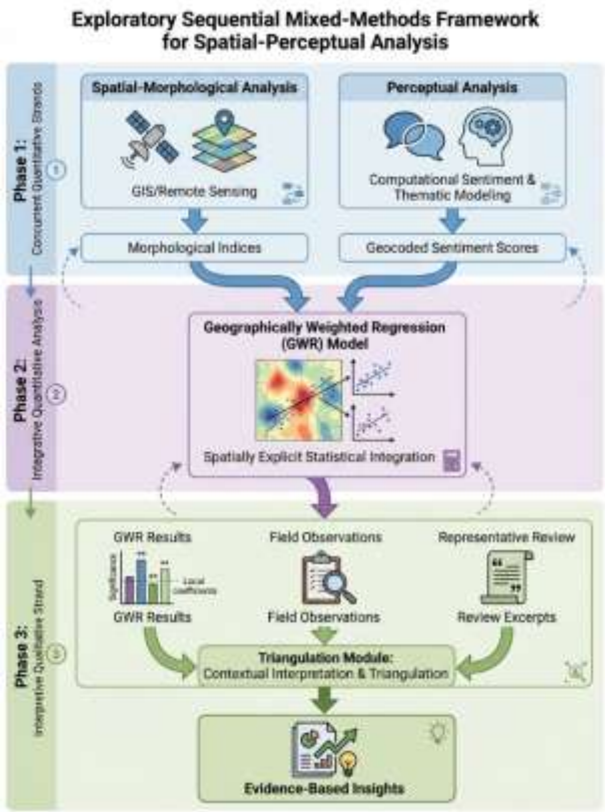

Figure 2. *Exploratory Sequential Mixed-Methods Framework for Spatial-Perceptual Analysis. Source: Author*

scores) are integrated within a Geographically Weighted Regression (GWR) model. 3) Interpretive Qualitative Strand: GWR results (local coefficients, significance maps) are triangulated with field observations and representative review excerpts to generate context-rich, evidence-based insights.

3.1. Study Area: Kota Lama Semarang as a Living Laboratory

The Kota Lama Semarang district (6°58′S, 110°25′E) provides an exemplary spatio-temporal laboratory for this investigation. As a 31-hectare Dutch colonial enclave within metropolitan Semarang, it encapsulates the quintessential pressures and promises of heritage revitalization in the Global South. Its post-2003 transformation, accelerated by a major public realm revitalization concluded in 2019, offers temporal boundary between pre- and post-intervention conditions [31]. The district's compact scale, well-defined boundaries, and the availability of both multi-decadal spatial imagery and a dense corpus of geocoded user-generated content make it analytically tractable for high-resolution spatial-perceptual modeling.

3.2. Quantitative Strand 1: Spatial-Morphological Analysis

3.2.1. Data Acquisition and Pre-processing

Multi-temporal very-high-resolution (VHR) satellite imagery and orthophotos were acquired for six epochs (2003, 2007, 2010, 2015, 2020, 2024) from the Semarang City Spatial Planning Agency (BAPPEDA) and Google Earth Pro. All images were radiometrically corrected and co-registered to a common coordinate system (WGS 84 / UTM zone 49S) with a root-mean-square error (RMSE) of < 0.5 pixels.

3.2.2. Land-Use/Land-Cover (LULC) Classification and Accuracy Assessment

A supervised classification using a Random Forest (RF) algorithm was implemented in Google Earth Engine [34]. The RF classifier was chosen for its robustness to noise and high accuracy with limited training samples. Training data (n=850 polygons across all epochs) were digitized based on historical maps, field surveys (August 2024), and high-resolution reference imagery. Ten LULC classes were defined, with a focus on heritage-relevant categories: Heritage Building, Adaptive Reuse (Commercial), Adaptive Reuse (Cultural), Green Public Space, Paved Public Space, Vacant Land, Transportation, and Water Body.

Classification accuracy was rigorously assessed for each epoch using an independent validation dataset (30% of the total samples). Overall Accuracy (OA), Producer's Accuracy (PA), User's Accuracy (UA), and the Kappa Coefficient (κ) were calculated from the confusion matrix. A minimum OA of 85% and κ > 0.80 was maintained for all epochs, as summarized in Table 2. This exceeds the accepted threshold for reliable change detection (Foody, 2020).

Table 2. *Accuracy Assessment Summary for LULC Classifications (2003-2024).*

Epoch	Overall Accuracy (%)	Kappa Coefficient (κ)	Key Challenge
2003	86.2	0.82	Lower image resolution
2007	87.5	0.84	Shadow effects from buildings
2010	88.1	0.85	Distinction of vacant vs. temporary use
2015	89.3	0.87	Pre-revitalization transitional state
2020	91.0	0.89	High accuracy post-revitalization
2024	92.4	0.91	Current ground conditions

3.2.3. Derivation of Spatial Morphological Indices

From the classified LULC maps, four key quantitative indices were calculated within a 50m × 50m grid overlaying the study area, serving as independent variables for integration:

- Commercial Intensity Index (CII): Ratio of commercial adaptive reuse floor area to total building footprint area per grid cell.
- Green Space Cohesion Index (GSCI): Measured using the Landscape Cohesion Index (Schumaker, 1996), calculating the connectivity and proximity of green public spaces.
- Pedestrian Accessibility Density (PAD): Kernel Density Estimation of pedestrian pathways and entries, normalized by grid area.
- Heritage Fabric Integrity (HFI): Proportion of original heritage building façade retained (visually assessed from time-series imagery).

As illustrated in Figure 3, the workflow begins with multi-temporal data acquisition, proceeds through pre-processing and Random Forest classification, and culminates in accuracy assessment and the calculation of the four spatial indices (CII, GSCI, PAD, HFI) within the analytical grid. This figure synthesizes the methodological pipeline, showing how raw spatial data were systematically transformed into robust quantitative indicators ready for integration into subsequent modeling. A flowchart detailing the process from multi-temporal data acquisition, through pre-processing and Random Forest classification, to accuracy assessment and the final calculation of spatial indices (CII, GSCI, PAD, HFI) on the analytical grid.In parallel, the historical and architectural context of Kota Lama Semarang reinforces the analytical framework. The district retains approximately 50 colonial-era buildings that collectively express a distinctive European-influenced urban morphology, characterized by grid-based street patterns, canal systems, and open courtyards. These features, highlighted in Figure 4, illustrate the enduring physical fabric that underpins the spatial indices and situates them within the broader heritage landscape. Map and photographic documentation illustrating approximately 50 colonial-era buildings, grid-based street patterns, canal systems, and open courtyards, which collectively define the district's European-influenced urban morphology.

