

Article

A Data-Driven Decision-Making Support Method for Priority Determination for an Intelligent Road Problem Reporting System

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Abstract: This paper presents a new decision support method aimed at prioritizing processing for an intelligent road problem reporting service. The proposed method uses advanced georeferencing technology to extract the longitude and latitude coordinates in the metadata of photos taken with the smartphone application to capture the complaint scene. This method not only maps out the processing times, but also applies a spatiotemporal clustering technique to link the complaint types and locations with the actual complaint processing times. A validation study of the frequency of reported locations per priority reveals that the complaint-processing prioritization method developed in this study aligns realistically with actual field complaint processing. Furthermore, recognizing the significance of location in processing complaints, the georeferencing technique appears suitable for identifying complaint locations for each report and incorporating this into the decision-making framework.

Keywords: decision-making support model; clustering; public complaint management; road problem reporting system

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1. Introduction

The Road Problem Reporting Service (RPRS) was developed by the Korea Ministry of Land, Infrastructure, and Transport (MOLIT) to enable the public to report civil complaints on highways, national roads, and local roads quickly and conveniently using smartphones. Since its inception in 2013, the service received an average of more than 33,000 complaints annually [1]. These complaints are categorized into five types: poor road condition, poor drainage condition, poor road facility condition, roadkill and obstacles, and others/unclassified. In contrast to general inconvenience complaints, complaints related to road usage often require immediate action. For instance, potholes, animal carcasses (roadkill), and obstacles that directly endanger vehicle safety can lead to significant accidents, and poor drainage facilities can pose substantial risks during the rainy season. However, it is practically impossible to address all complaints promptly.

To address these constraints, Jeon et al. [2] utilized the equivalent property damage only (EPDO) technique, a comprehensive approach that assesses the severity of reported complaints and suggests methods for prioritizing them. Their method involved dividing each complaint into sub-items and assessing the severity of each sub-item using EPDO to calculate severity weights. These weights were determined by selecting indicators such as accident risk levels, driving and walking safety, convenience, and the visual impact on the traffic environment. Although the method by Jeon et al. [2] offers a comprehensive

consideration of civil complaints in terms of safety, convenience, functionality, and environmental impact and has been noted for its remarkable effectiveness in providing objective severity measurements, it does not adequately consider the geographic locations of the complaints. The severity assigned to potholes may vary significantly depending on their locations, i.e., a pothole on a busy highway lane poses a different level of risk compared to one on a less traveled local road shoulder, yet the previous method does not differentiate based on such criteria.

This study addresses the need to factor in geographic data by utilizing geotagging technology, a cutting-edge tool that records the longitude and latitude coordinates in the metadata of photos taken with smartphones. This allows for identifying complaint locations such as roads, buildings, neighborhood facilities, social overhead capital (SOC) facilities, and railways. The analysis of complaints processed in 2021 and 2022 utilizes these coordinates to further classify road-related complaints according to a detailed road hierarchy: highway/trunk road, general national road, local road, roads in city/county/district, residential road/back road, pedestrian road, farm road/forest road, service road, and unclassified road. By linking the complaint types and locations with the actual outcomes of complaint processing, this study not only maps out the processing times, but also applies clustering techniques to the data. This methodology facilitates the formulation of recommendations for complaint prioritization based on the understanding of complaint processing times (CPT) across different types of locations.

This paper is organized as follows: Following the introduction, the next section addresses a comprehensive review of relevant research efforts. The section of analysis presents an overview of the complaint data, providing both descriptive and comparative analyses to identify factors affecting the priorities of complaint processing. The details of the decision-making support model development are presented with the model results in the next section, followed by conclusions and recommendations.

2. Literature Review

This section summarizes the literature review, mainly focusing on data-driven approaches to prioritize and manage public complaints in various domains, from urban infrastructure to customer service and highway maintenance.

Mak and Jones [3] proposed a scoring-based methodology to determine the priority of highway improvement projects. Categorizing 26 parameters established for the project evaluation into six groups, such as need, deficiency, continuity, benefit-cost, local opinion, and social-economic and environmental consequences, the authors evaluated the parameters and assigned weight factors to each parameter group for each project. The weight factors were determined by state transportation board members, department of transportation (DOT) agencies, and local transportation planners, obtained from a state-wide panel survey in Georgia, USA. The final score for each project was estimated by summing the weight factors, and the priority is determined based on the estimated score: higher score, higher priority.

Minaei-Bidgoli and Akhondzadeh-Noughabi [4] adopted an association rule mining method to identify patterns in customer complaints and improve complaint management. The authors applied the a priori algorithm to a large dataset of complaints submitted to Tehran's municipality to identify relationships among factors such as season, complaint type, and citizen demographics. By analyzing these relationships, the proposed method prioritized responses and enhanced service quality by addressing frequent and region-specific complaints.

Akhondzadeh-Noughabi et al. [5] developed a novel urban management model to improve the quality of the response to citizen complaints in Tehran, Iran. To this end, the authors combined citizen relationship management (CiRM) and data mining techniques to better understand the primary needs of citizens and optimize municipal services. Employing key factors for identifying and prioritizing citizen needs, such as frequency, time interval, and satisfaction, the study categorized urban needs into primary, secondary, and

uncommon groups by applying clustering methods to the key factors. The results demonstrate that the CiRM-clustering combined method can significantly enhance urban management practices by allowing municipalities to better target and address citizens' most pressing concerns. This model also addressed potential applications in broader public sector customer relationship management (CRM), offering a structured, data-driven approach to improve service delivery and citizen satisfaction.

