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Strategic Urban Warehouse Location Optimization Using a Socio-economic Center of Gravity Approach

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ABSTRACT

In the context of rapid urbanization and growing e-commerce activity, optimizing warehouse location is a crucial factor in ensuring efficient logistics performance and maintaining service-level agreements (SLAs). This study addresses the operational challenges faced by a digital commerce platform in Indonesia, particularly its overburdened warehouse in Ciracas, East Jakarta. The company currently serves over 300 daily transactions from a limited 211 m² facility, leading to delayed deliveries and suboptimal coverage across 50 sub-districts in the Greater Jakarta area (Jabodetabek). To determine a more strategic location, this research applies a weighted Center of Gravity (CoG) method incorporating two key indicators: permanent urban population and per capita disposable monthly income. These socio-economic variables are normalized and used to compute the optimal warehouse coordinates. The resulting CoG, which is located near Halim Perdanakusuma in East Jakarta, offers balanced proximity to all target areas and improved accessibility via major transportation routes, including toll roads and the Halim airport. While the exact coordinate falls within a residential zone, the surrounding area presents viable alternatives for warehouse development. Relocating to this vicinity is expected to reduce delivery lead times, enhance SLA compliance, and support expanded inventory management. This study demonstrates the value of spatial analytics and composite weighting in facility location decisions and offers a replicable framework for logistics optimization in dense urban regions.
Keywords: *Warehouse Location Optimization, Center of Gravity Method, Spatial Logistics Planning, Urban Distribution Network, Weighted Demand Modeling*

INTRODUCTION

In the current era of rapid e-commerce growth and urban consumer demand, logistics systems are under increasing pressure to provide faster and more reliable last-mile delivery services. For companies delivering Fast-Moving Consumer Goods (FMCG), fresh produce, electronics, and other household items, achieving timely and accurate deliveries is not only a service expectation but a competitive imperative. One of the most critical performance metrics in such environments is adherence to the Service Level Agreement (SLA), which, in this case, is defined as delivery completion within one working day. The studied company, a fast-growing digital commerce platform based in Indonesia, maintains a high SLA Key Performance Indicator (KPI) target of 98% for all transactions, reflecting its commitment to operational excellence.

Despite this commitment, internal delivery data show inconsistencies in SLA performance. As shown in Figure 1, a significant portion (55%) of deliveries are completed at the upper limit of the 3-day SLA threshold, while only 9% are delivered within one day. This skewed distribution reveals that many deliveries are barely compliant, rather than proactively efficient. Additionally, 36% of deliveries occur within two days, which is less than ideal yet not entirely unsuccessful. Such patterns point to systemic inefficiencies, likely stemming from poor spatial allocation of

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logistics assets, suboptimal warehouse location, or overburdened delivery hubs. Compounding this issue are observable data quality problems in operational dashboards, including missing or erroneous timestamps, inconsistent status logging, and manual entry errors. These deficiencies hinder real-time monitoring and root-cause analysis of SLA violations.

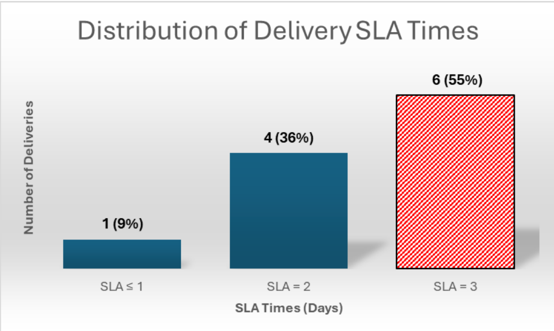

Figure 1. Distribution of Delivery SLA Times

The operational bottleneck is further exacerbated by capacity limitations. The company's Ciracas warehouse, originally intended as a small-scale fulfillment center, now handles over 300 daily transactions despite having only 211 m² of operational space. This site, initially chosen without a formal spatial analysis, is currently misaligned with both transaction volume and geographic distribution. As the company expands its operations from 30 to 50 sub-districts within the Greater Jakarta area (including Jakarta, Bogor, Depok, Tangerang, and Bekasi), as shown in Figure 2, having a high-capacity warehouse in a strategic location is essential. Company management has proposed relocating this warehouse to the area with a minimum space requirement of 1,000 m². This change aims to accommodate an increased diversity of SKUs and facilitate a shift from daily replenishment to a more efficient stocking system.