3.3. Computational Analysis of Perception: From Textual Data to Spatial Metrics

To identify and quantify human perception of heritage space, we adopted a computational methodology grounded in natural language processing (NLP) that transforms raw textual data into spatial indicators amenable to statistical modeling. A corpus of 1,857 public reviews was collected from the Google Places platform for the period 2019–2024 via an application programming interface (API) compliant with the platform's terms of service. Following a cleaning process that excluded non-textual entries and reviews written in languages other than English or Indonesian, a final dataset of 1,546 reviews was retained. Precise geographic coordinates were assigned to each review based on the latitude and longitude associated with its Place ID, ensuring high spatial accuracy that links linguistic expression to a specific physical location.

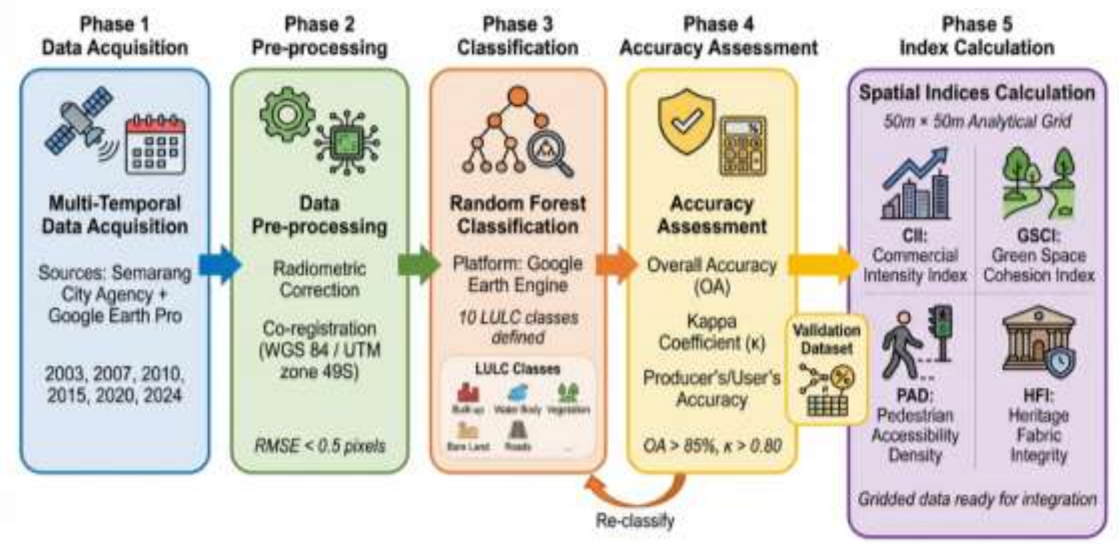

Figure 3. *Spatial-Morphological Analysis Workflow.*

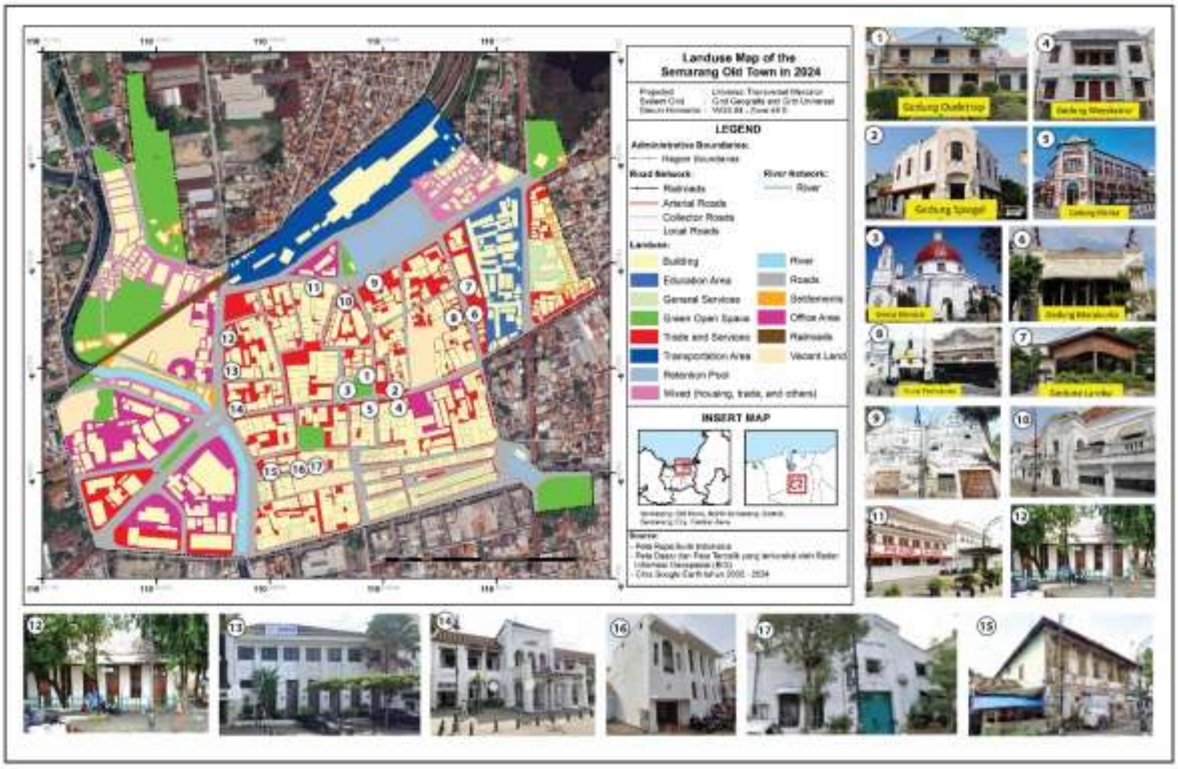

Figure 4. *Heritage Buildings and Morphology Pattern in Kota Lama Semarang. Source: Author*