Bansal and Toshniwal [6] attempted to analyze urban civic complaints, such as pavement condition, traffic congestion, noise, and drainage, by applying clustering methods. The proposed analysis framework consisted of two components: (1) a dynamic grid-based clustering and (2) a location-based clustering. The dynamic grid-based clustering conducted complaints analysis based on spatial attributes of an urban area, taking into consideration the spatial connectivity of the urban street network. The location-based clustering focused on the types of complaints to group each complaint based on (1) density of complaints (DF) and (2) temporal patterns of complaints (TF). Utilizing the kernel density clustering method [5], DF was measured to quantify the concentration of a complaint to evaluate its significance. TF was employed to estimate the temporal correlation of each complaint group to determine the weighted scores. By combining DF and TF, the criticality score of each complaint group was estimated to finalize the priority. The proposed framework was applied to New York City, USA, and Bangalore, India. The results show that the proposed framework helped urban planning strategies increase civilians' satisfaction level with the service of complaints.

Ghodousi et al. [7] examined three clustering algorithms, such as K-means, fuzzy C-means (FCM), and independent component analysis (ICA), to assess public needs in terms of citizen relationship management (CiRM). Using data from public complaints in Bojnourd, Iran, the authors analyzed levels of satisfaction and classified citizen needs by identifying similar complaint patterns based on the frequency, recency, and satisfaction level of each reported complaint. The K-means algorithm was chosen for its straightforwardness, while FCM was utilized to capture overlapping clusters where complaints could belong to various categories. ICA was also applied to find hidden patterns that might be overlooked by conventional clustering methods. This analysis enabled city officials to pinpoint prevalent citizen complaints, assess satisfaction with resolutions, and prioritize issues according to urgency and public significance. The findings indicate that these clustering techniques could effectively categorize public needs and expose trends, assisting policymakers in prioritizing actions to enhance public services. This study underscored the real-world application of data science in urban management by demonstrating how clustering can help match public services with the changing needs of citizens, ultimately boosting community satisfaction and optimizing resource use.

Hubert et al. [8] presented a visual analytics model to support municipal authorities in managing citizen complaints. The tool was designed to perform map-based visualizations that help officials investigate patterns in citizen requests and complaints, particularly by leveraging geospatial clustering and heatmaps to identify highly affected areas within cities. By employing DBSCAN [9], the tool groups requests by location and frequency, identifying clusters where service issues are concentrated. It also supports hierarchical clustering to reveal subclusters within major complaint areas. By providing such features, the tool was envisioned to enable city officials to prioritize resources and improve response strategies based on visualized citizen feedback. The authors stated that this approach facilitates a better understanding of urban issues, thereby enhancing the decision-making process for public service improvements.

Lee et al. [10] conducted a study to prioritize service areas for urban safety and disaster management by analyzing civic complaints using big data analytics. The authors retrieved keywords related to safety and disaster management from unstructured text messages conveying civic complaints to identify major policy demands. They then filtered the dataset using these keywords and performed a panel analysis to investigate the effects of residents' policy demands on safety and disaster management in 16 local jurisdictions.

According to the study, policy requirements varied depending on the socio-cultural factors, such as age, gender, economic status, and proportion of migrants. The conclusion was that city governments should provide tailor-made services to address the specific needs of their residents.

Cerna et al. [11] proposed a decision support system (DSS) for managing complaints in Ethiopia's technical and vocational education and training (TVET) institutions. TVET institutions encountered various challenges in handling complaints due to limited resources and inefficient systems. The proposed DSS integrates a web-based interface and a mobile application, allowing users to submit complaints from anywhere and track their progress in real time. The system notifies users via SMS and enables administrators to prioritize and resolve issues more efficiently. It also includes reporting features for data analysis, helping decision-makers identify trends and improve service quality. The authors suggested that the DSS framework can enhance accountability and responsiveness in TVET institutions, supporting the goals of good governance and citizen satisfaction.

Ghodousi et al. [12] developed a framework to improve public service responses and understand community needs by utilizing 137 databases from Bojnourd, Iran, which track and classify citizen complaints. The proposed framework integrates (1) data mining techniques, such as the recency, frequency, and monetary value (RFM) model, and (2) clustering algorithms, including K-means [13] and the bees algorithm (BA) [14], to analyze complaint trends. While the K-means method provides a simple and popular clustering technique, BA, inspired by the foraging behavior of bees, offers a more refined approach to optimally cluster citizen needs. The comparison highlights the efficiency of BA in segmenting and prioritizing complaints for actionable insight. Using the framework, the authors were able to successfully identify key areas of public dissatisfaction and prioritize actions based on citizens' needs. The implementation results show that the proposed framework provides valuable feedback for city officials to streamline complaint resolution, enhance service quality, and ultimately boost citizen satisfaction by focusing resources on high-priority needs identified from the data. Such data-driven management approaches appeared to support better public engagement by addressing citizens' concerns more effectively.

In Taufiq et al. [15], a decision-support model powered by a simple additive weighting (SAW) technique for evaluating employee performance was presented. SAW is a multi-criteria decision-making approach that helps organizations assess employee performance by assigning weights to various criteria. SAW allows for a systematic and objective ranking of employees based on their performance across different metrics. The authors demonstrated the practical implementation of SAW in a performance appraisal system, where criteria such as attendance, work quality, and skills are assessed. By scoring and weighting each criterion, the model provides a ranking to identify top performers and those needing improvement, aiding managers in making promotion, training, or development decisions. The implementation results also reveal that the SAW-based model enhances transparency and consistency in evaluations, making it a valuable tool for human resource management in organizations aiming to foster productivity and employee development.

Similar to [15], Jumaryadi and Nugroho [16] also proposed a SAW-based decision-support model to prioritize customer complaints effectively. This study specifically focused on evaluating various complaint types by assigning weights to factors such as urgency and customer impact, allowing organizations to determine which complaints require immediate attention. The authors discovered that the SAW-based model provides a straightforward, quantifiable method for complaint prioritization, helping engineers and managers improve response times and increase customer satisfaction. This method also aligns with company goals by focusing on key performance indicators (KPIs) related to complaint resolution, ultimately fostering better customer service and operational efficiency in competitive business environments.