To address these challenges, this paper applies the Center of Gravity (CoG) method, which is a quantitative locational optimization model, to identify an optimal warehouse location with minimum average delivery distance while preserving coverage of all designated sub-districts. By integrating spatial sales volume data, vehicle efficiency, and fuel cost metrics, the proposed model aims to enhance SLA compliance, reduce delivery lead time, and improve inventory responsiveness. This research contributes to the growing body of work on urban logistics and facility location optimization, particularly within high-density, high-growth markets. The findings are positioned to offer both practical value for decision-makers and methodological rigor for scholarly contribution.

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Figure 2. Coverage Area for the Hub

As shown in Table 1, the CoG method is widely used for determining optimal warehouse and distribution center locations to minimize transportation costs and improve operational efficiency (Hanif et al., 2021; Margana et al., 2021; Sutaji & Hasibuan, 2021). However, the CoG method can produce biased results when data contamination or outliers are present, necessitating alternative approaches (Gao & Cui, 2021). To enhance decision-making, researchers often combine CoG with other methods such as the Analytical Hierarchy Process (AHP) to consider multiple criteria beyond just location (Sutaji & Hasibuan, 2021). The *p*-median method is another technique used alongside CoG to optimize warehouse locations (Hanif et al., 2021). Implementing these methods can lead to significant cost savings and improved distribution efficiency for businesses, as demonstrated in case studies of paper packaging products, utility stores, and a hijab-producing SME (Hanif et al., 2021; Margana et al., 2021; Sutaji & Hasibuan, 2021).

Recent research has increasingly examined the nuanced relationship between population metrics and demand estimation across various domains. One study proposed a modeling approach to represent electric vehicle populations for optimizing charging schedules and enabling more effective demand response strategies (Kovacevic & Vasak, 2023). Another challenged the conventional assumption that population size is the dominant driver of mobile spectrum demand, using machine learning and crowdsourced data to construct more accurate predictive models (Parekh et al., 2023). From a theoretical perspective, the concept of a representative consumer in aggregate demand has been re-evaluated, with findings suggesting that its existence does not imply optimal income distribution (Jerison, 2023). In an applied context, machine learning and interpretability techniques have been used to explore nonlinear relationships between population inflow and related factors, revealing that boosting algorithms outperform other models and exhibit pronounced nonlinearities, threshold effects, and interaction effects (Hu et al., 2023). Finally, a spatial modeling framework for locating perishable goods fulfillment centers near consumers was developed using population density as a proxy for demand (Ekanayake et al., 2023). Collectively, these studies underscore the complexity of using population data as a surrogate for demand and highlight the importance of incorporating multi-dimensional modeling approaches and advanced analytical techniques in demand analysis.

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Table 1. Related Works

Author(s)	Location Decision Techniques	Weight Approximation	Weight Normalization
(Hanif et al., 2021)	Center of Gravity (CoG) Method	Weekly demand or quantity of goods move from/to the store *i*.	No
(Margana et al., 2021)	Center of Gravity (CoG) Method	Quantity of goods move from/to the store *i*.	No
(Sutaji & Hasibuan, 2021)	Center of Gravity (CoG) Method	Quantity of goods move from/to the store *i*.	No
(Ekanayake et al., 2023)	The Centrality and Borda Count	Population density.	No
(Li et al., 2023)	Center of Gravity (CoG) Method	Permanent urban population. Floor area. Building energy consumption. Building carbon emissions of province *i*	No
(Yuan & Yuan, 2023)	Center of Gravity (CoG) Method	Permanent urban population.	No
(Wu et al., 2022)	Center of Gravity (CoG) Method	Permanent urban population. Per capita disposable monthly income of urban residents.	Yes
This Paper	Center of Gravity (CoG) Method	Permanent urban population. Per capita disposable monthly income of urban residents.	Yes

More recent research explored the integration of Ward's hierarchical clustering with K-means to identify logistics hubs while accounting for transportation costs (Nurprihatin et al., 2023). That work underscored the value of multi-stage clustering when locating cost-efficient hubs, inspiring our adaptation of weighted CoG to better reflect urban complexity and demand heterogeneity.

