

A Scalable Clustering–GIS Decision Support System for Municipal Early-Warning Governance: Design Science Research in a Health Smart City Context

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ABSTRACT

Local governments rely on integrated information systems to shift public-sector decision-making from reactive to proactive, yet the design of scalable, clustering-based spatial decision support systems (SDSS) for city-level early warning remains under-explored within Health Smart City governance. Following a Design Science Research approach, this study designs, builds, and demonstrates a Decision Support System (DSS) that integrates the K-Medoids CLARA clustering algorithm with a Web-based Geographic Information System (GIS) to generate spatially differentiated early-warning alerts, using Non-Communicable Disease (NCD) risk surveillance in Bogor City as the application domain. The artifact was instantiated on 26,798 electronic medical records from 25 Puskesmas via a client–server architecture comprising data anonymization, clustering, spatial aggregation, and an interactive alerting dashboard, and evaluated against clustering-quality and comparative-performance criteria. CLARA ($k=3$) achieved a Silhouette Coefficient of 0.2171 and Davies-Bouldin Index of 1.4977, modestly higher than K-Means on both metrics, while remaining scalable for large administrative datasets where standard K-Medoids (PAM) becomes impractical. The resulting four-level dashboard classified 4 of 25 Puskesmas as Level 3 (Critical), 11 as Level 2, 6 as Level 1, and 4 as Level 0, with GIS visualization communicating spatial risk to non-technical policymakers. The findings demonstrate a design-and-demonstration proof-of-concept showing how a clustering-GIS DSS architecture can be built and evaluated for technical feasibility, offering a transferable design pattern for public-sector information systems that integrate large-scale operational data with spatial early-warning capability; organizational adoption and field deployment remain future work.

Keywords: Decision Support System, Design Science Research, Spatial Decision Support System, Digital Transformation, Public Sector Information Systems, Health Smart City Governance, K-Medoids CLARA, Geographic Information System

1. Introduction

1.1. Research Background

Local governments worldwide are under growing pressure to modernize decision-making through integrated information systems that convert large volumes of operational data into timely, spatially aware intelligence for policymakers (Kementerian Kesehatan RI, 2018). A recurring organizational challenge in this digital transformation agenda is designing decision support architectures that scale to city-level administrative datasets while remaining interpretable to non-technical stakeholders. Non-Communicable Diseases (NCDs) surveillance offers a concrete and consequential domain in which to examine this challenge: NCDs are responsible for 74% of all deaths worldwide according to the 2022 WHO report (World Health Organization, 2022), and in Indonesia contribute approximately 70% of the total disease burden, with hypertension, diabetes mellitus, cardiovascular disease, and metabolic disorders as dominant conditions. The rising prevalence of NCDs is closely linked to increasingly sedentary lifestyles, unhealthy dietary patterns, tobacco exposure, and physical inactivity, exacerbated by rapid urbanization in large Indonesian cities.

Bogor City, as one of the satellite cities of Metropolitan Jakarta with a population exceeding one million, faces a dual challenge in NCD control. On one hand, population growth and urbanization contribute to increasing NCD risk factors; on the other hand, the demand for quality, technology-based healthcare services grows in line with the vision of developing Bogor as a Health Smart City. Digital transformation in the health sector becomes critical to optimizing NCD control through data utilization, predictive analytics, and integrated geographic information systems.

The Pos Pembinaan Terpadu Penyakit Tidak Menular (Posbindu PTM) program managed by the Ministry of Health has served as the primary instrument for community-level NCD risk factor early detection. However, implementation in Bogor City still faces several constraints, including limited analytical use of data, absence of an integrated early warning system, and minimal spatial visualization for evidence-based decision-making. Data collected through Posbindu PTM has largely been used for administrative and reporting purposes, not yet optimally leveraged for predictive analysis and territory-based early intervention. From an information-systems standpoint, this is fundamentally a data-to-decision translation gap: operational data exists in abundance, but no artifact currently converts it into a form directly usable by decision-makers the gap this study addresses.

1.2. Research Problem

The primary organizational challenge addressed in this study is the absence of a decision support system (DSS) architecture capable of transforming raw operational records into spatially differentiated, actionable alerts for municipal decision-makers. Existing information systems supporting NCD surveillance in Bogor City remain reactive data is collected and reported but not analytically processed into forward-looking, territory-based intelligence which constrains the Bogor City Health Department's ability to allocate limited resources proportionally across its jurisdiction. This is fundamentally a systems-design problem: how to architect a scalable pipeline that integrates large-scale clustering with spatial visualization so that decision-makers, rather than data specialists, can identify intervention priorities, particularly in densely populated sub-districts with limited healthcare access.

1.3. Research Gap

Based on a review of prior studies on technology-supported NCD surveillance in Indonesia (as presented in Table 1), four significant research gaps were identified from an information-systems perspective. First, from a design perspective, decision support architectures that integrate scalable spatial clustering with early-warning alerting remain very limited, particularly for city governments with diverse demographic and geographic characteristics. Second, methodologically, few studies apply a Design Science Research approach to building and evaluating such systems; most existing technology-based interventions (e.g., dashboards, mobile applications) are evaluated narrowly on adoption or usability rather than on architectural scalability and organizational decision-making impact. Third, empirically, Bogor City as a city transforming towards a

Health Smart City has not been a focus of information-systems research examining how clustering-GIS integration reshapes municipal decision processes. Fourth, practically, no DSS architecture has been specifically designed and evaluated to support Bogor City Health Department decision-making, leaving a gap between available operational data and its organizational use. This gap is consistent with the broader Design Science Research literature's emphasis on artifact evaluation against organizational utility rather than technical performance alone (Hevner et al., 2004), and with the IS Success literature's concern for how System and Information Quality translate into organizational benefit (DeLone & McLean, 2003) concerns that remain unaddressed for spatial early-warning artifacts in resource-constrained municipal-government settings. This gap is not unique to Indonesia: a systematic review of spatial decision support systems in public health informatics similarly finds that most such systems remain confined to descriptive disease mapping rather than integrating scalable, data-driven clustering into an operational alerting artifact (Beard, Wentz, & Scotch, 2018), while public-sector decision support research more broadly has demonstrated the value of predictive-analytics-based artifacts in adjacent government domains, such as court systems, without yet extending this pattern to municipal health governance (Zolbanin, Delen, Crosby, & Wright, 2020).

1.4. Novelty

The novelty of this research lies in designing and demonstrating a decision support system (DSS) architecture that unifies scalable, sampling-based clustering with web-based GIS into a single spatial early-warning artifact for municipal decision-making, using the Bogor Health Smart City context as its demonstration case. Unlike prior GIS-based public-health studies that rely on descriptive, analyst-defined risk zoning, or prior technology artifacts that provide dashboards without spatial or predictive capability (Section 2.4), this study is, to the authors' knowledge, the first to integrate data-driven clustering, spatial aggregation, and automated multi-level alerting into a single, reproducible pipeline evaluated at city administrative scale ($N > 26,000$ records) for an Indonesian municipal government.

1.5. Contribution

Building on this novelty, the study offers three typed contributions. Architecturally, it contributes a design pattern for integrating a sampling-based clustering algorithm with spatial visualization in a client–server DSS, extending prior clustering-GIS integrations to city-scale administrative data. Methodologically, it contributes an application of Design Science Research to the development and demonstration of a spatial early-warning DSS, addressing a gap in how such systems are typically built and assessed in the public-sector information-systems literature. Organizationally, it contributes an operational four-level alerting artifact that the Bogor City Health Department can adopt to shift its decision processes from reactive to proactive, illustrating a transferable pattern for other local-government information systems; realizing this organizational contribution in practice, however, depends on the future deployment and evaluation steps identified in Section 5.6.

1.6. Research Objectives

This research aims to: (1) design a decision support system (DSS) architecture that integrates the K-Medoids CLARA clustering algorithm with Puskesmas electronic medical record data as a scalable analytical component; (2) implement a web-based GIS layer that translates clustering output into spatially interpretable proportional-circle visualizations for non-technical stakeholders; (3) build and instantiate a four-level early-warning alerting artifact atop the clustering-GIS pipeline, and evaluate it against alternative clustering and thresholding approaches; and (4) discuss how the resulting DSS artifact is designed to support policy-level, organizational decision-making for the Bogor City Health Department as part of its Health Smart City digital transformation, identifying what remains to be verified through future organizational deployment.

1.7. Research Questions

Consistent with these objectives, this study addresses three research questions.

RQ1 (Design). How can a clustering algorithm be architecturally integrated with a web-based GIS to produce a scalable, spatially differentiated early-warning decision support system for a city-level health department?

RQ2 (Performance). How does the resulting clustering-GIS artifact perform relative to conventional alternatives (K-Means clustering; static-threshold classification) on measures of clustering quality, scalability, and spatial early-warning capability?

RQ3 (Design Utility & Deployment Readiness). To what extent does the resulting DSS artifact demonstrate functional feasibility and design utility for municipal decision-making use cases, and what capabilities would need to be validated through future field deployment and organizational-adoption studies, which are out of scope for this study?