Lee et al. [17] proposed a framework to determine the service priority of pavement maintenance on rural highways by employing spatial big data analytics. The authors first datalized the past pavement maintenance records, including the location, duration, and traffic control of various roadworks, such as pothole repair, roadkill treatment, micro-surfacing, and emergency infrastructure maintenance, to establish a database. The authors restructured the data to train a machine learning model to estimate the priority of pavement maintenance service. The proposed framework was expected to be deployed to practical uses in helping local governments establish short and mid-term pavement maintenance strategies in rural areas.

More recently, Helmy et al. [18] presented an advanced decision-support model designed to enhance how e-commerce businesses handle customer complaints, focusing on increasing customer satisfaction and trust. The authors integrated various tools and algorithms to categorize complaints, allocate resources efficiently, and monitor the effectiveness of complaint resolution strategies. In particular, by employing association rule mining [19], the model identifies common complaint patterns and trends, which help businesses proactively address recurring issues. Through case studies testing the proposed model, the authors proved that effective complaint management can significantly improve customer satisfaction and reduce negative word-of-mouth, which can damage a brand's reputation. The authors also demonstrated that effectively addressing complaints provides an opportunity for continuous improvement as businesses gain insights into potential areas for service and product enhancement. The authors addressed how e-commerce companies can foster trust, loyalty, and long-term customer relationships by systematically addressing customer complaints and using technology to streamline processes.

In summary, it is discovered that various methodologies utilize data-driven strategies to effectively address and manage public complaints across different areas, including urban infrastructure, customer service, and highway maintenance. Each examination applies distinct models and techniques, such as clustering, scoring, association rule mining, and decision-support systems, to analyze complaints and improve service responsiveness. These methods showcase the benefits of systematic, algorithm-based approaches in enhancing service quality, boosting citizen and customer satisfaction, and optimizing resource allocation. By recognizing complaint patterns and prioritizing needs based on data, organizations and municipalities can customize their responses to urgent issues, promoting a proactive, efficient, and transparent method of service management. The research highlights the promise of data-driven decision-making in positively influencing public satisfaction, operational efficiency, and strategic planning across various service domains.

3. Analysis

3.1. Complaint Processing Time Data Overview

This study analyzed 65,680 complaints recorded by the RPRS app from January 2021 to December 2022. The dataset includes various details such as the types of complaints, dates of complaint submission, action dates, addresses, and brief descriptions provided by the complainants. Additionally, it contains photos taken by the complainants, along with the longitude and latitude coordinates of each complaint location.

The date the service receives a complaint is automatically recorded by the app and referred to as the "complaint report date." The "action date," which marks the completion of complaint processing, is manually entered by the responsible official. The time between action dates and complaint report dates indicates the time required for processing the corresponding complaints, although differences from the actual processing time may exist due to manual entry.

Prior to analyzing the complaint processing time (CPT) data, 452 complaints that showed processing times exceeding five weeks (0.7% of the total dataset) were removed, as such lengthy durations are considered highly atypical. Additionally, 767 complaints

processed in less than 4 h (1.2% of the dataset) were excluded, presuming that a minimum of 4 h is necessary for a complaint to be acknowledged and processed by an official. After these adjustments, the analysis proceeded with 64,461 valid complaint records.

In addition to analyzing CPTs, this study utilized longitude/latitude coordinates to determine the locations of complaints. Conducting a meaningful analysis with only these coordinates is not feasible. To enhance the utility of the geographic data, we employed the Nominatim (Version 4.5.0) georeferencing application programming interface (API) [20], provided by OpenStreetMap [21], to obtain detailed information regarding the locations where individual complaints were reported. The specific locations of complaints are classified into the following categories: (1) areas around buildings, (2) neighborhood facilities, (3) roads, (4) social overhead capital (SOC) facilities, and (5) railways, as outlined in Table 1. Notably, roads are further divided into detailed sub-types. As appeared in the sub-types in Table 1, this research deals with complaints reported from any types of roads in and around the presented location types.

Table 1. Summary of complaint location type.

Complaint Location Types	Specific Sub-Types
Roads	Motorways, trunk roads, general national roads, local roads, roads in city/county/district, residential roads, residential streets, pedestrian roads, farm roads/forest roads, service roads, and unclassified roads.
Neighborhood facilities	Any types of roads in and around neighborhood facilities commonly used by tourists or residents, including toilets, public phones, banks, pharmacies, cafes, parking lots, schools, etc.
Buildings	Any types of roads near Individual or interconnected buildings, including offices and shops.
Railway	Includes railways and railroad crossings.
SOC facilities	Any types of roads near retaining walls, seawalls, harbor piers, harbor berth facilities, etc.

Finally, we measured the CPTs using the complaints data from 2021 to 2022, categorized by both complaint type and location type. We applied statistical analysis techniques to identify factors influencing the prioritization of complaints based on these categories. Considering the severity of different road sub-types, we also analyzed how each sub-type affects the processing time of complaints.

3.2. Descriptive Analysis of CPT

As shown in Table 2, over 91% of complaints were processed within two weeks. Notably, 4% of complaints were resolved within 24 h of receipt, while 2.2% of complaints, totaling 378, required more than four weeks to process. The average CPT was 246.3 h, approximately 10 days.

Table 2. Number of processed complaints.

