Proceedings of the International Conference on Industrial Engineering and Operations Management

Publisher: IEOM Society International, USA DOI: 10.46254/AP06.20250178
Published: August 5, 2025

Strategic Hospital Cluster-based Delivery Planning for Centralized Healthcare Additive Manufacturing Systems

Chanipa Nivasanon
Department of Industrial Engineering
Kasetsart University
Bangkok, Thailand
chanipa.ni@ku.th

Pornthep Anussornnitisarn
Department of Industrial Engineering
Kasetsart University
Bangkok, Thailand
fengpta@ku.ac.th

Kasin Ransikarbum
Faculty of Engineering
Ubon Ratchathani University
Ubon Ratchathani, Thailand
kasin.r@ubu.ac.th

Abstract

This study investigates the spatial classification of hospitals to evaluate the potential for centralized and decentralized healthcare logistics systems supported by additive manufacturing (AM) technology. Using a case study of 24 hospitals in Thailand, geographic coordinates (latitude and longitude) were analyzed, and the K-Means clustering algorithm was applied to determine the optimal number of hospital clusters. The analysis identified three spatially coherent clusters. These cluster centroids were then visualized using Quantum Geographic Information System (QGIS) to map their geographic distribution. The results suggest that geographic clustering can inform the strategic placement of centralized AM production units, serving as potential printing hubs near healthcare service points. Ongoing work aims to compare centralized and decentralized AM network models by evaluating lead time, healthcare demand, and logistics costs, to inform the optimal design of AM networks for healthcare applications.

Keywords
Healthcare Network, Additive Manufacturing Technology, K-Means Algorithm, Centralized Supply Chain

1. Introduction

Additive Manufacturing (AM) in the healthcare sector has accelerated significantly over the past decade, driven by the need for rapid, patient-specific solutions and resilient supply chains. The global medical AM market was valued at approximately USD 2.8 billion in 2022 and is projected to exceed USD 9.8 billion by 2030, reflecting a compound annual growth rate of over 17% as shown in Figure 1 (Grand View Research, 2023). This growth is largely attributed to the rising demand for customized prosthetics, surgical instruments, anatomical models, and implants. Moreover, more than 70% of hospitals in developed countries have adopted AM technologies for a range of medical applications, enabling faster responses to emergencies and reducing dependence on traditional centralized manufacturing and long-distance logistics. These data highlight the strategic role of AM in advancing decentralized, point-of-care production models and transforming healthcare operations.

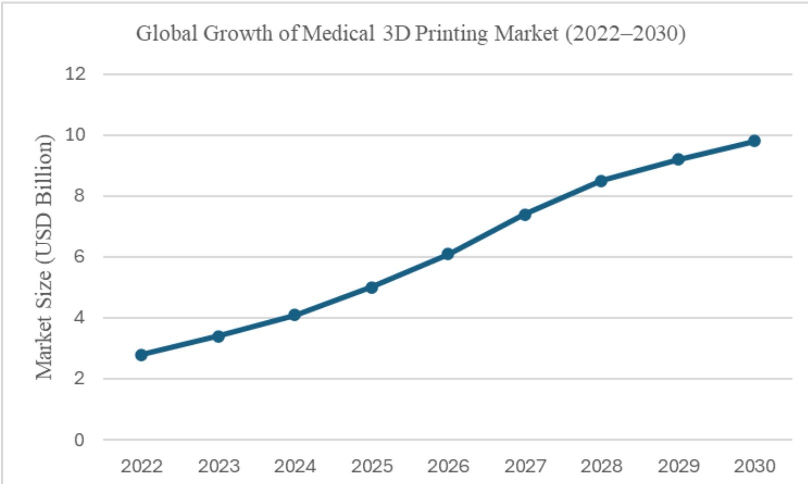

Figure 1. Expected Global Growth of Medical AM Market (2022–2030)

Supply Chain Management (SCM) in the healthcare system plays a vital role in ensuring health system resilience, particularly during crises. Recent pandemics have highlighted the limitations of supply chain design, including delays, vulnerabilities, and shortages of medical supplies and equipment (Kamble et al., 2024). As a result, investigating centralized and decentralized supply chain for Healthcare Supply Chain (HSC) becomes an on-going interesting problem (Piffari et al., 2024). Besides, AM or 3D Printing (3DP) technology has gained interest from practitioners and academics for potential digital manufacturing technology in diverse applications (Nivasanon et al., 2024; Anussornnitisarn et al., 2025). Thus, applying AM technology for network design in HSC has attracted growing interest for researchers and practitioners as a flexible and adaptive solution for enhancing efficiency and effectiveness of SCM (Ben-Ner and Siemsen 2017; Ransikarbum and Mason, 2022).

Designing efficient logistics system with production and distribution activities in a network of HSC remains challenging, especially in determining the most appropriate locations for healthcare hubs and medical supply distribution centers. These hubs must be able to effectively respond to the specific needs of hospitals across different regions, in which both centralized and decentralized strategies may be applied (Tyagi 2024; Ransikarbum et al. 2024). The application of K-Means clustering technique emerges as a powerful tool for grouping locational service areas based on shared factors such as geographic coordinates, service capacity, and levels of demand in the HSC literature. This enables the planning of point-of-care production and localized distribution strategies that bring resources closer to where they are needed most. However, an application of K-means clustering for the HSC, in which AM technology plays a critical technology component is lacking and called for.