METHODS

The methodological framework adopted in this study follows a structured, quantitative approach to determine the optimal warehouse location using the CoG method. The steps are designed to ensure spatial efficiency, data integrity, and managerial relevance in warehouse location planning, as illustrated in Figure 3.

Step 1: Problem Identification
The study begins by identifying operational inefficiencies in the existing warehouse network, particularly focusing on SLA violations, capacity limitations, and high last-mile delivery costs. These problems motivate the need for relocation and optimization of warehouse placement.

Step 2: Define Coverage Area
The intended service area is defined in terms of geographic scope, comprising 50 sub-districts across the Greater Jakarta region (Jabodetabek). This step includes boundary delimitation and area segmentation to ensure representativeness in the spatial analysis.

Step 3: Data Collection
Quantitative data are collected from BPS-Statistics Indonesia, including permanent urban population and per capita disposable monthly income of urban residents for each sub-district. Geographic coordinates (longitude and latitude) of demand points are obtained using Google Maps.

Step 4: Weight Assignment
Each sub-district is assigned a weight based on two indicators, such as permanent urban population and per capita disposable monthly income of urban residents. The data on

permanent urban population and per capita disposable monthly income of urban residents are normalized by Equations (1) (Wu et al., 2022).

$$z_i' = \frac{z_i - z_{min}}{z_{max} - z_{min}} \quad (1)$$

where:

- z_i' : the indicator data after normalization.
- z_i : the indicator of location i (i = 1, 2,...,n).
- z_{min} : the minimum value of the indicator of location i (i = 1, 2,...,n).
- z_{max} : the maximum value of the indicator of location i (i = 1, 2,...,n).

This weighting ensures that high-demand areas exert a greater influence on the center of gravity calculation.

Step 5: Center of Gravity Calculation
Using the CoG formula, the weighted average coordinates are calculated using Equations (2) and (3) (Li et al., 2023).

$$X = \frac{\sum_{i=1}^{n} x_i W_i}{\sum_{i=1}^{n} W_i} \quad (2)$$

$$Y = \frac{\sum_{i=1}^{n} y_i W_i}{\sum_{i=1}^{n} W_i} \quad (3)$$

where:

- i : 1, 2,…,n.
- X : the longitude of the center of gravity.
- Y : the latitude of the center of gravity.
- x_i : the longitude of the geographical center of gravity of location i.
- y_i : the longitude of the geographical center of gravity of location i.
- W_i : the normalized weight, approximated by permanent urban population and per capita disposable monthly income of urban residents.

This computation yields the optimal central location that minimizes the weighted average distance to all demand points.

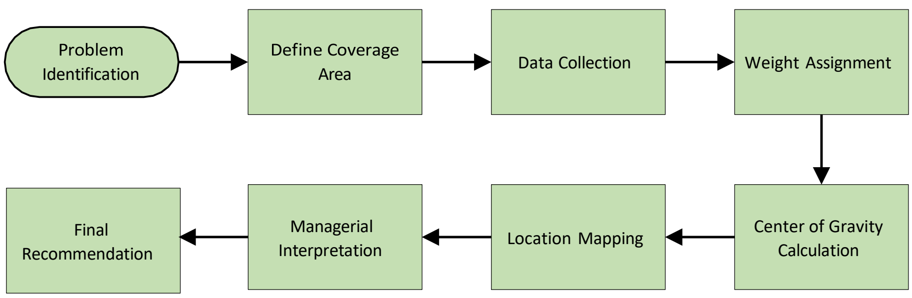

Figure 3. Research Flow Chart

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Step 6: Location Mapping
The resulting coordinates are plotted using Google Maps to verify their geographic feasibility.

Step 7: Managerial Interpretation
The spatial results are then analyzed from a strategic and operational standpoint. Factors such as warehouse operating costs, land availability, accessibility for inbound and outbound logistics, and alignment with company expansion goals are considered.

Step 8: Final Recommendation
Based on the spatial analysis and managerial review, a final recommendation is made regarding the proposed warehouse location. This recommendation balances quantitative optimization with practical feasibility, providing a robust basis for decision-making in strategic warehouse planning.