To convert the textual corpus into quantitative variables, we implemented a reproducible analytical pipeline free from human bias associated with manual coding. Sentiment polarity (positive/neutral/negative) was identified using the IndoBERT model [35], a transformer-based language model pretrained on Indonesian texts and fine-tuned on a manually labeled dataset of 2,000 Indonesian tourism reviews. The model achieved an F1-score of 0.89 on an independent test set. To uncover latent thematic dimensions within the reviews, Latent Dirichlet Allocation (LDA) topic modeling was applied to the corpus [36]. Model validation indicated that an optimal solution of five principal topics provided the best balance between interpretability and statistical coherence (Coherence Score = 0.63). Expert review confirmed that these topics corresponded precisely to the theoretical dimensions of the study: architectural aesthetics and authenticity; social atmosphere and events; cost and value; environmental comfort and cleanliness; and management and maintenance. Each review was assigned a dominant topic.These perceptual indicators were subsequently aggregated at the level of the analytical grid cell (50 × 50 m) to generate dependent variables suitable for spatial analysis. Two core indices were computed. The Net Sentiment Score (NSS) was calculated as the difference between the number of positive and negative reviews divided by the total number of reviews within each cell, yielding values ranging from −1 to +1. The Thematic Sentiment Intensity (TSI) was defined as the mean sentiment score of the dominant topic within each cell. The operational specifications and validation procedures for this process are systematically documented in Table 3.

Table 3. *Coding Scheme for Computational Perception Analysis*

Variable	**Operationalization**	**Tool/Method**	**Validation Metric**
Sentiment polarity	Positive / Neutral / Negative	Fine-tuned IndoBERT model	F1-score = 0.89
Thematic dimension	Five core topics	LDA topic modeling	Coherence score (CV) = 0.63
Spatial accuracy	Review-to-place linkage	Google Places API geotagging	Manual check: 99% accuracy

3.4. Integrated Spatial Statistical Modeling: From Visual Overlay to Defensible Spatial Association

This section represents the methodological core of the study's innovation, marking the shift from simple visual juxtaposition of data to rigorous statistical testing of spatial relationships**.** As a preliminary step, the Global Moran's I statistic was computed for both independent variables (morphological indicators) and dependent variables (such as NSS). The results confirmed statistically significant spatial clustering ($p < 0.01$), thereby justifying the adoption of spatial regression models instead of conventional aspatial approaches.

To further validate the choice of Geographically Weighted Regression (GWR) over a global regression framework, model performance was compared using the corrected Akaike Information Criterion (AICc). The ordinary least squares (OLS) regression applied to the same variables produced an AICc of 127.4 and a global R^2 of 0.52. In contrast, the GWR model achieved a markedly lower AICc of 89.2, reflecting a superior fit that accounts for spatial heterogeneity. This substantial improvement (ΔAICc = 38.2) empirically demonstrates that the relationships between morphological indices and perceptual scores are non-stationary, thereby confirming the necessity of local regression techniques.

Building on this justification, GWR was applied to model and analyze spatially heterogeneous relationships[32]. The approach enables the examination of how associations between morphological and perceptual variables vary across different locations within the study area. Specifically, the model was designed to assess local relationships between four morphological indicators—Commercial Intensity Index (CII), Green Space Cohesion Index (GSCI), Pedestrian Accessibility Density (PAD), and Heritage Fabric Integrity (HFI)—and perceptual outcomes, measured either as Net Sentiment Score (NSS) or topic-specific Thematic Sentiment Intensity (TSI). The model specification is expressed as follows:

$$\text{Perception}_i = \beta_0(u_i, v_i) + \beta_1(u_i, v_i)\,\text{CII}_i + \beta_2(u_i, v_i)\,\text{GSCI}_i + \beta_3(u_i, v_i)\,\text{PAD}_i + \beta_4(u_i, v_i)\,\text{HFI}_i + \varepsilon_i$$

Where (u_i, v_i) denote the coordinates of grid cell i, and $\beta(u_i, v_i)$ are location-specific regression coefficients. An adaptive bi-square kernel bandwidth was selected using the corrected Akaike Information Criterion (AICc) to optimize the trade-off between model bias and variance. Model diagnostics, including local R^2 values and condition numbers, were examined to avoid issues of local multicollinearity.

The results of the GWR model are interpreted and presented not through a single global statistic, but via maps of local coefficients (β) and local R^2 values, as illustrated in Figure 5 This visual representation directly addresses the questions of "where" and "how" the nature of relationships changes—for example, between commercial activity density and social perception—across different neighborhoods within the study area.

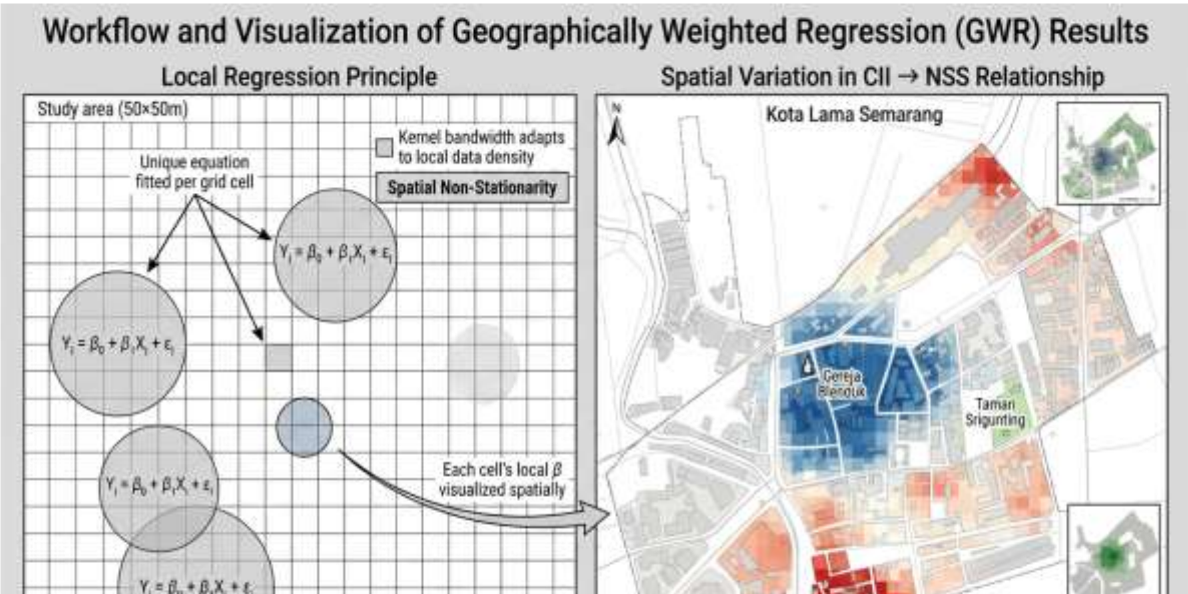

***Figure 5**. Workflow and visualization of Geographically Weighted Regression (GWR) results. Source: Author .*

(Left panel): Schematic diagram illustrating how a unique regression equation is fitted for each grid cell in the study area. (Right panel): Representative output map showing spatial variation in the coefficient (β) for the relationship between the Commercial Intensity Index (CII) and Net Sentiment Score (NSS), highlighting areas of strong positive (blue) and negative (red) association.