	Less than 12 h	~1 Day	~2 Days	~4 Days	~1 Week	~2 Weeks	~3 Weeks	~4 Weeks	More than 4 Weeks	Total
Number of processed complaints	840	1768	4868	11,543	18,572	21,184	4276	1032	378	64,461

(%) (1.3) (2.7) (7.6) (17.9) (28.8) (32.9) (6.6) (1.6) (0.6) (100)

Figure 1 illustrates the distribution of CPTs by complaint type, revealing generally similar patterns across most categories, except for the roadkill/rockslide category. While the percentage of complaints processed within 12 h typically ranged from 0.4% to 1.5% across various complaint types, the roadkill/rockslide complaints were processed at a much higher rate of nearly 7%. Additionally, this category also exhibited higher processing rates within 1, 2, and 4 days compared to other types. This difference is attributed to the prioritization of roadkill/rockslide complaints, which are deemed urgent and thus processed more rapidly.

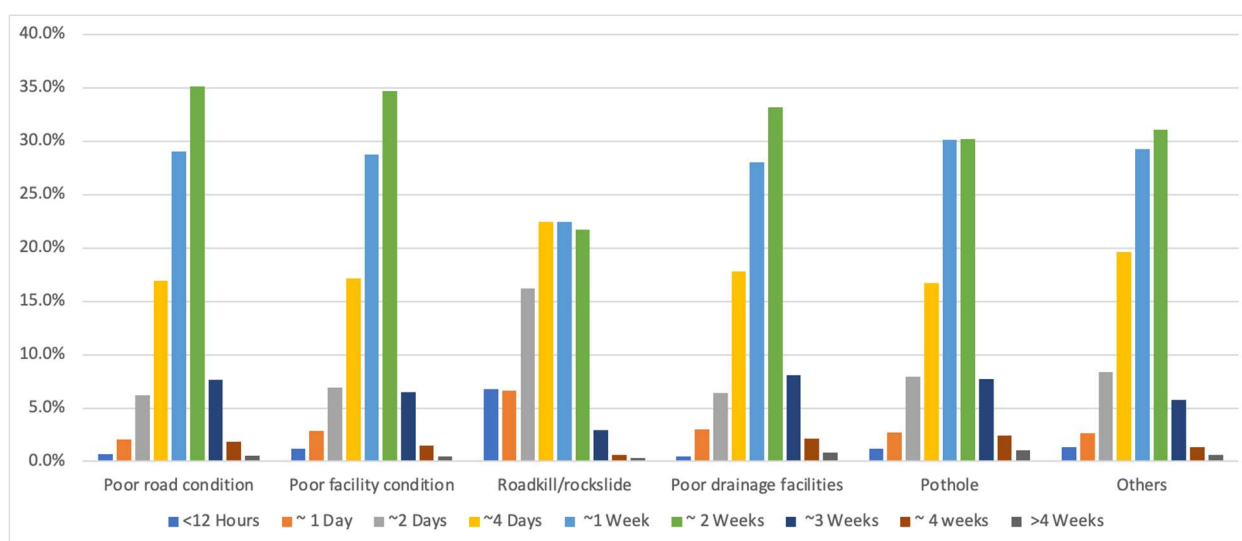


Figure 1. Distribution of CPTs by complaint types.

Table 3 presents the average CPTs organized by complaint location. We excluded roadkill/rockslide and drainage facilities from this analysis due to their low incidence (seven and three cases, respectively) when reported from SOC facilities and railways. The analysis revealed variability in average CPTs based on location and complaint type. For instance, SOC facilities exhibited the longest processing time for poor road condition complaints (232.8 h) but showed the shortest time for pothole complaints (174.8 h). Overall, this location type had the longest processing times for all complaint types, except for poor drainage facilities and potholes.

Table 3. Average CPTs by complaint location.

Civil Complaint Types	Average CPT (Unit: Hour)				
	Areas Around Buildings	Neighborhood Facilities	Road	SOC Facilities	Railway
Poor road condition	178.6	171.2	179.7	232.8	172.7
Poor facility condition	160.5	172.9	172.4	177.9	167.1
Roadkill/rockslide	106.6	127.3	117.7	-	-
Poor drainage facilities	168.4	167.7	182.4	174.8	-
Pothole	189.6	179.3	177.2	174.8	181.0
Others	156.6	163.1	162.9	172.5	147.6

3.3. Comparative Analysis of CPT

The comparative analysis of CPTs has thus far been based solely on average values, without considering the diversification effect per complaint type or reported civil complaint location. To address this, a one-tailed significance test was conducted for the average CPTs across various complaint types and locations, guided by the following null and alternative hypotheses:

$$\text{Null hypothesis (H}_0\text{): } \mu_1 - \mu_2 = 0, \quad (1)$$

$$\text{Alternative hypothesis (H}_1\text{): } \mu_1 - \mu_2 < 0, \quad (2)$$

where μ_1 and μ_2 represent the average CPTs for the comparison targets.

Table 4 presents the results from the one-tailed tests for the average CPTs of the reported complaint locations by complaint types. Firstly, the results indicate that the average processing times for poor road conditions in areas around buildings, neighborhood facilities, roads, and railways were not statistically significant. However, complaints categorized as poor road conditions in SOC facilities were processed statistically faster than those reported from other locations. Secondly, it was revealed that complaints regarding poor road conditions reported from areas around neighborhood facilities were processed significantly faster than those from areas around buildings or roads. Complaints pertaining to poor road facility conditions did not exhibit significant differences in processing times across most locations; however, complaints from areas around buildings were processed more quickly than those from neighborhood facilities, roads, and SOC facilities. Thirdly, for the complaints of roadkill/rockslide, location generally did not significantly influence the average processing time, although complaints from areas around buildings were processed quicker than those from neighborhood facilities. Fourthly, complaints regarding poor drainage facilities exhibited statistically shorter processing times when occurring in areas around buildings and neighborhood facilities compared to those reported from roads. In other cases, no significant differences were observed. Finally, complaints concerning potholes reported from roads were processed more quickly than those from areas around buildings, although similar processing times were noted in other comparisons. In addition, the complaint type categorized as “others” reported from areas around buildings had shorter processing times than when reported from neighborhood facilities, SOC facilities, and roads.