RESULTS AND DISCUSSION

This study extends the multi-stage clustering framework, where Ward's method identifies cluster groupings followed by K-means to finalize hub positions by shifting the analytical lens toward weighted spatial analytics (Rembulan & Nurprihatin, 2023). By emphasizing population and income distributions, the weighted CoG model in this paper offers a more nuanced resolution to last-mile delivery challenges in dense urban settings, as shown in Table 2.

Weight Assignment

To capture a more accurate representation of demand across the Jabodetabek area, this study assigns weights to each sub-district using two socio-economic indicators: permanent urban population and per capita disposable monthly income. These two variables are normalized using the min-max normalization technique (Equation 1) to ensure comparability and avoid skewed influence due to differences in scale.

The population variable reflects the potential market size or delivery volume, while the income variable serves as a proxy for purchasing power and order frequency. For instance, sub-districts in Jakarta Selatan (e.g., Jagakarsa, Pasar Minggu, and Kebayoran Baru) showed high weights due to the combination of large population and higher income levels. In contrast, some sub-districts in Bogor and Bekasi regencies had relatively lower weights due to lower income and population values.

This dual-indicator weighting system is in line with recent literature (Wu et al., 2022; Yuan & Yuan, 2023), which suggests that using composite indicators improves the precision of spatial optimization models. The final weights are then computed as the average of the normalized population and income scores. These weights serve as the basis for subsequent CoG computation, ensuring that the spatial center reflects both volume and value dimensions of demand.

Table 2. Weight Assignment and CoG Calculation

No	District	Municipality/ Regency	Latitude (X)	Longitude (Y)	Population in 2024 (People)[a]	Per Capita Disposable Monthly Income of Urban Residents in 2024 (IDR)[b]	Normalized Population	Normalized Expenses	Weight (W)	(X)(W)	(Y)(W)
1	Gunung Putri	Bogor Regency	-6.42886	106.9241	296,424	1,321,439	0.42510	0.00000	0.212551	-1.36646	22.72684
2	Cileungsi	Bogor Regency	-6.40597	106.9949	304,747	1,321,439	0.44184	0.00000	0.220919	-1.41520	23.63722
3	Klapanunggal	Bogor Regency	-6.48766	106.9169	142,166	1,321,439	0.11492	0.00000	0.057459	-0.37277	6.14334
4	Jonggol	Bogor Regency	-6.47649	107.0303	151,637	1,321,439	0.13396	0.00000	0.066981	-0.43380	7.169021
5	Cilodong	Depok Municipality	-6.43698	106.8355	184,950	2,823,228	0.20095	0.76886	0.484903	-3.12131	51.80483
6	Cinere	Depok Municipality	-6.33608	106.7883	100,988	2,823,228	0.03212	0.76886	0.400487	-2.53752	42.76731
7	Beji	Depok Municipality	-6.37588	106.8237	170,627	2,823,228	0.17215	0.76886	0.470502	-2.99987	50.26080
8	Sukmajaya	Depok Municipality	-6.38533	106.8473	255,723	2,823,228	0.34326	0.76886	0.556058	-3.55062	59.41335
9	Cimanggis	Depok Municipality	-6.36445	106.8591	251,002	2,823,228	0.33377	0.76886	0.551312	-3.50880	58.91270
10	Tapos	Depok Municipality	-6.40996	106.8768	278,704	2,823,228	0.38947	0.76886	0.579164	-3.71242	61.89917
11	Pancoran Mas	Depok Municipality	-6.39716	106.8001	254,701	2,823,228	0.34121	0.76886	0.555031	-3.55062	59.27736
12	Menteng	Jakarta Pusat	-6.19603	106.8331	85,016	2,443,794	0.00000	0.57460	0.287301	-1.78012	30.69324
13	Senen	Jakarta Pusat	-6.19345	106.8503	119,388	2,443,794	0.06912	0.57460	0.321859	-1.99342	34.39070
14	Johar Baru	Jakarta Pusat	-6.18305	106.8562	134,250	2,443,794	0.09900	0.57460	0.336801	-2.08246	35.98928
15	Cempaka Putih	Jakarta Pusat	-6.18267	106.8680	95,404	2,443,794	0.02089	0.57460	0.297745	-1.84086	31.81941
16	Kebayoran Baru	Jakarta Selatan	-6.24362	106.8001	148,241	3,274,714	0.12713	1.00000	0.563567	-3.51870	60.18900
17	Cilandak	Jakarta Selatan	-6.28452	106.8001	220,968	3,274,714	0.27337	1.00000	0.636687	-4.00127	67.99825
18	Mampang Prapatan	Jakarta Selatan	-6.25061	106.8208	152,437	3,274,714	0.13557	1.00000	0.567786	-3.54901	60.65131
19	Pasar Minggu	Jakarta Selatan	-6.29398	106.8237	324,691	3,274,714	0.48194	1.00000	0.740971	-4.66366	79.15326
20	Jagakarsa	Jakarta Selatan	-6.33491	106.8237	379,385	3,274,714	0.59192	1.00000	0.795961	-5.04234	85.02746
21	Pancoran	Jakarta Selatan	-6.25230	106.8473	174,542	3,274,714	0.18002	1.00000	0.590010	-3.68892	63.04098
22	Tebet	Jakarta Selatan	-6.23185	106.8473	231,318	3,274,714	0.29419	1.00000	0.647093	-4.03259	69.14015
23	Setiabudi	Jakarta Selatan	-6.21956	106.8326	113,147	3,274,714	0.05657	1.00000	0.528283	-3.28569	56.43786
24	Kebayoran Baru	Jakarta Selatan	-6.24362	106.8001	148,241	3,274,714	0.12713	1.00000	0.563567	-3.51870	60.18900
25	Cakung	Jakarta Timur	-6.18262	106.9477	582,327	2,430,017	1.00000	0.56755	0.783774	-4.84578	83.82285
26	Duren Sawit	Jakarta Timur	-6.22954	106.9182	445,443	2,430,017	0.72475	0.56755	0.646150	-4.02522	69.08520