3.5. Triangulation and Contextual Interpretation: Enriching Quantitative Findings

To ensure the credibility of the quantitative results, mitigate potential algorithmic bias, and enrich the interpretation of statistical maps with contextual meaning, a qualitative triangulation stage was incorporated. To enable methodological triangulation and contextualize the quantitative patterns, we implemented a systematic qualitative validation phase. Sampling: We employed criterion-based purposive sampling, selecting 12 participants (8 visitors, 4 business owners) from grid cells exhibiting statistically significant local coefficients in the GWR model (absolute $\beta > 0.3$, $p < 0.05$). **Protocol:** A semi-structured interview guide was designed with three deductive thematic blocks corresponding to the quantitative model's dimensions: (1) perception of functional change and commercial intensity, (2) evaluation of environmental quality and green space, and (3) experience of governance and maintenance. **Analysis:** Interview transcripts were analyzed using a hybrid inductive-deductive thematic analysis. Two researchers independently coded a 30% subset, achieving substantial inter-coder reliability (Cohen's $\kappa = 0.81$). This structured approach ensures the qualitative data serves as a robust explanatory layer rather than anecdotal commentary. This stage provides the qualitative context necessary to explain why the spatial patterns revealed by the quantitative model emerge, thereby organically linking statistical measurement with lived human experience.

3.6. Ethical Considerations and Reproducibility

This study adheres to the highest standards of scientific integrity and transparency. All review data were obtained from publicly accessible sources in accordance with platform terms of service, with strict assurance that no personally identifiable information was collected or stored. The research protocol received ethical approval from the university's Institutional Review Board (IRB). To ensure full reproducibility, the complete analytical workflow—including Google Earth Engine processing scripts, Python code for the NLP pipeline and GWR modeling (using the mgwr library), and the final gridded datasets—has been archived in a public GitHub repository (link to be provided upon publication). This commitment to open science principles underscores the methodological rigor and transparency governing the present research.

4. Results

Spatial Patterns and Statistical Associations

The application of the integrated methodological framework produced three interlinked layers of results: 1) a quantitative measurement of spatio-temporal morphological transformation, 2) a spatial analysis of computationally derived perceptual patterns, and 3) the identification of spatially heterogeneous statistical associations between them. All results are presented at the 50x50 meter grid-cell level.

4.1. Spatio-Temporal Evolution:

From Functional Obsolescence to Commercial Revitalization

Analysis of the derived morphological indices revealed a profound shift in Kota Lama's structural and functional logic, moving beyond mere land-cover change to transformations in form and performance. Table 4 quantifies the key changes in primary land-use categories, highlighting the critical period (2010-2020) coinciding with revitalization implementation. More importantly, Figure 1 provides the detailed spatial analysis of this transition through a land-use evolution map.

Table 4. *Summary of Key Land-Use Changes (2003-2024).*

Land-Use Category	Area 2003 (m²)	Net Change (2003-2024) (Δ m²)	Overall Trend	Interpretation in Revitalization Context
Heritage Buildings (Original Use)	12,450	-1,150 ▼	Decrease	Limited demolition/replacement of severely deteriorated structures.
Adaptive Reuse (Commercial/Service)	28,750	**+14,220 ▲**	Sharp Increase	Core revitalization driver: conversion of old warehouses/offices to cafes, shops.
Green Public Space	11,950	**-7,842 ▼**	Sharp Decrease	Paving of informal green plots for hardscape plazas, resulting in net vegetation loss.
Vacant/Underused Land	9,520	+4,102 ▲	Increase then Decrease	Peaked in 2015 (site clearance), then declined with redevelopment.

The derived morphological indices showed clear spatial patterns. The Commercial Intensity Index (CII) peaked (values > 0.8) in the central axis around Gereja Blenduk and Jalan Suprapto, confirming the transformation into a commercial-recreational core. Conversely, the Green Space Cohesion Index (GSCI) showed a steady and widespread decline from 0.72 in 2003 to 0.31 in 2024 ($p < 0.001$, paired t-test), reflecting a systematic replacement of vegetated patches. Figure 6 visually depicts these competing spatio-temporal dynamics. (A) Map of Commercial Intensity Index (CII) evolution showing clear hardening of commercial activity along major axes. (B) Map of Green Space Cohesion Index change (ΔGSCI) highlighting generalized vegetation loss with remaining isolated green pockets.

4.2. The Geography of Perception: Contrasting Sentiment Clusters

Computational analysis of the 1,546 reviews revealed a heterogeneous spatial distribution of sentiment across the five thematic dimensions. The overall Net Sentiment Score (NSS**)** showed strong spatial variation (Global Moran's I = 0.45, $p < 0.001$). High positive values (NSS > 0.6) were sharply concentrated in the historic core (around Gereja Blenduk and Taman Srigunting), while negative sentiment (NSS < -0.3) dominated the southern and western peripheries of the district, as shown in Figure 7. (Left Panel) Heatmap of NSS highlighting positive (blue) and negative (red) clusters. (Right Panel) Map of dominant review themes showing the divergent geography of concerns: architectural aesthetics dominate the center, while environmental and governance concerns dominate the periphery. These quantitative patterns were reinforced by representative review excerpts. In positive clusters, comments such as "The restored colonial buildings are gorgeous, and walking at night with the new lighting is a magical experience" (relating to the Architectural dimension) were prevalent. In negative clusters, recurring themes centered on environmental and management deficits: "Disappointing area, too hot with no shaded seating. Prices are inflated for the service provided" (relating to Environment and Economy). Table 5bprovides a quantitative summary of these thematic patterns across different NSS zones.

