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An AI-Enabled Multi-Stakeholder Participation Model and Decision Support System for Urban Community Environmental Governance

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Abstract: The challenges in urban environmental governance include achieving consensus among diverse stakeholders and supporting decision-making grounded in data. This study offers a novel framework by using an AI-based decision support system in conjunction with agent-based modeling to improve engagement among diverse stakeholders. The proposed methodology has two phases. In the first phase, a simulation using an agent-based model was run over 12 months with 50,000 agents across a metropolitan area of 100 square kilometers, generating 182.5 million GPS records (10% sampled: 18 million) and 240,000 incident reports. In the second phase, the proposed methodology was validated over six months using 3,847 governance cases. Trajectory mining showed a correlation of 0.68 for air quality and 0.54 for noise complaints. In addition, the stakeholder network increased to 3,856 connections, up from 1,247 connections. Moreover, the AI system achieved a recommendation accuracy of 78.34%, reducing the response time by 91%, although its performance declined in complex cases.

Keywords: Agent-based modeling, urban environmental governance, multi-stakeholder participation, spatio-temporal data mining.

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1. Introduction

Urban societies face significant challenges in environmental governance, especially during periods of rapid urbanization. To effectively address environmental challenges, it is crucial to involve government, the public, business, and civil society in the decision-making processes. A meta-analysis of 305 case studies shows that stakeholder participation can improve environmental governance outcomes when decision-making power is distributed (Newig et al., 2023; Jager et al., 2020). Effective citizen participation can enhance nature-based solutions in terms of environmental stewardship and social inclusion (Kiss et al., 2022). However, conventional governance systems face challenges in meeting the needs of diverse stakeholders, making it essential to use methodologies that can accommodate collaborative processes. The collaborative green transition is a complex process that demands careful coordination among various dimensions (Nielsen et al., 2024). Multi-level governance platforms are promising, but they also suffer from participation inequalities (Moreno-Serna et al., 2024).

The fields of AI and urban computing offer unique methodologies to tackle issues in governance. Agent-based modeling can be used as an efficient method to simulate complex urban systems by studying the effects of micro-level behaviors on macro-level phenomena (Crooks et al., 2021; Fischbach et al., 2021). These models have the potential to mimic complex behaviors that are usually observed in practical decision-making processes (Barr and Ge, 2023). Apart from these simulation-based techniques, spatio-temporal data mining is another major advancement in urban computing, addressing issues of heterogeneity, dependency, and scalability (Hamdi et al., 2022). Modern urban computing involves integrating location-based service data, transport system data, and environmental sensor data (Zheng et al., 2014). Foundation models have shown promise in extending these models through knowledge transfer capabilities (Liang et al., 2025).

However, the integration of multi-stakeholder participation with the decision support provided by AI is still a challenge. The development of multi-stakeholder participation in collaborative urban platforms through differential privacy-based methods is still in its nascent stage (Jain et al., 2016). This classification of urban data is more focused on technical optimization rather than the implementation of multi-stakeholder participation schemes (Tékouabou et al., 2022). Only a small percentage (less than 20%) of machine learning tasks in urban decision support systems are focused on participation

(Zheng et al., 2024; Wang et al., 2023). The literature on collaborative governance has shown that decentralized decision-making systems produce better environmental outcomes than centralized systems (Bodin, 2017). The theoretical perspectives of multi-level governance and network governance have highlighted the importance of relationships between different actors in solving boundary-spanning problems, in addition to the characteristics of the actors (Newig and Fritsch, 2009). Agent-based modeling provides further substantiation of the micro-foundations hypothesis by showing the macro effects of micro actions. Socio-technical approaches focus on the effects of artificial intelligence on organizational processes and interpersonal relations (Janssen et al., 2020).

Indeed, there is a noticeable omission in the existing literature on this topic. Even though agent-based models (ABMs) have been used to simulate various elements of urban systems, and machine learning has been leveraged to monitor environmental conditions, relatively few efforts have been made to merge the two within a unified governance framework. The role that the integration of AI-powered analysis may play in collaborative decision-making processes in the presence of diverse stakeholders has not yet been clarified. Current research considers computational modeling and stakeholder involvement as separate issues rather than as an integral part of the governance system.

This study aims to present a proposed framework for agent-based modeling and multi-stakeholder decision support systems in urban environmental governance, based on artificial intelligence. It also offers a simulation tool for modeling multi-level interactions in the social domain, as well as a spatiotemporal framework based on trajectory mining and machine learning methods. This proposed methodology has two major steps: (1) simulation through agent-based modeling, and (2) validation of the simulated results in a real-world environment. The validation process measures the performance of the system in various dimensions of governance. Furthermore, artificial intelligence has the potential to make urban governance not only more efficient, inclusive, and effective but also sustainable, technologically advanced, and scientifically informed.

2. Methods and Data

2.1. AI-Enabled Multi-Stakeholder Participation Model

The complexity in urban community environmental governance stems from the intricate relationships between various stakeholders at different geographical levels. The aim of this study is to develop a multi-stakeholder participation model that utilizes artificial intelligence tools in decision-making for urban community environmental governance. Agent-based modeling has proven to be effective in simulating self-organizing social phenomena (Nagai and Kurahashi, 2021).

As shown in Fig. 1, the proposed model consisted of four major parts that worked together to facilitate the formulation of data-informed policies. The multi-stakeholder's involvement comprised the government, the public, business organizations, and social organizations. The multi-scale system included three levels: city-scale policy formulation, district-scale resource allocation, and community-scale problem identification.