27	Pulogadung	Jakarta Timur	-6.19360	106.8912	297,922	2,430,017	0.42811	0.56755	0.497831	-3.08337	53.21379
28	Matraman	Jakarta Timur	-6.20328	106.8621	182,981	2,430,017	0.19699	0.56755	0.382269	-2.37132	40.85006
29	Jatinegara	Jakarta Timur	-6.23070	106.8827	318,819	2,430,017	0.47013	0.56755	0.518841	-3.23274	55.45517
30	Makasar	Jakarta Timur	-6.27119	106.8945	221,367	2,430,017	0.27418	0.56755	0.420862	-2.63931	44.98788
31	Kramat Jati	Jakarta Timur	-6.28258	106.8591	317,427	2,430,017	0.46734	0.56755	0.517442	-3.25087	55.29337
32	Cipayung	Jakarta Timur	-6.32725	106.9004	306,965	2,430,017	0.44630	0.56755	0.506923	-3.20743	54.19030
33	Ciracas	Jakarta Timur	-6.32311	106.8709	320,779	2,430,017	0.47408	0.56755	0.520812	-3.29315	55.65964
34	Pasar Rebo	Jakarta Timur	-6.32616	106.8562	236,387	2,430,017	0.30438	0.56755	0.435964	-2.75798	46.58542
35	Pulogadung	Jakarta Timur	-6.19360	106.8912	297,922	2,430,017	0.42811	0.56755	0.497831	-3.08337	53.21379
36	Kelapa Gading	Jakarta Utara	-6.16045	106.9055	144,911	3,045,738	0.12044	0.88277	0.501606	-3.09012	53.62439
37	Tambun Utara	Bekasi Regency	-6.17876	107.0658	218,021	1,898,977	0.26745	0.29568	0.281563	-1.73971	30.14572
38	Tambun Selatan	Bekasi Regency	-6.26119	107.0421	427,718	1,898,977	0.68911	0.29568	0.492393	-3.08297	52.70682
39	Cikarang Barat	Bekasi Regency	-6.30048	107.0894	201,159	1,898,977	0.23354	0.29568	0.264609	-1.66717	28.33686
40	Cikarang Selatan	Bekasi Regency	-6.32589	107.1256	165,881	1,898,977	0.16260	0.29568	0.229141	-1.44952	24.54683
41	Setu	Bekasi Regency	-6.36343	107.0421	201,835	1,898,977	0.23490	0.29568	0.265289	-1.68815	28.39709
42	Cibitung	Bekasi Regency	-6.23351	107.1071	258,282	1,898,977	0.34841	0.29568	0.322041	-2.00745	34.49290
43	Jatisampurna	Bekasi Municipality	-6.36208	106.93	133,237	3,132,705	0.09696	0.92730	0.512130	-3.25821	54.76208
44	Bantar Gebang	Bekasi Municipality	-6.33964	106.989	112,370	3,132,705	0.05500	0.92730	0.491150	-3.11372	52.54769
45	Pondok Melati	Bekasi Municipality	-6.31092	106.93	132,448	3,132,705	0.09538	0.92730	0.511337	-3.22701	54.67726
46	Mustikajaya	Bekasi Municipality	-6.30285	107.0185	239,726	3,132,705	0.31109	0.92730	0.619195	-3.90269	66.26532
47	Jatiasih	Bekasi Municipality	-6.31013	106.9536	270,344	3,132,705	0.37266	0.92730	0.649979	-4.10145	69.51755
48	Rawalumbu	Bekasi Municipality	-6.27789	107.0008	226,482	3,132,705	0.28446	0.92730	0.605879	-3.80364	64.82958
49	Pondok Gede	Bekasi Municipality	-6.27002	106.93	253,935	3,132,705	0.33966	0.92730	0.633481	-3.97194	67.73811
50	Bekasi Barat	Bekasi Municipality	-6.23820	106.9654	286,309	3,132,705	0.40476	0.92730	0.666030	-4.15483	71.24215
51	Bekasi Utara	Bekasi Municipality	-6.20640	107.0008	349,943	3,132,705	0.53272	0.92730	0.730008	-4.53072	78.11144