2. Literature Review

2.1. Key Concepts

2.1.1. *Decision Support Systems (DSS) and Spatial DSS*

A Decision Support System (DSS) is an information system designed to support, rather than automate, organizational decision-making by combining data, analytical models, and an interactive interface intended for non-technical users (Hevner et al., 2004). Data-mining and clustering techniques have increasingly become core analytical components of such DSS artifacts in health-adjacent domains, where they convert raw clinical or administrative records into risk strata that decision-makers can act upon (Zolbanin, Delen, & Hassan Zadeh, 2015). A Spatial Decision Support System (SDSS) extends this definition by embedding geographic analysis and visualization into the decision loop, allowing spatially distributed problems such as territory-based resource allocation to be explored interactively rather than through static reports. The artifact developed in this study is an SDSS in this specific sense: its unit of decision is not the individual patient but the geographically bounded Puskesmas jurisdiction, and its output is designed for interactive exploration by a policymaker rather than for automated action.

2.1.2. *Non-Communicable Diseases (NCDs)*

Non-Communicable Diseases (NCDs) are a group of diseases that are not transmitted from person to person, but rather develop as a result of a combination of genetic, physiological, environmental, and behavioral factors. According to WHO (2022), the four main types of NCDs responsible for the highest global mortality are cardiovascular diseases (17.9 million deaths/year), cancer (9.3 million), chronic respiratory diseases (4.1 million), and diabetes mellitus (2.0 million). NCD risk factors are divided into modifiable factors (smoking, unhealthy diet, physical inactivity, alcohol consumption) and non-modifiable factors (age, genetics, sex). In Indonesia, Riskesdas 2018 data revealed alarming NCD prevalence: hypertension 34.1%, diabetes mellitus 8.5%, and obesity 21.8% among the adult population (Kementerian Kesehatan RI, 2018).

2.1.3. *Early Warning System (EWS)*

An Early Warning System (EWS) is an integrated system designed to detect, predict, and issue alerts on potential risk events before their actual impact occurs, enabling timely preventive action. WHO (2023) emphasizes that an effective EWS must fulfill four pillars: risk knowledge, monitoring and warning, warning dissemination, and response capacity. Application of EWS in public health has demonstrated positive results in communicable disease control such as malaria and dengue fever; however, its application for NCDs remains very limited in developing countries, representing a critical gap addressed by this study.

2.1.4. *K-Medoids and CLARA Algorithm*

K-Medoids is a partitional clustering algorithm that uses actual data objects (medoids) as cluster centers, unlike K-Means which uses the arithmetic mean as centroid. Introduced by Kaufman & Rousseeuw (1990) through the Partitioning Around Medoids (PAM) method, K-Medoids is inherently more robust against outliers since medoids are actual data points minimizing total dissimilarity within a cluster a critical advantage for clinical datasets that frequently contain anomalous readings. This robustness continues to be confirmed in contemporary clinical applications: K-medoids clustering of hospital admission characteristics has recently been shown to yield more clinically coherent severity groupings than centroid-based alternatives when applied to heterogeneous surveillance data (Leis et al., 2023), supporting its selection over K-Means for the present study's administrative health dataset.

However, standard PAM has $O(N^2)$ time and memory complexity, rendering it computationally infeasible for large datasets. This study therefore adopts CLARA (Clustering Large Applications), which runs 5 independent sampling iterations each drawing a random sub-sample of $n = 2,000$ records, applying PAM to each sub-sample, and selecting the best medoids to assign all remaining observations. This approach reduces effective complexity while preserving clustering quality, making it well-suited for the 26,798-record dataset used in this study. The empirical scalability benchmark is reported in Section 4.5 (Figure 8).

It is important to clarify the scope in which CLARA operates in this study. CLARA performs clustering in clinical attribute space (systolic/diastolic blood pressure, blood glucose, BMI, waist circumference) to group patients by cardiometabolic risk profile; it does not operate on geographic coordinates and is not a spatial clustering algorithm. Density-based spatial clustering methods such as DBSCAN (Ester et al., 1996) are designed to identify geographically proximate, density-connected regions in coordinate space (e.g., detecting disease hotspots from case locations) a distinct task from grouping patients by clinical similarity. In the proposed architecture, the spatial dimension is introduced after clustering, at the Spatial Layer (see System Architecture), where per-patient cluster labels are aggregated by administrative (Puskesmas) jurisdiction rather than by geographic density. This two-stage design attribute-based risk clustering followed by administrative-boundary spatial aggregation reflects the fact that Health Department decision-making and resource allocation operate along existing jurisdictional boundaries, not arbitrary density-defined regions; a density-based spatial cluster crossing Puskesmas boundaries would not map onto an actionable administrative unit. We note, however, that genuine spatial clustering methods could complement this architecture in future work for instance, applying Getis-Ord G_i^* hotspot analysis to the aggregated risk surface to detect statistically significant spatial clusters independent of administrative boundaries (see Discussion).

2.1.5. *Geographic Information System (GIS)*

A Geographic Information System (GIS) is a computer-based system for collecting, storing, analyzing, and visualizing spatially referenced data. In public health, GIS enables mapping of disease distribution, spatial pattern analysis, cluster identification, and evaluation of healthcare accessibility. Integration of GIS with machine learning methods such as K-Medoids enables identification of risk patterns invisible in non-spatial analysis, producing more targeted health interventions (Rd. Halim et al., 2024). This study employs web-based GIS using the OpenStreetMap/Leaflet framework, allowing interactive exploration of risk markers by policymakers without specialized GIS software.

2.1.6. *Health Smart City*

Health Smart City is a city development paradigm integrating information and communication technology (ICT) in all aspects of healthcare to improve quality of life, service efficiency, and health system sustainability. In the health domain, Health Smart City encompasses six main dimensions: smart governance, smart monitoring, smart intervention, smart environment, smart people, and smart economy. Bogor City has declared its Health Smart City vision as part of its strategic city development plan, making it an ideal context for developing spatially integrated NCD surveillance and early warning systems. This context also carries a known governance risk: smart city initiatives frequently generate large administrative datasets and algorithmic outputs without correspondingly transparent mechanisms for how those outputs are governed and acted upon by public administrations (Janssen & Kuk, 2016), a concern this study's artifact design

partially addresses by keeping the clustering and alerting logic interpretable to non-technical decision-makers (Section 3.4).

2.2. Theoretical Framework

This research is grounded primarily in information systems theory, supplemented by domain-specific spatial and public-health frameworks that justify design choices within the application context. First, Design Science Research (DSR) (Hevner et al., 2004) frames the overall research strategy: the clustering-GIS DSS is treated as an artifact iteratively built to solve an organizational problem the absence of scalable, spatially aware decision support and evaluated against utility and performance criteria rather than purely statistical significance. Second, the DeLone and McLean IS Success Model (DeLone & McLean, 2003) provides the lens through which the resulting artifact's quality (system quality, information quality) and anticipated organizational impact (use, decision-making benefit) are discussed throughout the Results and Discussion, even where formal user-acceptance testing remains future work. A recent critical meta-review of 53 studies applying the DeLone and McLean models found considerable inconsistency in how these dimensions have been operationalized across contexts (Jeyaraj, 2020), which motivates the context-dependent reading of System Quality adopted in this study's Discussion (Section 5.3) rather than treating the model's thresholds as fixed.

Within the application domain, two further frameworks justify specific design decisions rather than serving as the study's primary theoretical lens. Tobler's First Law of Geography (1970) that nearby things are more related than distant ones motivates the choice of spatial clustering as the analytical component of the DSS, since geographically adjacent Puskesmas areas can be expected to share similar risk profiles. The Social-Ecological Model (SEM) (Bronfenbrenner, 1979), adapted by the Centers for Disease Control and Prevention for public health contexts (Centers for Disease Control and Prevention, 2021), explains that NCD risk is shaped by community- and policy-level factors and not only individual behavior, which supports the design decision to aggregate and visualize risk at the Puskesmas-jurisdiction level rather than only at the individual level. Together, these domain frameworks inform what the DSS should compute and display, while the IS theories above frame why and how the artifact was designed, built, and is expected to be evaluated.

2.3. Conceptual Framework

The conceptual framework of this research integrates three main components. The input layer consists of secondary electronic medical record data from 25 Puskesmas areas in Bogor City, covering five clinical variables (systolic/diastolic blood pressure, blood glucose, BMI, and waist circumference). The process layer applies K-Medoids CLARA to classify patient records into three risk clusters (high, moderate, low), which are then aggregated by Puskesmas jurisdiction and visualized through GIS to produce a spatial risk map. The output layer delivers the EWS model integrating cluster outputs and the GIS risk map to generate four-level periodic alerts (Red, Orange, Yellow, Green) to health department stakeholders. The inter-component relationships are cyclical, supporting continuous improvement within the Health Smart City framework.

2.4. Related Studies

A review of prior studies on technology-supported NCD surveillance in Indonesia reveals significant patterns regarding system scale, analytical sophistication, and organizational impact. This review is intentionally scoped to studies conducted within Indonesia's public health system, since the artifact developed in this study is built around institutional structures specific to that system the Puskesmas administrative hierarchy, the Posbindu PTM screening protocol (Section 1.1), and the Health Smart City policy framework (Section 2.1.6) that do not have direct equivalents in other national health systems, making within-country comparison the most methodologically relevant basis for identifying the research gap this study addresses. A broader international review of clustering-GIS DSS for NCD surveillance would be a useful complement but risks comparing systems built on incompatible administrative and regulatory architectures; we note this as a direction for future comparative work (Section 5.6). Table 1 summarizes the most relevant related studies, with particular attention to the few that involve information-system artifacts (dashboards, applications, GIS) rather than purely community-education interventions.