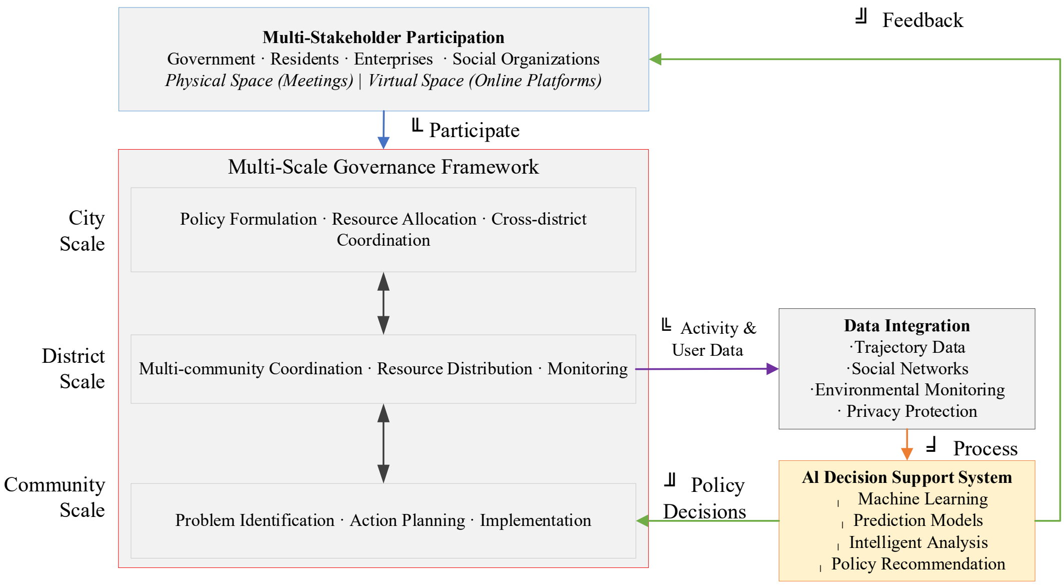


Fig. 1. Proposed AI-enabled multi-stakeholder participation model for urban community environmental governance

In agent-based simulation, the behavior of the stakeholders was represented by aggregating the decisions of stakeholders (Bruch and Atwell, 2015). The data integration module integrated the trajectory data, social network data, and environmental data, while maintaining the privacy of the stakeholders. Machine learning methods in the decision support system analyzed the aforementioned data sources. Recommendations were generated based on stakeholder preferences as well as environmental constraints. The model operated through a five-step closed-loop system in which stakeholder input was used for data collection, artificial intelligence processing was used for policy decisions, and feedback mechanisms were used for communicating results to stakeholders.

Agent configuration was based on data collected from census and administrative data on similar metropolitan environments. The agent population of 50,000 was derived from the actual number of active stakeholders in urban environmental governance structures, which have shown proportional representation: 68% residents (based on recorded participation), 12% government representatives (based on staffing), 15% enterprises (based on business registries), and 5% social organizations (civil society registries). The behavioral parameters aggregated three types of evidence. The participation rates were informed by three-year longitudinal data from a pilot district and meta analyses of collaborative governance. The response times corresponded to observed times in administrative workflows. The thresholds for network formation were informed by iterative comparisons between simulation results and stakeholder surveys. Expert elicitation was utilized to fill knowledge gaps, such as those related to preference weights in decision-analytic modeling.

2.2. Spatio-Temporal Data Model and Multi-source Data Integration

The spatio-temporal data model is a fundamental framework for conceptualizing dynamic urban activities at different levels of governance. In this study, a spatio-temporal data point is defined as shown in Eq. (1).

$$D_i = (l_i, t_i, a_i) \tag{1}$$

where $l_i \in \mathbb{R}^2$ represents geographic coordinates, $t_i \in T$ denotes temporal information, and a_i contains contextual attributes such as activity type and stakeholder identity. A trajectory can be formally expressed as $Tr = D_1, D_2, ..., D_n$ with temporal ordering $t_1 < t_2 < ... < t_n$, enabling the model to track individual movement patterns and interaction sequences over time.

Since data were collected from different sources, it was imperative to integrate them, including data from diverse sensors installed to monitor different aspects of the environment. The sensors were installed in strategically chosen locations to enable the continuous monitoring of the environment. Trajectory data could be used to monitor the movements of residents through mobile applications (Zheng et al., 2018). Additionally, social media content provided insight into community views on the environment, as issues were raised across diverse platforms. The feedback mechanisms also provided avenues through which the community can raise issues of interest, thus contributing to the discourse on governance using mobile devices.

The trajectory mining component employed clustering algorithms to identify salient locations where residents spent considerable time, as expressed in Eq. (2).

$$StayPoint = \{D_i \mid \Delta t_i > \theta_t \wedge \Delta d_i < \theta_d\} \tag{2}$$

Here θ_t and θ_d minimum duration and maximum distance thresholds, respectively. Spatiotemporal social networks were formed when the proximity criteria of two or more individuals, defined by $dist(l_i, l_j) < r_{contact}$ were satisfied within a time window. Machine learning algorithms processed the heterogeneous data sources to obtain pattern information, which is useful for policy-making (Wang and Ren, 2025).