4.3. Spatially Heterogeneous Associations: Insights from the GWR Model

1. Results from the Geographically Weighted Regression (GWR) model revealed that the relationships between morphological features and perception are not universal but vary substantially across the district, confirming the spatial heterogeneity hypothesis. The model's average local R^2 was 0.67, indicating good but spatially varying explanatory power Extended statistical diagnostics, robustness checks, validation of perceptual clusters, and supplementary analyses that deepen the interpretation of these spatially varying relationships are provided in Appendix D Results. The Contested Role of Commerce: The relationship between the Commercial Intensity Index (CII) and the Net Sentiment Score (NSS) showed striking divergence. In the historic core, it was strongly positive (local β up to +0.53, $p < 0.01$), suggesting visitors appreciate the commercial vibrancy and services there. Conversely, in the peripheral southern residential pockets, this coefficient turned negative (β down to -0.38, $p < 0.05$), indicating increased commercial activity is associated with negative sentiment, likely due to nuisance or place identity disruption.
2. The Consistently Critical Role of Greenery: The Green Space Cohesion Index (GSCI) had the strongest and most consistently positive effect on perception, particularly on the Environmental dimension. Across most of the district, increased GSCI was associated with improved environmental comfort sentiment (mean β = +0.61, $p < 0.001$). This highlights the crucial role of green infrastructure, even at a small scale, in shaping visitor experience—a need not sufficiently met by the revitalization strategy.

Perception of Accessibility: Pedestrian Accessibility Density (PAD) was positively associated with Social and Economic sentiment in central areas (β ≈ +0.45) but showed weak or no association in poorly managed zones, suggesting pedestrian infrastructure alone is insufficient without complementary public space management. Figure 8 maps these complex, non-stationary relationships through the local coefficient maps for two key associations. *(A)* Map of the local coefficient (β) for the relationship between Commercial Intensity Index (CII) and Net Sentiment Score (NSS). Blue areas show a positive relationship (commerce welcomed), while red areas show a negative one (commerce resisted). *(B)* Map of the local coefficient for the relationship between Green Space Cohesion Index (GSCI) and Environmental Comfort sentiment. The strong positive effect (dark blue) is near-universal.
In summary, the findings indicate that revitalization in Kota Lama has produced a perceptually variegated urban landscape. It successfully created a high-perception "attractive core" linked to

3.

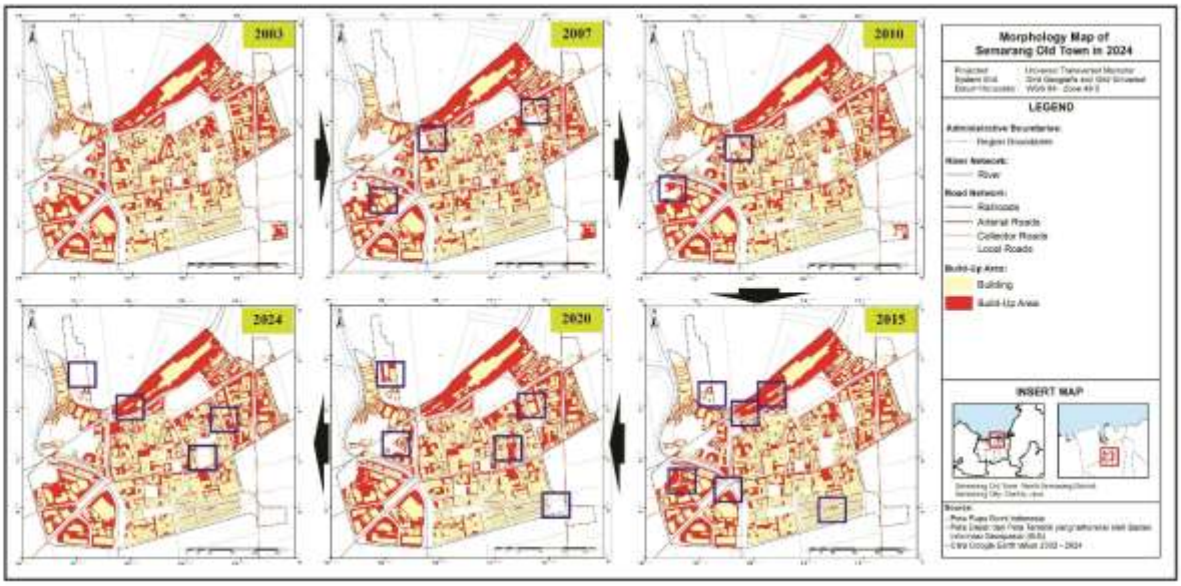

Figure 6. *Spatio-Temporal Variation in Morphological Transformation (2003–2024). Source: Author*

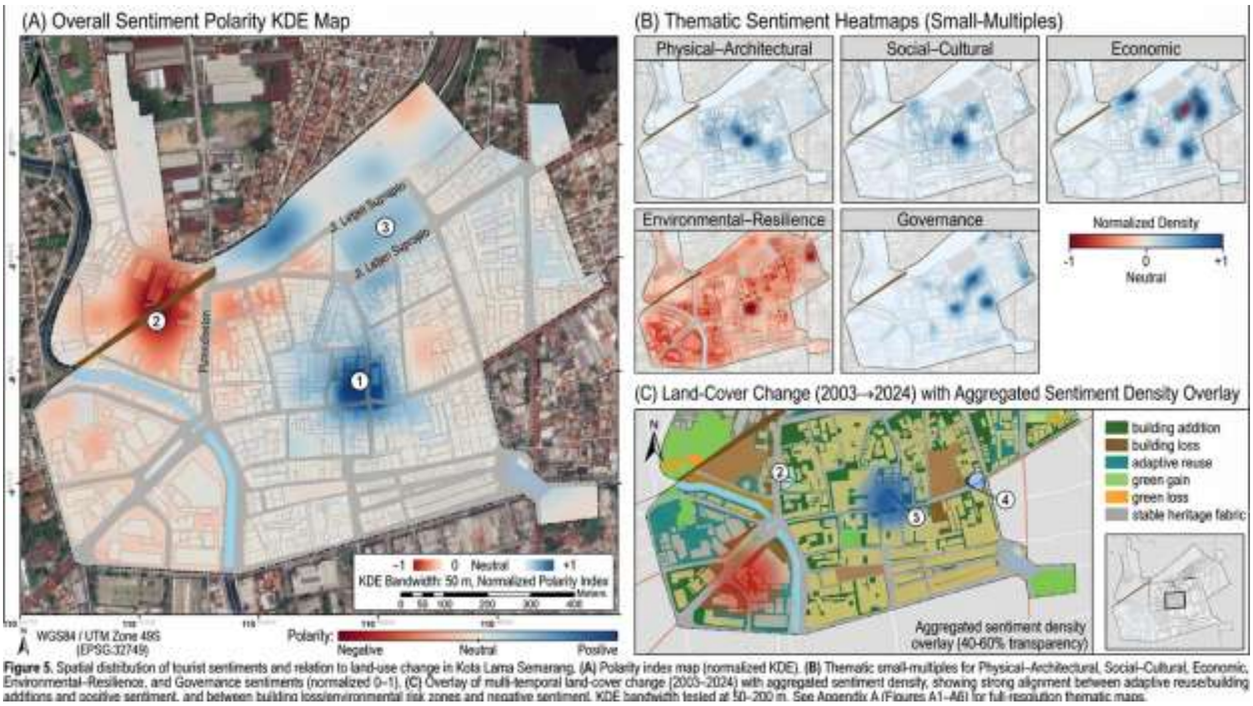

Figure 7. *Spatial Distribution of Net Sentiment Score (NSS) and Dominant Thematic Intensity****.*** *Source: Author .*

