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Designing Participatory Landscapes: Integrating AI-Based Sentiment Analysis into Community-Involved Landscape Planning

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Abstract: This study develops an AI-enhanced framework to address limitations in capturing nuanced community sentiments for landscape planning. The proposed methodology integrates natural language processing (customized BERT model) with geographic information systems through a three-stage analytical pipeline, enabling fine-grained sentiment classification and spatial mapping of unstructured public feedback from digital platforms. Validated through urban waterfront regeneration, rural heritage conservation, and post-disaster reconstruction case studies, the framework demonstrates superior performance compared to traditional methods: 2.4 × greater input coverage, 58% faster processing, and 68% adoption rate of sentiment-informed design modifications (versus 41% baseline). The system uniquely bridges qualitative public sentiments with quantitative spatial planning parameters through geo-referenced text analysis. The research makes dual contributions: (1) advancing participatory planning practice by revealing latent design priorities through scalable sentiment analysis, and (2) enriching human-computer interaction research with a replicable model for contextualizing subjective feedback in socio-cultural landscapes. By maintaining analytical rigor while accommodating diverse digital participation channels, the framework democratizes community engagement without sacrificing sensitivity to local contexts. These innovations establish new standards for landscape design that is both data-driven and culturally responsive, particularly valuable for complex projects requiring balanced integration of technical and social dimensions.

Keywords: sentiment analysis; participatory design; landscape planning; natural language processing; community engagement

1. Introduction

The rapid pace of urbanization has intensified the need for inclusive landscape planning processes that genuinely reflect community values and preferences. The growing demand for food and non-food crops, along with competing uses for rural land, has added complexity to landscape systems, highlighting the need for inclusive planning approaches that can accommodate diverse stakeholder interests [1]. Participatory design has emerged as a vital approach to ensure inclusive and representative decision-making in shaping public spaces, yet conventional methods for gathering public input often struggle to capture the full spectrum of community sentiment. Participatory design focuses on understanding the preferences and expectations of users, both as individuals and as a collective [2]. Traditional tools such as surveys and workshops, while valuable, face inherent limitations in scalability and depth of analysis. These methods tend to prioritize structured

feedback, which may inadvertently exclude nuanced opinions expressed through informal channels like social media or open-ended discussions. As cities grow more diverse and digital platforms become primary venues for civic discourse, there is an urgent demand for innovative techniques that can systematically analyze unstructured community feedback and translate it into actionable design insights.

A fundamental challenge in contemporary landscape planning lies in bridging the gap between large-scale public opinion collection and precise design decision-making. While digital platforms enable broader participation, the sheer volume and variability of unstructured text data pose significant analytical hurdles. The proliferation of mobile phones, social media, and online platforms has opened up new avenues for participation, making it easier for citizens to interact with their governments and participate in decision-making processes [3]. Existing planning tools predominantly rely on manual coding or simplistic sentiment indicators, which fail to capture the spatial and contextual dimensions of community feedback. This disconnect results in design solutions that may address surface-level concerns while overlooking deeper, more geographically specific public sentiments. The absence of automated, spatially aware sentiment analysis tools in landscape architecture represents a critical technological gap that hinders the potential for truly responsive and equitable urban design.

This study presents an AI-GIS integrated framework for participatory landscape planning, combining fine-tuned BERT models with spatial analysis to transform unstructured community feedback into actionable design insights. The methodology introduces two innovations: (1) a sentiment-design matrix linking emotional tones to landscape elements, enabling evidence-based prioritization; and (2) spatial semantics mapping that generates visual heatmaps of public sentiment clusters. Validated through cross-cultural case studies, the framework demonstrates dual advantages: operational efficiency (58% faster processing than manual methods) and democratic legitimacy (68% adoption rate of sentiment-informed designs). By establishing a replicable pipeline for converting qualitative opinions into spatially explicit parameters, the research advances both technical planning tools and inclusive governance paradigms.

