The Digital Frontline: A Thematic Analysis of User Grievances and Satisfaction Drivers for Indonesian Public Service Apps

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Abstract. This research assesses Indonesia's digital public service ecosystem by analyzing 50 mobile applications from a wide range of state agencies. Using a computational content analysis of metadata and user reviews from the Google Play Store, this study presents a dual-faceted evaluation. First, a thematic analysis of negative reviews (1-2 stars) reveals that user grievances are overwhelmingly dominated by foundational issues, such as login/access problems, slow performance, and technical glitches, rather than a lack of advanced features. Second, a corresponding analysis of positive reviews (5 stars) identifies that user satisfaction is primarily driven by high-quality features, ease of use, and overall application reliability. Quantitative findings show significant performance disparities across institutional categories, with Ministry-developed apps receiving the lowest average user satisfaction. An Importance-Performance Quadrant Analysis further uncovers a critical paradox: many high-download, mandatory apps suffer from low user ratings, indicating a clear disconnect between enforced adoption and user-centric quality. The research concludes that enhancing digital public services requires a strategic shift from feature proliferation to foundational reliability. Ensuring robust core functionalities is paramount to building citizen trust and achieving a successful digital transformation.

Keyword: E-Government, Public Service, Quadrant Analysis, Thematic Analysis, User Satisfaction.

1. Introduction

The digitalization of the public sector represents a significant change in the way citizens and governments interact through services, processes, and regulations to make them digital, and to increase overall efficiency, citizen effectiveness, and government accountability. However, this development brings several challenges, from the digital divide and cultural change within organizations to security threats. Digitalization enhances operational productivity, speeds up service processes, and promotes accountability through transparent data and performance documentation [1], [2] . Digital services help increase citizen-satisfaction and enable a more citizen-centred service design in the citizen-government interaction [3]. Digitalisation can cut operational costs, eliminate maladministration, and thereby support bureaucratic reform [4], [5]. Citizen-centred demand, readiness, and participation are critical factors for the successful adoption of e-government. Good frameworks focus on citizen orientation over channels and technology orientation [6], [7]. E-government combines multiple channels (web, mobile, cloud, AI, blockchain) to integrate systems for greater efficiency and innovation in public services [8]. E-government frameworks include national plans and policies, technology standards, cross-agency cooperation, and public-private partnerships for sustainability and scalability [9], [10]. Modern e-government frameworks should incorporate data protection, privacy, and alignment with sustainable development goals [11], [12]. Mobile apps allow citizens to access government services anywhere and anytime, increasing efficiency, convenience, and speed [13]. Some apps allow citizens to report urban issues and feedback and to participate in decision-making, enhancing public participation [14]. The use of mobile apps can lead to citizens' satisfaction in public service and trust in government, provided they are user-friendly, secure, and prompt in delivering services [15].

More government apps are not always better or more usable. Quality of service, ease of use, and relevance to citizen needs matter far more than the sheer number of available apps. Reliability, security, accessibility, information quality, interactivity, and responsiveness are among the dimensions that have the highest influence on citizens' perceptions of an application's usefulness. High service quality positively affects citizens' intention to use an application [16], [17]. Citizens appreciate functional and efficient applications more than those focusing on transparency without offering actual solutions, since they prefer apps that help them find a solution quickly [18]. User satisfaction and perceived value are pivotal in mediating the impact of service quality on continued use intention; if an app does not meet their expectations or is inadequate, they are likely to abandon it [19]. Studies have shown a significant gap in the perception of service quality between government agencies and the public. It is common that governments claim their services are adequate, while the public feels unsatisfied with the services they receive [20], [21].

A user-centred perspective judges the success of digital services primarily based on user experience, needs, and perception rather than solely on technical or administrative criteria. The success of digital services depends significantly on user experience (UX) and user engagement during co-creation [22]. The direct measure of user activity, such as the active usage ratio, can be used as an objective indicator for the success of a digital service [23]. User-generated data such as ratings, text reviews, and download counts from the Google Play Store are valuable and reliable primary data for evaluating the quality, satisfaction, and user preferences of digital applications. Classifying applications based on factors of importance and performance is crucial for understanding user behaviour and informing development strategy. Several studies have combined Importance-Performance Analysis with app store data to identify priorities for feature development and strategic improvement [24]. Text reviews, another key data source, can be processed with NLP and machine learning to understand sentiment and major themes. Studies have verified that both ratings and reviews can be used to predict application quality and identify areas for improvement [25], [26], [27]. Evidence-based policy (EBP) is an essential foundation for improving public service quality and sustainability by enhancing policy legitimacy and public trust [28], [29].

2. Research Method

This research employs a computational content analysis design with a quantitative cross-sectional strategy. This architecture was selected as it is appropriate for systematically and objectively analysing large volumes of unstructured user review content and structured application metadata. The cross-sectional nature of the study is reflected in data collected at a specific point in time (October 13, 2025) to sample the ecosystem of Indonesian public service apps. The entire process of data crawling and thematic classification was automated using Python scripts to ensure transparency, scalability, and methodological replicability.

2.1. *Preliminary Search and Data Collection*

The first step was to compile a list of 50 common names of public service applications in Indonesia to be used as search keywords. To achieve depth and functional institutional diversity, we included a wide variety of cases (including applications from ministries, regional governments, and state-owned enterprises). We used the google-play-scraper Python library to perform the data retrieval. The script automatically conducted a search on the Google Play Store (region: Indonesia) and returned up to five candidate applications for each keyword. The single best application among the candidates was selected using a custom filtering algorithm (calculate_relevance_score) that considers the similarity between the application name and the search term. This procedure ensured that every app in the final sample demonstrated maximum relevance for its intended purpose, yielding 50 apps validated for analysis.

After the population was decided, two forms of data from each application were gathered: (1) extensive metadata (over 30 characteristics, including app_name, developer, rating, downloads) to create the Apps_Data dataset and (2) user reviews. A complex retrieval strategy for reviews was performed, including "Most Relevant," "Newest," and "Rating" sorts. The reviews were then merged and deduplicated by reviewId to form a unique corpus. From this corpus, two derived datasets were created: Summary_Rating, which summarizes the star rating distribution, and Reviews_Data, which contains the review text for qualitative analysis.

2.2. *Text Pre-processing*

The raw text from the collected user reviews underwent a standard pre-processing pipeline to prepare it for thematic analysis. This pipeline, applied to the Indonesian-language text, included five steps:

1) Case Folding (transforming the text to its lowercase form),

2) Punctuation and Character Removal,

3) Stopword Removal (removing common words using the Sastrawi library with an additional custom list),

4) Stemming (transforming words into their root form using an Indonesian stemmer from Sastrawi), and

5) Tokenization and Filtering (splitting the text into single words and filtering tokens with a length of less than three characters).

2.3. *Rule-Based Thematic Classification*

A rule-based thematic classification approach was used to cluster the content of user reviews, selected for its transparency and ability to detect pre-specified themes. To provide a balanced perspective as suggested by the reviewers, this analysis was conducted in two separate phases:

1) Analysis of Negative Reviews (1-2 Stars): A domain lexicon (problem_categories) was manually created based on a preliminary observation of high-frequency words in the negative review corpus. This ontology includes 10 problem types (e.g., technical_issues, login_access, slow_performance) associated with a collection of relevant keywords.
2) Analysis of Positive Reviews (5 Stars): A similar process was conducted exclusively for 5-star reviews. A distinct lexicon of positive themes (satisfaction_categories) was developed to identify the primary drivers of user satisfaction, with categories such as good_features, easy_to_use, and fast_performance.

For both analyses, a multi-label classifier was used. This algorithm scanned each pre-processed review for keywords from the respective lexicon. A review could be assigned multiple labels if it contained keywords from different categories, allowing for the encoding of complex feedback within a single message. The classified data was then aggregated for quantitative analysis to compute the frequency of each problem and satisfaction category.

2.4. Importance-Performance Quadrant Analysis

To generate deeper strategic insights as suggested by the reviewers, we conducted an Importance-Performance Quadrant Analysis (IPQA). This method plots all 50 applications on a 2x2 matrix based on two key metrics:

1) Importance (X-axis): Represented by the total number of user downloads. This metric serves as a proxy for an application's public reach, relevance, or mandated use.
2) Performance (Y-axis): Represented by the average user rating (from 1 to 5 stars). This metric reflects user-perceived quality and satisfaction.

The axes were divided based on the mean downloads and mean rating calculated for each institutional category, creating four distinct quadrants: (1) High Performance-High Importance, (2) High Performance-Low Importance, (3) Low Performance-High Importance, and (4) Low Performance-Low Importance. This visualization helps identify strategic priorities and performance gaps across the digital service landscape. Categories falling into the 'Low Performance-High Importance' quadrant, for instance, represent critical areas requiring immediate resource allocation and strategic improvement to meet user expectations. Conversely, the 'High Performance-High Importance' quadrant identifies key strengths to be maintained, while the 'High Performance-Low Importance' quadrant may signal an inefficient use of resources on services that are not highly valued by users.