Geospatial clustering also supports the strategic placement of AM units at the local level, aligning with the growing trend toward localized and resilient SCM and network design. This spatial approach not only enhances responsiveness to regional healthcare demands but also reduces dependency on centralized production and long-distance transportation in HSC (Niemsakul et al. 2022; Song et al., 2025). The development of a 3D printing-enabled medical supply chain ecosystem also requires robust local partnerships and a flexible, dynamic network design capable of adapting to rapid environmental and market changes (Kamble et al., 2023). Furthermore, AM can also facilitate local production by minimizing geographical constraints and reducing logistics costs, thereby significantly reshaping traditional organizational structures and supply chain models (Ben-Ner and Siemsen 2017). These insights underscore the potential of AM to transform healthcare logistics through production strategies in the HSC.

This study is our initial study aiming to apply K-Means clustering to group hospitals based on geospatial and logistical data and to propose optimal locations for AM units within each cluster. The output from the current study will be used to support the design of a HSC network with AM technology integration as illustrated in Figure 2 with the schematic flow of AM-embedded HSC. That is, by identifying spatially coherent hospital clusters, we plan to extend this work by comparing the performance of centralized versus decentralized AM network configurations. Our final goal is to develop a robust decision-making framework for designing adaptive AM-enabled supply chains tailored to the unique demands of the healthcare sector.

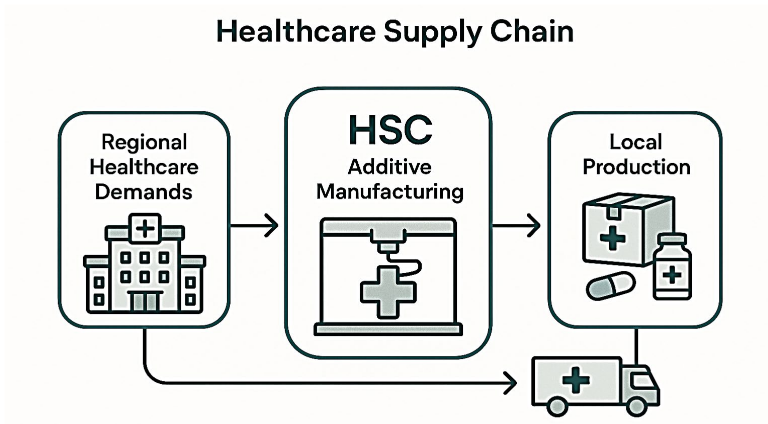

Figure 2. The Schematic Flow of Healthcare Supply Chain (HSC)

2. Literature Review for AM Technology-embedded HSC

AM offers significant advantages in process and production planning by enabling greater flexibility, customization, and responsiveness. Unlike traditional manufacturing methods, AM allows for rapid prototyping and small-batch production without the need for costly tooling or long setup times. Several studies highlight the benefits of AM within the HSC context. For instance, Zhou et al. (2024) illustrate the role of community-led AM initiatives in quickly mitigating equipment shortages during the pandemic, demonstrating AM's potential to support emergency response through decentralized production. Nuñez Rodriguez et al. (2022) expand on these advantages by noting that AM can streamline logistics processes, reduce the need for extensive inventory storage, and accelerate the time-to-market for critical medical products. This logistical simplification is particularly valuable in healthcare, where demand is often volatile and time-sensitive. Ivanov et al. (2021) further argue that AM facilitates the development of highly adaptable supply chains by enabling real-time, localized production that can be dynamically adjusted to meet specific regional healthcare demands. Collectively, these findings underscore the transformative potential of AM in enhancing the agility, resilience, and efficiency of healthcare supply chains, especially in the face of disruptions and rapidly evolving healthcare needs.

AM technology has also notably reshaped supply chain network design in SCM, particularly within the healthcare sector as pointed out in diverse applications (Özceylan et al., 2017; Ransikarbum et al. 2020). AM plays a critical role not only in enhancing operational efficiency but also in shaping the strategic design of supply chains. By enabling decentralized and on-demand production, AM allows for more flexible, responsive, and regionally adaptive supply chain architectures. This is especially vital in healthcare applications, where the ability to produce customized medical devices, implants, and tools locally can significantly reduce lead times and improve patient outcomes (Khajavi et al., 2018; Özceylan et al., 2018; Roozkhosh et al., 2024). According to Ben-Ner and Siemsen (2017), AM facilitates decentralized and localized production, enabling the creation of goods nearer to where they are needed. This reduces logistical challenges and enhances the resilience of supply chains. Such advantages are also especially vital in healthcare, where the prompt delivery of personalized medical items is critical (Verboeket et al., 2021; Peron et al., 2025). Kamble et al. (2022) discuss the obstacles to implementing AM-based local supply chains, pointing to the necessity of regional cooperation, strong local partnerships, and robust digital infrastructure. The authors assert that building a localized and adaptive supply chain requires integrating flexible network designs and advanced analytical tools to navigate fast-changing environments effectively.