The privacy protection mechanisms addressed the sensitivity of stakeholder data. Personal identifying information was suppressed during data collection, while the coordinates of the trajectory were obscured through the application of Laplacian noise with epsilon of 0.5. Data access was restricted based on the role, while the output for grouped data required a minimum sample size of ten. Differential privacy was used to ensure that individuals' information was not reverse engineered from published statistics. The privacy budget was distributed proportionally across analysis tasks. The study proposed a two-phase approach for simulation modeling and validation in real-world settings.

The simulation phase modeled the behavior of 50,000 agents within a metropolitan region of 100 km^{2}over a period of 12 months, generating 182.5 million GPS traces. Of these, 18 million were sampled for analysis, along with 240,000 incident reports. In the validation phase, 3,847 de-identified case records were obtained from the administrative database of a metropolitan district environmental management system in China during 2024, and the analysis was carried out over 6 months. The area under consideration covered 100 km^2, representing established administrative boundaries, and the number of agents was set to 8% of the actual population and registered stakeholders. The geographic features, such as industrial, residential, and transport areas, were distributed among the cells of the simulation grid. Calibration of the model was carried out by comparing the results from the simulation with six months of historical incident data to assess their congruence.

2.3. AI-Enabled Decision Support System Architecture

The architecture of the decision support system, as shown in Fig. 2, had functional modules for the processing of spatio-temporal data. The architecture had five layers, each of which was responsible for a different computational task. Data ingestion consisted of gathering raw data from environmental sensors, GPS-enabled trajectory databases, social media, and community feedback sites. In the data processing and standardization layer, disparate formats were converted into a homogeneous format through cleansing, integration, feature extraction, and normalization. In this process, the records could be correlated based on their locations and times. Intelligent algorithms are explained in detail in the next paragraph; they consisted of three separate systems that analyzed the processed data features using machine learning, pattern identification, and forecasting models. Decision-making and coordination involved considering multiple stakeholders' viewpoints, generating policies, and resolving conflicts through consensus-building techniques. The visualization and user interface layer at the top rendered analytical outputs through interactive maps, temporal charts, and dashboards for real-time monitoring.

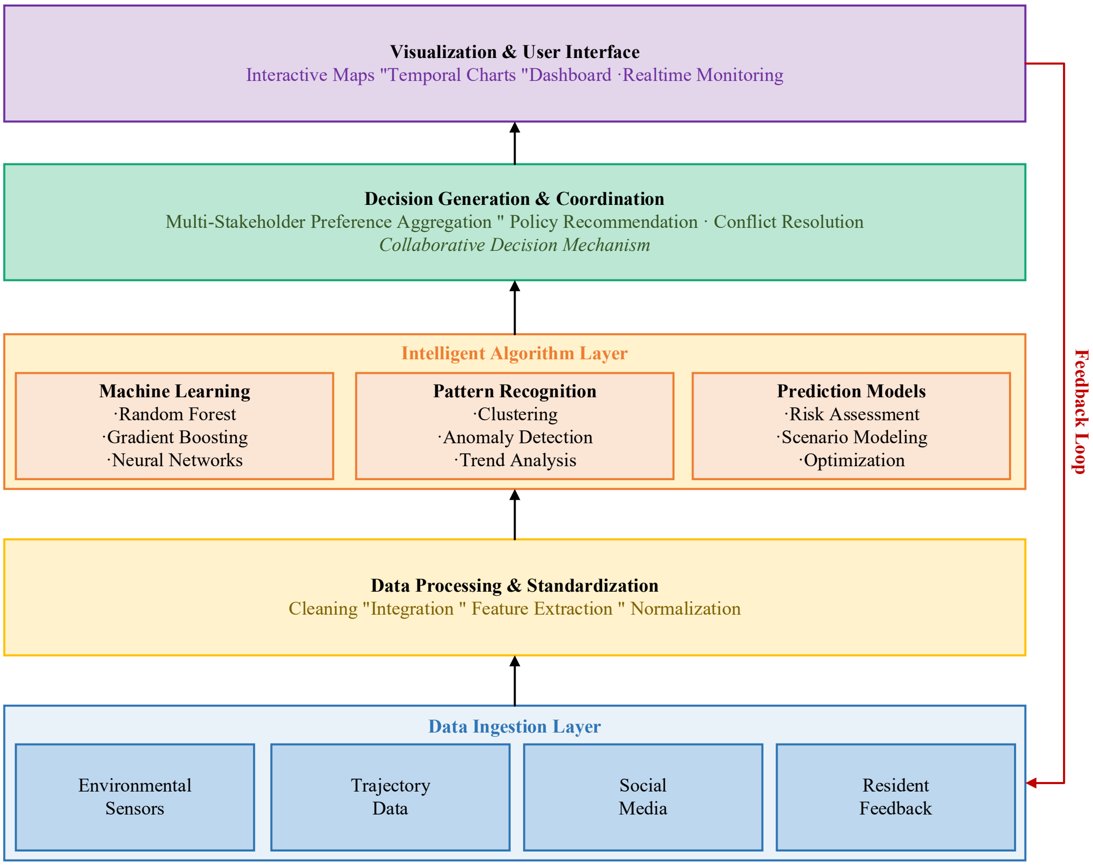


Fig. 2. Five-layer architecture of AI-enabled decision support system with continuous feedback mechanisms

The intelligent algorithm layer had three components that ran concurrently to evaluate the processed data from different analytical points of view. More specifically, in the machine learning module, a Random Forest algorithm with 100 decision trees and a maximum depth of 15 was used, while a Gradient Boosting algorithm with a learning rate of 0.1, 150 estimators, and a maximum depth of 6 was applied. In addition, neural networks were used for pattern detection. Pattern recognition included clustering, anomaly detection, and trend analysis to track temporal patterns in zones of the communities. Predictive models included risk assessment, scenario modeling, and optimization to develop intervention strategies (Wang et al., 2023).