Table 5 shows test results on the differences in average CPTs per complaint type across various locations. Firstly, among the complaints reported from areas around buildings, roadkill/rockslide was processed more rapidly than all other complaint types at the 95% confidence level. On the other hand, complaints categorized as potholes were processed slower than all other types within the same confidence level. Notably, complaints related to road facilities were resolved quicker than those pertaining to poor road conditions. Secondly, with respect to complaints from neighborhood facilities and roads, roadkill/rockslide was addressed first compared to other types at the 95% confidence level. Furthermore, complaints concerning road facilities and those categorized as “others” reported from roads received prioritization over all other complaint types, except roadkill/rockslide. Thirdly, complaints reported from SOC facilities were statistically significant in general; however, none were processed particularly quickly, with poor road condition complaints requiring longer processing times on average compared to other types. Finally, no significant differences in CPTs were observed at the 95% confidence level for railways. However, at the 90% confidence level, the complaint type “others” was processed quicker than those related to poor road conditions.

Table 4. One-tailed t test results for the average CPTs.

Civil Complaint Types	Reported Civil Complaint Locations	Areas Around Buildings	Neighborhood Facilities	Road	SOC Facilities	Railway
Poor road condition	Areas around buildings		0.969	0.373	0.000 *	0.691
	Neighborhood facilities	0.031 *		0.004 *	0.000 *	0.448
	Road	0.627	0.996		0.000 *	0.718
	SOC facilities	1.000	1.000	1.000		0.998
	Railway	0.309	0.552	0.282	0.002 *	
Poor road facility condition	Areas around buildings		0.001 *	0.000 *	0.044 *	0.282
	Neighborhood facilities	0.999		0.565	0.330	0.678
	Road	1.000	0.435		0.309	0.669
	SOC facilities	0.956	0.670	0.691		0.755
	Railway	0.718	0.322	0.331	0.245	
Roadkill/rock-slide	Areas around buildings		0.045 *	0.167	-	-
	Neighborhood facilities	0.955		0.822	-	-
	Road	0.833	0.178		-	-
	SOC facilities	-	-	-		-
	Railway	-	-	-	-	
Poor drainage facilities	Areas around buildings		0.528	0.079 **	0.410	0.481
	Neighborhood facilities	0.472		0.045 *	0.409	0.476
	Road	0.921	0.955		0.590	0.608
	SOC facilities	0.590	0.591	0.410		0.541
	Railway	0.519	0.524	0.392	0.459	
Pothole	Areas around buildings		0.878	0.975	0.781	0.612
	Neighborhood facilities	0.122		0.616	0.594	0.477
	Road	0.025 *	0.384		0.553	0.450
	SOC facilities	0.219	0.406	0.447		0.425
	Railway	0.388	0.523	0.550	0.575	
Others	Areas around buildings		0.046 *	0.024 *	0.066 **	0.778
	Neighborhood facilities	0.954		0.528	0.214	0.880
	Road	0.976	0.472		0.205	0.878

	SOC facilities	0.934	0.786	0.795		0.940
	Railway	0.222	0.120	0.122	0.060 **	

* Significance level: 0.05 ($\alpha = 0.05$); ** significance level: 0.1 ($\alpha = 0.1$).

Table 5. Differences in average CPTs by complaint locations and types.

Reported Civil Complaint Locations	Types of Civil Complaints	Poor Road Condition	Poor Road Facility Condition	Roadkill/Rockslide	Poor Drainage Condition	Pothole	Others
Areas around buildings	Poor road condition		1.000	1.000	0.875	0.038 *	1.000
	Poor facility condition	0.000 *		1.000	0.167	0.000 *	0.849
	Roadkill/Rockslide	0.000 *	0.000 *		0.000 *	0.000 *	0.000 *
	Poor drainage condition	0.125	0.833	1.000		0.025 *	0.930
	Pothole	0.962	1.000	1.000	0.975		1.000
	Others	0.000 *	0.151	1.000	0.070 **	0.000 *	
Neighborhood facilities	Poor road condition		0.331	1.000	0.675	0.109	0.979
	Poor facility condition	0.669		1.000	0.745	0.173	0.993
	Roadkill/Rockslide	0.000 *	0.000 *		0.001 *	0.000 *	0.001 *
	Poor drainage condition	0.325	0.255	0.999		0.125	0.719
	Pothole	0.891	0.827	1.000	0.875		0.993
	Others	0.021	0.007 *	0.999	0.281	0.007 *	
Road	Poor road condition		1.000	1.000	0.198	0.876	1.000
	Poor facility condition	0.000 *		1.000	0.001 *	0.008 *	1.000
	Roadkill/rockslide	0.000	0.000		0.000	0.000	0.000
	Poor drainage condition	0.802	0.999	1.000		0.914	1.000
	Pothole	0.124	0.992	1.000	0.086 **		1.000
	Others	0.000 *	0.000 *	1.000	0.000 *	0.000 *	
SOC facilities	Poor road condition		0.998	-	0.912	0.988	0.999
	Poor facility condition	0.002 *	-		0.541	0.564	0.640
	Poor drainage condition	0.088 **	0.459	-		0.500	0.530

Railway	Pothole	0.012 *	0.436	-	0.500	0.547
	Others	0.001 *	0.360	-	0.470	0.453
	Poor road condition		0.631	-		0.390
	Poor facility condition	0.369		-	-	0.314
	Pothole	0.610	0.686	-	-	0.896
	Others	0.067 **	0.117	-	-	0.104

* Significance level: 0.05 ($\alpha = 0.05$); ** significance level: 0.1 ($\alpha = 0.1$).