Evaluating clusters is essential for effective supply chain design in SCM, as it helps identify patterns, segment demand, and optimize resource allocation based on regional or functional needs (Ransikarbum et al. 2023; Keskin et al., 2025). In healthcare applications, accurate cluster analysis can enhance service delivery by grouping facilities, patient needs, or logistics flows, enabling more targeted and efficient planning as pointed out by various applications (Zamiela et al., 2022). For example, Khedr et al. (2023) introduce advancements to the conventional K-Means clustering algorithm aimed at enhancing prediction precision and minimizing centroid identification errors. Applied within healthcare logistics, their approach demonstrated notable accuracy in forecasting critical parameters, including delivery and delay times, underscoring the efficacy of machine learning techniques in HSC. Evaluated using real-world hospital data, the proposed model improves forecasting performance and highlighting its applicability in optimizing logistics operations and resource distribution in complex healthcare supply networks. A recent case study by Awad et al. (2022) explore the potential of decentralized manufacturing of 3D printed medicines, emphasizing the role of AM in producing on-demand, personalized pharmaceuticals close to the point of care. According to the authors, the proposed model can significantly reduce delivery time and alleviates the dependence on centralized pharmaceutical supply chains. The authors' rationale aligns closely with spatial segmentation strategies in healthcare logistics, where local production hubs serve clustered populations based on geographic and demographic factors.

Despite various advancements, significant gaps remain in the integration of spatial clustering and evaluating centralized or decentralized strategies for AM deployment within HSC. While AM enables on-demand and localized production, determining the optimal placement of production hubs is critical to maximizing its impact. Combining geographic clustering methods with localized AM strategies is expected to offer a promising pathway to enhancing supply chain performance in this study. Regardless, the application of cluster analysis specifically for AM in HSCs remains limited. A systematic and data-driven use of clustering techniques can greatly improve decision-making related to AM deployment—such as identifying strategic production sites, tailoring supply chain configurations, and aligning AM capabilities with regional healthcare needs.

3. K-Means Clustering Methods

This research adopts a quantitative research methodology, utilizing data clustering techniques specifically the K-Means Clustering algorithm to classify hospitals based on attributes relevant to HSC management. The goal is to identify patterns or groupings that could inform centralized or decentralized strategies for production and distribution planning, such as AM deployment. A key step in applying K-Means Clustering is determining the optimal number of clusters (k). The K-Means technique has been found in diverse applications in SCM (Prabhu et al., 2020; Ransikarbum and Madathil 2022). The core concept of the K-Means algorithm is to identify the centroid of each cluster and assign data points to the nearest centroid based on distance, typically using the Euclidean metric. The process begins by specifying the desired number of clusters, k, and randomly initializing k centroids. Each data point is then assigned to the nearest centroid, after which the centroids are recalculated based on the current cluster assignments. This assignment and update process is repeated until the centroids stabilize and no longer change significantly, indicating convergence. The Euclidian distance between a data point x and the centroid μ of each cluster is shown in Equation (1). Besides, Equation (2) presents the objective of K-Means to minimize the total squared distance between all data points and their corresponding cluster centroids, respectively.

$$Distance\left(x_j, \mu_j\right) = \sqrt{\sum_{i=1}^{n}\left(x_i - \mu_i\right)^2} \tag{1}$$

Where:

x_i is the value of data point x in dimension j

μ_i is the value of centroid μ in dimension j

$$J = \sum_{j=1}^{k} \sum_{x_i \in C_j} \left\| x_i - \mu_j \right\|^2 \tag{2}$$

Where:

C_i is the set of data points in cluster i

μ_i is the centroid of cluster i

Next, to evaluate the number of clusters (k), the Elbow Method (Cui, 2020) is applied in this study, which is a widely used heuristic in cluster analysis to determine the optimal number of clusters for unsupervised learning techniques inclusive of the K-Means clustering. The fundamental objective of clustering is to partition data points into groups (clusters) such that intra-cluster similarity is maximized and inter-cluster similarity is minimized. In particular, the algorithm attempts to minimize the Within-Cluster Sum of Squares (WCSS), which quantifies the total variance within each cluster as shown in Equation (3).

$$WCSS = \sum_{j=1}^{k} \sum_{x_i \in c_j} \left\| x_i - \mu_j \right\|^2 \tag{3}$$

Where:

k	is the number of clusters
c_i	is the set of data points in cluster i
μ_i	is the centroid of cluster i
$\left\| x - \mu_i \right\|^2$	is the squared Euclidean distance between a data point and the cluster centroid.

As the number of clusters increases, the WCSS typically decreases because the clusters become more compact and well-defined. However, after a certain point, the rate of decrease in WCSS slows significantly. This turning point, known as the 'elbow point' represents the optimal balance between model complexity and performance (Kuraria et al., 2022). The key steps of the Elbow Method is as follows. Initially, a range of k values usually from 1 to 10 is assessed and the K-Means algorithm is run for each selected k value to compute the corresponding WCSS. Next, these values are plotted with k on the x-axis and WCSS on the y-axis. Then, the elbow point is identified where the sharp decline in WCSS begins to level off, indicating the most appropriate number of clusters. This method provides a visual guide to avoid underfitting (i.e., too few clusters) and overfitting (i.e., too many clusters). The method is found a practical and efficient technique, particularly valuable in domains like healthcare and logistics where interpretability and speed are crucial.

K-Means is particularly valuable in domains such as healthcare logistics and supply chain segmentation, where spatial and resource-based clustering supports decision-making in network design and localized resource deployment. In this study, we initially apply the K-Means clustering technique to determine the hospital cluster using location coordinates to support supply chain segmentation. This analysis enables targeted recommendations for localized AM deployment and for further potential resource allocation strategies in healthcare systems in our on-going future study.