2.5. Research Tools

The entire investigation was conducted using a suite of software tools. The primary programming language was Python (version 3.9+). Key libraries included: google-play-scraper for data scraping; pandas and numpy for data manipulation; Sastrawi and nltk for Natural Language Processing; and re (Regular Expressions) and openpyxl for text processing and data export.

3. Result and Discussion

Our analysis provides a multi-dimensional view of Indonesia's digital public service application ecosystem. This section first presents the qualitative findings from a dual-faceted thematic analysis of user reviews to understand the core drivers of citizen satisfaction and grievances. Subsequently, we present a strategic mapping of the ecosystem through an Importance-Performance Quadrant Analysis to identify performance gaps and strategic priorities.

3.1. Thematic Analysis of User Reviews

To understand the qualitative experiences behind the quantitative ratings, we first analyzed the content of thousands of user reviews, separating them into grievances (1-2 star reviews) and satisfaction drivers (5-star reviews). The analysis of negative reviews reveals a critical insight: user frustration stems not from a lack of advanced features, but from consistent failures in core functionalities. Figure 1 summarizes the distribution of the most common complaint categories. The data shows that foundational issues are the primary source of user grievances. Slow Performance is the most cited problem, appearing in 9,568 reviews (affecting 62.7% of the review corpus). This is closely followed by Login & Access issues, mentioned in 9,435 reviews (61.9%). Problems where a Feature is Not Working and general Technical Issues also represent a significant portion of complaints. The fact that these basic usability barriers are prevalent across all 50 sampled applications indicates a systemic challenge in delivering stable digital services.

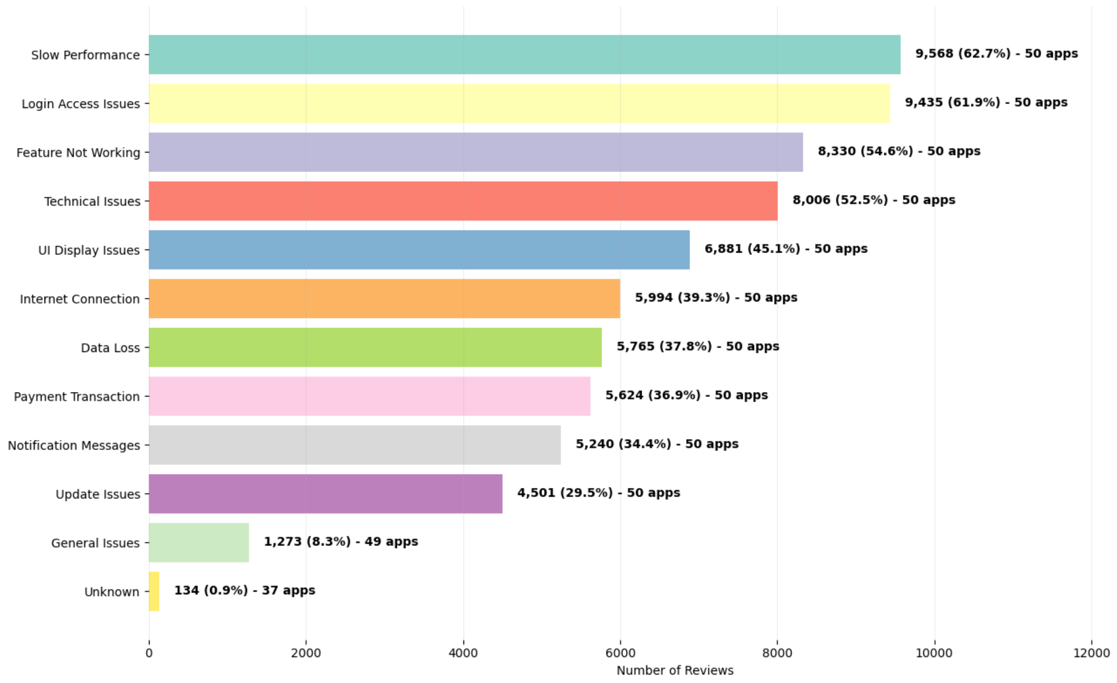

Figure 1. Distribution of Complaint Categories from Negative User Reviews.

Conversely, to provide a balanced perspective as suggested by the reviewers, we conducted a parallel analysis of 5-star reviews. The findings, illustrated in figure 2, highlight what users value most. Overwhelmingly, the most dominant driver of satisfaction is the presence of Good Features, cited in 4,287 positive reviews (76.3%). This suggests that when functionalities are well-implemented and genuinely useful, users respond very positively. This is followed by Ease of Use, which was mentioned in 2,342 reviews (41.7%). This data clearly indicates that a successful digital public service app is one that not only works reliably but is also simple and straightforward for the average citizen to navigate.

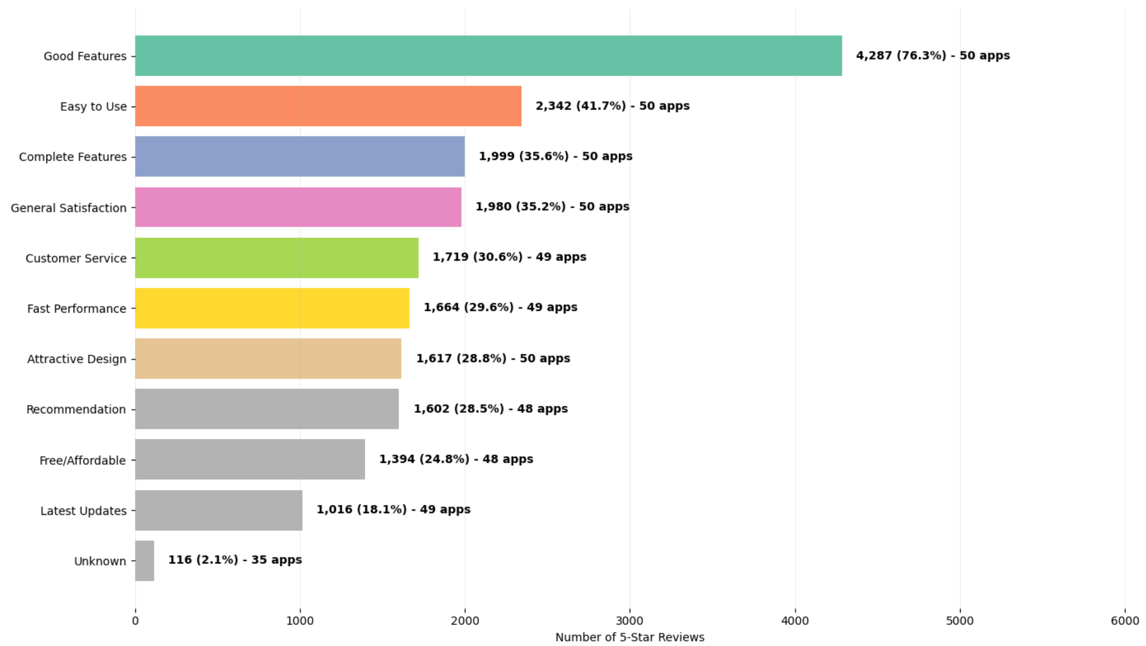

Figure 2. Distribution of Positive Feedback Categories from 5-Star User Reviews.

3.2. *Importance-Performance Analysis*

To generate deeper strategic insights, we conducted an Importance-Performance Quadrant Analysis (IPQA) to map applications based on their public reach (Importance, via downloads) and perceived quality (Performance, via rating). The analysis reveals a clear performance hierarchy across institutional categories, with each group facing unique strategic challenges. The analysis begins with Ministries of the Republic of Indonesia, which exhibits the most significant challenges. The performance benchmarks for this group, which form the axes of the quadrant, are set at a mean rating of 3.60 and mean downloads of 11,022,178. As detailed in table 1 and visualized in figure 3, a critical finding is that applications with the highest importance (e.g., SATUSEHAT Mobile, Identitas Kependudukan Digital, Aplikasi Cek Bansos) fall squarely in the "Low Performance - High Importance" quadrant. These are often mandatory apps that, despite their vast reach, create widespread user dissatisfaction, posing a significant risk to public trust.

In contrast, the State-Owned Enterprises (SOEs) category demonstrates a strong correlation between market competition and quality. The axes for this group are set at a mean rating of 3.73 and mean downloads of 19,115,160 (see table 2 for details). As shown in figure 4, apps in competitive sectors like banking (BRImo) and transportation (Access by KAI) are clear leaders in the "High Performance - High Importance" quadrant. Conversely, apps for newer or monopolistic services, such as Whoosh - Kereta Cepat and Sobat IndiHome, lag behind, suggesting that market pressure is a significant driver of quality. This dynamic seemingly compels established apps in competitive spaces to innovate rapidly based on user feedback, whereas newer or monopolistic services lack the same urgent incentive to iterate.