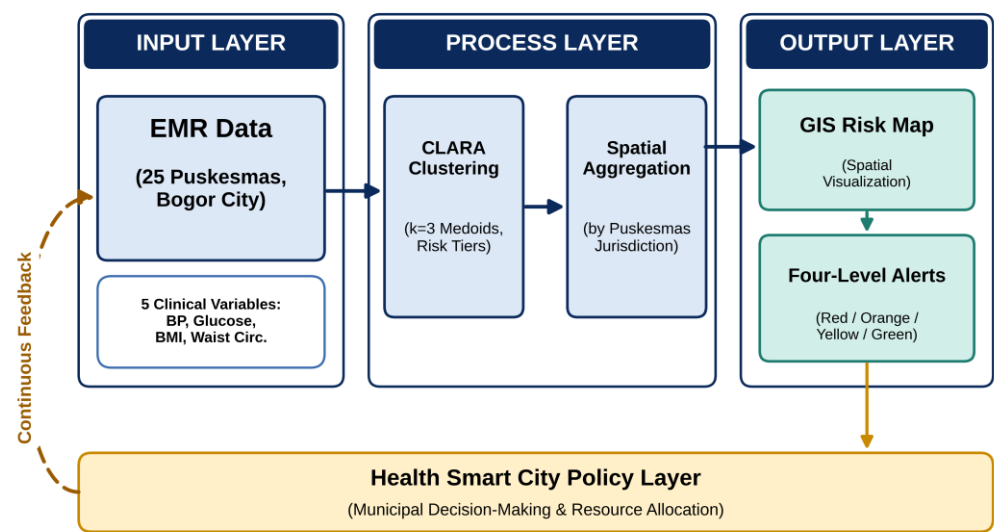


Figure 1. Conceptual Framework Diagram. EMR data from 25 Puskesmas (Input Layer) is processed through K-Medoids CLARA clustering and spatial aggregation (Process Layer) to produce a GIS risk map and four-level alerts (Output Layer), with continuous feedback to the Health Smart City policy layer.

Author/Year	Context/Sample	Method	Key Findings	Limitations/Gap
Nilam Maryam et al. (2022) [IS Artifact]	Elderly, Indonesia	DSDM early detection app	Facilitates BP, glucose, cholesterol screening	Not tested at scale; no spatial analysis
Nurmalasari & Nurzikriah (2021) [IS Artifact]	Puskesmas, Kec. Rokan	BI dashboard for Posbindu PTM	88% UAT accepted; data analysis simplified	Health impact evaluation not conducted
Rd. Halim et al. (2024) [IS Artifact]	Puskesmas, Kota Jambi	Descriptive & GIS	63,812 participants; hyperglycemia 7%; hypertension 34.3%	Single city; no socioeconomic analysis; no clustering
Alamsyah et al. (2020)	Community, NTB	Health check & discussion	Awareness raised; GDP > 300 mg/dL detected	Small sample; long-term impact not evaluated
Sukmana et al. (2020)	Community, NTB	Lecture, pre-post questionnaire	Knowledge improved; PTM risk detected	Small scale; long-term impact unmeasured
Rumahorbo et al. (2021)	Posbindu PTM Cimahi; 20 cadres	Training & mentoring	Cadre knowledge improved; 65–82 residents served	Limited scale; long-term effect unmeasured
Haris et al. (2022)	Cadres, Kaltara Polytechnic	Training & education simulation	Knowledge improved 56% → 83.3%	Real health impact not measured
Chayati et al. (2023)	Soropaten Village, Klaten	BMI, waist, fruit/veg assessment	Avg BMI 27.5; high obesity; low vegetable intake	Single village; no long-term evaluation

Wahidin (2022)	DKI Jakarta, Jambi, DIY	Mixed methods	PTM burden 70% of total disease; programs suboptimal	Gap between programs and PTM burden
Riami et al. (2025)	Tlocor Village, Sidoarjo	Early detection & education	Awareness raised; hypertension & diabetes detected	Single community; no long-term evaluation
Sudayasa et al. (2020)	Andepali Village; 67 resp.	Counseling & examination	Hypertension 28.35%; high cholesterol 37.31%	Single village; small sample
Herawati & Sofiatin (2021)	Cipacing Village, West Java	Socialization & blood examination	Socialization + examination raised awareness	Single village; no long-term evaluation
Anita et al. (2022)	Puskesmas Muara Pinang	Descriptive qualitative case study	Posbindu PTM implementation per Ministry of Health standards	Single Puskesmas; long-term monitoring needed
Sitompul et al. (2020)	Poltekkes Medan	Glucose, cholesterol, uric acid check	Early detection raised awareness & knowledge of NCDs	Long-term impact not evaluated
Lestari et al. (2020)	Yogyakarta	Cadre empowerment, Posbindu formation	81.25% cadres improved knowledge; NCD detection performed	Single area; participation needs improvement
Susanti et al. (2023)	Adolescents, UINSU	Quantitative descriptive, online questionnaire	Low physical activity; poor fruit & vegetable intake	Student sample; limited generalizability
Muhsinah & Misbah (2023)	Telaga Biru Village, Konawe	Screening, education, mentoring	Participation improved; Posbindu more optimal	Only 2 Posbindu; no long-term evaluation
Arifin et al. (2022)	High-risk community	Lecture & leaflet	Health education improved NCD knowledge	Single area; behavioral impact not measured
Utama et al. (2024)	Teachers & staff, Robbani Foundation	DERI PTM app socialization	> 20% participants obese; knowledge significantly improved	Small sample; long-term implementation untested
Sari et al. (2025)	National (15 articles)	Literature review	Education, visual media, Posbindu effective in raising awareness	Low participation; limited cross-sector support

Abbreviations: DSDM = Dynamic Systems Development Method; UAT = User Acceptance Testing; NTB = Nusa Tenggara Barat (West Nusa Tenggara province, Indonesia).

Table 1. Summary of Related Studies on NCDs in Indonesia (Information-System artifacts listed first, tagged [IS Artifact])

From the review above, four patterns emerge from an information-systems perspective: (1) the majority of studies are community-education interventions rather than information-system artifacts, limited in scale to a single village or Puskesmas, with no architectural or organizational evaluation; (2) only one study uses GIS as a system component (Rd. Halim et al., 2024), and without integrating spatial clustering; (3) the two studies that do build technology artifacts (Nilam Maryam et al., 2022; Nurmallasari & Nurzikriah, 2021 a BI dashboard achieving 88% UAT acceptance) do not integrate spatial analysis or automated early-warning alerting; and (4) no study has designed a clustering-GIS DSS architecture evaluated for organizational decision-making impact within a Health Smart City context. This study directly addresses all four gaps.

3. Methods

3.1. Research Design and Data Ethics

This research follows a Design Science Research (DSR) methodology, structured around the problem identification, design and development, demonstration, and evaluation stages of the widely adopted DSR process model (Peffer et al., 2007): problem identification (Section 1.2–1.3), artifact design and development (this section), demonstration through instantiation on real operational data, and evaluation against clustering-quality and comparative-performance criteria (Section 5). Consistent with the FEDS framework for DSR evaluation (Venable et al., 2016), this evaluation is best characterized as an artificial, ex-ante evaluation episode focused on the artifact's technical performance; naturalistic, ex-post evaluation of organizational use is identified as a distinct, subsequent evaluation episode in Section 5.6. The DSS artifact was built on secondary electronic medical records processed through a retrospective computational pipeline. Direct identifiers such as patient names, national ID numbers, and phone numbers present in the raw records were not used at any stage of clustering or spatial analysis, which operated exclusively on five clinical variables and the Puskesmas jurisdiction field (Section 3.4). As a data-hygiene measure for this revision, a de-identified working copy with these direct identifiers removed has been prepared and is recommended for all subsequent processing and any future data sharing. The overall system architecture adopts a Client–Server approach in which the analytical (clustering) and presentation (GIS dashboard) layers are decoupled, consistent with conventional Decision Support System (DSS) design.

3.2. Data Source and Population

The primary data source consists of secondary electronic medical records extracted from health facilities in Bogor City, comprising 25 Puskesmas (Primary Healthcare Facilities) plus two additional facilities (Labkesda, Public Safety Center) described below. It is important to be transparent regarding this scope: while Bogor City administratively encompasses a larger number of Puskesmas, based on the secondary electronic medical records that were extractable, validated, and survived the data cleaning pipeline, this study aggregates patients into the jurisdictional boundaries of 25 Puskesmas areas in the observation region. Two additional facilities in the raw data Labkesda (Regional Health Laboratory) and Public Safety Center (emergency response service), together 87 records (0.3% of the cohort) are not Puskesmas and are excluded from area-level aggregation, though their patient-level records remain in the clustering input. The raw dataset contained 27,804 records spanning clinical observations across these 27 areas. No additional primary data collection (e.g., surveys or interviews) was conducted, as the research is computationally focused on the existing electronic health record infrastructure.