4. Data Collection

In this study, a case study of hospital locations in Ayutthaya Province, Thailand, serves as the basis for hospital cluster analysis within the HSC. As previously mentioned, the findings from this analysis are intended to inform the evaluation of an AM technology-embedded HSC network, enabling a comparison between centralized and decentralized models for our on-going study. That is, the conceptual framework integrates geographic clustering within the context of healthcare logistics. The primary goal is to support the efficient planning of healthcare production and distribution systems particularly through the use of AM technology installations to enhance the responsiveness and resilience of the HSC. The overall data collection and analysis procedure is presented in Figure 3. That is, the current phase of the research is to assess special clustering analysis for potential AM-embedded hospital hub in the regional case study. Then, the output from the first phase will be used as input to the second phase to evaluate multi-objective routing optimization and demand analysis with diverse scenarios through vehicle routing analysis and methodologies (Ransikarbum et al. 2021). Then, the third phase of the study is to investigate network configuration (Ahmed et al. 2023), in which both centralized and decentralized AM technology-embedded HSC will be compared and examined.

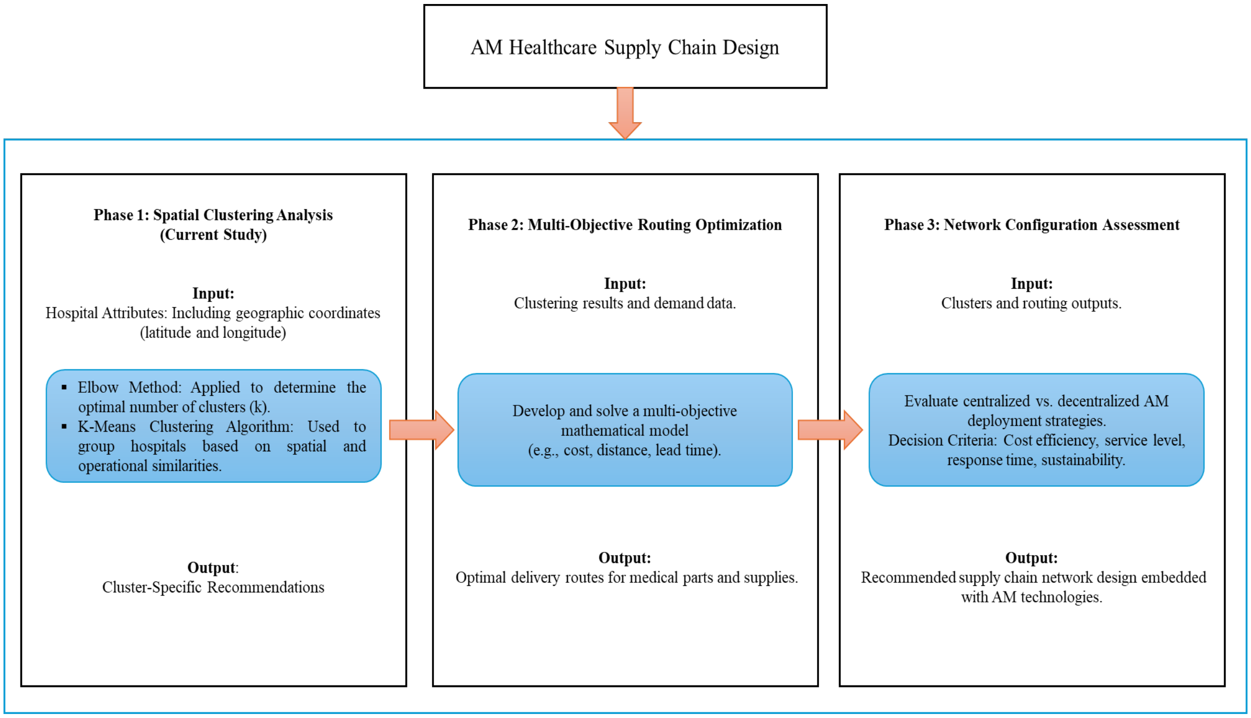

Figure 3. The overall framework for AM HSC evaluation and research plan

The geographic coordinates inclusive of latitude and longitude of 24 hospitals located in Ayutthaya Province, Thailand, which serve as the foundational data for the clustering analysis in this study are collected as shown in Table 1. These coordinates represent the spatial distribution of healthcare facilities across the region, providing valuable input for identifying natural groupings based on proximity. The variation in latitude and longitude values indicates a broad geographical spread. This diversity in location is essential for meaningful cluster analysis, as it allows the K-Means algorithm to detect patterns and form clusters that reflect real-world logistical groupings. The spatial data will be further used later when evaluating centralized versus decentralized systems in HSC.

Table 1. Hospital Location Data

Hospital Name	Latitude	Longitude
Hospital 1	14.354619	100.648959
Hospital 2	14.247962	100.490685
Hospital 3	14.458990	100.403912
Hospital 4	14.373903	100.525838
Hospital 5	14.267775	100.408253
Hospital 6	14.464313	100.695347
Hospital 7	14.474716	100.424363
Hospital 8	14.256098	100.526049
Hospital 9	14.341235	100.431297
Hospital 10	14.444860	100.609012
Hospital 11	14.473380	100.611726
Hospital 12	14.238628	100.543539
Hospital 13	14.457996	100.434467
Hospital 14	14.364669	100.573953
Hospital 15	14.245556	100.517638
Hospital 16	14.298429	100.606020
Hospital 17	14.447715	100.476458

Hospital 18	14.424726	100.477463
Hospital 19	14.470829	100.593096
Hospital 20	14.268617	100.487402
Hospital 21	14.338626	100.474337
Hospital 22	14.220170	100.488935
Hospital 23	14.417725	100.583718
Hospital 24	14.498828	100.507994