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52	Bekasi Timur	Bekasi Municipality	-6.23625	107.0244	261,795	3,132,705	0.35547	0.92730	0.641383	-3.99983	68.64367
53	Bekasi Selatan	Bekasi Municipality	-6.25824	106.9772	214,400	3,132,705	0.26017	0.92730	0.593732	-3.71572	63.51580
								Total	25.77264	-161.862	2755.191
								Longitude	$\frac{-161.862}{25.77264} = \mathbf{-6.280398166}$		
								Latitude	$\frac{2755.191}{25.77264} = \mathbf{106.9036815}$		

[a]Sources: (BPS-Statistics Indonesia Bekasi Municipality, 2025; BPS-Statistics Indonesia Bekasi Regency, 2025; BPS-Statistics Indonesia Bogor Regency, 2025; BPS-Statistics Indonesia Depok Municipality, 2025; BPS-Statistics Indonesia Jakarta Pusat Municipality, 2025; BPS-Statistics Indonesia Jakarta Selatan Municipality, 2025; BPS-Statistics Indonesia Jakarta Timur Municipality, 2025; BPS-Statistics Indonesia Jakarta Utara Municipality, 2025)

[b]Sources: (BPS-Statistics Indonesia Bekasi Municipality, 2024; BPS-Statistics Indonesia Bekasi Regency, 2024; BPS-Statistics Indonesia Bogor Regency, 2024; BPS-Statistics Indonesia Depok Municipality, 2024; BPS-Statistics Indonesia Jakarta Pusat Municipality, 2024; BPS-Statistics Indonesia Jakarta Selatan Municipality, 2024; BPS-Statistics Indonesia Jakarta Timur Municipality, 2024; BPS-Statistics Indonesia Jakarta Utara Municipality, 2024)

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Center of Gravity Calculation

The next phase involves applying the weighted average CoG formula (Equations 2 and 3) to compute the optimal latitude and longitude based on the assigned weights and sub-district coordinates. The total weighted summation for longitude and latitude was calculated by multiplying the geographic coordinates of each sub-district by their corresponding weight and then dividing by the sum of all weights.

The final CoG coordinates are:
Latitude: -6.280398166
Longitude: 106.9036815

These coordinates point to Halim Perdanakusuma, located in East Jakarta. The central location is strategically situated to minimize the average delivery distance across all 50 covered sub-districts. This result suggests a significant potential for improving delivery efficiency and achieving better SLA compliance, which is particularly in areas previously underserved due to the remote positioning of the current Ciracas warehouse. However, the exact point is the residential area, so the company needs to find another area around this point while considering the toll road and the Halim Perdanakusuma Airport, which is only around 8.6 km away as the inbound and outbound logistics route.