4. Development of Decision-Making Support Method

4.1. Overview

Based on the analysis of average complaint processing times by type, location, and required time intervals, this section proposes a method for prioritizing complaint processing. This study employs a data clustering technique, specifically the density-based spatial clustering of applications with noise (DBSCAN) [9] method, to organize and analyze the complaint data. The DBSCAN algorithm is a non-parametric technique for clustering spatial data with noise. The algorithm detects clusters of data points that are closely grouped together, using a predefined number of neighboring points. It also identifies any data points that are significantly different from the rest and located in locations with low density. This clustering approach is capable of effectively handling clusters with different forms and noise, unlike other methods such as K-means [13] and hierarchical clustering, which are more suitable for compact and well-separated spherical clusters. DBSCAN relies on two main parameters, including (1) neighborhood radius: a small value classifies more outliers, while a large value merges clusters; and (2) a minimum number of points within the neighborhood radius to form a cluster: at least one more than the number of dimensions in the dataset with a minimum dimension of 3. By subdividing the entire set of complaint processing times using the suggested methods, we constructed the dataset, applied the DBSCAN technique, and identified clusters with optimal priority.

Initially, this study categorized the road type among complaint locations more finely, as road-related complaints constitute the majority of cases, approximately 81%. The characteristics of each sub-category within the road types are markedly distinct. As shown in Table 1, the current road type sub-categories include highways, general national roads, local roads, urban road, residential roads, residential streets, pedestrian roads, unclassified roads, farm/forest roads, and service roads. When prioritizing complaint processing within these sub-categories, issues arise, such as complaints concerning potholes on highways and service roads potentially being assigned the same priority. To preemptively address these potential discrepancies, we refined the subdivision of road types among complaint locations. Other location types, such as areas around buildings, neighborhood facilities, social overhead capital facilities, and railways, were not further subdivided after determining that their sub-categories do not significantly impact the prioritization process, as reviewed in Table 1.

4.2. Prioritization Decision

This section presents the data-driven complaint-processing prioritization decision method. Figure 2 illustrates a high-level stepwise procedure for conducting the proposed prioritization method. This study utilizes the required complaint processing time classifications suggested in Table 2.

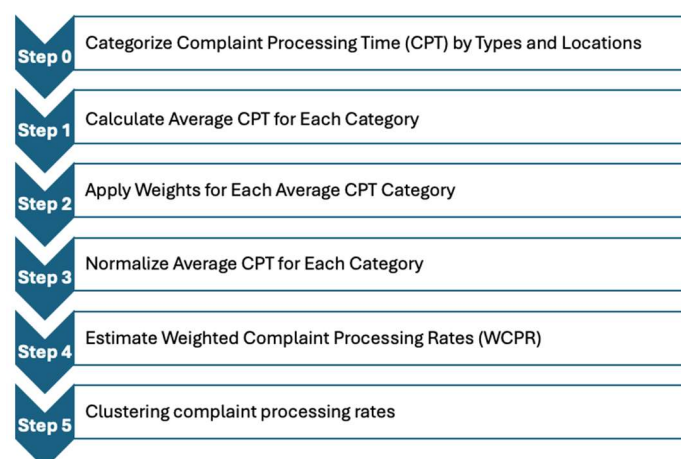


Figure 2. Overall distribution of weight average CPR.

4.2.1. Average CPT

Average CPT, measured in hours per complaint, is calculated with reported civil complaint locations and types. This includes using the subdivided road type in addition to the existing reported civil complaint location types. The comprehensive list of reported civil complaint locations now includes buildings, neighborhood facilities, social overhead capital facilities, railways, highways (motorway + trunk road), general national roads, local roads, urban road, residential roads, residential streets, other roads, unclassified roads, pedestrian roads, and service roads. In classifying Korea's road hierarchy, the OpenStreet Map differentiates roads into motorways and trunk roads based on the Korean Road Act [22]. However, this study merges motorways and trunk roads into highways for clearer classification.

4.2.2. Apply Weights for Each Required Complaint Processing Time Section

Weights are applied to the complaint processing rates (CPRs) for each complaint type and location across each required processing time section. This approach reflects the assumption that complaint type–location combinations with shorter processing times should be prioritized higher in the decision-making process. Various methods can determine these weights. Initially, we experimentally assigned values ranging from 100 to 1 based on the required complaint processing time sections, as outlined in Table 6. As indicated, combinations requiring more than four weeks to process were assigned a weight of 1, and those processed within 12 h received a weight of 100. This weighting implies that complaints resolved within 12 h are considered 100 times more urgent than those taking more than four weeks, aligning with the observed ratio of the average processing times—approximately 95.7 ($=746.5/7.9$). By applying different weights to each required processing time section, we ensure that the actual processing time is factored into the prioritization of complaints.

Table 6. Weights by CPT section.

	Less than 12 h	~1 d	~2 d	~4 d	~1 Week	~2 Weeks	~3 Weeks	~4 Weeks	More than 4 Weeks
Weight	100	90	70	50	30	10	5	3	1

4.2.3. Normalize Average CPT

The weights assigned to each required CPT section as shown in Table 6 are applied to every complaint type–location combination, thereby producing the weighted average CPT (WACPT).

WACPT for each required processing time is normalized based on complaint types and locations. That is, the normalized WACPT indicates the weighted complaint processing rate (CPR) in processed complaints per hour, as it is calculated by taking the reciprocal of each WACPT. Consequently, combinations of complaint types and locations with shorter required processing times are prioritized over others.

4.2.4. Clustering Complaint Processing Rates

Data clustering was performed based on the weighted processing rates calculated for each complaint type–location combination. Figure 3 presents the overall distribution of weighted average CPR for these combinations (e.g., poor road condition on highway, roadkill/rockslide on local road). Although different rates were observed across combinations, consistent groupings emerged. Among various clustering techniques, this study employed DBSCAN algorithm to capture the groups. The DBSCAN algorithm is a non-parametric technique for clustering spatial data with noise. The algorithm detects clusters of data points that are closely grouped together, using a predefined number of neighboring points. It also identifies any data points that are significantly different from the rest and located in locations with low density. This clustering approach is capable of effectively handling clusters with different forms and noise, unlike other methods method, and hierarchical clustering, which are more suitable for compact and well-separated spherical clusters.