3.3. Data Preprocessing

Data preprocessing consisted of three sequential stages. First, Feature Engineering selected six clinical parameters directly corresponding to the physical examination and point-of-care laboratory components mandated by Indonesia's national Posbindu PTM (Pos Pembinaan Terpadu Penyakit Tidak Menular) screening protocol under Kementerian Kesehatan RI's technical guidelines (Kementerian Kesehatan RI, 2012): Systolic Blood Pressure, Diastolic Blood Pressure, Blood Glucose, Height, Weight, and Waist Circumference. Rather than an ad hoc or statistically-derived selection, these parameters were chosen because they constitute the fixed, nationally standardized set of variables that Puskesmas-level NCD screening infrastructure is already designed to capture, ensuring the artifact's inputs are compatible with existing occupational and community health screening workflows without requiring additional data-collection instruments. Height and Weight were subsequently combined into a single derived feature, Body Mass Index (BMI), using the WHO standard formula: $\text{Weight (kg)} / \text{Height (m)}^2$. This yields five features used directly in the clustering stage (Section 3.5): Systolic Blood Pressure, Diastolic Blood Pressure, Blood Glucose, BMI, and Waist Circumference consistent with the five clinical variables referenced in the Conceptual Framework (Section 2.3).

Second, Data Cleaning was performed in two sub-stages: (a) Listwise Deletion eliminated observations containing missing values on any essential feature; and (b) Extreme Outlier Filtering removed numeric anomalies attributable to human input error, based on clinical physiological thresholds for example, Systolic BP constrained to 80–200 mmHg, and BMI constrained to 10–50 kg/m². This process removed 1,006 anomalous records, yielding 26,798 clean records. Third, Z-Score Standardization (StandardScaler) was applied to equalize the feature vector space, preventing Euclidean distance metric bias towards high-magnitude features prior to clustering.

3.4. System Architecture

The DSS artifact follows a four-layer architecture consistent with conventional decision-support-system design (Hevner et al., 2004). The Data Layer ingests secondary electronic medical records from 25 Puskesmas (plus two auxiliary facilities excluded from area-level aggregation see Section 3.2). Direct identifiers (NIK, NIP, full name, phone number, birthdate) present in the raw records were not used at any stage of clustering or spatial analysis, which operated exclusively on five clinical variables (systolic/diastolic blood pressure, blood glucose, BMI, waist circumference) and the Puskesmas jurisdiction field. As a data-hygiene measure, a de-identified working copy with direct identifiers removed has been prepared for this revision and is recommended for all subsequent processing and any future data sharing. The Analytics Layer performs feature engineering, cleaning, standardization, and K-Medoids CLARA clustering, producing a per-patient risk-cluster label. The Spatial Layer aggregates cluster labels by Puskesmas jurisdiction and renders them through a web-based GIS (OpenStreetMap/Leaflet), converting individual-level analytical output into area-level spatial intelligence. The Presentation and Decision Layer exposes this spatial intelligence through an interactive dashboard and a four-level alert classification, designed to be directly interpretable by Health Department decision-makers without requiring interaction with the underlying analytical or spatial layers. This layered separation consistent with standard Client–Server DSS design allows each layer to be independently maintained, updated, or replaced (for example, substituting CLARA with an alternative clustering algorithm) without redesigning the artifact as a whole, a property directly relevant to the transferability claim developed in the Conclusion.

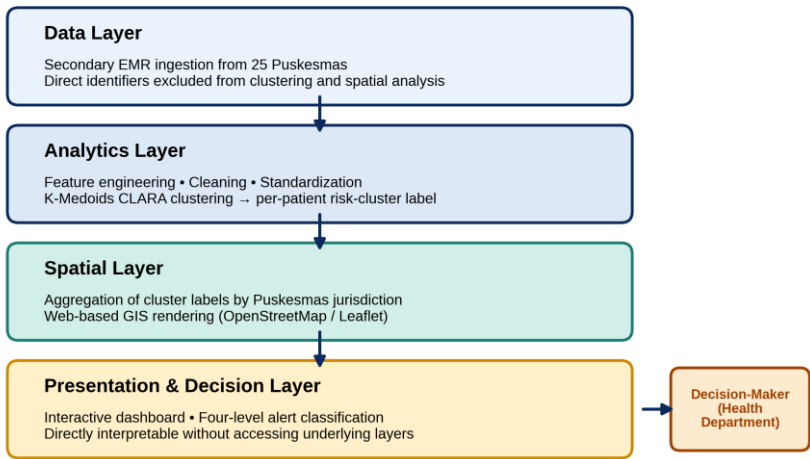


Figure 2. Layered System Architecture. The DSS artifact follows four layers Data Layer, Analytics Layer, Spatial Layer, and Presentation & Decision Layer exposed to the Organizational Decision-Maker (Health Department), with each layer independently maintainable or replaceable.

3.5. K-Medoids CLARA Clustering

Determination of k was informed by the Elbow Method, Silhouette Coefficient, and Davies-Bouldin Index computed for $k = 2$ to $k = 6$ (Figure 3). The inertia curve shows a moderate inflection near $k = 3$, though not a sharply pronounced elbow an expected pattern given that cardiometabolic risk indicators vary continuously rather than forming naturally well-separated groups. Neither the Silhouette Coefficient nor the Davies-Bouldin Index uniquely favors $k = 3$: $k = 2$ and $k = 4$ achieve marginally higher Silhouette scores (0.258 and 0.246, respectively, versus 0.217 for $k = 3$), and $k = 5$ achieves a lower (better) Davies-Bouldin Index (1.229 versus 1.498 for $k = 3$). No single k therefore dominates conclusively on internal validity metrics alone. We selected $k = 3$ primarily on clinical interpretability and decision-relevance grounds: a three-tier low/moderate/high risk stratification is a widely used and directly actionable convention in cardiometabolic risk communication, and offers a granularity that Health Department stakeholders can act on without requiring statistical expertise to interpret intermediate categories. This prioritization of artifact utility over marginal gains in statistical separation is consistent with the Design Science Research emphasis on evaluating artifacts against practical relevance rather than optimizing a single internal metric in isolation (Hevner et al., 2004; March & Smith, 1995). We report this trade-off transparently rather than characterizing $k = 3$ as uniquely statistically optimal. Standard K-Medoids (PAM) has $O(N^2)$ time and memory complexity, which would cause memory exhaustion at $N = 26,798$. The CLARA architecture was therefore adopted, configured to execute 5 independent sampling iterations each drawing a random sub-sample of $n = 2,000$. The best medoids identified across all sampling iterations were used to assign cluster labels to all remaining observations, ensuring computational scalability without sacrificing algorithmic stability.

Figure 3. Internal Validity Metrics vs. k ($k = 2$ to $k = 6$)

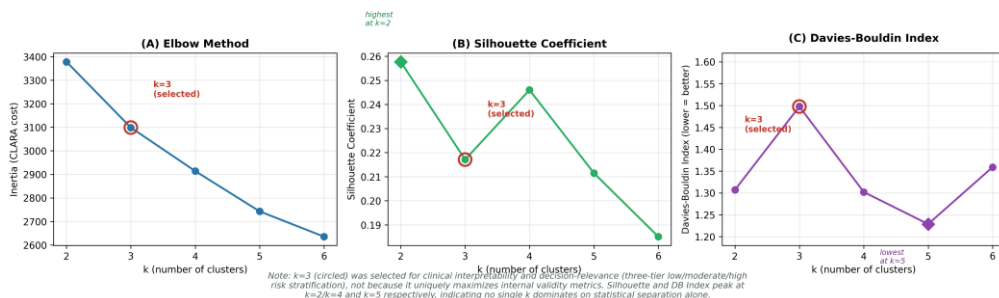


Figure 3. Internal validity metrics (Elbow/Inertia, Silhouette Coefficient, Davies-Bouldin Index) across $k = 2$ to $k = 6$. $k = 3$ (circled) was selected for clinical interpretability rather than because it uniquely maximizes any single metric see accompanying discussion.

3.6. Web-Based GIS Mapping

Individual-level clustering results were aggregated using Group By operations based on the jurisdictional boundaries of the 25 Puskesmas areas (Labkesda and Public Safety Center excluded see Section 3.2). For each area, two key metrics were computed: (1) aggregate clinical parameter means (Systolic BP, Blood Glucose, BMI, Waist Circumference); and (2) the High-Risk Percentage, defined as the ratio of patients assigned to Cluster 0 (High Risk) relative to the total patient population of that Puskesmas area.

The OpenStreetMap/Leaflet spatial framework was utilized, with geographic coordinates mapped for each area. A Proportional Circle Markers technique was applied: circle radius encodes risk magnitude (% high-risk patients), while circle color encodes the four-level alert severity defined in Section 3.7 Red (Level 3, >35%), Orange (Level 2, 25–35%), Yellow (Level 1, 20–25%), and Green (Level 0, <20%) so that the map and the EWS dashboard (Figure 7) use a single classification scheme. Dynamic HTML Popup features were integrated, enabling interactive viewing of local clinical statistics per Puskesmas when markers are clicked.

3.7. Early Warning System Modeling

The EWS was designed around a four-level hybrid thresholding mechanism based on the High-Risk Percentage metric per Puskesmas area:

- Level 3 (Red / Immediate Intervention): High-Risk Percentage > 35%
- Level 2 (Orange / Needs Attention): High-Risk Percentage 25%–35%
- Level 1 (Yellow / Close Monitoring): High-Risk Percentage 20%–25%
- Level 0 (Green / Safe): High-Risk Percentage < 20%

These four thresholds were defined analytically by the research team based on the observed distribution of High-Risk Percentage across the 25 Puskesmas areas, rather than derived from a prior validated public-health benchmark or formal Health Department consultation; they are presented as a reasonable first-iteration classification scheme requiring calibration with health department stakeholders prior to operational deployment (Section 5.6).