Model building divided the data into training, validation, and testing sets in proportions of 70%, 15%, and 15%, respectively, using a stratified sampling approach (Shulajkovska et al., 2024). In the decision generation layer, the model incorporated stakeholders' opinions by using weighted voting and conflict resolution techniques. The visualization layer displayed analytical outcomes as interactive maps, charts, and dashboards.

3. Results

3.1. Multi-Stakeholder Interaction Patterns and Social Activity Analysis

Simulation experiments on agent behavior over 12 months show variations in stakeholder participation levels in activities associated with the urban environmental management system. The simulation starts with 50,000 agents representing the government, residents, enterprises, and social organizations. The interactions between the agents take place physically and virtually, as described in Table 1. The residents have the highest rate of participation at 47.28%, but they also show the greatest variation in participation compared to the other stakeholders.

The involvement of government agencies is stable at 68.47%. High levels of engagement are also noted for face-to-face meetings, which reach a peak of 82.3%. The response time stands at 2.31 days, which reflects an established process and human resources for addressing environmental issues. The degree of centrality is 0.42, which suggests that the government actors are centrally positioned in the process of participation. They thus act as gatekeepers between different domains of environmental governance and other actors, which would otherwise show low levels of interaction.

Enterprise participation is moderate and stands at 34.73%. Most enterprises focus on the level of resource distribution within the district and align themselves with the discussion outcomes. Enterprise participation in physical meetings stands at 41.8%. However, enterprise participation via the virtual platform stands at only 27.59%. The social organization attains participation levels of 41.15%, and physical meetings show higher rates of participation (55.92%) compared to the virtual platform (26.5%).

Table 1. Stakeholder participation statistics and behavioral characteristics analysis

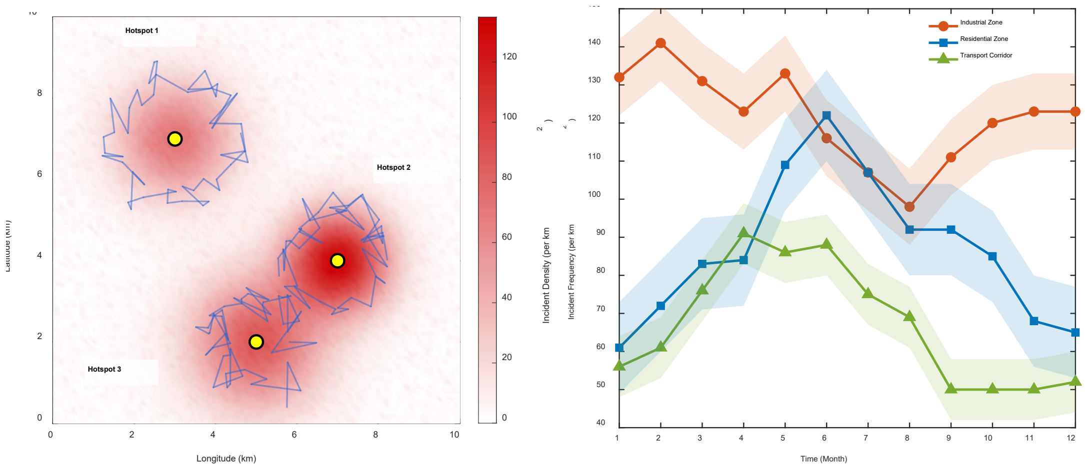
Stakeholder Type	Overall Participation Rate (%)	Physical Meeting Attendance (%)	Virtual Platform Engagement (%)	Average Monthly Activities (activities/month, ± SD)	Response Time (days)	Network Degree Centrality
Government Agencies	68.47	82.3	54.71	8.2 ± 1.4	2.31	0.42
Residents	47.28	39.14	55.5	4.6 ± 2.1	5.83	0.18
Enterprises	34.73	41.8	27.59	3.1 ± 1.6	4.18	0.24
Social Organizations	41.15	55.92	26.5	5.4 ± 1.8	3.07	0.38

Note: Data derived from a 12-month agent-based simulation tracking 50,000 individual agents across three governance scales (city, district, and community levels). Overall participation rate represents the percentage of stakeholders engaging in at least one governance activity per month. Physical meeting attendance and virtual platform engagement indicate the proportion of active participants using each channel; stakeholders may use both channels, resulting in combined percentages exceeding the overall rate. Average monthly activities are indicated by the mean values and the corresponding standard deviations. Response time is the mean duration of time from the identification of the issue to the taking of action. Network degree centrality is the proportion of the total possible connections that each type of stakeholder maintains.

Techniques for pattern recognition identify clusters of activities in which feedback from the residents prompts inquiries from the government. These inquiries, in turn, ensure enterprises compliance and confirm the existence of response mechanisms for the various stakeholders. The simulation traces interaction patterns using nodes for stakeholders and lines for collaborative efforts, revealing scale-dependent network properties. The density of city-level networks is observed to be lower compared to community levels because city-level policies engage less often, with more stakeholders involved in the discussion process. The simulation uses betweenness centrality metrics to measure the effect of collaboration and finds that bridging positions are mostly held by government representatives and social organization coordinators rather than being evenly distributed. This implies that convergence points exist in the information flow of the governance process.