In contrast to other clustering techniques that require a pre-set number of clusters, DBSCAN allows for flexibility in this aspect. However, as there is no established basis for arbitrarily determining the number of clusters, we experimented with numbers ranging from 2 to 10. It is worth noting that 10 more clusters would not be practically applicable; we decided to apply 10 as the maximum number of clusters. Clustering was performed for each scenario, and the optimal number of clusters was determined using the silhouette score technique [23]. To verify the robustness of the DBSCAN results, we also applied the K-means clustering technique [13] for comparison.

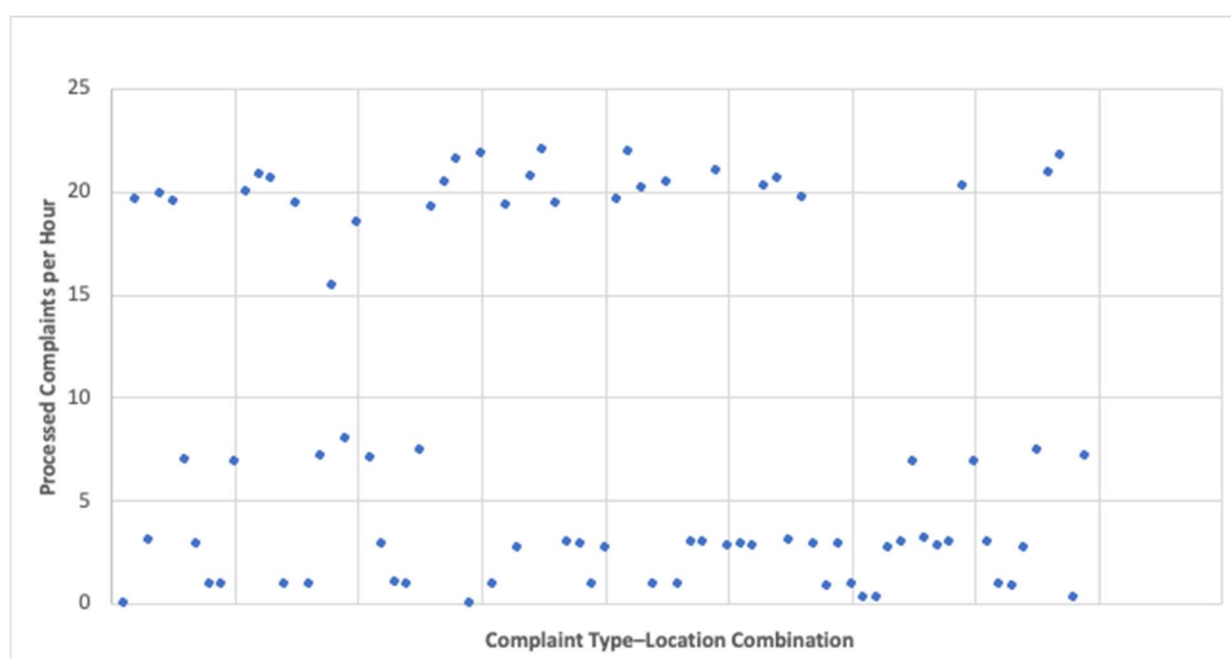


Figure 3. Overall distribution of weight average CPR.

5. Results

After implementing the DBSCAN technique with the number of clusters ranging from 2 to 10 as input variables, the silhouette score for each cluster was estimated, as depicted in Figure 4. In general, silhouette scores range from -1 to 1 , with values closer to 1 indicating a more optimal cluster configuration. The analysis revealed that with four (4) clusters, the silhouette score reached a peak value of 0.91 . This optimal clustering was confirmed through parallel analysis using the K-means clustering technique, which yielded the same result.



Figure 4. Silhouette score for each cluster.

Choosing the four (4) clusters as the final priority group based the silhouette score result, the boundary values for each cluster, representing the minimum and maximum complaint processing rate totals, are summarized in Table 7. Clusters were evaluated based on their complaint processing rate totals, with corresponding priority levels of high, neutral, low, and very low assigned to clusters 1–4, respectively, as detailed in Table 7. Table 8 further delineates the types of complaint locations associated with each complaint type according to their designated priority level.

Table 7. Boundary Values for Each Priority Level.

Cluster	Minimum Value	Maximum Value	Priority Levels
1	15.45	22.543	High
2	6.868	7.477	Neutral
3	2.698	3.138	Low
4	0.045	1.019	Very low

Table 8. Priority level by complaint locations and types.

Priority Level	Civil Complaint Types	Reported Civil Complaint Locations (Sum of Complaint Processing Rates)
High	Poor road condition	Highway (22.5); local road (21.8); residential road (21.5); general national road (20.5); city road (19.2); neighborhood facilities (18.5)
	Poor road facility condition	Neighborhood facilities (22.0); general national road (21.9); Local road (20.5); highway (20.3); residential road (20.2); urban road (19.6); other roads (19.4); buildings (19.3)