Table 1. Matrix of public service applications for the ministry category

Application Name	Developer Category	Rating	#User Ratings	#User Reviews	#User Downloads
SATUSEHAT Mobile	Ministry of Health	3.3436103	1,111,035	444,171	92,413,565
Identitas Kependudukan Digital	Ministry of Home Affairs	3.0526392	68,353	38,941	25,167,824
M-Pajak	Ministry of Finance	2.6617782	10,875	6,480	5,274,984
Aplikasi Cek Bansos	Ministry of Social Affairs	3.5596802	69,923	51,360	16,660,808
SP4N LAPOR!	Ministry of Administrative and Bureaucratic Reform	2.4	3,105	2,240	229,549
OSS Indonesia	Ministry of Investment	3.3846154	3,398	1,912	1,023,676
Ruang GTK	Ministry of Primary and Secondary Education	4.8989396	224,920	21,027	5,263,326
Rumah Pendidikan	Ministry of Primary and Secondary Education	4.52	666	307	414,062
Portal DJKI	Ministry of Law and Human Rights	3.642857	70	35	17,038
Safe Travel	Ministry of Foreign Affairs	3.6633663	978	318	107,076
SIAPkerja	Ministry of Manpower	2.6302326	4,211	2,899	2,189,679
Sentuh Tanahku	Ministry of Agrarian Affairs and Spatial Planning	4.833157	37,974	20,157	3,550,684
SIGA MOBILE	Ministry of Trade	3.1806312	17,232	4,832	1,098,292
MitraDarat	Ministry of Transportation	4.625	12,739	2,881	899,935

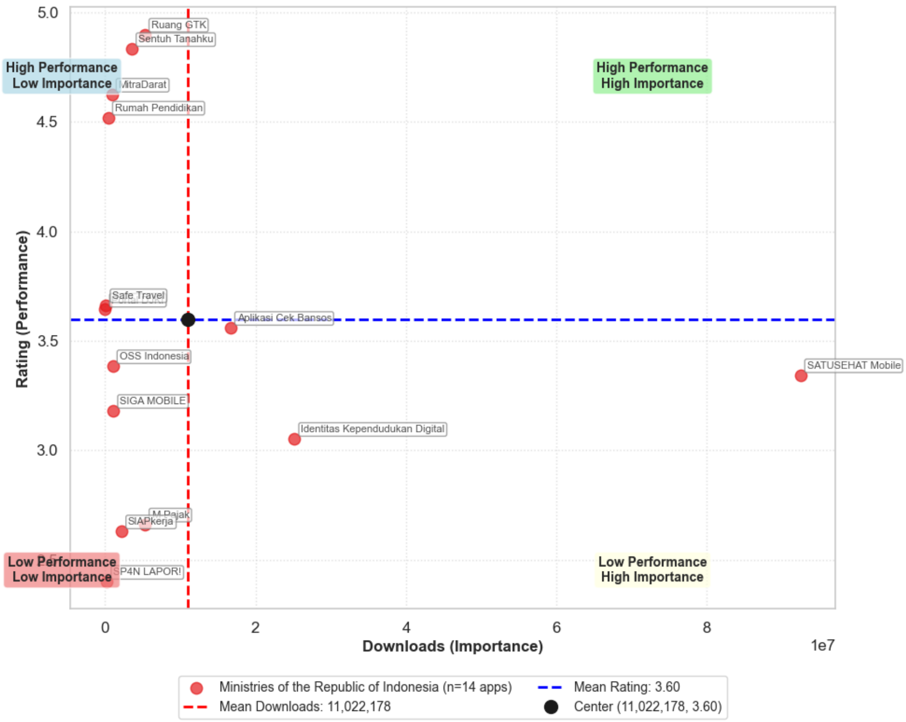

Figure 3. IPQA for Ministries of the Republic of Indonesia Mobile Apps.

Table 2. Matrix of public service applications for state-owned enterprises (SOEs)

Application Name	Developer Category	Rating	#User Ratings	#User Reviews	#User Downloads
PLN Mobile	PT PLN (Persero)	4.904367	1,310,966	630,753	25,980,165
Access by KAI	PT Kereta Api Indonesia (Persero)	4.724571	385,927	131,625	25,407,811
MyPertamina	PT Pertamina (Persero)	4.578091	466,065	222,741	22,096,917
Taspen Otentikasi	PT TASPEN (Persero)	3.263439	54,492	32,547	6,997,975
Ferizy	PT ASDP Indonesia Ferry (Persero)	3.503372	16,280	9,154	3,282,358
Tring! by Pegadaian	PT Pegadaian (Persero)	3.825311	105,474	58,962	10,434,325
POSPAY	PT Pos Indonesia (Persero)	3.500894	42,077	27,294	12,067,847
FlyGaruda	PT Garuda Indonesia (Persero) Tbk	4.139299	27,173	9,589	2,688,759
BRImo	Bank Rakyat Indonesia (BRI)	4.707823	2,013,382	855,810	79,117,684
Livin' by Mandiri	Bank Mandiri	4.09464	668,158	291,742	46,146,234
wondr by BNI	Bank Negara Indonesia (BNI)	4.835134	678,563	68,835	11,375,878
BYOND by BSI	Bank Syariah Indonesia (BSI)	3.194337	65,911	52,645	5,986,359
bale by BTN	Bank Tabungan Negara (BTN)	3.949721	28,726	16,793	7,944,810
MyTelkomsel – Buy Internet	PT Telkom Indonesia (Persero) Tbk	3.984676	11,254,814	2,849,178	153,743,453

Application Name	Developer Category	Rating	#User Ratings	#User Reviews	#User Downloads
Sobat IndiHome	PT Telkom Indonesia (Persero) Tbk	1.130952	1,623	1,328	292,455
PosAja!	PT Pos Indonesia (Persero)	4.052718	18,275	7,653	883,728
PELNI	PT PELNI (Persero)	2.929453	5,734	3,658	1,832,841
DAMRI Apps	Perum DAMRI	3.927129	11,073	6,198	1,346,146
E-meterai Scanner	Perum PERURI	2.1	192	145	77,944
Travoy	PT Jasa Marga (Persero) Tbk	4.755725	13,082	1,929	652,292
Kimia Farma Mobile - Beli Obat	PT Kimia Farma Tbk	3.552358	16,327	13,894	1,300,391
Whoosh - Kereta Cepat	PT KCIC	2.384106	1,549	980	877,157

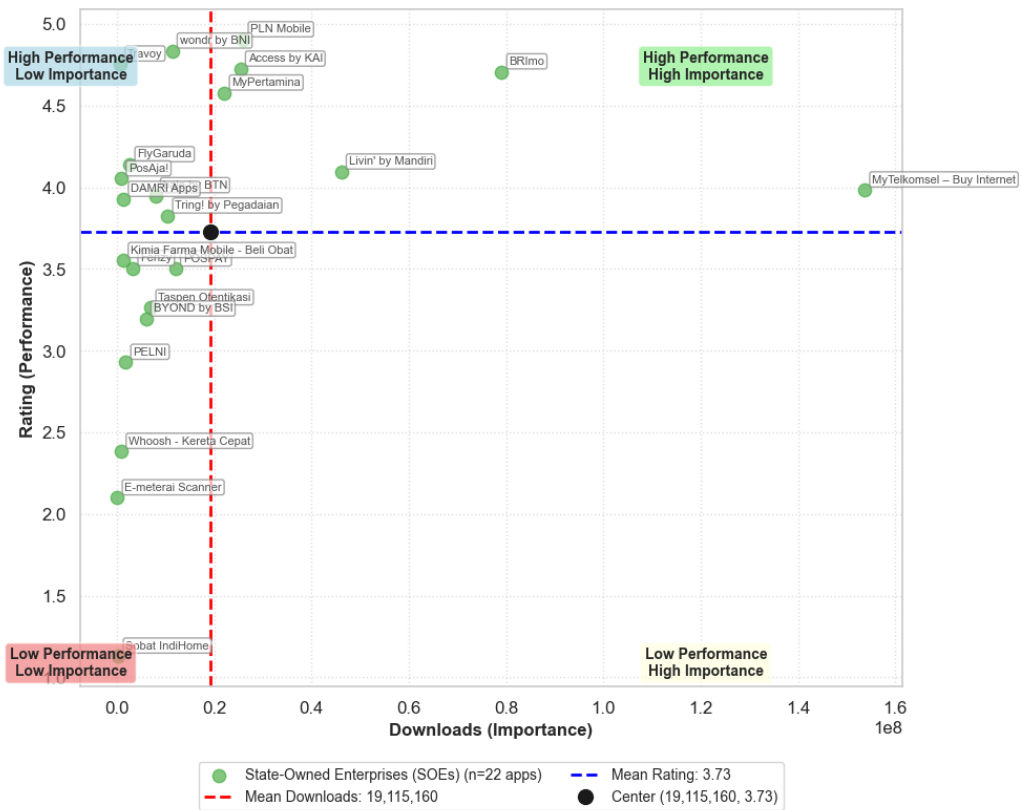

Figure 4. IPQA for State-Owned Enterprises mobile apps.