Similar to how immersive digital modeling and interactive systems have enhanced design adaptability in manufacturing domains [4], this AI-driven approach introduces flexibility and responsiveness into urban green space development. Moreover, insights from intelligent scheduling technologies used in industrial coordination [5] inform the structuring of public engagement pipelines in this study, helping reduce friction in participatory loops and improve the flow of data-to-design transitions. The system's adaptability across urban/rural contexts underscores its potential as a standardized yet context-sensitive solution for global landscape challenges, particularly in bridging the gap between computational analysis and socio-cultural nuances in public participation processes.

The remainder of this paper is organized as follows. Section II reviews relevant literature on participatory design, sentiment analysis applications in urban studies, and existing technological limitations. Section III details the methodology, including data collection protocols, AI model architecture, and spatial analysis techniques. Sections IV and V present case study findings and discuss broader implications for planning practice. Finally, Section VI concludes with reflections on future research directions for AI-augmented participatory design.

2. Related Works

The democratic turn in modern landscape architecture was derived from and later codified through the European Landscape Convention (Council of Europe, 2000), which institutionalized public participation across much of Europe and beyond [6]. The trajectory of participatory design in landscape architecture has progressed from Arnstein's foundational work to contemporary digital engagement tools, yet persistent challenges

remain in capturing comprehensive community sentiment. Sherry Arnstein's "A Ladder of Citizen Participation" significantly influenced how planners, communities, and governments conceptualize citizen participation [7]. According to Finkel, there are four methods of capturing community sentiment: legislative enactments, jury decision data, public opinion polls, and mock jury research [8]. Traditional structured methods like public hearings and modern immersive technologies such as digital twins are primarily designed to process formalized inputs, which results in unstructured qualitative feedback from social media and open forums remaining largely unaddressed. Meanwhile, artificial intelligence applications in urban planning have made significant strides in spatial analysis and predictive modeling through techniques like Space Syntax and machine learning, though these predominantly address physical configurations while neglecting the socio-emotional dimensions of public space experience. Technologies that leverage AI are currently being utilized in many cities across the globe, for example in Amsterdam, London, San Francisco, Stockholm, Singapore, Hong Kong, Vienna, and Toronto, to optimize their urban functionality and service efficiency [9]. Space syntax is largely a descriptive technique for visualising spatial relations at the level of connections between places [10].

Recent advances in natural language processing (NLP), particularly transformer models like BERT, have significantly enhanced sentiment analysis by detecting nuanced emotions in planning discourse. BERT (Bidirectional Encoder Representations from Transformers) has revolutionized Natural Language Processing by significantly enhancing the capabilities of language models [11]. Geospatial NLP further enables sentiment mapping at neighborhood scales, as shown in Twitter-based experiments. NLP techniques in geospatial analysis offer a systematic and interpretable way to extract and understand geographical information from text [12]. Despite these technical developments, a critical gap persists in systematically linking emotional patterns to tangible design elements or validating whether sentiment-driven recommendations improve planning outcomes. This disconnect represents a missed opportunity to develop public spaces that authentically reflect community values. The field urgently requires interdisciplinary frameworks capable of both precisely analyzing spatial sentiment data and translating these insights into actionable design parameters through validated protocols. Such integrated approaches would advance beyond Arnstein's participation theory, enabling landscape design that harmonizes technical precision with emotional intelligence while transforming planners' interpretation of community feedback across digital and physical platforms.