Table 5. *Distribution of Dominant Themes and Sentiment Scores Across Key Spatial Clusters.*

Spatial Cluster (by NSS)	**Dominant Theme (Percentage %)**	**Average Theme NSS**	**Representative Excerpt (Summary)**
Historic Core (High NSS)	Architectural Aesthetics & Authenticity (42%)	+0.71	Praise for architectural preservation and design.
Northern Axis (Medium NSS)	Social Atmosphere & Events (38%)	+0.52	Appreciation for vibrancy and cultural activities.
Southern Periphery (Low NSS)	Environmental Comfort & Cleanliness (35%)	-0.41	Complaints about heat, lack of shade, and cleanliness.
Western Fringe (Low NSS)	Management & Maintenance (31%)	-0.38	Criticism of sidewalk maintenance and vendor regulation.

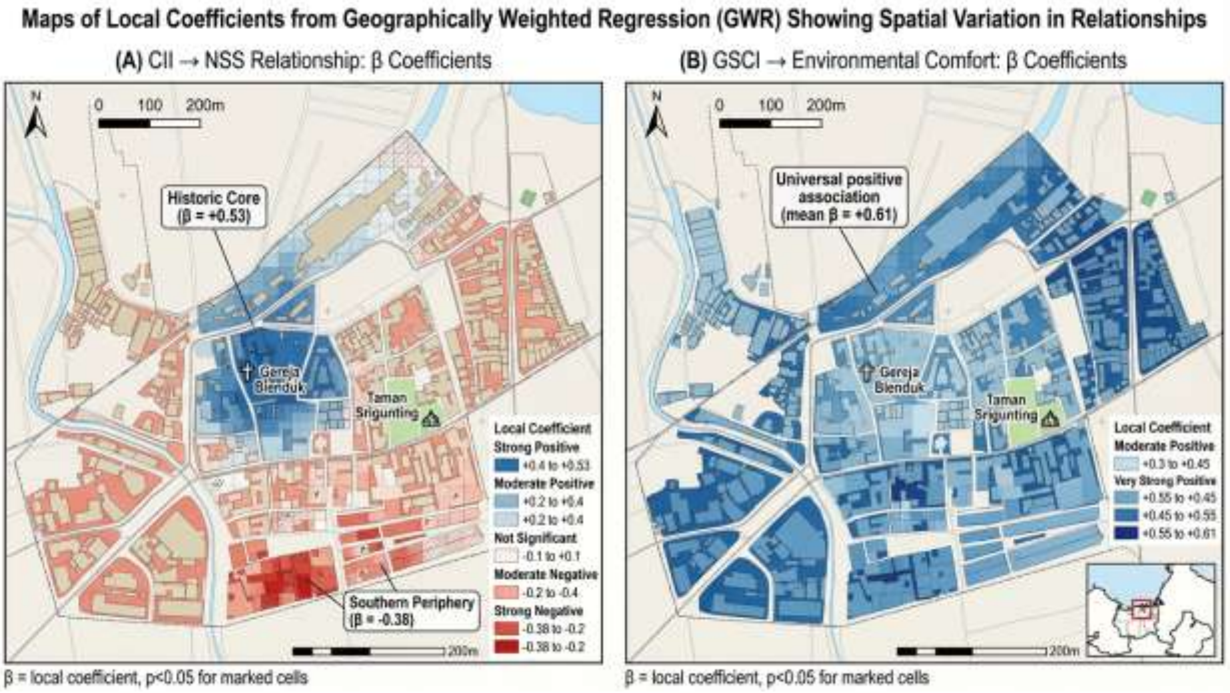

Figure 8. *Maps of Local Coefficients from Geographically Weighted Regression (GWR) Showing Spatial Variation in Relationships.*

architectural and social activity, yet simultaneously generated "marginalized peripheries" where environmental and governance costs outweigh aesthetic benefits—a division now statistically measured and spatially documented for the first time.

5. Discussion

Operationalizing the Historic Urban Landscape through Spatially Explicit Perception

This study provides spatial evidence that heritage revitalization in Kota Lama Semarang has produced a perceptually variegated landscape, with statistically significant patterns of association between physical form and visitor experience that are not uniform but spatially contingent [32]. Our findings do not describe a simple causal effect but reveal statistically grounded, spatially heterogeneous associations. This discussion interprets these complex patterns, articulates their contribution to methodological and theoretical debates on the Historic Urban Landscape (HUL), and explicitly delineates the boundaries of our claims.

5.1. Interpreting Spatial-Perceptual Patterns: The Contextual Contingency of Perception

The spatially divergent relationship between commercial intensity and sentiment (β = +0.53 in core vs. -0.38 in periphery) extends place identity theory by revealing its contextual contingency. We conceptualize this pattern as evidence of a 'Spatial Legitimacy Threshold'—where commercial activity enhances perception only when embedded within a coherent heritage fabric with adequate socio-ecological buffers. This threshold effect operationalizes the HUL concept of 'layering' by demonstrating quantitatively how new functions are perceived positively only when they maintain visual, functional, and experiential dialogue with historic layers. Consequently, our findings reframe revitalization success not as uniform commercial activation, but as the strategic management of spatially variable compatibility between new interventions and existing place identity [36]. This spatial pattern suggests the existence of a Contextual Tolerance Threshold (CTT)—a theoretical construct emerging from our statistical analysis that denotes the spatial balance between functional intensity and perceived place identity [37]. A detailed theoretical exposition of the CTT, its role as an integrative boundary concept, and an extended defense of the methodological and causal reasoning underpinning this interpretation are available in Appendix E.