The Regional Government and Enterprise category, while the smallest, showcases the high potential of localized digital platforms. With performance benchmarks at a mean rating of 3.92 and mean downloads of 1,821,951 (table 3), the integrated "Super App" Sapawarga successfully occupies the "High Performance - High Importance" quadrant (figure 5), demonstrating a model for achieving both high adoption and user satisfaction at a regional level.

Table 3. Matrix of public service applications for regional government and enterprise

Application Name	Developer Category	Rating	#User Ratings	#User Reviews	#User Downloads
JAKI - Jakarta Kini	Provincial Government of DKI Jakarta	3.918641	12,696	6,151	3,621,223
Sapawarga - Jabar Super Apps	Provincial Government of West Java	4.216306	11,926	6,178	3,596,046
MyMRTJ	PT MRT Jakarta (Perseroda)	4.500666	52,219	2,281	990,697
TJ:Transjakarta	PT Transportasi Jakarta	4.11368	5,210	3,597	846,230
LRTJ Apps	PT LRT Jakarta	2.86	152	66	55,558

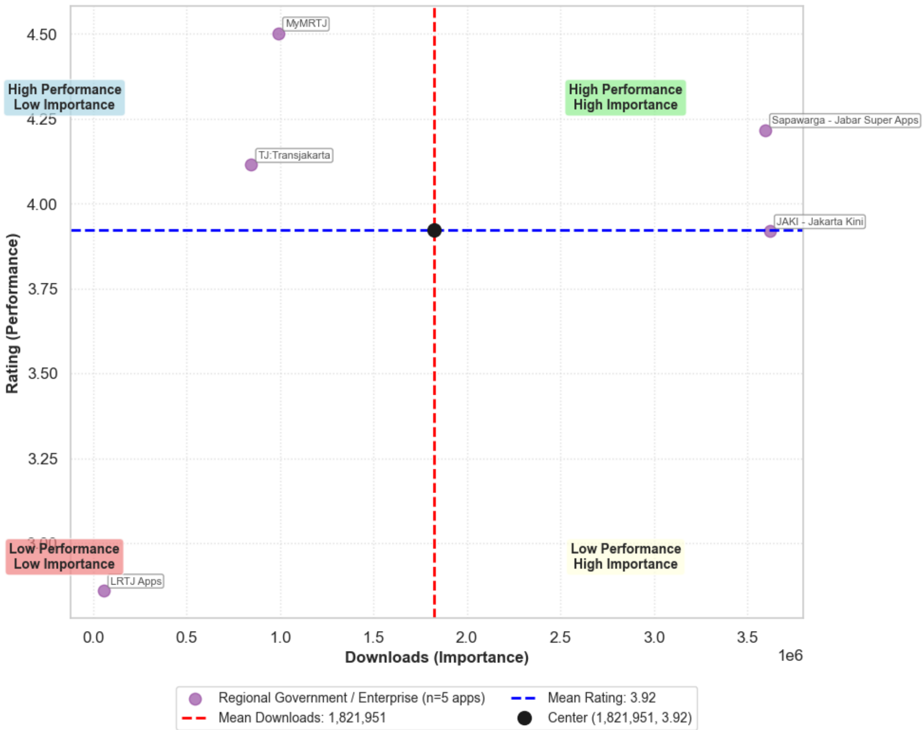

Figure 5. IPQA for Regional Government and Enterprise.

Finally, the Non-Ministerial Government Institutions category features some of the ecosystem's top performers. Centered on a mean rating of 3.85 and mean downloads of 18,472,869 (table 4), essential social security apps JMO (Jamsostek Mobile) and Mobile JKN are dominant figures in the "High Performance - High Importance" quadrant (figure 6). Their success serves as a benchmark, proving that public agencies can deliver world-class digital services.

Table 4. Matrix of public service applications for non-ministerial government institutions

Application Name	Developer Category	Rating	#User Ratings	#User Reviews	#User Downloads
Mobile JKN	Health Social Security Administering Body (BPJS)	4.424765	900,427	360,053	76,822,259
JMO (Jamsostek Mobile)	Social Security Administering Body for Employment	4.731549	3,895,707	546,663	49,838,934
Super App Polri	Indonesian National Police (POLRI)	4.647931	104,598	40,200	8,955,378
Info BMKG	Agency for Meteorology, Climatology, and Geophysics (BMKG)	4.332178	82,245	23,598	10,188,984
Jaga	Corruption Eradication Commission (KPK)	3.090909	2,339	1,360	674,545
iPusnas	National Library of Indonesia (Perpusnas)	2.149019	36,403	22,948	3,642,076
MyASN BKN	National Civil Service Agency (BKN)	4.176537	17,817	8,191	5,351,509
BPOM Mobile	National Agency of Drug and Food Control (BPOM)	2.466667	3,763	2,170	1,757,480
SIGNAL–SAMSAT DIGITAL NASIONAL	Indonesian National Police (POLRI)	4.63169	264,570	90,690	9,024,656

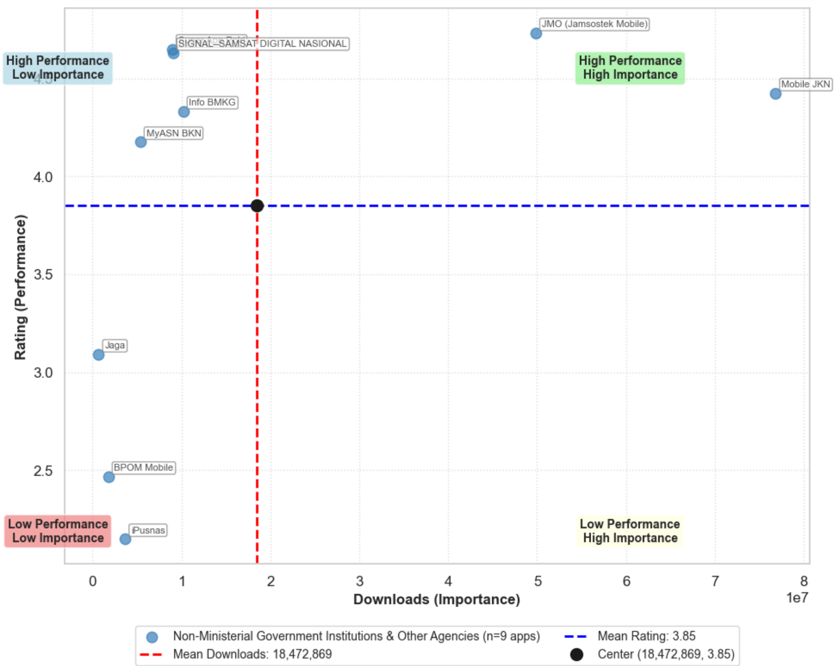

Figure 6. IPQA for Non-Ministerial Government Institutions.

Integrating these findings reveals the central paradox of this study: popularity does not equal quality. High download numbers are often a function of policy or necessity, not user choice. The "Low Performance" status of an app like SATUSEHAT Mobile, as detailed in table 1, is directly explained by the high prevalence of user complaints regarding login access issues and slow performance found in our thematic analysis. Conversely, the "High Performance" status of JMO (table 4) corresponds to positive feedback praising its good features and easy to use. The true measure of success, as revealed by user reviews, lies in fundamental reliability and usability.

4. Conclusion

This study conducted a comprehensive evaluation of Indonesia's digital public service application ecosystem through a dual-faceted computational analysis. Our findings reveal a landscape of stark contrasts. The thematic analysis of user reviews identified a fundamental crisis: the primary sources of user grievances are not missing features but failures in core reliability, including issues with login/access, performance, and technical stability. Conversely, our analysis of positive reviews showed that users highly value applications that are reliable, feature-rich, and easy to use. This highlights a clear path forward: foundational quality must precede feature complexity.

The Importance-Performance Quadrant Analysis further uncovered a critical paradox where massive download volumes, particularly for mandatory applications developed by Ministries, do not correlate with user satisfaction. This signals that adoption is often driven by necessity rather than quality, creating a significant trust deficit. The IPQA provides a strategic map whose underlying causes are explained by the thematic analysis. The "Low Performance" status of an app like SATUSEHAT Mobile, for instance, is a direct result of the high prevalence of login/access and slow performance issues identified in user reviews. In contrast, institutions operating in more competitive environments or with a clear user-centric focus (notably in the SOE and Non-Ministerial Agency categories) have proven capable of delivering highly successful and well-regarded digital services.

This research offers two primary contributions. Academically, it presents a replicable methodological framework for conducting a large-scale, bottom-up audit of an E-Government ecosystem using user-generated data. By combining dual-faceted thematic analysis with a strategic quadrant model, our approach offers a holistic method for evaluating digital service performance. Practically, our findings offer a clear roadmap for policymakers and developers in Indonesia. The strategic imperative is to shift focus from merely launching new applications to ensuring their fundamental reliability and accessibility. Investment must be prioritized to strengthen the technological foundation, ensuring seamless login processes, responsive performance, and stable core functionalities.