3.2. Spatio-temporal Analysis and Trajectory Mining Results

Based on the analysis of spatio-temporal data, there is a variation in the geographic distribution of reported incidents in the virtual city region. As shown in Fig. 3(a), kernel density analysis of 240,000 reported incidents indicates that there are three hotspot locations. Hotspot 2 has the highest density of 127 reports/km²/month due to industrial activities. Hotspot 1 has a medium density of 70 reports/km²/month, while Hotspot 3 has 85 reports/km²/month. In addition, analysis of 18 million GPS traces (each representing ten traces per agent) shows that residents' activities are not uniformly distributed but rather concentrated in hotspot locations. Furthermore, a strong correlation exists between these traces and complaint locations.



(a) Spatial hotspot distribution with trajectory overlay (b) Temporal evolution of hotspot intensities

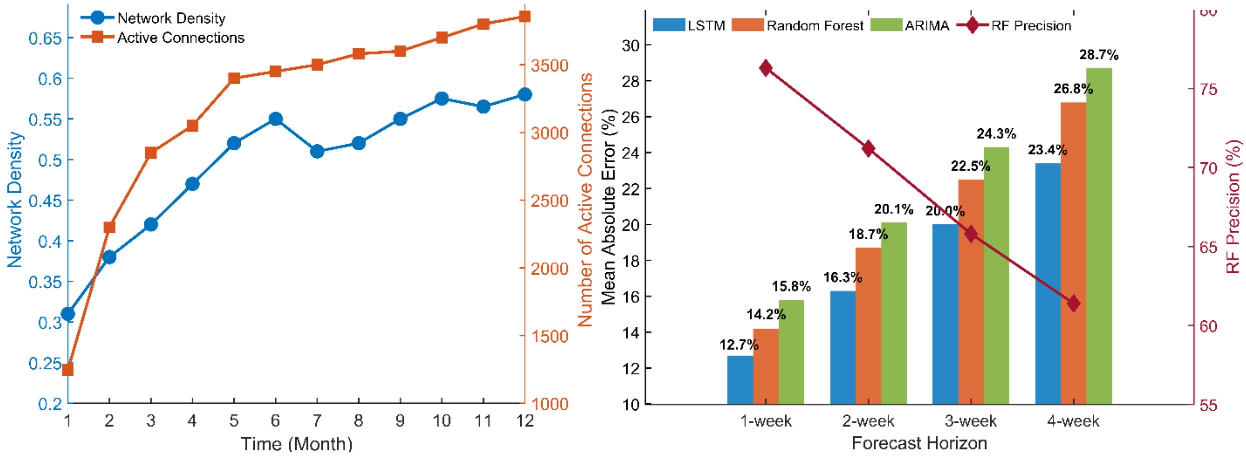
Fig. 3. Spatio-temporal analysis from agent-based simulation

Note: Panel (a) is a schematic representation based on simulation results, showing relative spatial relationships in a 10km × 10km area rather than actual geographic coordinates. Simulation tracks 50,000 agents over 12 months. Hotspot 2 exhibits peak density at 127 incidents per km².

These spatial patterns are further supported by quantitative analysis. Correlation analysis, conducted over 1 km² grid cells on a weekly schedule (n = 4,800 cell-weeks), shows that the reporting rates are associated with trajectory density. In detail, the Pearson correlation coefficients for the relationship between air quality reporting rates and trajectory density are 0.68 ($p < 0.001$, 95% CI: 0.64 -0.72), and for the relationship between noise complaint reporting rates and trajectory density, the Pearson correlation coefficient is 0.54 ($p < 0.001$, 95% CI: 0.49-0.59). Direct exposure is more strongly related to reporting rates than proximity is. However, correlation does not imply causation. Potential confounding factors include socioeconomic factors and temporal autocorrelation.

Yearly changes occur in development patterns across different zones. Fig. 3(b) shows the incidence frequency in industrial, residential, and transport zones. The frequency of the incidence in the industrial zone is stable, on average at 125 per km² per month, ranging from 98 to 141. This signifies a low variability effect, implying a consistent effect due to the operation of the system. The number of incidents in the residential zone varies, starting at a total of 61 in the first month, reaching 122 in the sixth month, and then dropping to 65 in the twelfth month. In the transport zones, the incidents show a constant medium level as the number ranges between 50 and 91 km², with a declining trend towards the end.

The cooperative dynamics of the stakeholders involved in the environmental governance activities are analyzed. The active links in the connection network increase gradually from 1,247 in the first month to 3,856 in the twelfth month, as shown in Fig. 4(a). The density of the network also rises from 0.31 to 0.58 over the same period, though there are some dips around the sixth month. These dips are characteristic of a time when the rate of link formation exceeds integration. The mean path length, which is the average number of steps to get from one node to another, is 3.2. This is favorable for communication, considering the size of the network.



(a) Social network growth dynamics (b) Prediction model performance comparison

Fig. 4. Network dynamics and machine learning model performance evaluation

Note: The left panel displays the temporal evolution of network density and active connections over a 12-month period. The right panel compares the prediction accuracy of three machine learning approaches (LSTM, Random Forest, ARIMA) across different forecast horizons, with Random Forest precision for spatial prediction shown as a trend line.