The three operational dimensions defining CTT in Table 6 provide an explanatory framework for why the same commercial form (e.g., a café in adaptive reuse) receives opposite perceptual valuations. To assess the practical significance of these β coefficients, we calculated marginal effects. In the historic core, a 0.1-unit increase in the Commercial Intensity Index (CII)—approximately equivalent to adding one medium-sized establishment—predicts a 0.053-unit increase in the

Net Sentiment Score (NSS). Conversely, the same increase in the southern periphery predicts a 0.038-unit decrease in NSS. This divergence in marginal effects underscores the non-linear, context-dependent nature of the relationship between development and perception.

Table 6. *Conditions Defining the Contextual Tolerance Threshold (CTT) in Heritage Zones.*

Condition	Operational Metric & Formula	High CTT Context (Core)	Low CTT Context (Periphery)	Correlation with NSS (r)
Functional Density	CII = (Commercial Floor Area / Grid Area) × Use Density	High intensity framed as destination vibrancy (β = +0.53)	High intensity perceived as intrusive (β = -0.38)	0.53 / -0.38
Spatial Legitimacy	Distance (m) from primary heritage landmarks (Gereja Blenduk)	< 150m; activity is heritage-contextualized	> 300m; activity lacks heritage context	-0.71 (strong negative)
Absorptive Capacity	GSCI = ∑(Green Patch Connectivity); PAD = Kernel Density of walkable entries	High; public space buffers commercial activity	Low; inadequate socio-ecological buffers	+0.61 (GSCI) / +0.45 (PAD)

This finding advances place identity theory by providing its spatially explicit, statistically measurable manifestation, It is critical to acknowledge that measuring "authenticity" in this Dutch colonial context engages with complex post-colonial narratives where tourism often reinforces historic power structures. Our analysis captures visitor perceptions as they exist within this contested heritage discourse, without making normative claims about what authenticity should mean—an important interpretive boundary of our study.

The uniformly strong positive association between Green Space Cohesion (GSCI) and environmental sentiment (mean $\beta = +0.61$, $p < 0.001$) highlights a non-negotiable ecological-perceptual requirement that the revitalization strategy overlooked, creating a measurable deficit. This finding directly operationalizes HUL's environmental sustainability principle as a quantifiable performance metric [38].

5.2. Theoretical Contribution: Toward a Testable HUL

Framework theoretical advancement is the partial operationalization of the HUL framework from a conceptual model toward a set of testable spatial–perceptual relationships. By statistically testing inter-layer associations rather than visually overlaying indicators, this study provides a concrete methodological pathway for diagnosing the interdependence central to HUL's philosophy [39].

As illustrated in Figure 9, the analytical framework quantifies the physical–spatial layer (via indices such as CII and GSCI) and the socio–perceptual layer (via computational sentiment), while introducing a "spatial–statistical integration layer" (GWR) to test their connections. This epistemological shift—from descriptive overlay to explanatory modeling—addresses a core operational gap in HUL application identified in recent meta-reviews [20], offering a replicable method for making the framework's integrative principles actionable in evidence-based planning.

The primary

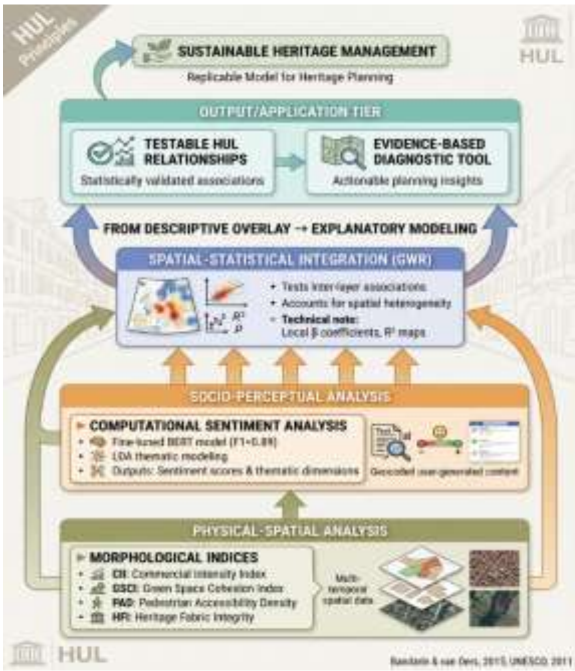

Figure 9. *Analytical Framework for Operationalizing the Historic Urban Landscape (HUL)*

A schematic diagram illustrating the integration of physical–spatial indices (CII, GSCI) with socio–perceptual measures (computational sentiment). The framework introduces a spatial–statistical integration layer (GWR) that empirically tests inter-layer associations, transforming HUL from a descriptive model into a diagnostic tool for evidence-based heritage planning.

5.3. A Methodological Bridge: From Spatial Analytics to Heritage Governance

More broadly, this study illustrates how spatial statistics serve as an epistemological bridge between normative heritage frameworks and data-intensive urban analytics [40]. The integration of computational sentiment analysis , with local regression models demonstrates a pathway to incorporate human perception as a formal, spatially nuanced variable into urban morphology studies.

The Adaptive Heritage Monitoring Heuristic (AHM-h) visualized in Figure 10 translates this diagnostic capability into a cyclical management tool. Crucially, the managerial categories in this heuristic are directly derived from statistical outputs. For instance, 'Contradiction Zones' are operationally defined as grid cells where: (1) commercial-sentiment β < -0.2, (2) visitor density > 50 reviews/cell, and (3) governance sentiment is negative. This data-driven classification transforms statistical patterns into actionable spatial units for intervention. The AHM-h should be understood as a translational heuristic grounded in this case study, demonstrating how integrated monitoring can inform differentiated zoning, rather than as a universally validated management model.