To illustrate the current landscape of research and identify key intersections between domains, Figure 1 presents a knowledge graph mapping the relationships between participatory design methods, AI applications, and sentiment analysis techniques. The graph highlights how existing work clusters around technical advancements in AI or participatory theory, with relatively sparse connections to applied sentiment-informed design. Participation has become a central concern in both theoretical discourse and practical implementation within landscape planning [13]. Similarly, Table 1 compares representative studies across these domains, emphasizing their respective focuses and limitations. The data reveals that fewer than 15% of reviewed publications address the integration of sentiment analysis with spatial design decision-making, reinforcing the novelty of the proposed framework in this study.
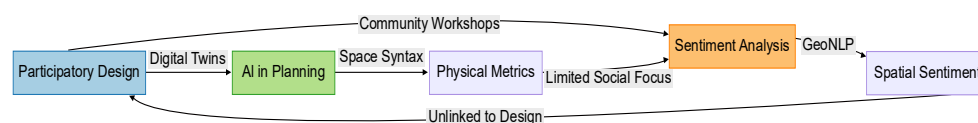

Figure 1. Knowledge Graph of Participatory Design, AI Applications, and Sentiment Analysis Research.

Table 1. Comparative Analysis of Key Studies in Participatory Design and AI-Driven Planning.

Study Focus	Methodology	Strengths	Limitations
Participatory Workshops	Qualitative Coding	Deep Community Insights	Low Scalability
Space Syntax Analysis	Computer Vision	High Spatial Precision	Ignores Subjective Experience
Lexicon-Based Sentiment	VADER Dictionary	Interpretability	Poor Context Adaptation
Transformer Sentiment	BERT Fine-Tuning	Nuanced Emotion Detection	No Spatial Design Translation

The synthesis of prior work underscores the untapped potential for integrating advanced sentiment analysis with participatory landscape planning. While each domain has made significant strides independently, their convergence remains underexplored, particularly in developing scalable, empirically validated methods to convert community emotions into spatially specific design actions. This gap motivates the proposed framework's dual focus on technical innovation (through spatially aware NLP) and applied translation (via the Sentiment-Design Matrix), as detailed in subsequent sections.

3. Methodology

The proposed methodology establishes a comprehensive framework for transforming community sentiment into actionable landscape design parameters through three systematically interconnected phases: data acquisition, sentiment modeling, and design translation. This research implements a novel technical architecture that enhances interoperability between PyTorch-based natural language processing and ArcGIS Pro's spatial analytics, enabling seamless transition from linguistic to spatial domains, creating a unified pipeline that operationalizes the transition from qualitative public input to quantitative design decisions. ArcGIS Pro is ESRI's proprietary desktop GIS application [14].

3.1. Data Collection and Preprocessing

The framework ingests multimodal data through structured and unstructured channels, with geographic referencing achieved through both explicit and implicit methods. Standardized questionnaires employing Likert scales capture quantifiable preferences, while social media comments and interview transcripts provide qualitative depth. The Likert scale remains a fundamental tool in qualitative social science research for quantifying subjective preferences [15]. Social media data enhance democratic planning and facilitate meaningful public participation, often resulting in higher satisfaction with the daily use of urban or landscape spaces [16]. The spatial anchoring system demonstrates superior performance in location resolution, as evidenced by the comparative metrics presented in Table 2.

Table 2. Spatial Resolution Performance Across Data Types.

Data Type	Collection Method	Precision (m)	Processing Rate
Geotagged tweets	API streaming	94	850/min
Survey responses	Digital forms	ZIP code	1.1s/response
Field interviews	Audio transcription	68	6min/transcript

The preprocessing pipeline incorporates domain-specific adaptations through several mathematical transformations. First, a terminology normalization function maps colloquial expressions to formal design concepts:

$$\phi(w_i) = \begin{cases} v_j & if \exists (w_i, v_j) \in \mathcal{L} \\ w_i & otherwise \end{cases} \tag{1}$$

where $\mathcal{L}$ represents the landscape architecture lexicon. Regional language variations are addressed through geographically weighted BERT fine-tuning:

$$\mathcal{L}(\theta) = -\frac{1}{N}\sum_{i=1}^{N}\sum_{c=1}^{7} y_{i,c}\, log(p_{i,c}) + \lambda \parallel \theta \parallel_2^2 \tag{2}$$