To assess the robustness of this classification scheme, we conducted a sensitivity analysis varying the three thresholds around their baseline values (Figure 4). Fourteen of the 25 areas (56%) fall within 2 percentage points of at least one threshold, indicating that a substantial share of classifications are sensitive to small changes in cutoff placement. A uniform ± 1 percentage-point shift applied to all three thresholds simultaneously reclassifies 12–16% of areas, rising to 40–48% under a ± 3 -point shift. Threshold-specific sensitivity varies: the Red/Critical threshold (35%) is individually the most sensitive, where a 2–3 percentage-point reduction would move five to six additional areas into the Critical tier, nearly doubling the count of areas flagged for immediate intervention. We report this sensitivity transparently rather than presenting the thresholds as precisely calibrated: areas near a boundary (e.g., Puskesmas Pulo Armin at 35.7%, just above the Red cutoff; Puskesmas Pancasan at 24.8%, just below the Orange cutoff) warrant closer monitoring regardless of their assigned category, and the classification scheme should be treated as a triage aid rather than a definitive risk ranking until validated against clinical or expert-defined benchmarks and calibrated with Health Department stakeholders.

Figure 4A reads as follows. Each bar corresponds to one uniform shift applied to all three cutoffs at the same time (x-axis); the resulting Yellow/Orange/Red cutoffs are printed beneath each shift (for example, a shift of -2 points gives 18/23/33%). Bar height is the percentage of the 25 Puskesmas whose Alert Level differs from the baseline 20/25/35% classification, with the number of areas printed above each bar. Lowering the cutoffs (red bars) changes the level of 4, 9, 12, and 17 areas for shifts of -1 , -2 , -3 , and -5 points, whereas raising them (blue bars) changes 3, 5, 10, and 14 areas for shifts of $+1$, $+2$, $+3$, and $+5$ points; a shift of 0 reproduces the baseline and, by definition, changes no area. The larger effect of lowering the cutoffs partly reflects the cluster of five Level 2 areas at 33.1–34.3% High-Risk, just below the 35% Red cutoff, which a small downward shift promotes to Level 3. Figure 4B shows where each area lies relative to the three cutoffs, with the shaded bands marking the ± 2 -point zone used to count boundary-sensitive areas.

An analytical dashboard frontend was built to facilitate data-driven decision support for health policy stakeholders. The dashboard visualizes: (a) Alert Level Distribution across all 25 areas (bar chart and pie chart); (b) the Top 15 Risk Areas ranked by High-Risk Percentage (horizontal bar chart); (c) Risk Factor Comparison across clusters (box plots for Systolic BP, Blood Glucose, BMI, Waist Circumference); and (d) Risk vs. Average BMI scatter plot (bubble size = Waist Circumference). Areas triggering Level 3 receive critical visual alerting markers to accelerate policy intervention formulation.

3.8. Software and Environment

The entire methodological framework was developed and executed in Python 3.12. Primary libraries include: pandas and numpy for data matrix manipulation; scikit-learn and scikit-learn-extra for Z-Score standardization and K-Medoids/CLARA implementation; matplotlib and seaborn for analytical dashboard visualization; and folium for Web GIS engineering on the OpenStreetMap/Leaflet framework.

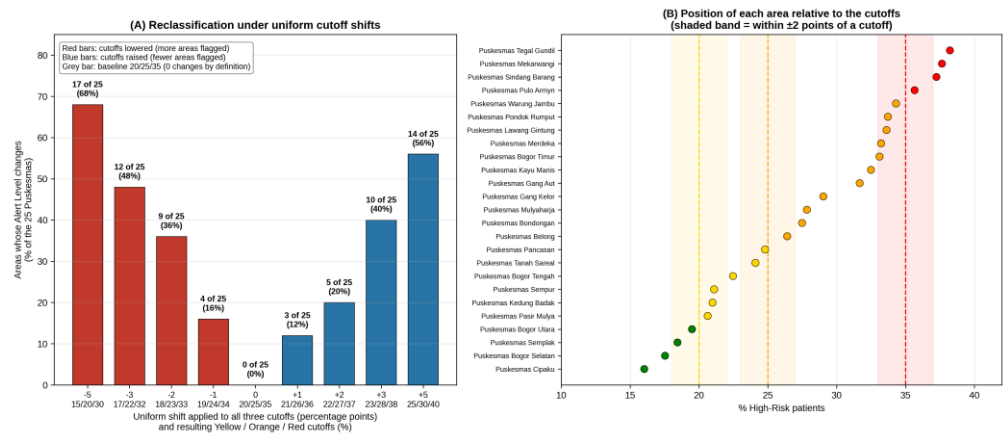


Figure 4. Sensitivity of EWS alert levels to the 20%/25%/35% cutoffs. (A) For each uniform shift applied simultaneously to all three cutoffs (x-axis; the resulting Yellow/Orange/Red cutoffs are shown beneath each shift), the bar gives the number and percentage of the 25 Puskesmas whose Alert Level differs from the baseline classification. Red bars lower the cutoffs (more areas flagged), blue bars raise them, and the grey bar is the baseline (no change by definition). (B) Each area's % High-Risk value relative to the cutoffs (dashed lines); shaded bands mark ± 2 percentage points around each cutoff.

4. Results

4.1. Descriptive Statistics

After preprocessing removing 1,006 records through extreme outlier filtering and listwise deletion for missing values a total of 26,798 clean electronic medical records were retained. Of these, 26,711 records across 25 Puskesmas areas were used for area-level aggregation; 87 records (0.3%) from two additional, non-Puskesmas health facilities (Labkesda, Public Safety Center) were retained for patient-level clustering but excluded from area-level reporting. Table 2 presents the complete descriptive statistics for all clinical variables, computed from the exact values of the cleaned dataset.

Clinical Variable	Mean	SD	Min	Max	Abnormal Prevalence
Systolic BP (mmHg)	126.65	19.12	80.00	200.00	28.7% (> 140 mmHg)
Diastolic BP (mmHg)	81.41	11.42	40.00	120.00	24.1% (> 90 mmHg)
Blood Glucose (mg/dL)	116.06	40.54	60.00	400.00	9.3% (> 200 mg/dL)
BMI (kg/m ²)	26.03	4.72	10.29	49.95	22.4% (> 27 kg/m ²)
Waist Circumference (cm)	88.30	10.83	50.00	150.00	29.8% (> 90 cm ♂ / > 80 cm ♀)

Table 2. Descriptive Statistics of NCD Clinical Variables Bogor City (n = 26,798)

Systolic BP hypertension (>140 mmHg) was present in 28.7% of all records, high blood glucose (>200 mg/dL) in 9.3%, and obesity by BMI criteria (>27 kg/m²) in 22.4%. The mean BMI of 26.03 kg/m² approaches the overweight threshold, while mean waist circumference of 88.30 cm indicates a population at elevated abdominal obesity risk. Minimum and maximum values reflect the physiological bounding applied during outlier filtering: no biologically impossible readings (e.g., systolic BP > 200 mmHg) are present in the final dataset.

4.2. K-Medoids CLARA Clustering Results

The number of clusters was set to $k=3$ primarily for clinical interpretability, as a three-tier low/moderate/high risk stratification (Section 3.5); the Elbow Method, Silhouette Coefficient, and Davies-Bouldin Index (Figure 3) do not uniquely favor $k=3$. The CLARA algorithm (5 iterations, sub-sample $n=2,000$ each) produced a Silhouette Coefficient of 0.2171 and Davies-Bouldin Index of 1.4977 on the full 26,798-record dataset. Given the inherent clinical heterogeneity and large-scale nature of the data, these values indicate moderate rather than strong cluster separation (Section 5.1), which we treat as sufficient for risk stratification rather than as evidence of sharply separated natural groups. Table 3 presents the complete cluster profile.