The comparison of the prediction models involves three machine learning models used to forecast the environmental incident rate over various periods of time. The mean absolute error percentage is shown in Fig. 4(b), which includes the LSTM, Random Forest, and ARIMA models for one to four weeks. The LSTM model has the lowest error rate at 12.7% for the one-week forecast, but its error rate increases to 23.4% for the four-week forecast. The precision level of the Random Forest technique is found to be medium, with error rates varying from 14.2% to 26.8%. On the other hand, the precision level of the ARIMA technique is found to be the lowest, with error rates varying from 15.8% to 28.7%. In the case of hotspot location prediction, the precision level of the Random Forest technique is found to decrease from 76.3% to 61.4% when the prediction period is increased from one week to four weeks, owing to the natural evolution of the conditions. The results show that the most important factors are the number of previous complaints, the density of the resident population, and the level of industrial activities. The importance of weather is moderate and uneven for the various types of environmental problems.

3.3. Decision Support System Performance and Validation

After the agent-based simulation, the validation process is carried out in the same metropolitan district over six months, covering 3,847 governance cases. Quantitative measures, as well as user feedback, are used to validate the effectiveness of the system. Cases involving at least two factors, such as coordination, conflict with three or more parties, uncertain environmental standards, or the presence of mixed environmental and political factors, are considered complex cases, while the rest are considered routine cases.

The accuracy of recommendations in classifying environmental issues reaches 78.34%, as shown in Table 2. The response time reduces from 28 seconds (in the traditional method) to 2.43 seconds, a 91% improvement. The time taken to solve the problems decreases from 18.73 days to 12.28 days, a reduction of 34%. The engagement level improves from

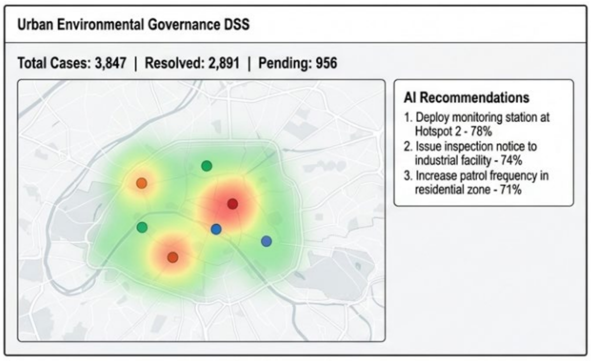
42.31% to 64.68%. The cost per case reduces from $67.80 to $23.50 after excluding development costs, making a reduction of 65%. The success rate of complex cases decreases from 71.63% to 58.42%, thus creating a deficit of 18%. The time taken to coordinate multi-jurisdictional cases increases by 102%. This rises from 2.08 days to 4.21 days.

Table 2. Performance Comparison: AI-Enabled System vs. Traditional Governance Approaches

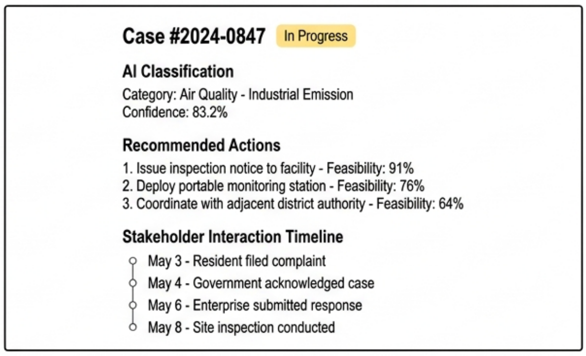
Performance Metric	AI-Enabled System	Traditional Approach	Change
Average Response Time	2.43 seconds	28 seconds	91%↓
Issue Resolution Time	12.28 days	18.73 days	34%↓
Recommendation Accuracy	78.34%	N/A	N/A
Stakeholder Engagement Rate	64.68%	42.31%	53%↑
Cost per Case (USD)*	$23.50	$67.80	65%↓
Complex Case Success Rate	58.42%	71.63%	-18%↓
Multi-jurisdiction Coordination	4.21 days	2.08 days	+102%↑
User Satisfaction Score (1-5)	3.82	3.41	12%↑

Note: Operational marginal cost per case, excluding initial development investment. Data was collected during a six-month deployment period, totaling 3,847 cases of governance. In complex cases, various stakeholders are involved across different jurisdictions. Therefore, there is a need to engage in negotiations. The traditional method includes verification steps as well as approval processes.

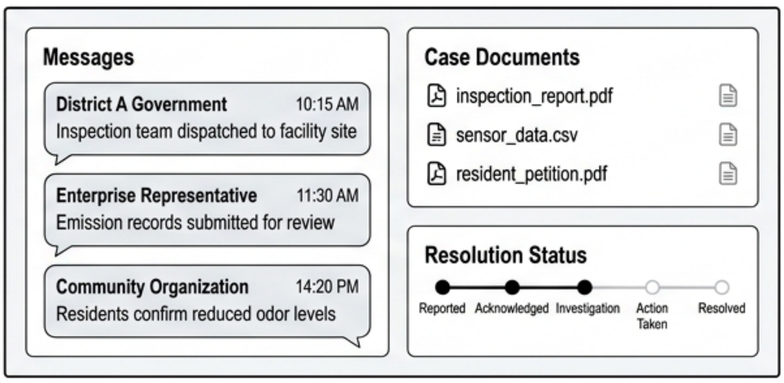
Fig. 5 shows examples of screenshots from the deployed interface of the decision support system. The main dashboard shown in Fig. 5(a) helps governance stakeholders evaluate the real-time distribution of incidents using heat map overlay, where the color intensities represent the number of trajectories in the area. Colored icons indicate various issue types, while the side panel displays a list of AI-driven recommendations with confidence scores. In Fig. 5(b), a screen shot for the detail of one governance case is shown. For each case, the system predicts the category of the issue along with the confidence score and recommends actions with feasibility levels. Below this information, the timeline shows all stakeholder interactions in resolving the issue, from when the complaint is lodged to the site inspection stage. In Fig. 5(c), a coordination module for handling cases involving multiple stakeholders is shown. Government authorities, enterprises, and other community stakeholders collaborate with one another through the same message interface, while documents like inspection reports and sensory data are also stored against each case.