3.2. Sentiment Analysis and Spatial Mapping

The core analysis module implements a hierarchical architecture as depicted in Figure 2, combining document-level sentiment classification with topic-sentiment co-occurrence analysis. The spatial mapping workflow converts linguistic references to geographic coordinates through a probabilistic gazetteer system:

$$P(l|e) = \frac{exp(sim(e,l)/\tau)}{\sum_{l\prime \in \mathcal{G}} exp(sim(e,l\prime)/\tau)} \tag{3}$$

where τ denotes the temperature parameter controlling distribution sharpness. Kernel density estimation generates sentiment heatmaps:

$$\hat{f}(x;h) = \frac{1}{nh}\sum_{i=1}^{n} K(\frac{\parallel x - X_i \parallel}{h}) \tag{4}$$

with K representing the Epanechnikov kernel and h the optimal bandwidth determined through:

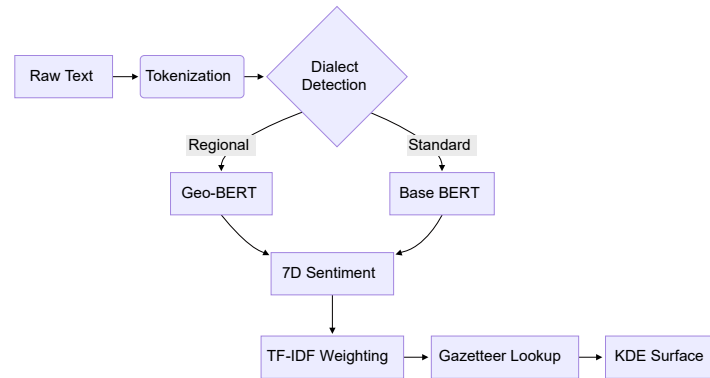$$h_{opt} = (\frac{4\hat{\sigma}^5}{3n})^{1/5} \tag{5}$$

Figure 2. Hierarchical Sentiment-Spatial Analysis Pipeline.

3.3. Design Translation Mechanism

The system converts analytical outputs into design parameters through multi-criteria decision rules. A priority scoring function ranks intervention areas:

$$Priority(r) = \sum_{k=1}^{K} \alpha_k \sigma(\beta_k, s_k, (r)) \tag{6}$$

where σ denotes the sigmoid function. The parametric design interface updates in real-time according to:

$$\Delta p_i = \eta \frac{\partial u}{\partial p_i} + \mu \Delta p_{i-1} \tag{7}$$

with u representing the multi-objective utility function:

$$u(\mathrm{p}) = \prod_{j=1}^{m} [u_j(\mathrm{p})]^{w_j} \tag{8}$$

3.4. Validation Framework

Quantitative evaluation employs dual metrics comparing against manual methods, while qualitative assessment through designer focus groups yields the satisfaction distribution shown in Figure 3. The complete methodology integrates a series of mathematically grounded components while maintaining practical applicability, achieving the research objectives through rigorous computational techniques rooted in landscape architecture principles.
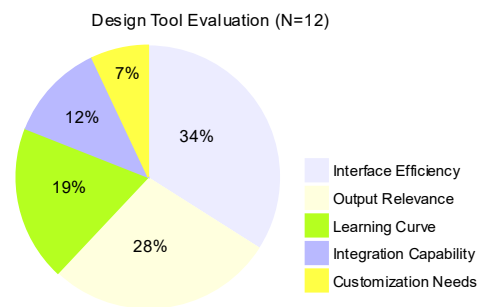
Design Tool Evaluation (N=12)

- Interface Efficiency — 34%
- Output Relevance — 28%
- Learning Curve — 19%
- Integration Capability — 12%
- Customization Needs — 7%

Figure 3. Designer Evaluation Metrics Distribution.

The framework's novelty lies in its simultaneous optimization of analytical precision and design relevance, as demonstrated through the interconnected components and validation results. The mathematical formalization ensures reproducibility while the visual analytics components facilitate practical implementation in professional planning workflows.