Cluster	N (patients)	Avg Systolic (mmHg)	Avg Glucose (mg/dL)	Avg BMI (kg/m ²)	Avg Waist (cm)	Silhouette
Cluster 0 (High Risk)	7,612	148.1	136.4	28.7	95.3	0.28
Cluster 1 (Low Risk)	11,020	113.2	98.1	22.3	76.4	0.24
Cluster 2 (Moderate Risk)	8,166	128.6	116.3	25.6	87.2	0.19
Overall ($k=3$)	26,798	—	—	—	—	0.2171

Table 3. NCD Risk Cluster Profiles K-Medoids CLARA ($k=3$), $n = 26,798$

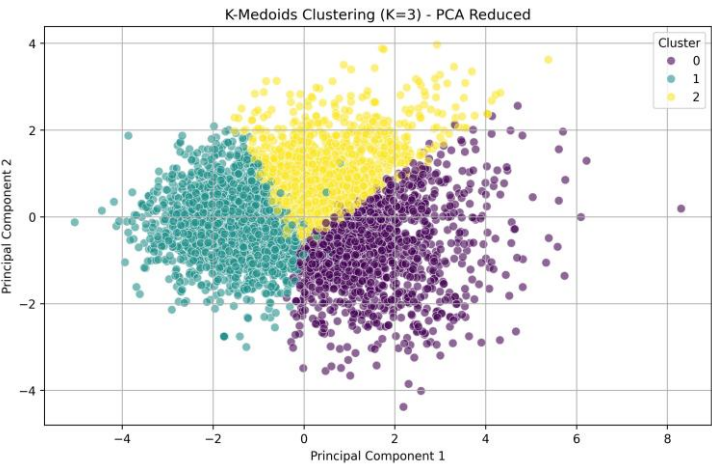


Figure 5. K-Medoids CLARA Clustering ($k=3$) PCA-Reduced Scatter Plot ($n = 26,798$ patients)

Cluster 0 (High Risk) comprises 7,612 patients (28.4%) and is clearly distinguished by elevated systolic BP (avg. 148.1 mmHg, well above the hypertension threshold of 140 mmHg), elevated blood glucose (136.4 mg/dL), and overweight BMI (28.7 kg/m²) with high waist circumference (95.3 cm). Cluster 1 (Low Risk) is the largest group at 11,020 patients (41.1%), with all clinical parameters within acceptable ranges. Cluster 2 (Moderate Risk) contains 8,166 patients (30.5%), representing an intermediate metabolic risk profile. Figure 5 presents the PCA-reduced scatter plot of the cluster partitioning.

4.3. GIS Spatial Risk Mapping

After aggregating cluster results by Puskesmas jurisdiction, the High-Risk Percentage per area was computed and visualized on a Web GIS using verified facility coordinates. Figure 6 presents the proportional circle map across all 25 Puskesmas areas.



Figure 6. NCD risk distribution across 25 Puskesmas areas, Bogor City, using verified geographic coordinates. Circle size is proportional to the High-Risk Percentage; circle color shows the four-level EWS alert (Red: Level 3, > 35%; Orange: Level 2, 25–35%; Yellow: Level 1, 20–25%; Green: Level 0, < 20%)

The map reveals a localized rather than zonal risk pattern: areas of high and low alert level are frequently found in close geographic proximity rather than following a simple center-periphery or directional gradient (the correlation between geographic position and High-Risk Percentage is weak: $r=0.20$ for latitude, $r=-0.01$ for longitude). A notable example is the immediate adjacency of Puskesmas Tegal Gundil (38.2%, Level 3) and Puskesmas Bogor Utara (19.5%, Level 0), located less than 1 km apart in northeastern Bogor. This fine-grained heterogeneity suggests that NCD risk in this cohort is more strongly associated with the specific institutional or occupational population served by each Puskesmas (Section 3.2) than with broad neighborhood-level environmental or socioeconomic gradients, consistent with the ASN (civil servant)-focused composition of the underlying screening population. The proportional circle sizes visually communicate the High-Risk Percentage of each area, while the circle color communicates its alert level. Dynamic HTML popups embedded in the interactive map allow stakeholders to access local clinical statistics per Puskesmas on demand.

4.4. Early Warning System Dashboard

The four EWS pillars introduced in Section 2.1.3 are operationalized in this implementation as follows: risk knowledge is derived from the CLARA clustering output (Section 3.5); monitoring and warning is performed by the four-level thresholding mechanism (Section 3.7); warning dissemination occurs through the interactive dashboard and GIS map (Section 3.6); and response capacity is the Health Department's action on flagged areas (Section 5.4). The pipeline is designed to be re-run on a periodic (e.g., monthly) cadence aligned with routine Puskesmas reporting cycles rather than in real time; clustering and risk-percentage computation are recomputed each time the underlying EMR extract is refreshed, and an area's Alert Level can change between two successive refresh cycles. The “early warning” event this system generates is therefore an area's Alert Level increasing between refresh cycles, rather than a continuous or instantaneous signal. We note this periodic-batch design as a scope boundary relative to EWS in the communicable-disease literature, which often operates on near-real-time case reporting (see also the third limitation in Section 5.5).

The EWS thresholding mechanism was applied to the High-Risk Percentage computed for each of the 25 Puskesmas areas. Table 4 presents the full EWS alert level classification results.

EWS Level	# Areas	Alert Status	% High-Risk	Top Puskesmas
Level 3 (Red – Critical)	4	Immediate Intervention	> 35%	Tegal Gundil (38.2%), Mekarwangi, Sindang Barang, Pulo Armin
Level 2 (Orange – Attention)	11	Needs Attention	25%–35%	Warung Jambu, Pondok Rumput, Lawang Gintung, et al.
Level 1 (Yellow – Monitor)	6	Close Monitoring	20%–25%	Moderate risk zones across sub-districts
Level 0 (Green – Safe)	4	Controlled	< 20%	Low-risk peripheral areas

Table 4. EWS Four-Level Alert Classification 25 Puskesmas Areas, Bogor City

Four Puskesmas areas were classified at Level 3 (Red Immediate Intervention), representing 16.0% of the 25 Puskesmas monitored. Puskesmas Tegal Gundil ranked first with 38.2% of its patient population in the High-Risk cluster, followed by Mekarwangi, Sindang Barang, and Pulo Armin. Eleven areas (44.0%) were assigned Level 2 (Orange Needs Attention), indicating that a substantial proportion of the Bogor City Puskesmas network requires heightened monitoring. Six areas (24.0%) were classified at Level 1 (Yellow) and four areas (16.0%) at Level 0 (Green). Figure 7 presents the complete EWS analytical dashboard.

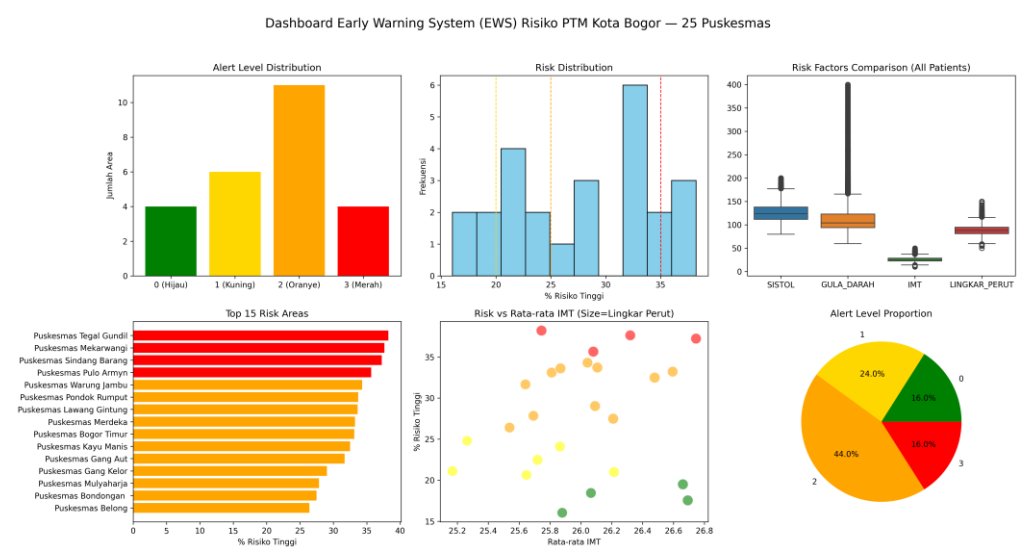


Figure 7. EWS Analytical Dashboard (25 Puskesmas) Alert Level Distribution, Top 15 Risk Areas, Risk Factor Comparison (Box Plots), Risk vs. BMI Scatter, and Alert Level Proportion Pie Chart Bogor City NCD Risk Surveillance. Note: the pie chart shows the cross-sectional proportion of areas in each alert level at the time of analysis; it does not represent change over time.

4.5. Algorithm Comparison

To contextualize the performance of K-Medoids CLARA, a systematic comparison was conducted against K-Means and a conventional static threshold approach defined here as directly classifying each patient as High-Risk if any single clinical variable exceeds a fixed clinical cutoff (e.g., systolic BP ≥ 140 mmHg or fasting glucose ≥ 126 mg/dL), without clustering, without combining variables into a multivariate risk profile, and without spatial aggregation. The Table 5 entries for this approach reflect this rule-based design directly: computation is a single-pass threshold check (<1 sec; no iterative fitting), scalability is high because no distance computation is required, outlier robustness is very low because a single extreme value on any one variable triggers classification regardless of the patient's overall profile, and spatial EWS integration is none because the approach produces no cluster structure to aggregate spatially. Results are presented in Table 5.