	Road-kill/rockslide	Highway (21.0); general national road (20.6); urban road (20.2); local road (19.7)
	Pothole	Residential road (21.7); general national road (20.9); highway (20.3)
	Others	General national road (20.8); residential road (20.7); urban road (20.0); highway (19.7); buildings (19.6); neighborhood facilities (19.5); local road (19.5)
Neutral	Poor road condition	Service road (7.4); buildings (7.1); other roads (7.0)
	Poor drainage facilities	Residential road (6.9)
	Pothole	City road (7.5); local road (7.2); neighborhood facilities (6.9)
	Others	Other roads (6.9); service road (6.9)
Low	Poor road condition	Unclassified roads (2.9)
	Poor road facility condition	Unclassified roads (3.0); pedestrian roads (2.9); service road (2.7)
	Road-kill/Rock-slide	Residential road (3.1); buildings (3.0); other roads (2.9); unclassified roads (2.8); neighborhood facilities (2.8)
	Poor drainage facilities	Local road (3.1); general national road (3.0); neighborhood facilities (2.9); buildings (2.9); city road (2.7)
	Pothole	Other roads (3.00); buildings (2.8); service road (2.8)
	Others	Unclassified roads (2.9)
Very Low	Poor road condition	Pedestrian roads (1.0); railway (0.9); social overhead capital facilities (0.9); residential streets (0.0)
	Poor road facility condition	Residential streets (1.0); social overhead capital facilities (1.0); railway (0.9)
	Poor drainage facilities	Other roads (1.0); highway (0.9); unclassified roads (0.3); service road (0.3)
	Pothole	Unclassified roads (1.0); social overhead capital facilities (0.9); residential streets (0.3)
	Others	Residential streets (1.0); pedestrian roads (1.0); railway (0.9); social overhead capital facilities (0.9)

To validate how closely the calculated complaint-processing priorities align with actual complaint-handling practices, we analyzed the frequency of reported civil complaint locations for each priority level. As depicted in Figure 5, locations categorized with a “high” priority predominantly include high-traffic and high-speed roads such as highways, national roads, and local roads. Conversely, the “very low” priority category frequently encompasses SOC facilities, residential streets, and railways. This distribution suggests that the data-based complaint-processing prioritization method proposed in this study aligns well with established social conventions and reflects practical traffic management needs effectively.

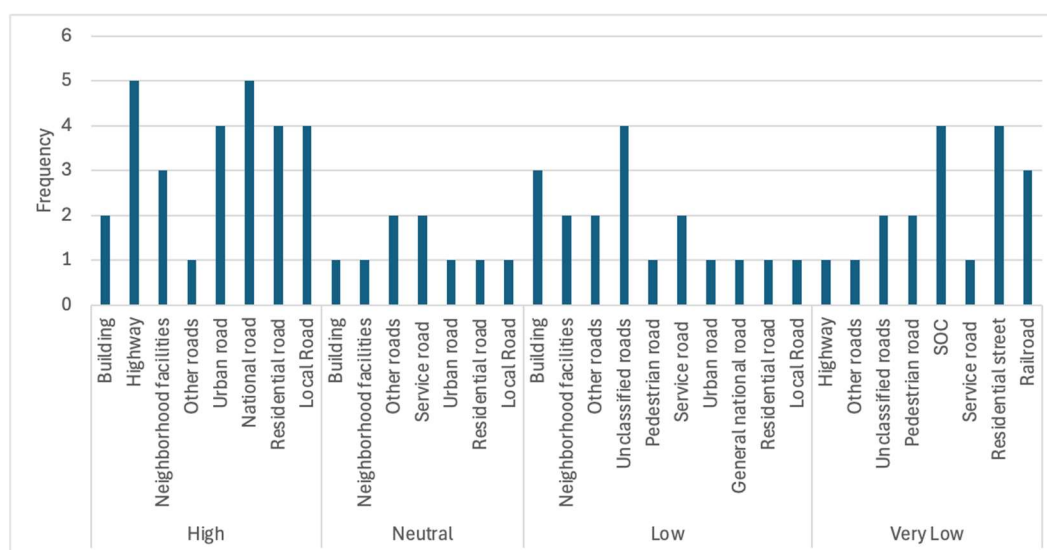


Figure 5. Frequency of reported civil complaint locations by each priority level.

6. Conclusions and Recommendations

This study presents a data-driven decision-making support method aimed at improving the quality of public service to efficiently handle various public complaints about road use. To achieve this goal, this study first examined complaint processing times categorized by type (such as poor road facility condition, poor road condition, roadkill/rock-slide, pothole, inadequate drainage facilities, and others) and by location (including areas around buildings, neighborhood amenities, roads, social overhead capital facilities, and railways) utilizing two years of data from the road problem reporting service. We determined processing rates for complaints (the number of civil complaints addressed per hour) for each type–location combination, applied weights between 1 and 100 based on the necessary processing time, and aggregated these weighted rates. A validation study assessing the frequency of reported locations by priority showed that the proposed method accurately reflects actual field processing of complaints. Additionally, given the importance of location in complaint handling, the georeferencing technique seems appropriate for pinpointing complaint locations for each report and integrating this into the decision-making framework.

The DBSCAN clustering technique was used to organize complaint types and locations into groups, resulting in four final priority clusters (high, neutral, low, and very low), determined via the silhouette score test. Additionally, we applied the K-means clustering technique to the same data, cross-validated the results with those obtained from the DBSCAN technique, and confirmed their consistency. Additionally, understanding the importance of location in handling complaints, we applied georeferencing methods to pinpoint civil complaint locations for every report, integrating this into our analytical and decision-making system. This strategy, particularly if integrated into future complaint-processing prioritization techniques, has the potential to greatly improve the usefulness and relevance of georeferencing methods.

Despite the possibility of containing minor errors identified during the analysis, the dataset used in this research was direct observations from complaint processing sites and may include minor data entry errors. Nevertheless, the dataset is considered highly valuable as it reflects a variety of real-world situations encountered during complaint handling.

Previous research in this field proposed a method for automatically extracting issues from complaint-related photos and assigning priority rankings using machine learning techniques. Enhancing this model by integrating reported civil complaint locations could

lead to the development of more precise artificial intelligence (AI)-based prioritization decision models, representing a promising direction for future research.

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