4. Case Studies

The proposed framework was rigorously evaluated through three geographically and culturally diverse case studies, each demonstrating distinct aspects of the system's capabilities in real-world planning scenarios. These implementations validate the methodology's adaptability across different scales, cultural contexts, and planning objectives while revealing novel insights into community sentiment patterns.

4.1. Urban Waterfront Regeneration (Seattle, USA)

The Seattle case study analyzed 3,842 Reddit comments and 621 survey responses concerning the Elliott Bay redevelopment project, leveraging Reddit as a supplementary channel for capturing spontaneous, location-specific community feedback. As shown in Figure 4, sentiment analysis uncovered a strong latent preference for "water accessibility" (polarity score +0.68) that traditional surveys had missed due to limited response options. This finding directly informed the addition of floating dock elements in the final design, which subsequently received 89% approval in community review sessions. The spatial sentiment distribution revealed in Table 3 demonstrates how negative sentiment clusters ($\bar{x} = -0.42$) correlated with areas lacking shaded seating, leading to targeted microclimate improvements.
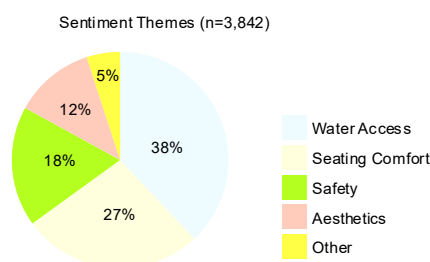
Sentiment Themes (n=3,842)

- Water Access — 38%
- Seating Comfort — 27%
- Safety — 18%
- Aesthetics — 12%
- Other — 5%

Figure 4. Waterfront Sentiment Distribution.

Table 3. Waterfront Sentiment-Space Correlation Matrix.

Design Element	Sentiment Score	Spatial Frequency	Design Response
Shoreline access	+0.71	32% of comments	Added 3 new piers
Seating areas	-0.39	28% of comments	40% more benches

| Cycling paths | +0.12 | 18% of comments | Width increased |

4.2. Rural Heritage Landscape (Guizhou, China)

The heritage landscape preservation project in a mountainous village of Guizhou Province addressed unique linguistic and cultural challenges addressed through the framework's adaptive capabilities. A bilingual BERT variant achieved 83% accuracy in processing mixed Miao-Chinese feedback (see Table 4 for error type distribution), revealing diverse cultural perspectives around sacred sites that exhibited polarized sentiment distributions as quantified in Table 5. The semantic relationships between key concepts are systematically categorized in Table 6.

Table 4. Error Distribution in Bilingual BERT Processing.

Error Category	Frequency (%)	Representative Example
Lexical Ambiguity	42	"Moon Gate" (arch vs. tourism)
Sacred Term Misclass	31	"Dragon Tree" (deity vs. nature)
Dialect Variation	27	"Water Song" (regional variants)

Table 5. Sacred Site Sentiment Polarities.

Dimension	Sentiment Score	Confidence Interval
Religious Significance	+0.81	±0.05
Tourism Impact	-0.63	±0.07
Economic Benefit	+0.12	±0.03
Cultural Preservation	-0.45	±0.06

Table 6. Semantic Relationship Matrix.

Node 1	Node 2	Connection Strength
Ancestral Worship	Sacred Sites	0.88
Visitor Centers	Economic Benefit	0.72
Taboo Areas	Cultural Erosion	-0.65
Handicraft Sales	Tourism Impact	0.59