(a) Main dashboard



(b) Case detail view



(c) Multi-stakeholder coordination module

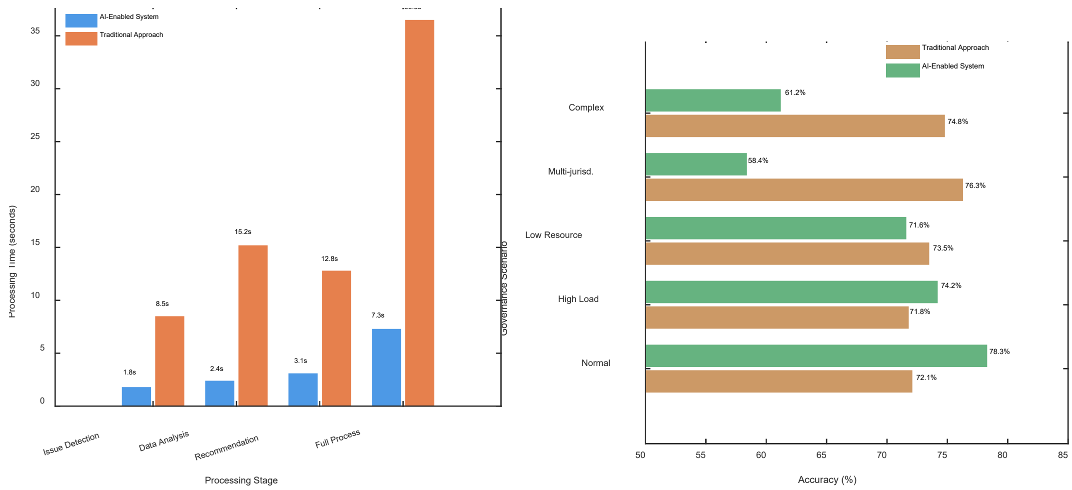
Fig. 5. Screenshots of the AI-enabled decision support system interface

Note: (a) Main dashboard with real-time incident mapping and trajectory heatmap overlay. (b) Case detail view showing

AI classification, recommended actions, and stakeholder interaction timeline. (c) Multi-stakeholder coordination module with message exchange, document management, and resolution tracking. Personal and location-identifying information has been anonymized.

An examination of failed complex cases reveals three patterns. First, jurisdictional boundary problems are most common in cases where the system is unable to deal with the overlapping authority that people normally manage through informal coordination. Second, stakeholder conflict problems occur when groups adopt incompatible positions, with political feasibility outweighing technical criteria. Third, novel types of pollution that are not present in the training data pose a smaller problem. An analysis using feature importance based on Gini values finds that the most important features are prior incident frequency (0.27), population density (0.21), and the degree of industrialization (0.18). Weather patterns and temporal patterns are secondary factors, with weights of 0.14 and 0.11, respectively. The accuracy of the model is 78.34%, which is significantly higher than the accuracy of random classification (25.0%) and distance-based heuristics (52.8%).

As shown in Fig. 6(a), the AI system exhibits time benefits in all stages of the process. The results show that it takes 1.8 seconds to identify issues, as opposed to 8.5 seconds using conventional methodologies. The data analysis process takes 2.4 seconds as opposed to 15.2 seconds using conventional methodologies. The recommendations take 3.1 seconds as opposed to 12.8 seconds using conventional methodologies. The entire process takes 7.3 seconds as opposed to 36.5 seconds using conventional methodologies. As shown in Fig. 6(b), the accuracy of the proposed method varies depending on the different governance scenarios. Under normal operating conditions, the proposed method achieves an accuracy level of 78.3%, while conventional methods achieve an accuracy level of 72.1%. Under high-load conditions, the proposed method achieves an accuracy level of 74.2%, while conventional methods achieve an accuracy level of 71.8%. In the resource-constrained scenario, the accuracy is 71.6%, whereas in the case where human judgment is used, the accuracy is 73.5%. In the multiple jurisdiction scenario, the accuracy is 58.4%, whereas human judgment achieves 76.3%. In the complex scenario, the accuracy is 61.2%.



(a) AI-Enabled vs. traditional approach (b) Performance across governance scenarios

Fig. 6. Performance comparison of AI-enabled and traditional governance systems

Note: The left-hand panel shows a comparison of processing times across workflow stages, whereas the right-hand panel shows a comparison of accuracy across governance scenarios. The data used for this graph were collected from a deployment that ran for six months and processed 3,847 cases. The efficiency shows the benefits of an AI approach in routine operations compared to the complex coordination required by the traditional approach.