5. Analysis and Results

Based on the collected data, the Elbow Method was employed to determine the optimal number of clusters for classification using the K-Means Clustering technique. By plotting k against the WCSS, an optimal balance between model complexity and performance can be observes. The core principle of the Elbow Method involves analyzing inertia, which represents the WCSS. As the number of clusters increases, inertia or WCSS naturally decreases, indicating tighter and more refined groupings. However, after a certain point, the rate of decrease diminishes significantly. This inflection point known as the 'elbow point' is later interpreted as the optimal number of clusters for the dataset . In this study, values of k ranging from 1 to 10 are tested, and the inertia values corresponding to each are calculated to identify the most suitable number of clusters as presented in Table 2.

Table 2. Inertia Values Obtained from Elbow Method Experiment.

Assessment of parameter k	**Inertia (WCSS)**
1	1.206404228
2	0.892969712
3	0.651433128
4	0.614971044
5	0.381421676
6	0.277768506
7	0.226082553
8	0.203433188
9	0.195841741
10	0.181874270

Based on the inertia values shown in Table 2, a graph was plotted to visualize how inertia decreases as k increases, helping to identify the point where the rate of decrease begins to level off. This point of inflection, known as the 'elbow point' indicates the most appropriate number of clusters for effectively partitioning the data. The resulting elbow curve is presented in Figure 4. The x-axis represents the number of clusters, and the y-axis represents the WCSS, a measure of cluster compactness where lower values indicate tighter clusters. As shown in the figure, as the number of clusters increases, the WCSS naturally decreases because adding more clusters reduces the distance between points and their cluster centers, where the goal is to find a point where the rate of decrease sharply slows down, forming an 'elbow' in the curve, which indicates an optimal balance between minimizing WCSS and avoiding too many clusters. In this plot, the curve noticeably flattens around k = 3, 4, and 5, suggesting these values as potential optimal cluster counts. Thus, choosing k within this range balances cluster compactness with model simplicity, making these k values good candidates for further analysis. In this study, the k = 3 cluster is chosen implying that the hospitals will be divided into three clusters for this analysis.

Next, Table 3 presents the results of applying K-Means clustering with three clusters (k = 3) to a set of hospitals based on their geographic coordinates (latitude and longitude). Each hospital is assigned to one of three clusters, labeled 1, 2, or 3, according to its proximity to the respective cluster centroid. The centroids for these clusters represent the average geographic location of hospitals within each group. The analysis also suggests that Cluster 1 includes hospitals primarily centered around latitude 14.32 and longitude 100.61, Cluster 2 groups hospitals near latitude 14.32 and longitude 100.30, and Cluster 3 clusters hospitals around latitude 14.57 and longitude 100.72, which is useful for region-specific analysis with resource allocation in HSC.

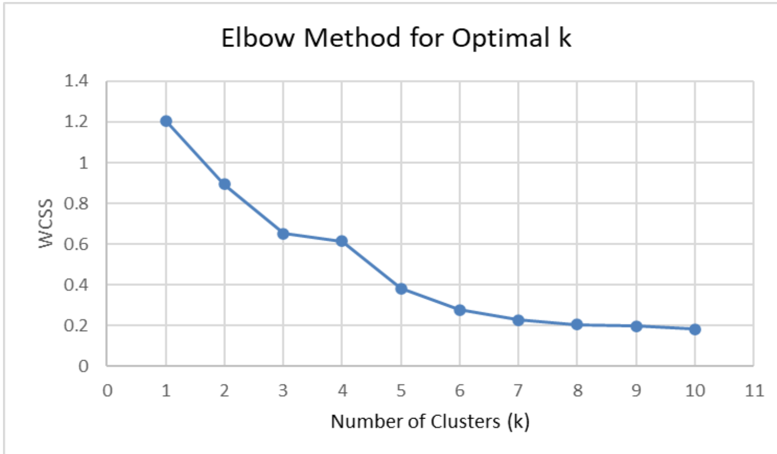

Figure 4. Inertia Values by Number of Clusters (k) Using the Elbow Method

Table 3. Hospital Clustering Results Using K-Means Clustering with k = 3

Hospital and Centroid	**k-cluster**
Hospital 1	1
Hospital 2	2
Hospital 3	3
Hospital 4	1
Hospital 5	1
Hospital 6	1
Hospital 7	1
Hospital 8	1
Hospital 9	2
Hospital 10	3
Hospital 11	2
Hospital 12	1
Hospital 13	2
Hospital 14	1
Hospital 15	3
Hospital 16	3
Hospital 17	1
Hospital 18	2
Hospital 19	1
Hospital 20	1
Hospital 21	2
Hospital 22	1
Hospital 23	1
Hospital 24	2
Centroid1 (14.3214858, 100.6115472)	C1
Centroid2 (14.3171474, 100.2950401)	C2
Centroid3 (14.5661187, 100.7209401)	C3

Next, to improve the spatial visualization of the hospital groupings obtained through clustering, the clustered data were imported into specific Geographic Information System (GIS) software. That is, by using QGIS (QGIS

Development Team, 2024), a detailed map was created that visually depicts the geographic distribution of hospitals categorized by their assigned clusters. This map, presented as Figure 5, provides an intuitive spatial representation to observe the geographic spread and concentration of hospitals within each cluster and across the region, which can be used to further support more informed decision-making regarding regional healthcare planning in HSC.