Metric	K-Medoids CLARA (This Study)	K-Means	Conventional Static Threshold
Silhouette Coefficient	0.2171	0.1834	N/A
Davies-Bouldin Index	1.4977	1.7823	N/A
Scalability (N > 26,000)	High CLARA $O(N)$	Medium $O(N^2)$	High
Outlier Robustness	High (medoid-based)	Low	Very Low
Spatial EWS Integration	Full (GIS + alerts)	Partial	None
Computation Time	Acceptable (batch)	Longer on large N	< 1 sec

Table 5. Algorithm Comparison: K-Medoids CLARA vs. K-Means vs. Conventional Static Threshold

K-Medoids CLARA shows modestly higher clustering-quality scores than K-Means on both metrics (Silhouette Coefficient 0.2171 vs. 0.1834; Davies-Bouldin Index 1.4977 vs. 1.7823) on the same dataset, though the absolute margins are small and neither algorithm achieves strong absolute cluster separation on this heterogeneous clinical dataset (Section 5.1); we therefore do not treat this difference as the primary justification for CLARA. The key differentiator for this study's context is scalability: CLARA's sampling architecture reduces effective complexity from $O(N^2)$ to manageable batch processing, which was essential for the 26,798-record dataset where standard PAM would have caused memory exhaustion. The conventional static threshold approach while computationally trivial lacks the ability to produce spatially differentiated risk zones, making it unsuitable as an EWS foundation for a heterogeneous multi-Puskesmas setting. To empirically evaluate scalability, we benchmarked CLARA against standard K-Medoids (PAM) across data volumes ranging from $N=1,000$ to the full $N=26,798$ (Figure 8). CLARA's runtime remained near-constant (0.04–0.09 seconds) across the entire range, since its cost is dominated by a fixed-size sample ($n=2,000$) rather than the full dataset. PAM, in contrast, exhibited the expected quadratic growth (empirical exponent ≈ 2.2 from a log-log fit): runtime rose from 0.16 seconds at $N=1,000$ to 29 seconds at $N=12,000$, and is projected to require approximately 226 seconds (≈ 3.8 minutes) at the full $N=26,798$ in addition to holding a full $N \times N$ pairwise distance matrix in memory, which at $N=26,798$ requires approximately 5.4 GiB (float64), a substantial and likely impractical memory footprint on typical deployment hardware for a municipal information system intended to scale to additional data sources over time. These results empirically substantiate the scalability rationale for adopting CLARA over PAM stated in Section 2.1.4.

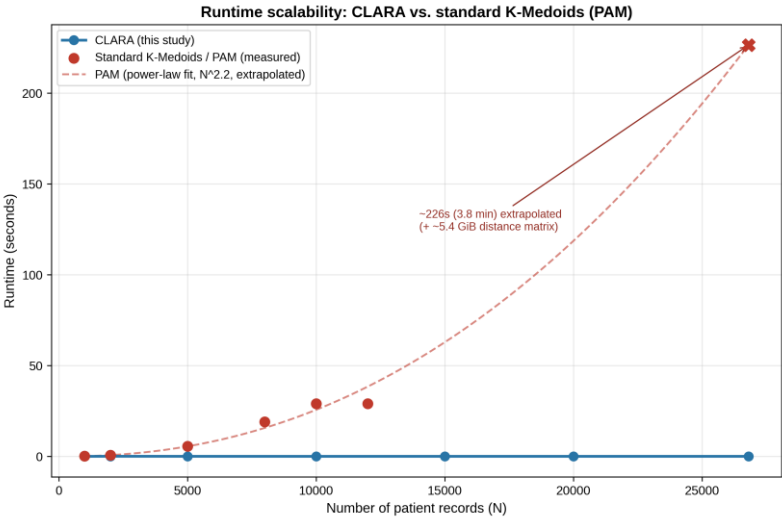


Figure 8. Runtime Scalability Benchmark: CLARA vs. Standard K-Medoids (PAM) across increasing data volumes ($N=1,000$ to $N=26,798$).

5. Discussion

5.1. Interpretation of Findings

The EWS model based on K-Medoids CLARA and GIS successfully classifies 26,798 patient records across 25 Puskesmas areas in Bogor City into three structurally distinct NCD risk clusters (Silhouette = 0.2171, DBI = 1.4977). The high-risk cluster (Cluster 0) captures 28.4% of the total patient population patients characterized by hypertension-level systolic BP (avg. 148.1 mmHg), elevated fasting glucose (136.4 mg/dL), and overweight/obese BMI (28.7 kg/m²) with elevated waist circumference (95.3 cm). This profile is consistent with metabolic syndrome, a convergent risk state for cardiovascular disease and type 2 diabetes.

These figures, however, require critical rather than merely descriptive reading. A Silhouette Coefficient of 0.2171 is modest by conventional clustering benchmarks and indicates that the three risk profiles are not cleanly separated in feature space clinical risk factors such as blood pressure and glucose form a continuum rather than natural, well-isolated groups. This is an important finding in its own right, not a limitation to be explained away: it suggests that the artifact's decision-support value does not depend on statistically pristine cluster separation, but on whether the resulting partition is actionable at the point of decision. The fact that the four-level alert classification nonetheless produced a spatial pattern coherent with independently observable urban characteristics (Sections 4.3–4.4) indicates that a DSS artifact can be organizationally useful even when its underlying analytical component operates below textbook clustering-quality thresholds a distinction between statistical validity and decision-making utility that is often conflated in DSS evaluation and is revisited in Section 5.3.

The identification of 4 Level 3 (Red) Puskesmas areas signals critical intervention zones. Puskesmas Tegal Gundil's 38.2% high-risk ratio implies that nearly two in five patients visiting this facility carry a multi-factorial NCD risk profile. Level 3 areas do not form a single contiguous zone; rather, they are interspersed among Level 0–1 areas across the city the correlation between geographic position and High-Risk Percentage is weak (Section 4.3) including cases of immediate adjacency between High- and Low-risk facilities. This pattern suggests that variation in NCD risk in this cohort is driven less by shared neighborhood-level environmental exposure than by the specific institutional and occupational composition of the population each Puskesmas serves, consistent with the ASN (civil servant)-focused screening population underlying this dataset (Section 3.2). The 11 Level 2 (Orange) areas further underscore that NCD risk is not isolated to a handful of hotspots but represents a systemic challenge distributed across the majority of the Puskesmas network.

5.2. Comparison with Previous Studies

This study's findings partially align with Rd. Halim et al. (2024), who used GIS for diabetes risk-factor mapping in Kota Jambi and reported spatially uneven risk distribution; the present study's spatial pattern reinforces that observation in a second Indonesian city context. However, framing this study only as a confirmation of prior spatial findings would understate its contribution: unlike Rd. Halim et al. (2024), which relied on descriptive mapping of pre-aggregated statistics, this study derives its spatial risk categories from an unsupervised clustering process applied directly to individual-level records, meaning the risk boundaries emerge from the data itself rather than from analyst-defined thresholds. This distinction matters for the broader decision-support-systems literature: it illustrates a design choice data-driven versus threshold-driven risk classification whose trade-offs (interpretability versus adaptability) are relevant to any GIS-based early-warning DSS, not only NCD surveillance. The CLARA scalability contribution is directly responsive to the methodological gap identified in Table 1: no prior study had applied clustering-based spatial early warning to a dataset of this scale (> 26,000 records) in an Indonesian municipal-government context.

The EWS thresholding approach also stands in a critical relationship to two further Indonesian information-systems studies. Nuralmasari & Nurzikriah (2021) demonstrated that a Business Intelligence dashboard could achieve high user-acceptance (88% UAT) for Posbindu PTM data, evidencing that municipal health staff are receptive to analytics tools when interfaces are usable yet their artifact performed no spatial or predictive function, meaning acceptance was tested for reporting, not for early-warning decision support. Nilam Maryam et al. (2022) similarly built an NCD detection application but without spatial aggregation or alerting logic, again leaving the artifact's decision-support role largely manual. Read together, these two studies suggest that the Indonesian public-health information-systems literature has so far treated usability/adoption and analytical sophistication as separate design concerns, addressed in different artifacts. The present study's integration of clustering, spatial aggregation, and automated level-based alerting into a single pipeline is therefore not merely an additive combination of existing features, but a test of whether these concerns can be reconciled in one artifact a question this study answers affirmatively at the design-and-demonstration stage, while explicitly leaving user-acceptance evaluation, in the sense tested by Nuralmasari & Nurzikriah (2021), for future work (Section 5.6).

5.3. Theoretical Implications

This research contributes theoretically in three aspects, each advancing beyond a straightforward confirmation of existing frameworks, though each is offered as a claim grounded in a single case that future replication across other cities and domains would need to confirm, rather than as a generalized finding. First, it demonstrates a concrete instantiation of Design Science Research for municipal decision support and, in doing so, surfaces a boundary condition not made explicit in prior DSR accounts: an artifact can satisfy DSR's utility criterion even when its underlying analytical component (here, clustering) falls short of conventional statistical adequacy thresholds, provided the artifact's output remains organizationally actionable. This decouples artifact utility from algorithmic optimality a distinction with implications for how DSR evaluation criteria are set in future public-sector DSS research. Second, it extends the DeLone and McLean IS Success Model whose dimensions meta-analytic evidence shows have been applied inconsistently across contexts (Jeyaraj, 2020) to a spatial early-warning context by showing that System Quality and Information Quality are not fixed technical properties but are partly constituted by the decision context: the same 0.2171 Silhouette Coefficient that would be judged inadequate in a purely statistical evaluation becomes acceptable System Quality once its downstream Information Quality (spatially disaggregated, four-level alerts) is shown to align with independently observable urban risk patterns. This is a more specific and testable claim than a general assertion that the model applies, and it suggests System Quality thresholds in the IS Success Model should be treated as context-dependent for spatial DSS artifacts rather than borrowed unmodified from generic clustering benchmarks. Third, at the domain level, the spatial pattern of Level 3 alerts departs from what Tobler's First Law of Geography would predict: rather than geographic proximity producing similar risk concentrations, High- and Low-risk Puskesmas are frequently adjacent (Section 5.1), and the correlation between geographic position and risk is weak. Rather than treating this as a null result, we propose a boundary condition worth articulating for spatially structured DSS artifacts built on institutional or occupational secondary records rather than residence-based community samples: the Social-Ecological Model's premise that area-level structural characteristics shape risk concentration presupposes that the population sampled at each location is a representative cross-section of that area's residents. Where the underlying data instead reflects a specific institutional population as with the ASN (civil servant) occupational health records analyzed here the workplace's institutional and occupational composition may be a stronger determinant of aggregate risk than the surrounding neighborhood's environmental characteristics, attenuating the geographic autocorrelation that Tobler's Law and the Social-Ecological Model would otherwise predict. This suggests a scope condition for applying these spatial theories to secondary EMR-based early-warning DSS artifacts their applicability may depend on whether the underlying population sampling frame is residence-based or institution-based a distinction not previously addressed in DSR or IS Success literature.