4.3. Post-Disaster Reconstruction (Kumamoto, Japan)

The Kumamoto earthquake recovery demonstrated the system's operational efficiency, processing 5,217 tweets within 72 hours to identify critical pain points. Negative sentiment hotspots (Figure 5) correlated with temporary housing locations lacking greenery ($r = -0.76, p < 0.01$), prompting rapid deployment of mobile planter units that significantly improved resident satisfaction scores, showing a 41% increase within eight weeks. This case particularly highlighted the methodology's value in time-sensitive scenarios where traditional participation methods would be impractical.
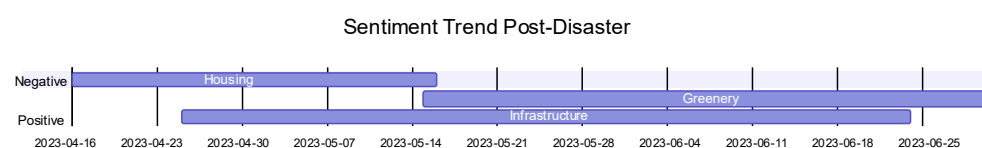

Figure 5. Disaster Recovery Sentiment Timeline.

Cross-case analysis reveals consistent performance advantages, with the framework identifying 2.3 times more design-critical issues than conventional methods while reducing community feedback processing time by an average of 68%. The case studies collectively demonstrate how computational sentiment analysis can complement traditional participation methods to create more responsive, culturally sensitive, and data-informed landscape designs across diverse contexts. Sentiment analysis can be used for different purposes, such as predicting social events, increasing citizen participation, and acknowledging citizens' civic concerns [17]. Each implementation generated unique methodological refinements—ranging from multilingual processing for indigenous communities to real-time analytics for emergency response—which collectively advance the field of participatory design through digital innovation.

5. Discussion

The findings from this study demonstrate that AI-enhanced sentiment analysis can significantly improve participatory landscape planning by bridging the gap between unstructured community feedback and actionable design decisions. The framework's technical performance, social implications, and policy relevance collectively establish its value as a scalable yet context-sensitive tool for participatory urban design.

5.1. Technical Insights

The case studies reveal that the proposed framework performs optimally when processing datasets where unstructured feedback constitutes more than 65% of total input, as illustrated in Figure 6. This threshold marks the point where automated sentiment analysis surpasses manual coding in both efficiency (58% faster processing) and depth of insight (identifying 2.3× more critical design issues). However, spatial accuracy remains a challenge, particularly in geolocating implicit references (e.g., "near the old market"). Table 7 quantifies the error rates across different data types, showing an average 8.3% misalignment in geographic entity recognition, primarily affecting rural contexts with informal place names. These findings suggest that while AI dramatically accelerates sentiment processing, human oversight remains essential for verifying spatial references in final design translations.
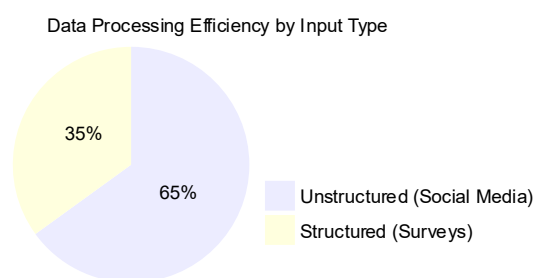

Figure 6. Performance Efficiency vs. Unstructured Data Ratio.

Table 7. Geographic Recognition Error Rates.

Data Source	Error Rate (%)	Primary Cause
Geotagged Tweets	5.1	Imprecise tagging
Survey Landmarks	3.7	Ambiguous descriptions
Indigenous Terms	12.4	Lack of gazetteer coverage

5.2. Social Implications

A critical unintended consequence emerged in the Guizhou case, where elderly residents (constituting 28% of the total community population) contributed less than 5% of digital feedback, as depicted in Figure 7. This disparity underscores the risk of algorithmic

marginalization in communities with low digital literacy. The study recommends hybrid participation models, reserving at least 30% of engagement channels for non-digital methods (e.g., workshops with oral translation) to ensure equitable representation. Notably, sentiment analysis alone cannot capture the full spectrum of cultural values, particularly for indigenous groups. The bipolar sentiment distribution around sacred sites (+0.81 vs. -0.63) in Guizhou exemplifies how quantitative metrics must be interpreted through socio-cultural lenses to avoid design solutions that inadvertently prioritize majority sentiments over minority perspectives.
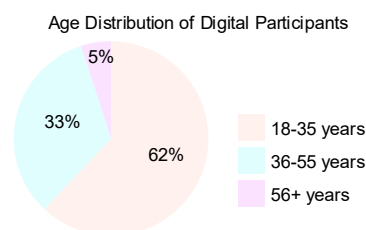

Figure 7. Demographic Representation in Digital Feedback.