The clustering analysis identified three distinct groups of hospitals; each defined primarily by their geographic proximity to one another. The centroids, representing the central points of each cluster, were determined as follows: Cluster 1 centers around Hospital 17 at latitude 14.3214858 and longitude 100.6115472, Cluster 2 is anchored by Hospital 13 located at latitude 14.3171474 and longitude 100.2950401, and Cluster 3 is defined by Hospital 3 at latitude 14.5661187 and longitude 100.7209401. These locations are to be used for AM technology installation, which can inform decision makers for better locational and distribution planning in HSC next.

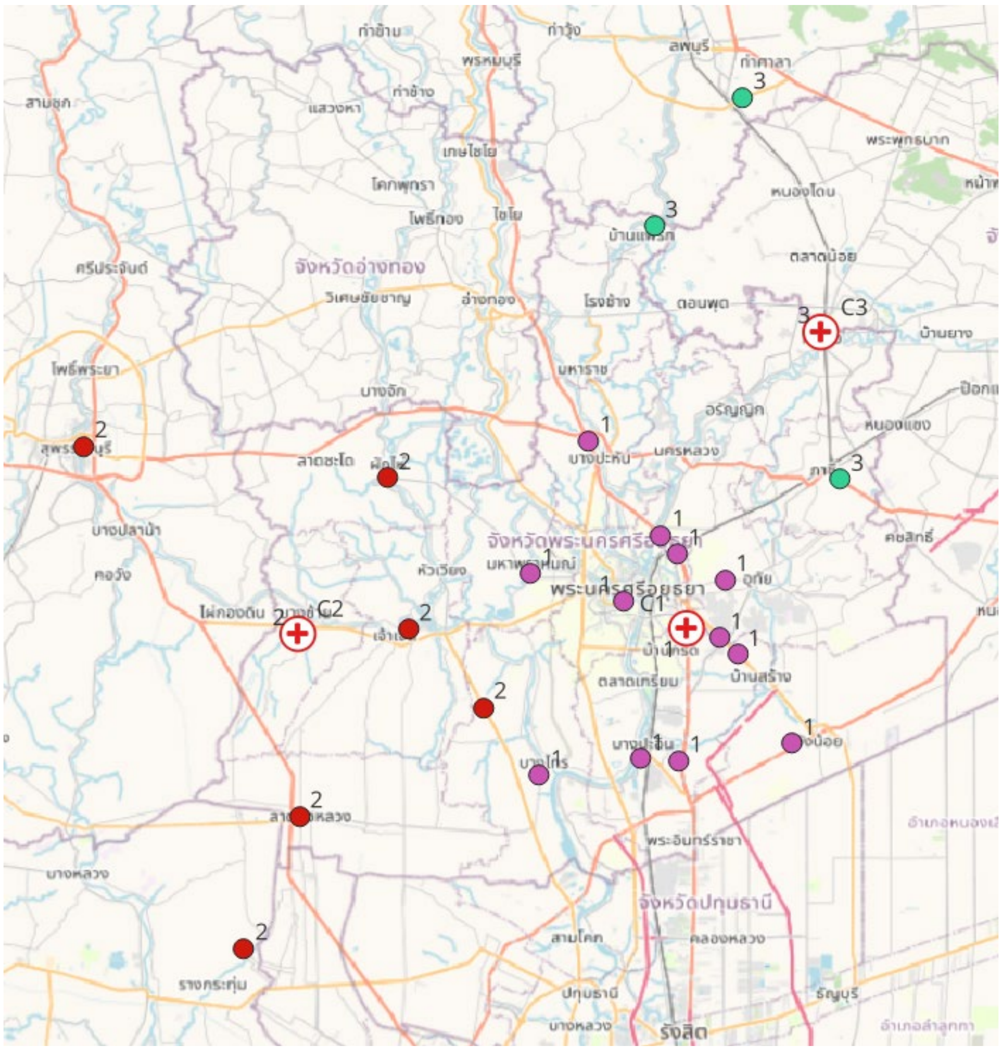

Figure 5 Map Showing Hospital Clustering Results Using K-Means Clustering (k = 3) Visualized with QGIS

The findings of this current study offer valuable policy and operational insights for enhancing HSC design through spatial analysis. By applying geographic clustering, policymakers and healthcare administrators can identify strategic locations for placing AM printers used for point-of-care medical production near cluster centroids to maximize accessibility and responsiveness. These cluster centers can also serve as regional production hubs or distribution nodes, enabling more efficient delivery of medical supplies to nearby hospitals. This approach supports the development of a demand-driven SCM that affects transportation time, logistics costs, and system resilience, which is an on-going assessment for AM technology-embedded HSC in our research plan.

6. Conclusion

This study demonstrates the practical research of K-Means clustering in analyzing the spatial distribution of hospitals to support more effective and responsive healthcare logistics systems in HSC. Three optimal clusters were identified among hospitals in the regional case study in Thailand, with spatial coherence confirmed through geographic visualization using QGIS. These clusters highlight natural groupings that can inform the strategic placement of future AM facilities—such as hub units for medical equipment units—either as decentralized nodes close to service points or as centralized hubs serving multiple hospitals. Looking ahead, our on-going future research will extend this framework by comparing centralized and decentralized AM network configurations. This includes evaluating trade-offs in logistics costs, lead time, and demand fulfillment using multi-objective mathematical optimization procedure to determine the optimal network design for various healthcare contexts and scenarios. Further studies could also incorporate real-time healthcare demand data and capacity constraints and evaluate complexity issues and computational efforts. Such research will help develop comprehensive models for data-driven healthcare logistics systems tailored to local and regional needs for future AM technology-embedded HSC.