While this study provides valuable insights, we acknowledge its limitations. The cross-sectional data, collected at a single point in time, provides a snapshot of the ecosystem; a longitudinal study could track performance changes over time. Furthermore, our analysis is confined to the Android ecosystem via the Google Play Store and does not capture the experiences of iOS users or non-users of public service apps. Future research could adopt a longitudinal approach to monitor improvements or a comparative analysis with the iOS App Store to provide a more complete picture of the national digital service landscape. By addressing the core issues identified in this study, government institutions can bridge the gap between the promise of digital transformation and the reality of citizen experience, ultimately building the trust required for a successful digital nation.

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Harnessing the Potential of the Blue Economy in Central Java: Mapping, Strategic Development, and Macroeconomic Analysis

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Abstract. The findings reveal significant disparities among the southern coastal, northern coastal, and non-coastal areas. The southern coastal regions exhibit higher BEI values compared to their northern coastal and non-coastal counterparts, which fall below the average. Results from the Two-Step System GMM regression analysis indicate that internet usage, infrastructure, and the COVID-19 period exert significant effects on the BEI. Specifically, infrastructure development, proxied by Nighttime Light (NTL), demonstrates a negative impact on the BEI, suggesting that environmentally unsustainable infrastructure may undermine the sustainability of the blue economy. Meanwhile, access to digital technology through internet usage plays a crucial role in fostering inclusive blue economy growth. Based on these findings, the proposed policy recommendations include optimizing environmentally friendly infrastructure development, leveraging digital technology to expand market access, and strengthening the resilience of the blue economy through Adaptive-Responsive-Innovative (ARI) crisis policies. Consequently, the development of the blue economy in Central Java is expected to enhance the sustainable welfare of coastal communities while fully optimizing the potential of coastal areas.
Keyword: Big Data, Blue Economy, Blue Economy Index, Central Java, Two-Step System GMM

Introduction

The Blue Economy is a sustainability-oriented economic concept that harnesses marine resources wisely while taking into account economic, social, and environmental dimensions in the long run [1]. This concept has become a strategic focus for Indonesia's development, particularly in achieving the vision of Indonesia Emas 2045. The development of the blue economy is regarded as a source of inclusive and sustainable growth, as it generates substantial economic and social benefits while serving as a game changer in Indonesia's development agenda.

Central Java Province, with a coastline stretching 971.52 kilometers across 17 regencies, is among the regions with the greatest blue economy potential in Indonesia. Its marine area covers 1.7 million hectares and encompasses 45 small islands, making it a strategic zone for the development of the fisheries sector. Various key fishery commodities—such as catfish (Clarias), tilapia (Oreochromis), milkfish (Chanos chanos), seaweed, and vannamei shrimp (Litopenaeus vannamei)—play a crucial role in providing high-protein food, creating employment opportunities, and increasing foreign exchange earnings.

The fisheries sector in Central Java holds a strategic role in national economic development. The provincial government has set a target to develop this sector into one that is self-reliant, advanced, and resilient. According to the vision of the Central Java Marine and Fis

heries Office, marine and fisheries development is directed toward realizing sovereignty, sustainability, and the welfare of coastal communities and fisheries actors. Ultimately, this development is expected to improve community welfare, generate employment, and promote a fisheries sector that is both independent and competitive.

Despite the immense potential of the blue economy and fisheries sector in Central Java, coastal communities have not fully benefited from its development. This is reflected in the fact that 12.5 percent of Central Java's poverty is concentrated in coastal areas, highlighting a gap between vast economic potential and the welfare of coastal populations. In principle, sustainable marine resource management should drive inclusive economic growth; however, this has not yet been fully achieved in the coastal regions of Central Java [1].

Despite the immense potential, a significant gap persists between the blue economy's promise and the welfare of coastal communities in Central Java. A primary reason for this disconnect is a critical research gap in how the blue economy is measured and analyzed at a sub-national level. Previous studies on Indonesia's blue economy have predominantly relied on conventional, aggregated national statistics. Such data often masks significant local disparities and fails to provide the granular, real-time insights necessary for effective, evidence-based policymaking at the regency and municipal levels. This limitation makes it difficult to identify specific areas that are underperforming or the precise factors driving success.

This study directly addresses this gap in two fundamental ways. First, it pioneers the use of big data, including satellite imagery and digital sensors, to construct a comprehensive Blue Economy Index (BEI) for all 35 regencies/municipalities in Central Java. This approach overcomes the limitations of traditional secondary data by offering a more detailed and dynamic mapping of blue economy potential. Second, much of the existing research employs static analytical models that fail to capture the complex, dynamic, and potentially endogenous relationships between macroeconomic factors and blue economy performance. To fill this methodological gap, this study utilizes a Two-Step System GMM approach. This dynamic panel data model is specifically chosen for its ability to address issues of endogeneity and persistence over time, thereby providing more robust and reliable insights into the true drivers of the blue economy.

Research Method

Conceptual Framework

Based on the literature review, the conceptual framework proposed in this study is as follows:

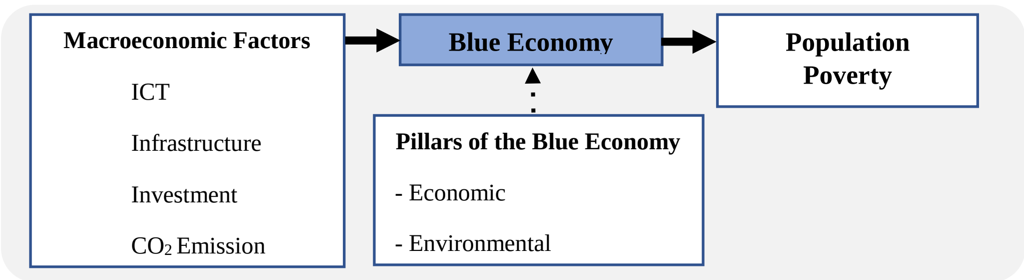

Figure 1. Conceptual Framework of The Study.

Data Sources and Operational Variables

This research employs secondary data and big data, covering 35 regencies/municipalities in Central Java for the period 2019–2023, with the research variables presented in Appendix 1. Secondary data were obtained from statistical publications by Statistics Indonesia (BPS) and the Ministry of Marine Affairs and Fisheries (Kemen-KKP). Other data were derived from satellite imagery processing and digital sensing results (Appendices 3 to 6), which enable monitoring of environmental conditions such as the number of marine tourism sites, mangrove forest area, and CO_2 emissions.

Measurement of the Blue Economy Index (BEI)

Constructing the framework and determining variables

The BEI developed in this study is based on three dimensions of the blue economy: Economic (E), Environmental (L), and Social (S) pillars (Appendix 2).

The selection of variables for the BEI, particularly the Environmental (L) pillar, was governed by the principles of data availability and spatial granularity at the regency/municipality level. While a comprehensive measure of marine ecosystem health would ideally include factors like water quality and biodiversity metrics, the Environmental pillar was constructed using three robust, measurable indicators: waste management capacity (OL), critical coastal ecosystem health (LM), and general environmental quality (TP). This selection ensures a focused measure of human impact and natural resource protection, representing the most accessible and verifiable environmental data points available through both conventional and big data sources for this specific geographic scale. Future research, as data availability improves, can incorporate more indicators.

The selection of variables for the BEI, particularly the Environmental (L) pillar, was strategically governed by two factors: ecological importance and data granularity at the regency/municipality level. While an ideal BEI would include comprehensive indicators like water quality and biodiversity, the chosen variables (waste management capacity (OL), critical coastal ecosystem health (LM), and general environmental quality (TP)) serve as robust, verifiable proxies for measuring human impact and natural resource protection where sub-national data is scarce. We acknowledge that this limits the scope to key verifiable inputs but ensures the index remains a practical, policy-relevant tool for Central Java's local governments.

Data normalization

Data normalization was conducted since the variables used to construct the BEI have different measurement units. The method applied is min-max normalization, which transforms each indicator value into a scale ranging from 0 to 1 using the following formula:

$$l_k^t = \frac{x_k^t - (x_k)}{(x_{kmax}) - (x_{kmin})},\ k = 1,2,\ldots.,10; t = 1,2,\ldots,9 \tag{1}$$

Where: l_k^t : Normalized value of indicator k in year t — (x_{kmax}) : Maximum value of indicator k

x_k^t : Original value of indicator k in year t — (x_{kmin}) : Minimum value of indicator k

Weighting and aggregation process

The weighting process was carried out to derive the BEI and its sub-indices. This study applies the equal weighting method.

$$\underline{IEB_t} = \frac{\underline{\underline{SIE_t + SIL_t + SIS_t}}}{3} \tag{2}$$

$$\underline{SIE_t} = \frac{\sum_{i=1}^{4} SIE_{it}}{4}; \underline{SIL_t} = \frac{\sum_{i=1}^{3} SIL_{it}}{3}; \underline{SIS_t} = \frac{\sum_{i=1}^{4} SIS_{it}}{4}$$

Where:

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$\underline{IEB_t}$: Average Blue Economy Index in year t

$\underline{SIE_t}$: Average economic sub-index in year t

$\underline{SIL_t}$: Average environmental sub-index in year t

$\underline{SIS_t}$: Average social sub-index in year t

SIE_{it}: Economic index of region i in year t

SIL_{it}: Environmental index of region i in year t

SIS_{it}: Social index of region i in year t

Data Analysis and Econometric Model

The analytical techniques employed in this study consist of both descriptive and inferential analysis. Descriptive analysis was conducted using tables and thematic maps, while inferential analysis utilized an econometric regression model with panel data. Data processing was carried out using R, Python, and ArcGIS software.