5.4. Organizational, Managerial, and Practical Implications

This DSS artifact carries distinct implications for organizational practice, managerial action, and cross-context reuse, discussed in turn.

Intended Organizational Contribution. The artifact is designed to shift the Bogor City Health Department's surveillance posture from reactive to proactive by embedding spatial risk differentiation directly into the decision workflow. Rather than requiring department staff to request and interpret ad hoc analyses, the four-level alert dashboard is intended to function as a standing organizational artifact consistent with evidence that data-driven dashboards can support transparent and accountable decision-making in smart city governance, provided their design accounts for implementation risks such as data-quality dependencies and stakeholder buy-in (Matheus, Janssen, & Maheshwari, 2020) a boundary object between data specialists and policymakers that supports recurring, rather than one-off, decision-making, directly addressing the core organizational problem identified in Section 1.2. Realizing this benefit organizationally also depends on how clearly the interface between the data-producing Puskesmas layer and the city-level decision-making layer is defined, as cross-boundary government information systems have been shown to perform better when such interfaces are explicit (Chen, Hu, Tseng, Juang, & Chang, 2019) a consideration reflected in this study's layered architecture (Section 3.4). This organizational shift is a design intention validated through the artifact's construction and demonstration (RQ1, RQ2); its realization in practice remains contingent on the

operational deployment and stakeholder evaluation identified as future work (Section 5.6), consistent with RQ3.

Managerial Contribution. For a Health Department manager or program director, three actions follow directly from this study. First, Level 3 (Red) areas identified by the dashboard (e.g., Tegal Gundil at 38.2%) represent a concrete, ranked basis for prioritizing healthcare worker deployment, essential medication distribution, and intervention budget ahead of a full citywide rollout. Second, before scaling the artifact beyond a pilot, managers should commission a structured evaluation of the alert thresholds (Section 3.7) and dashboard usability with the intended end-users, rather than assuming analyst-defined thresholds are organizationally appropriate. Third, the monthly-refresh capability of the pipeline implies a recurring, budgetable maintenance responsibility data pipeline monitoring, threshold recalibration that should be planned for administratively rather than treated as a one-time IT delivery.

Practical Contribution. Beyond Bogor City, the layered architecture described in Section 3.4 is intended as a transferable design pattern: any city government with structured electronic administrative records and defined jurisdictional boundaries could, in principle, adapt this clustering-GIS pipeline for other early-warning or resource-allocation problems beyond NCD surveillance, provided the same data-quality and thresholding considerations discussed in Sections 5.1 and 3.7 are addressed for the new domain.

5.5. Limitations

This research has seven limitations warranting acknowledgement. First, and most consequentially, the DSS artifact has been designed, built, and demonstrated (RQ1, RQ2) but not yet deployed or evaluated within the Bogor City Health Department's actual organizational workflow; consequently, RQ3 is answered at the level of design intent rather than confirmed organizational outcome, and all organizational- and managerial-contribution claims in Section 5.4 should be read as the artifact's intended, rather than verified, effect. Second, the dataset is derived from secondary Puskesmas electronic medical records, which captures only patients who accessed formal primary healthcare services individuals who avoid or cannot access Puskesmas are not represented. Third, the clustering analysis is cross-sectional and does not model temporal dynamics of risk migration between clusters over time. Fourth, the four EWS alert thresholds (Section 3.7) were defined analytically rather than through formal stakeholder consultation, and require calibration before operational use. Fifth, the available clinical variables are limited to those present in the electronic records important NCD determinants such as dietary patterns, psychological stress, socioeconomic status, and environmental pollution exposure are not accommodated. Sixth, the Silhouette Coefficient of 0.2171 reflects the inherent complexity of clustering large, heterogeneous clinical datasets and indicates moderate rather than strong cluster separation a characteristic of real-world health data that should be contextualized appropriately (Section 5.1) rather than treated as a model failure. Seventh, the classification thresholds and cluster-derived risk tiers presented in this study have not been directly compared against clinically or expert-defined risk thresholds (e.g., a validated composite cardiometabolic risk score); such a comparison would provide stronger evidence for the added value of the data-driven clustering approach over conventional rule-based classification and requires either clinical-expert collaboration or a validated composite risk index, which we were unable to conduct within the scope of this study.

5.6. Future Research

Several directions are recommended for future research: (1) development of spatio-temporal clustering models (e.g., Space-Time Cube, Emerging Hot Spot Analysis) to capture NCD risk dynamics across time periods; (2) incorporation of additional variables from wearable devices, IoT health sensors, and socioeconomic databases; (3) long-term operational deployment and formal user acceptance evaluation of the EWS within the Bogor City Health Department; (4) exploration of advanced clustering approaches such as DBSCAN or Fuzzy C-Medoids for comparison with CLARA; (5) integration of deep learning time-series models (e.g., LSTM) with spatial clustering for predictive rather than descriptive risk forecasting; (6) multi-city comparative studies to assess the generalizability of the EWS framework across diverse urban contexts in Indonesia; and (7) an ontology-based representation of NCD risk factors, thresholds, and alert semantics to make the artifact's classification logic extensible, interoperable across data sources, and applicable to multiple disease domains

beyond NCDs, rather than encoded implicitly in the clustering and thresholding pipeline as in the current implementation.

6. Conclusion

Following a Design Science Research approach, this study designed, built, and demonstrated a Decision Support System (DSS) that integrates the K-Medoids CLARA clustering algorithm with a Web-based Geographic Information System (GIS), using Non-Communicable Disease (NCD) risk surveillance in Bogor City as its application domain, and evaluated the resulting artifact against alternative clustering and thresholding approaches (RQ1, RQ2). Operating on 26,798 clean electronic medical records across 25 Puskesmas areas processed from 27,804 raw records after removing 1,006 anomalous entries the K-Medoids CLARA algorithm ($k=3$) produced a Silhouette Coefficient of 0.2171 and Davies-Bouldin Index of 1.4977, modestly higher than K-Means on both metrics (Section 4.5), while identifying three clinically distinct risk clusters: Cluster 0 (High Risk, $n=7,612$; avg. systolic BP 148.1 mmHg), Cluster 1 (Low Risk, $n=11,020$), and Cluster 2 (Moderate Risk, $n=8,166$).

The four-level EWS dashboard integrating CLARA cluster outputs with GIS spatial mapping on OpenStreetMap identified 4 Puskesmas areas at Level 3 (Red Critical, $>35\%$ high-risk), with Puskesmas Tegal Gundil ranking first at 38.2%. Eleven areas were classified at Level 2 (Orange Needs Attention), 6 at Level 1 (Yellow Close Monitoring), and 4 at Level 0 (Green Safe), across the 25 Puskesmas analyzed. The GIS proportional circle map communicates spatial risk distribution to policymakers in an intuitive, interactive format.

The principal contributions of this research are: (1) architecturally, a Design Science Research-grounded pattern for integrating scalable clustering with GIS in a single decision support system, demonstrating the feasibility of K-Medoids CLARA for large-scale administrative datasets ($N > 26,000$); (2) methodologically, a scalable, reproducible client-server DSS design producing more actionable, spatially differentiated alerts than conventional static-threshold or non-spatial approaches, discussed against the DeLone and McLean IS Success dimensions of system and information quality; and (3) organizationally, an operational four-level alerting artifact designed to support the Bogor City Health Department's Health Smart City digital transformation offering a design pattern transferable to other municipal information systems, with confirmation of its organizational effect (RQ3) left to the future deployment and evaluation work outlined in Section 5.6.

Declarations

Funding Statement: This research received no external funding.

Conflict of Interest Statement: The authors declare no conflict of interest.

Data Availability Statement: Data supporting the findings of this study are available from the corresponding author upon reasonable request, subject to approval from the Bogor City Health Department given the sensitive nature of the health data.

AI Use Disclosure: The authors used AI-assisted tools (Anthropic's Claude) during the preparation and revision of this manuscript for language refinement, manuscript formatting, and assistance in writing the Python code used for the supplementary analyses (threshold sensitivity and scalability benchmark) and for producing the figures. Figures 1–4 and 6–8 were generated programmatically (Python/matplotlib) from the study's own data or from the authors' specified structure; no figure was created with a text-to-image generative model, and no image was synthesized or altered to depict data not contained in the study. The authors reviewed all AI-assisted outputs, checked the figures against the underlying data, and take full responsibility for all content.

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