Additionally, the weighted average method inherently prioritizes areas with high transaction potential, as evident from the dominant contribution of Jakarta Selatan and Jakarta Timur sub-districts in the CoG output. These results validate the methodological choice of weight-driven CoG over purely geometric or distance-based approaches.

Location Mapping

To verify the feasibility of the calculated CoG, the coordinates were plotted using Google Maps. The result places the optimal point within a residential zone in Halim Perdanakusuma. Although this zone may not be commercially viable for warehouse development, the surrounding area offers promising alternatives.

Crucially, the proposed area benefits from direct access to the Halim Perdanakusuma Airport, which is a critical node for air cargo and is located near several toll road junctions (e.g., JORR and Jakarta-Cikampek). This connectivity makes it highly favorable for inbound and outbound logistics operations.

The spatial mapping also shows that the CoG is equidistant from high-demand clusters such as South Jakarta, East Jakarta, and the southern part of Bekasi Municipality. This balance supports cost-efficient delivery routes and resource allocation across the service area. Compared to the existing warehouse in Ciracas, the proposed location reduces geographic skew and enables a more centralized replenishment and distribution strategy.

Overall, the mapping process confirms that while exact coordinates require practical adjustments due to zoning regulations, the general vicinity of the CoG represents a strategically sound and operationally advantageous area for warehouse relocation.

CONCLUSIONS

This study applied a quantitative CoG approach to optimize warehouse location for a growing e-commerce platform operating in Jabodetabek. By incorporating normalized population and income data, the model proposed the area of Halim Perdanakusuma, East Jakarta, as the optimal site. This location aligns strategically with both high-demand regions and transportation infrastructure.

The relocation will address several operational pain points: warehouse capacity overflow, non-compliance with SLA targets, and delivery inefficiencies. While the CoG point itself is within a residential zone, adjacent areas offer practical alternatives for real estate acquisition.

Managerial Implications

The findings from this study offer significant practical value for logistics managers and strategic decision-makers in the fast-growing e-commerce and retail distribution sectors. The use of a CoG model that integrates both demographic (population) and economic (income) indicators provides a data-driven foundation for warehouse relocation decisions. For the case company, relocating the current warehouse from Ciracas to the vicinity of Halim Perdanakusuma has the potential to alleviate operational bottlenecks, particularly in managing space constraints and improving adherence to the SLA. By situating the warehouse closer to the calculated CoG, logistics operations can benefit from reduced delivery lead times, more balanced coverage across the Jabodetabek region, and improved inventory responsiveness. Moreover, the proximity to toll roads and Halim Perdanakusuma Airport enhances accessibility for both inbound and outbound logistics, allowing for a more streamlined and scalable distribution network. From a managerial perspective, this study underscores the importance of aligning warehouse infrastructure with current and projected demand patterns using spatial analytics, rather than relying solely on legacy site decisions or ad-hoc heuristics.

Recommendation

While the CoG method demonstrated its utility in optimizing warehouse location using normalized socio-economic data, future research can further enhance the model's robustness and practical relevance. First, incorporating real-time transactional data such as actual order volume and delivery frequency would provide a more granular and dynamic basis for weighting demand points. Second, a multi-criteria decision-making (MCDM) framework, such as the Analytical Hierarchy Process (AHP) or Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), could be integrated to consider qualitative and operational factors, including land cost, traffic congestion, zoning regulations, and environmental constraints. The AHP and TOPSIS were successfully applied in the supplier selection process within the construction sector to evaluate additional qualitative factors like land cost, zoning regulations, infrastructure quality, and strategic alignment (Nurprihatin et al., 2022). Third, simulation models or geographic information system (GIS)-based route optimization tools may be employed to evaluate the performance of multiple location scenarios under varying logistical conditions. Lastly, the adoption of machine learning models for forecasting future demand distribution, which incorporates trends in urbanization, infrastructure development, and consumer behavior, can help organizations remain agile in evolving market contexts. These avenues will not only extend the methodological contributions of this study but also provide deeper insights for urban logistics planning in other metropolitan regions.

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