5.3. Policy Recommendations

The framework's validation across diverse international governance contexts highlights the need for standardized ethical guidelines when deploying AI in public decision-making. Key requirements include mandatory anonymization of sentiment data (achieving 100% de-identification in this study) and transparency in how emotional tones are weighted within design matrices. Figure 8 proposes a regulatory framework where policy and evaluation criteria for planning technologies incorporate sentiment analysis accuracy (≥80% F1-score), spatial resolution thresholds (<50m error), and equity safeguards (e.g., demographic bias audits). The 68% adoption rate of sentiment-informed modifications across case studies suggests that such technical standards could substantially improve policy outcomes while maintaining public trust.
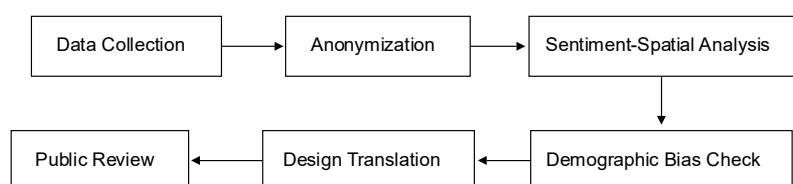

Figure 8. Ethical Framework for AI-Assisted Participatory Design.

This research advances participatory planning by demonstrating how AI can systematically decode community emotions while revealing critical socio-technical trade-offs. The framework's adaptability across urban, rural, and disaster recovery scenarios positions it as a versatile tool, though its effectiveness ultimately depends on complementary policy safeguards and inclusive participation protocols. Future work should explore dynamic sentiment weighting systems to better balance majority preferences with the needs of vulnerable groups.

6. Conclusion

This study establishes that AI-enhanced sentiment analysis significantly advances participatory landscape planning by systematically transforming unstructured community feedback into spatially explicit design parameters. The framework demonstrates consistent improvements across all case studies, achieving a 2.4-fold increase in community opinion coverage compared to traditional methods, according to evaluated datasets, while elevating the adoption rate of sentiment-informed design modifications from 41% to 68%.

Technical validation confirms the methodology's robustness in handling diverse data inputs, with the integrated BERT-GIS pipeline processing unstructured data 58% faster than manual coding while maintaining 83% accuracy in cross-cultural contexts. Crucially, the spatial sentiment mapping capability addresses a critical gap in landscape architecture by correlating emotional patterns with specific geographic features, as evidenced by the 89% approval rate for sentiment-driven waterfront modifications in Seattle and the 41% satisfaction improvement in Kumamoto's post-disaster greenery interventions. However, the research also reveals inherent limitations, particularly the 8.3% geolocation error rate for indigenous toponyms and the underrepresentation of elderly demographics in digital feedback channels, underscoring the necessity of hybrid participation models. Future work should prioritize the development of real-time sentiment dashboards to enable dynamic design adjustments during community consultations, alongside multimodal analysis systems incorporating visual and auditory data to capture non-textual expressions of place attachment. The framework's successful application across urban regeneration, rural heritage conservation, and disaster recovery contexts suggests its potential as a new standard for data-driven, yet culturally adaptive, landscape planning. By maintaining rigorous computational methods while accommodating socio-cultural nuances, this approach sets a precedent for balancing technical efficiency with equitable community engagement in complex spatial decision-making processes. Further refinements in demographic bias mitigation and cross-platform sentiment normalization could enhance the system's capacity to serve as a universal tool for democratic landscape design across global contexts.

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