References

Ahmed, R., Heese, H. S., and Kay, M., Designing a manufacturing network with additive manufacturing using stochastic optimisation, *International Journal of Production Research*, vol. 61, no. 7, pp. 2267–2287, 2023.

Anussornnitisarn, P., Nivasanon, C., Kim, N., and Ransikarbum, K., Sustainable technology selection in additive manufacturing: an integrated fuzzy decision analysis framework, *The International Journal of Advanced Manufacturing Technology*, pp. 1–20, 2025.

Awad, A., Trenfield, S. J., Goyanes, A., Gaisford, S. and Basit, A. W., 3D Printed Medicines: A New Era for Personalized Treatment, *Advanced Drug Delivery Reviews*, vol. 178, 2022.

Ben-Ner, A. and Siemsen, E., Decentralization and Localization of Production, *California Management Review*, vol. 59, no. 2, pp. 5–23, 2017.

Cui, M., Introduction to the k-means clustering algorithm based on the elbow method, *Accounting, Auditing and Finance*, vol. 1, no. 1, pp. 5–8, 2020.

Grand View Research, *3D Printing Medical Devices Market Size, Share & Trends Analysis Report by Component, by Technology, by Application, by End-use, by Region, and Segment Forecasts, 2023–2030*, 2023. Available: https://www.grandviewresearch.com/industry-analysis/3d-printing-medical-devices-market.

Ivanov, D., Tsipoulanidis, A. and Schönberger, J., Digital supply chain, smart operations and industry 4.0, *Global Supply Chain and Operations Management: A Decision-Oriented Introduction to the Creation of Value*, 3rd ed., Cham: Springer, pp. 481–526, 2019.

Kamble, S. S., Gunasekaran, A., Subramanian, N., Ghadge, A., Belhadi, A. and Venkatesh, M., Blockchain technology's impact on supply chain integration and sustainable supply chain performance: Evidence from the automotive industry, *Annals of Operations Research*, vol. 327, no. 1, pp. 575–600, 2023.

Kamble, S., Belhadi, A., Gupta, S., Islam, N., Verma, V. K. and Solima, L., Analyzing the Barriers to Building a 3-D Printing Enabled Local Medical Supply Chain Ecosystem, *IEEE Transactions on Engineering Management*, vol. 71, pp. 12974–12991, 2024.

Keskin, M. H., Koray, M., Kaya, E., Fidan, M. M. and Söğüt, M. Z., Additive Manufacturing for Remedying Supply Chain Disruptions and Building Resilient and Sustainable Logistics Support Systems, *Sustainability*, vol. 17, no. 6, article 2783, 2025.

Khajavi, S. H., Holmström, J. and Partanen, J., Additive manufacturing in the spare parts supply chain: Hub configuration and technology maturity, *Rapid Prototyping Journal*, vol. 24, no. 7, pp. 1178–1192, 2018.

Khedr, A. E., Alsahafi, Y. S. and Idrees, A. M., A Proposed Multi-Level Predictive WKM_ID3 Algorithm, Toward Enhancing Supply Chain Management in Healthcare Field, *IEEE Access*, vol. 11, pp. 125897–125908, 2023.

Kuraria, A., Jharbade, N. and Soni, M., Centroid selection process using WCSS and elbow method for K-mean clustering algorithm in data mining, *International Journal of Scientific Research in Science, Engineering and Technology*, vol. 4, no. 11, pp. 190–195, 2018.

Niemsakul, J., Ransikarbum, K., and Singkarin, D., Hospital-Location Classification and Analysis in the Healthcare Cold Chain using K-means Algorithm, *2022 International Conference on Engineering and Emerging Technologies (ICEET)*, pp. 1–6, Oct. 2022.

Nivasanon, C., Anussornnitisarn, P., and Ransikarbum, K., Techno-Economic Analysis between Traditional and Fused-Deposition Modeling-Based Additive Manufacturing, *Key Engineering Materials*, vol. 999, pp. 17–24, 2024.

Nuñez Rodriguez, J., Andrade Sosa, H. H., Villarreal-Archila, S. M., and Ortiz, A., The impact of additive manufacturing on supply chain management from a system dynamics model—Scenario: Traditional, centralized, and distributed supply chain, *Processes*, vol. 10, no. 12, p. 2489, 2022.

Özoğezylan, E., Çetinkaya, C., Demirel, N. and Sabırlıoğlu, O., Impacts of Additive Manufacturing on Supply Chain Flow: A Simulation Approach in Healthcare Industry, *Logistics*, vol. 1, no. 1, pp. 15–32, 2017.

Prabhu, R. M., Hema, G., Chepure, S. and Guptha, M. N., Logistics optimization in supply chain management using clustering algorithms, *Scalable Computing: Practice and Experience*, vol. 21, no. 1, pp. 107–114, 2020.

Peron, M., Saporiti, N., Coruzzolo, A. M., Lolli, F. and Holmström, J., The impact of Additive Manufacturing on supply chain resilience: a Delphi study, *Technological Forecasting and Social Change*, vol. 219, 2025.