The econometric method applied in this study is Dynamic Panel Regression with the Generalized Method of Moments (GMM) approach. This method was chosen because static panel regression models such as the Fixed Effects Model (FEM) tend to produce biased and inconsistent estimators in cases where the dynamics of variables over time are present [2]. The use of GMM helps mitigate issues related to heteroskedasticity, autocorrelation, and endogeneity.

The GMM procedure was implemented using the two-step system approach, due to the limited number of observations and time periods, as well as the weak instrument problem associated with the difference procedure [3]. The GMM model in this study incorporates the lag of the Blue Economy Index (BEI) as an explanatory variable and applies instrumental variable techniques to address potential endogeneity caused by bidirectional causality between the BEI and other endogenous variables.

The specification of the Dynamic Panel-Data estimation model with the Two-Step System Generalized Method of Moments (Two-Step System GMM) is formulated as follows:

$$IEB_{i,t} = \alpha + \beta_1 LIEB_{i,t-1} + \beta_2 LPOV_{i,t} + \beta_3 LNET_{i,t} + \tag{3}$$
$$+\beta_4 LNTL_{i,t} + \beta_5 LPMTB_{i,t} + \beta_6 LCO_{i,t} + \beta_7 COVID_{i,t} + \mu_{i,t} + \sigma_{i,t} + \varepsilon_{i,t}$$

Where:

$IEB_{i,t}$: Blue Economy Index for region *i* in year *t*

$IEB_{i,t-1}$: Lagged Blue Economy Index

$POV_{i,t}$: Poverty level

$NET_{i,t}$: Internet usage (ICT)

$NTL_{i,t}$: Infrastructure (proxied by Nighttime Light)

$PMTB_{i,t}$: Investment

$CO_{i,t}$: CO_2 emissions

$COVID_{i,t}$: COVID-19 dummy variable

μ_i : Region-specific effect

σ_t : Time-specific effect

$\varepsilon_{i,t}$: Error term

Result and Discussion

3.1 Descriptive Analysis

The poverty rate across districts and municipalities in Central Java Province in 2023 exhibits substantial variation, reflecting diverse socio-economic disparities among regions. Kebumen Regency recorded the highest proportion of poor residents, whereas several municipalities such as Salatiga and Magelang reported relatively low poverty levels. This inequality not only reflects differences in access to resources and economic opportunities but also highlights various structural factors influencing community welfare at the local level.

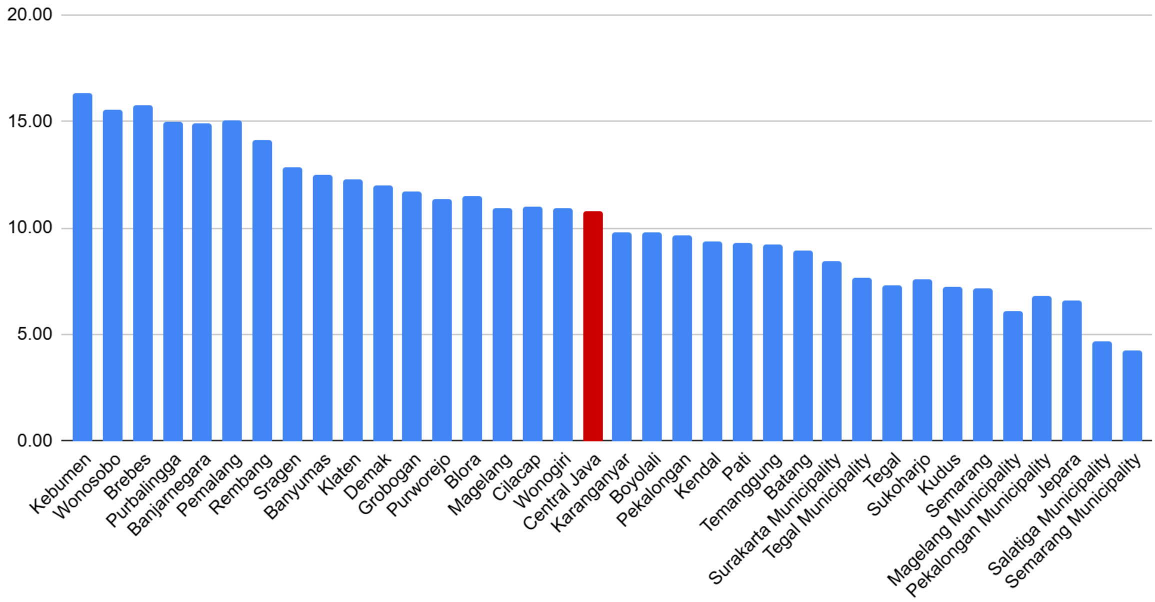

Figure 2. Poverty Rate of Districts/Municipalities in Central Java Province, 2023

The economic pillar of the blue economy is represented by the variables of Aquaculture Production (IB), Capture Fisheries Production (IT), Marine Tourism Activities (PB), and Fisheries Gross Regional Domestic Product (PD). Overall, IB has emerged as the fastest-growing sector, while IT has remained low and stagnant. PB experienced a decline, particularly during the COVID-19 pandemic, whereas PD remained stable, albeit not yet optimal. Future challenges lie in enhancing the marine tourism and capture fisheries sectors, which continue to lag behind, while sustaining the rapid growth of aquaculture.

The environmental pillar is represented by the variables of Percentage of Villages with Waste Management Mechanisms (OL), Mangrove Forest Area (LM), and Percentage of Villages Without Air, Marine, or Other Pollution (TP). On average, the extent of mangrove forests has fluctuated annually. Mangroves play a crucial role in maintaining coastal ecosystem balance and contribute to the sustainability of marine resources. OL has increased, indicating stronger efforts in waste management at the village level. In contrast, LM has remained relatively stable, though with a slight decline in 2020. Meanwhile, TP experienced a sharp decline in 2020 but gradually recovered in subsequent years. Collectively, these variables illustrate both the challenges and continuous efforts undertaken to preserve environmental balance and ecological sustainability.

The social pillar is represented by Fish Consumption Calorie Intake (KI), Monthly Per Capita Expenditure (PM), Human Development Index (HDI), and the Number of Fishers and Aquaculture Farmers (NT). KI and NT exhibited considerable fluctuations, with declines in certain years reflecting dynamics in consumption patterns and fisher engagement in the fisheries sector. Conversely, HDI and PM demonstrated stable and upward trends each year, indicating improvements in living standards and community welfare. This pattern reflects persistent challenges in the marine and fisheries sector, yet also highlights ongoing efforts to enhance social well-being.

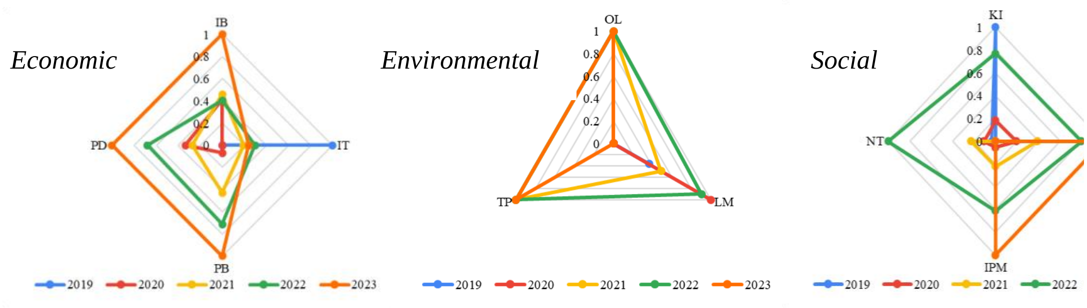

Figure 3. Radar Diagram of Sub-Index Indicators, 2019–2023 (Normalized Data)

Furthermore, the percentage of internet usage (NET) showed a substantial increase from 2019 to 2023. The NTL variable (proxy for infrastructure development) also recorded steady annual growth, whereas PM (proxy for investment) displayed a fluctuating pattern (Appendix 7).