In the assessment of adaptability, the system's functionality is tested at various operational levels, including elevated incident rates and stakeholder demographics. The system’s accuracy remains above 70%, except in highly complex cases. Aggregated anonymous feedback data from 284 stakeholders were collected through the system’s built-in feedback module. The analysis shows the average satisfaction rating stands at 3.82 out of 5, compared to 3.41 with traditional approaches, representing a 12% improvement. The government stakeholders report the highest satisfaction rating at 4.2, while enterprise stakeholders report the lowest at 3.3, due to a lack of specificity of activities in industry-specific domains.

4. Discussion

The agent-based model designed to promote multi-stakeholder engagement is found to be effective in simulating governance processes. Trajectory mining on the dataset of 18 million GPS traces shows that the mobility of residents is related to reporting behavior. Intensity of direct exposure is found to have a stronger relationship with reporting behavior than proximity. This aligns with the approach of urban computing, which includes behavioral data to analyze the urban complex systems (Kumar and Bassill, 2024). The correlation coefficients of 0.68 and 0.54 for air quality and noise complaints, respectively, demonstrate the viability of the spatiotemporal analytic approach to urban data mining (Wang et al., 2020).

The increase in the number of connections from 1,247 to 3,856 shows that these platforms facilitate the creation of trust, contradicting the idea that trust is created through physical interactions over time. The patterns of engagement that are observed from the multi-stakeholder interactions provide insight into the challenges that can be experienced when technology is used to facilitate engagement instead of enhancing it. The behavior of hybrid human-artificial intelligence agents challenges the theories of socio-technical neutrality, as it demonstrates that technology impacts power relations among stakeholders in public governance.

Although the AI-based decision support system increases the efficiency of governance, it faces challenges when it is used for complex decision-making situations. A 91% improvement in response time shows improvements in computational efficiency. However, an 18% drop in accuracy under complex scenarios and a 102% increase in response time for inter-jurisdictional coordination highlight difficulties for AI-based systems. Moreover, research on governmental AI adoption has also pointed out that change occurs alongside it (Janssen et al., 2020). The performance improvements observed could be explained by the digitization and machine learning capabilities that the municipality uses in making investment decisions. The proposed framework aims to address the challenges associated with the integration of big data analytics in urban governance (Lnenicka et al., 2024). Moreover, the integration of privacy protection through differential privacy and access control introduces computational complexity, which could affect the accuracy of the results (Kantarcioglu and Ferrari, 2019).

The validation is performed in a metropolitan area of 100 km² with a mixed land use, a tri-tier governance system, and contemporary issues of air and noise pollution. These findings relate to a mid-sized city in an emerging economy, with similar patterns of governance and infrastructural arrangements. From an operational perspective, network effects are dependent on effective engagement with all stakeholders. The limitations relate to the parameters set in the simulation, which are specific to urban settings. The limitations relate to simulation parameters that are specific (and in some cases unique) to urban settings. There exists uncertainty about the suitability of the model for urban settings due to differences in the demographic composition. Data quality issues affect approximately 8 to 12% of the dataset, necessitating retraining of the machine learning algorithms.

Further work should determine its generalizability to other cities by conducting comparative effectiveness studies. Federated learning approaches may also be used to further develop the model without compromising data sovereignty. Using data from various modalities, including satellite images, IoT devices, and crowdsourced data, provides opportunities to improve situational awareness. This study recommends that Explainable AI methods be explored for their potential to increase stakeholders confidence by making the underlying reasoning for recommendations transparent.

5. Conclusion

The current research proposes a combined model that integrates participatory agent-based modeling with an artificial intelligence decision support system to facilitate urban community environmental governance. During twelve months of simulation with 50,000 agents, the stakeholder network increased from 1,247 to 3,856 live interactions. Mining trajectories from 18 million GPS traces reveals that actual environmental exposure is more effective at stimulating incident reports than geographic proximity, with the Pearson correlation coefficient for air pollution cases at 0.68. Artificial intelligence achieves a recommendation accuracy of 78.34% and reduces the average time by a factor of nine. However, in multi-jurisdictional conflicts, coordination time increases by 102%, and the success rate is only 58.42%.

These results suggest specific changes to how governance decision-making processes should be structured. Simple cases could be handled using automated classification and recommendation systems, thereby allowing human effort to focus on politically complex cases where AI underperforms. For districts, resources can be allocated proactively based on hotspot forecasts, rather than reactively, as has been done before. In view of this disparity in performance when multiple jurisdictions are involved, it is clear that AI-supported governance should be an addition to current negotiating efforts, not a substitute.

The constraints of this study depend on its location, which is a mid-size metropolitan area in China; therefore, the generalizability of its results to cities with different governance structures is questionable. Data quality problems affect 8% to 12% of cases, and the model requires continuous retraining due to changing incident trends. Federated learning could enable model sharing across cities while protecting the integrity of their data; explainable AI could also be applied to overcome the problem of opaque recommendation mechanisms.

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Institutional Review Board Statement

This study is exempt from IRB review as it relied on de-identified administrative records and anonymous feedback data.

Declaration of Artificial Intelligence (AI) Tools

AI-assisted tools were used during the preparation of this manuscript for language editing and grammar checking. The AI tool used was ChatGPT-5. The tool was employed to improve the readability and grammatical accuracy of the text. The author takes full responsibility for the content, data analysis, interpretation of results, and conclusions presented in this manuscript. All scientific content, research design, data collection, and analytical decisions were made solely by the author without AI assistance.

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