Piffari, C., Lagorio, A. and Pinto, R., Challenges in Healthcare Supply Chain Resilience Management: A Conceptual Framework, *IFAC PapersOnLine*, vol. 58, no. 19, pp. 1126–1131, 2024.

QGIS Development Team, *QGIS Geographic Information System*, Version 3.28, Open Source Geospatial Foundation, 2024. Available: https://www.qgis.org

Ransikarbum, K., Chaiyaphan, C., and Pataratanased, R., Analysis of logistical aspect of food-safety system in the green supply chain using vehicle routing problem model, *2021 Research, Invention, and Innovation Congress: Innovation Electricals and Electronics (RI2C)*, pp. 48–53, Sept. 2021.

Ransikarbum, K., Kritchanchai, D., Chanpuypetch, W., and Niemsakul, J., Central Hospital Location and Distribution Planning Using Integrated K-Means and Vehicle Routing Algorithm in the Healthcare Chain, *Operations and Supply Chain Management: An International Journal*, vol. 17, no. 2, pp. 299–315, 2024.

Ransikarbum, K., and Madathil, S. C., Analysis of wood collection site in the biofuel supply chain using integrated K-means and rectilinear minisum location model, in *2022 Research, Invention, and Innovation Congress: Innovative Electricals and Electronics (RI2C)*, pp. 153–159, Aug. 2022.

Ransikarbum, K., and Mason, S. J., A bi-objective optimisation of post-disaster relief distribution and short-term network restoration using hybrid NSGA-II algorithm, *International Journal of Production Research*, vol. 60, no. 19, pp. 5769–5793, 2022.

Ransikarbum, K., Pitakaso, R., and Kim, N., A decision-support model for additive manufacturing scheduling using an integrative analytic hierarchy process and multi-objective optimization, *Applied Sciences*, vol. 10, no. 15, p. 5159, 2020.

Ransikarbum, K., Wattanasaeng, N., and Madathil, S. C., Analysis of multi-objective vehicle routing problem with flexible time windows: The implication for open innovation dynamics, *Journal of Open Innovation: Technology, Market, and Complexity*, vol. 9, no. 1, p. 100024, 2023.

Roozkhosh, P., Pooya, A., Soleimani Fard, O. and Bagheri, R., Designing a changeable multi-level supply chain network with additive manufacturing capability and costs uncertainty: A Monte Carlo approach, *Operational Research*, vol. 24, no. 1, article 5, 2024.

Song, C., Dennis, M., Burns, B., Levinson, D. and Moylan, E., Improved spatial equity in healthcare access from novel logistics strategies, *Journal of Transport Geography*, vol. 125, 104178, 2025.

Tyagi, S., Analytics in healthcare supply chain management in the new normal era: a review and future research agenda. Benchmarking, *An International Journal*, 31(6), pp 2151-2175, 2024.

Verboeket, V., Khajavi, S. H., Krikke, H., Salmi, M. and Holmstrom, J., Additive Manufacturing for Localized Medical Parts Production: A Case Study, *IEEE Access*, vol. 9, pp. 25818–25834, 2021.

Zamiela, C., Hossain, N. U. I. and Jaradat, R., Enablers of resilience in the healthcare supply chain: A case study of U.S healthcare industry during COVID-19 pandemic, *Research in Transportation Economics*, vol. 93, 2022.

Zhou, L., Miller, J., Vezza, J., Mayster, M., Raffay, M., Justice, Q., Al Tamimi, Z., Hansotte, G., Sunkara, L. D. and Bernat, J., Additive Manufacturing: A Comprehensive Review, *Sensors*, vol. 24, no. 6, article 2668, 2024.

Biographies

Chanipa Nivasanon is a Ph.D. candidate in the Department of Industrial Engineering at Kasetsart University, Thailand. Her research focuses on supply chain network design, additive manufacturing (AM), and multi-criteria decision-making (MCDM), particularly in the healthcare sector. Her research interests involve K-Means clustering for hospital grouping, multi-objective mathematical models for medical logistics routing, and the configuration of decentralized AM-integrated supply chains. Her recent work currently explores the strategic role of AM technologies in enhancing provincial healthcare and network systems. Through her interdisciplinary approach combining optimization modeling, spatial analysis, and sustainable production technologies, she addresses complex challenges in sustainable resource management.

Pornthep Anussornnitisarn is Head of the Department of Industrial Engineering at Kasetsart University, Thailand, with research expertise in operations research, production planning, logistics systems, and intelligent decision support. He holds a Ph.D. in Industrial Engineering from Purdue University and has published extensively on topics such as decentralized control, additive manufacturing, and healthcare logistics. His recent scholarly contributions reflect his interdisciplinary focus on smart systems and engineering optimization. With a strong academic footprint and leadership role, he actively advances the integration of digital and sustainable technologies into modern industrial applications and healthcare systems.

Kasin Ransikarbumb is an academic and researcher in the field of industrial engineering, currently affiliated with Ubon Ratchathani University, Thailand. He received the B.Eng. degree in Industrial Engineering from King Mongkut's University of Technology Thonburi (KMUTT), Bangkok, Thailand, the M.S. degree with dual title in Industrial Engineering and Operations Research from Pennsylvania State University (PSU), PA, USA, and the Ph.D. degree in Industrial Engineering from Clemson University, SC, USA. He has published papers in a number of prestigious, peer-reviewed journals and book chapters. His research interest includes supply chain and business management, logistics and transportation network, risk and humanitarian management, smart manufacturing and additive manufacturing, sustainability design, and renewable energies.