3.2 Results of the Blue Economy Index in Districts/Municipalities of Central Java

One of the primary objectives of this study is to identify and map the potential of the blue economy across 35 districts and municipalities in Central Java through the measurement of the Blue Economy Index (IEB). During the 2019–2023 period, the IEB exhibited a consistent upward trend. In 2019, the index value stood at 0.32, which increased to 0.36 in 2023. This indicates a steady improvement in productivity and the blue economy climate in Central Java.

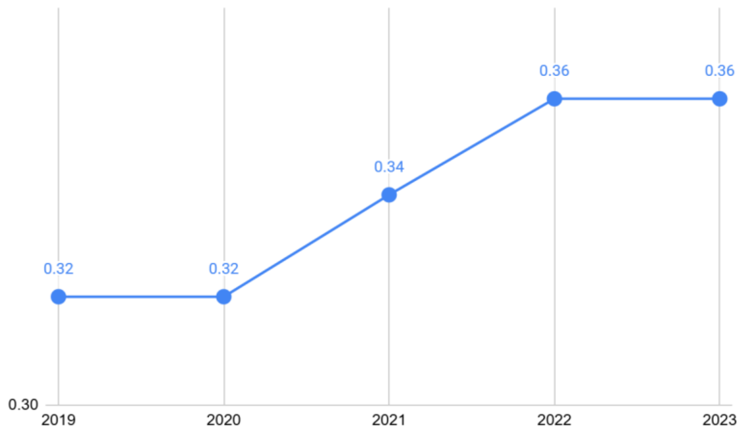

Figure 4. Average Blue Economy Index of Central Java, 2019–2023

In general, the IEB of Central Java demonstrates a positive trend, with notable increases in several districts and municipalities over the 2019–2023 period. However, significant disparities persist across regions, suggesting that the potential of the blue economy in certain areas has not been fully optimized. This highlights the need for development strategies that are more tailored to the specific characteristics of each locality to ensure balanced progress.

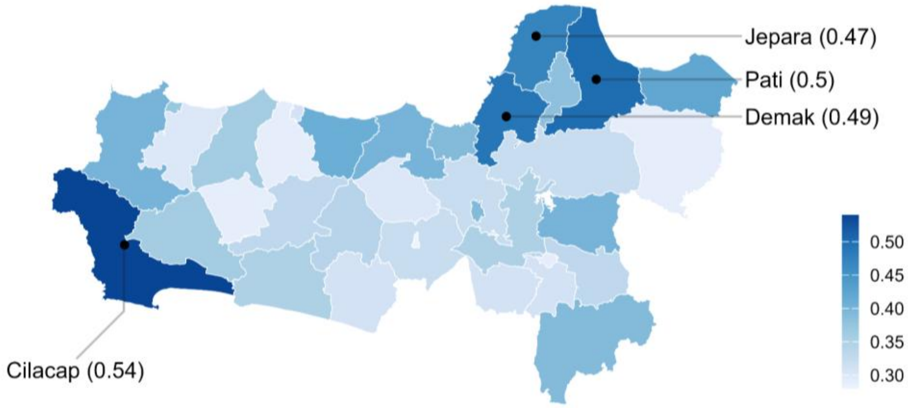

Figure 5. Blue Economy Index Map of Central Java, 2023

Cilacap Regency consistently recorded the highest IEB with a positive trend throughout 2019–2023. Its strategic geographical location as a key coastal regency is one of the main factors contributing to its strong performance. Similarly, Demak Regency also exhibited relatively high IEB values, albeit with some fluctuations, reflecting stability in the management of its blue economy sector. Conversely, several regencies reported lower IEB values. For instance, Tegal Regency recorded the lowest index in 2019, but showed improvement by 2023 due to initiatives in strengthening the blue economy sector, although its value remained below the provincial average.

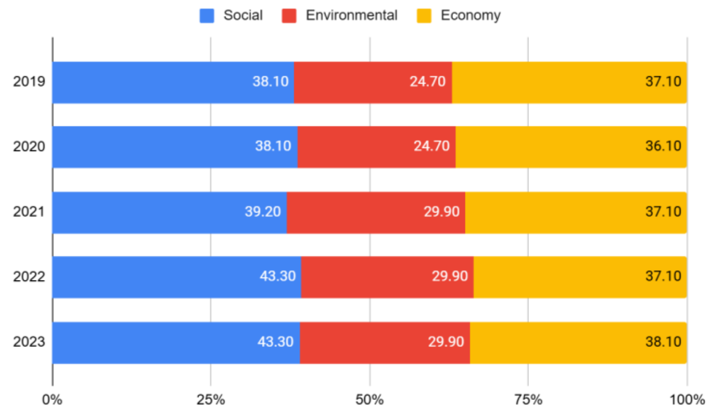

Figure 6. Percentage Distribution of IEB Sub-Index Values, 2019–2023

The IEB sub-indices in Central Java are predominantly driven by the social pillar, which experienced substantial growth during 2019–2023. This reflects an increasing emphasis on social factors such as unemployment, internet access, and human development. Meanwhile, the environmental dimension also exhibited a steady increase, indicating greater awareness of environmental sustainability. By contrast, the economic dimension showed a fluctuating pattern, underscoring the critical role of economic activities in supporting the development of the blue economy in Central Java.

3.3 Regression Results

3.3.1 Unit-Root Test

Stationarity testing (unit-root) was conducted to ensure the reliability of the model and to avoid spurious regression [4] (Appendix 14).

3.3.2 System GMM Regression Results

To examine the relationship between the blue economy and poverty levels, as well as to identify the macroeconomic determinants influencing the blue economy in Central Java, modeling was carried out using the System GMM regression method. This approach was chosen due to its ability to address endogeneity issues, account for variable dynamics, and incorporate heterogeneity across regions. The Blue Economy Index (IEB1) was employed as the dependent variable, while independent variables such as poverty rate, infrastructure networks, and other economic factors were included simultaneously to obtain more robust estimates. The model estimation results are presented in Table 1.

The estimation results reveal that several variables exert a significant influence on IEB. The lagged value of IEB (L1.IEB1) shows a significant positive coefficient, indicating that the blue economy performance in the previous period affects the outcomes in the subsequent period. Specifically, a one-unit increase in the lagged IEB (L1.IEB1) raises the current IEB1 by 1.030 units, ceteris paribus. This finding underscores the critical role of policy continuity and sustainability efforts in maintaining the growth momentum of the blue economy.

Table 1. System GMM Regression Results

Dependen: IEB1	**Coeff.**	**Std. Err**
L1. IEB1	1.030***	0.140
LPOV	-0.078	0.065
LNET	0.156***	0.035
LNTL	-0.056*	0.029
LPMTB	0.001	0.011
LCO	0.822	1.282
COVID	-0.038*	0.019
Diagnostic test:		
AR(1) p-value	0.005	
AR(2) p-value	0.625	
Sargan p-value	0.094	
Hansen p-value	0.056	
Obs.	175	
No. of Group (Region)	5	

Note: The GMM estimation was performed with robust standard errors using the *xtabond2* syntax in Stata (Hwang & Sun, 2018). The Arellano-Bond AR(1) test indicates the presence of first-order autocorrelation (reject H0), while the AR(2) test suggests no second-order autocorrelation (fail to reject H0), confirming that the dynamic model is statistically valid. The Hansen test, with a p-value greater than 0.05, implies that the instruments are uncorrelated with the standard errors and therefore valid for use. The Sargan test results indicate no overidentification issues across all model estimations. The p-values are based on two-tailed tests, where *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

The logarithm of internet usage (LNET) exhibits a significant positive effect on the Blue Economy Index (IEB). A 1% increase in internet users raises the IEB by 0.156%, *ceteris paribus*. This finding indicates that greater access to and adoption of digital technologies are crucial in supporting blue economy activities, consistent with the studies in [5] and [6].

In contrast, the logarithm of nighttime lights (LNTL) demonstrates a significant negative effect. A 1% increase in NTL reduces the IEB by 0.056%, *ceteris paribus*. This suggests that infrastructure expansion contributes to a decline in IEB. In line with [7], infrastructure development is generally accompanied by environmental degradation, which in turn adversely impacts the blue economy where environmental sustainability is a central consideration.

Finally, the COVID-19 pandemic (COVID) had a significant negative impact on the blue economy, reducing its performance in Central Java by 0.038%, *ceteris paribus*. Social restrictions, supply chain disruptions, declines in marine tourism, and limited access during the pandemic led to reduced activities in blue economy-related sectors [8].

3.3.3 Model Selection and Robustness Checks

A series of diagnostic tests were conducted to determine the most appropriate model specification and to assess robustness (Appendix 13).

To address the potential interpretive bias arising from the limited set of environmental indicators, a dedicated robustness check was performed. We re-estimated the Two-Step System GMM model using an alternative Blue Economy Index that excluded the entire environmental sub-index (L). The resulting coefficients for our primary determinants (Internet Usage, Infrastructure) remained statistically significant and consistent in direction and magnitude (The Nighttime Light (NTL) variable serves as an unbiased proxy for infrastructure, as it is derived from independent remote sensing data and has been empirically proven to exhibit a strong correlation with economic activity, regional development, and infrastructure across multiple cross-country studies in [9], [10]. [11], and [11]. This confirms that while the environmental pillar is foundational to the blue economy concept, the significant macro-determinants of the overall BEI are robust to potential measurement limitations within the environmental sub-index.