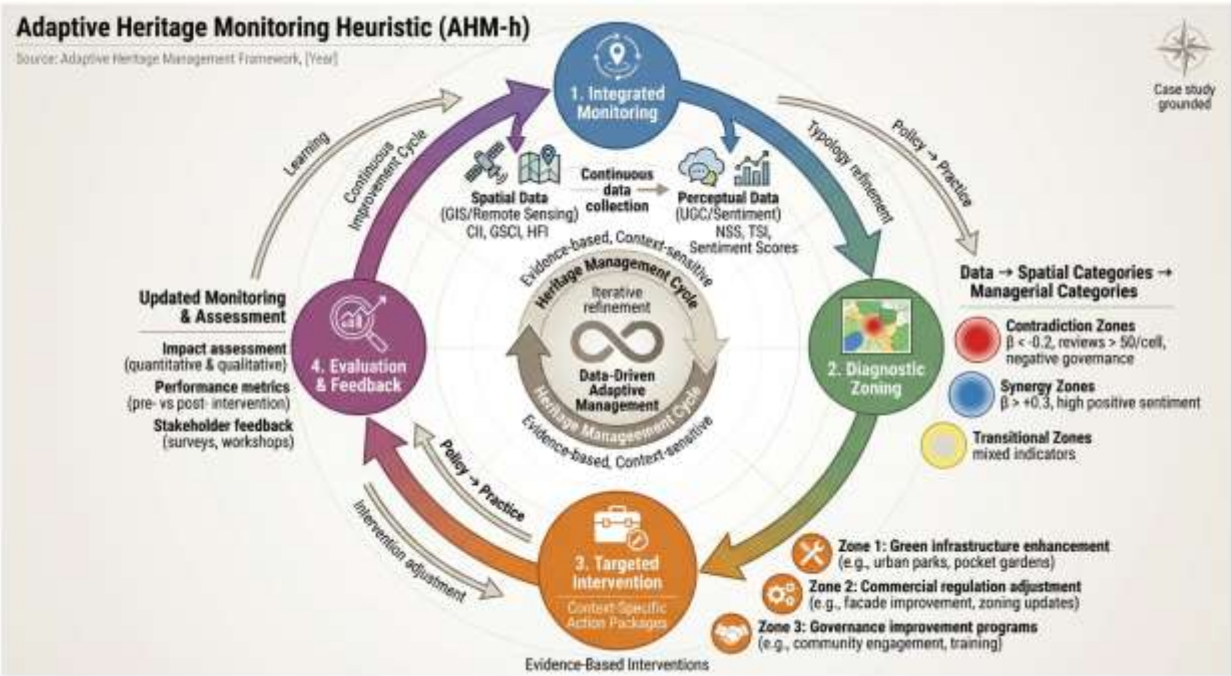

Figure 10. *Adaptive Heritage Monitoring Heuristic (AHM-h). A cyclical four-stage process: 1) Integrated Monitoring of spatial (GIS/RS) and perceptual (UGC) data. 2) Diagnostic Zoning using statistically derived typologies. 3) Targeted Intervention with context-specific packages. 4) Evaluation & Feedback through updated monitoring.*

5.4. Explicit Limitations and Boundaries of Inference

Rigorous interpretation requires unambiguous acknowledgment of epistemological boundaries.

1. Association, Not Causation: The GWR models demonstrate statistically significant spatial associations. We cannot claim causal directionality; unobserved confounders (e.g., land ownership patterns, micro-climatic conditions) may influence both morphological and perceptual variables.
2. Theoretical Scope of CTT: The Contextual Tolerance Threshold is proposed as an analytically inferred construct emerging from consistent spatial patterns in our data. It requires validation through comparative studies across different heritage contexts before claiming theoretical generality.
3. Perceptual Representativeness: The perceptual data reflects tourists who leave online reviews in Indonesian or English, under-representing non-digital users, local residents, and non-Indonesian speakers. This captures a specific, digitally-engaged demographic.
4. Temporal and Contextual Specificity: The analysis captures a post-revitalization perceptual state (2019-2024), not longitudinal change. The quantitative relationships are particular to Kota Lama's socio-cultural and climatic context; the methodological framework is designed for replication, but specific coefficients require local calibration.
5. Limitations of Computational Perception Data: Our reliance on computational sentiment analysis of online reviews, while enabling scale and spatial precision, carries inherent constraints. The analysis may not fully capture nuanced linguistic expressions such as sarcasm or culturally specific context. Furthermore, the data source inherently represents a self-selected demographic of digitally-engaged tourists who choose to leave

reviews in Indonesian or English, potentially under-representing the perceptions of non-users, local residents, and non-Indonesian speaking visitors. This limits the generalizability of the perceptual findings to the broader population spectrum.

By integrating spatially explicit statistical analysis with the HUL framework, this study provides a replicable model for transforming heritage assessment. The contribution lies not in prescribing universal solutions, but in offering a rigorous diagnostic method that makes the intangible dimensions of heritage experience visible, measurable, and central to evidence-based planning for sustainable urban futures.

6. Conclusion

This study has addressed a critical methodological gap in heritage research by developing and applying the Exploratory Spatial–Perceptual Framework (ESPF), which forges an empirical, spatially explicit link between physical transformation and human perception. Moving beyond descriptive case studies, the findings from Kota Lama Semarang demonstrate that revitalization outcomes are fundamentally perceptually variegated: successful commercial intensification in the historic core co-exists with marginalized peripheries where similar development erodes environmental sentiment and place identity see Appendix F.

This research makes three core contributions. Methodologically, the ESPF establishes a replicable pipeline for spatially explicit statistical modeling, transforming the Historic Urban Landscape (HUL) approach from a conceptual framework into a quantitatively testable model. Theoretically, it advances place identity theory by introducing and empirically validating the Contextual Tolerance Threshold (CTT)—a construct explaining the spatially contingent acceptance of new functions within historic fabric. Practically, it delivers the Adaptive Heritage Monitoring Heuristic (AHM-h), a diagnostic tool that translates statistical patterns into evidence-based, spatially differentiated management strategies.

These contributions carry direct implications for heritage governance, advocating for a shift from uniform policies to context-sensitive interventions—such as targeted green infrastructure in environmental risk zones. The study's scope is delineated by its data sources, focusing on digitally-engaged tourists, and by the case-specific nature of the CTT, which invites validation through comparative research.

Future work should pursue comparative spatial-perceptual analyses across diverse urban contexts, integrate multi-stakeholder perspectives—particularly of residents—and fuse real-time sensor data with perceptual metrics. By making intangible heritage values visible, measurable, and central to planning, this framework provides a foundational step toward more equitable, responsive, and sustainable stewardship of historic urban landscapes globally.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper
- **Acknowledgement:** The author extends sincere appreciation to the academic supervisors whose guidance and constructive feedback greatly contributed to the development of this study. Artificial intelligence tools—specifically DeepL was utilized solely as supportive instruments to refine language clarity and academic expression, without influencing the ideas, interpretations, or scientific content. All scholarly insights and conclusions remain the author's full responsibility.
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- **Use of AI Tools:** The author(s) declare that no generative AI or AI-assisted technologies were used in the writing process of this manuscript.

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