3.4 Discussion

The findings of this study, which covers 35 districts and municipalities in Central Java, highlight the presence of spatial variation in the Blue Economy Index (IEB), particularly between the northern, southern, and non-coastal regions. The southern coastal region consistently recorded higher IEB values compared to the northern coast. In 2023, the southern coastal area reached an average IEB of 0.37, while the northern coast registered 0.40. These differences are also reflected in the trends from 2019 to 2023, where the southern coastal region consistently outperformed the northern coastal region.

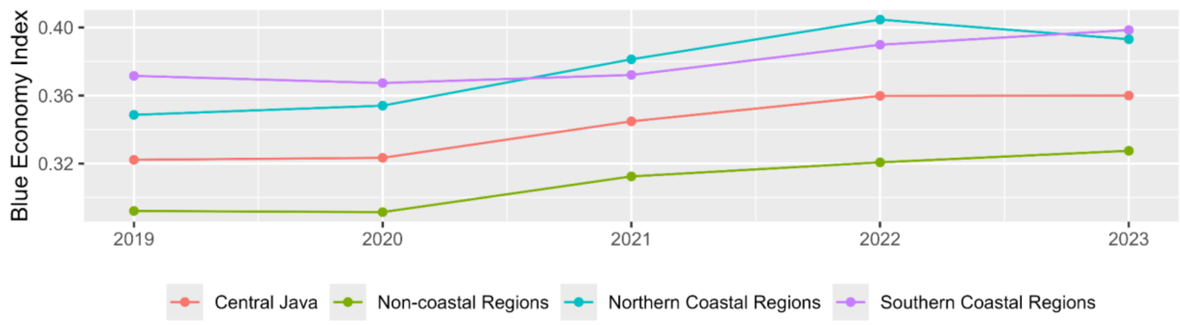

Figure 7. EB Trends by Geographic Region

The IEB results reveal significant variations across regions. The southern coastal areas tend to consistently achieve higher values compared to other regions, while the non-coastal areas generally record lower values. The differentiated contributions of each sub-index underscore the need for an integrated approach. Blue economy development cannot rely solely on a single dimension but instead requires a balanced strategy with targeted interventions based on the specific characteristics of each region to ensure inclusive and sustainable growth.

The expansion of information and communication technologies has proven to enhance blue economy outcomes in Central Java, as evidenced by the significantly positive effect of LNET. Regions with broader internet access tend to be better equipped to optimize technology in managing marine resources, whether in the context of fishing [13], seafood trade [14], tourism [15], or environmental management [16].

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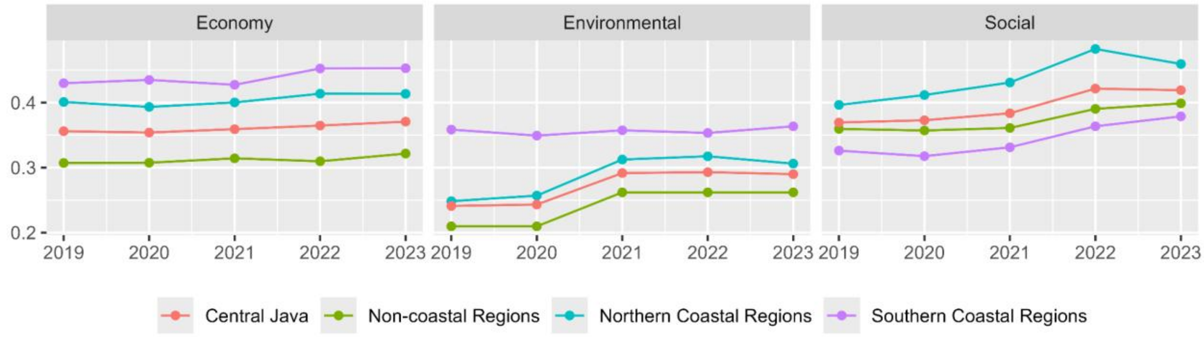

Figure 8. Sub-Index Trends of IEB by Geographic Region

Infrastructure development, proxied by LNTL, contributes negatively. This finding suggests that although infrastructure is important, its orientation has not fully supported the blue economy sector, as it is primarily directed toward industrial and commercial activities unrelated to the maritime economy, and often exacerbates coastal environmental degradation (rapid urbanization and ecosystem decline) [7]. Therefore, more strategically planned infrastructure development is required.

The COVID-19 crisis significantly reduced blue economy performance in Central Java across multiple dimensions. This global crisis adversely affected demand in the fisheries and tourism sectors [6][17]. Nonetheless, it also generated environmental benefits through reductions in marine, air, and water emissions due to the decline in economic activity [18].

The finding that infrastructure development, proxied by Nighttime Light (NTL), demonstrates a significant negative impact on the Blue Economy Index (BEI) in Central Java warrants critical examination. While infrastructure is generally expected to be a positive driver of economic growth, this counter-intuitive result suggests that the type and location of current infrastructure development are detrimental to long-term blue economy sustainability. This finding is likely rooted in two key contextual factors specific to Central Java's coastal development. First, the majority of recent infrastructure investment—such as coastal roads, industrial parks, and land reclamation projects—has been primarily land-oriented and focused on short-term economic gains, often neglecting marine protection measures. Second, and more critically, this development frequently results in environmental degradation, including the destruction of critical coastal ecosystems like mangroves and coral reefs for port expansion or pollution from increased industrial activity. As our BEI incorporates environmental sustainability, this destructive infrastructure growth undermines the long-term value of the blue economy, leading to the observed negative coefficient.

3.5 Limitations and Future Research

While the utilization of big data—specifically, satellite imagery for mapping resources like Mangrove Forest Area (LM)—provided the necessary sub-regional granularity, it is important to acknowledge its limitations. Proxies derived from remote sensing data, such as mangrove areas, represent physical presence but cannot fully capture ecological quality, biodiversity loss, or the degree of ecosystem functionality. Similarly, the Nighttime Light (NTL) proxy for infrastructure, while effective for measuring physical development, may not perfectly align with the specific infrastructure directly supporting blue economy activities. This reliance on proxy indicators for environmental and infrastructure metrics necessitates cautious interpretation and underscores the need for continuous on-the-ground validation in future studies.

Conclusion

This study demonstrates a consistent increase in the Blue Economy Index (BEI), indicating the presence of sustainable blue economy growth in Central Java. The southern coastal region shows higher BEI performance compared to the northern coastal region, while non-coastal areas generally remain below the average. These findings highlight the need for more targeted blue economy development strategies, without neglecting the northern coastal region as part of sustainable blue economy planning.

Furthermore, the variables of internet usage (LNET), infrastructure proxied by nighttime light (LNTL), and the COVID-19 period were found to have significant effects on the BEI. While the increasing use of the internet contributes positively, infrastructure development exhibited a negative effect, suggesting a potential imbalance between physical development and blue economy principles. The negative impact of infrastructure requires further exploration to ensure that development policies are aligned with the sustainability principles of the blue economy.

To ensure the sustainable development of the blue economy in Central Java, the study recommends a four-pronged approach. First, optimization in coastal regions (especially the north) is crucial, focusing on strengthening sustainable fisheries, ecotourism, and marine conservation area management. Second, infrastructure development must be carefully integrated with blue economy support, ensuring that new ports, roads, or public facilities in both northern and southern coastal areas do not compromise critical resources like marine ecosystems, coral reefs, or mangroves, while simultaneously modernizing fishing vessels and production facilities (Central Java Provincial Government, 2024). Third, digitalization of the blue economy needs to be advanced by improving access to technology and digital literacy to expand market opportunities and enable active contributions from all actors. Finally, strengthening the resilience of the blue economy is essential, using the ARI (Adaptive–Responsive–Innovative) framework to prepare for and address crises, starting with the household level as the foundational economic driver to minimize adverse impacts during turbulent times.

The novelty of this research is demonstrated through the development and spatial application of the Blue Economy Index (BEI) at the provincial level, incorporating digital and infrastructural dimensions into the evaluation of blue economy performance. This approach has rarely been explored in previous Indonesian regional studies. Despite these contributions, this study acknowledges several limitations, particularly the relatively narrow scope of environmental indicators, which may not fully capture the ecological complexity of coastal and marine systems.

Future research is encouraged to refine the BEI framework by incorporating more comprehensive ecological indicators (e.g., coastal water quality, biodiversity indices), adopting spatial econometric or machine learning models to capture complex spatial dependencies and nonlinear relationships, and extending the analysis to other provinces or national-level comparisons. Such advancements would deepen the understanding of the digital–infrastructure–environment nexus in supporting a sustainable blue economy.

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