ISSN 1816-6075 (Print), 1818-0523 (Online)
Journal of System and Management Sciences
Vol. 14 (2024) No. 4, pp. 191-214
DOI:10.33168/JSMS.2024.0413

A Data-Driven Approach for Real-Time Urban Sustainability Assessment Using Crowdsourced Data

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Abstract. This study presents an innovative sustainability assessment framework leveraging crowdsourced data from social media and review platforms. The model encompasses 12 carefully chosen indicators across social, economic, and environmental dimensions. Analysis of four major Indonesian cities reveals comparative strengths and weaknesses, categorizing them into clusters to inform targeted policy improvements. The findings validate crowdsourced data as a robust real-time data source for sustainability assessments. This research provides a strategic roadmap to guide smart city initiatives tailored to the unique ecosystems of each urban area.

Keywords: crowdsourced data, city sustainability, smart city assessment, social, economic, environment

1. Introduction

Smart cities aim to be at the forefront of innovation. Their goals extend beyond intelligence, focusing on sustainability, efficiency, and enhancing the overall quality of life for their inhabitants. By 2050, it's projected that over two-thirds of the world's population will live in urban areas. This rapid urban growth stresses essential resources such as water, food, and energy (Lai et al., 2020). Recognizing this, there's a pressing need to understand urban ecosystems deeply to ensure long-term sustainability (Toli & Murtagh, 2020). Integrating digital technology with urban infrastructure has become vital for managing these ecosystems. Yet, the rise in urbanization and resource demand calls for effective smart city solutions. Their success is often hampered by limited evaluation methods and outdated data sources. The lack of standardized assessment criteria across cities further complicates this, emphasizing the need for better, real-time evaluation strategies.

Traditional evaluation methods typically rely on two distinct types of data: primary and secondary. Primary data is gathered through methods such as questionnaires, interviews, and field observations. Secondary data, conversely, is obtained from resources including census data and annual reports (Sharifi, 2020). Each data type has its inherent challenges. Gathering primary data is not only resource-intensive but also costly and time-consuming. In contrast, secondary data can be static, and its reliability may become outdated (Patrão et al., 2020). Notably, neither offers real-time insights. One major drawback of traditional data is its inability to holistically represent urban ecosystems (Sharifi, 2019), potentially resulting in fragmented insights that may not accurately reflect of real time city status.

Urban sustainability evaluations have historically faced challenges due to the lack of comprehensive, cost-effective, and real-time data. Addressing this, the recent influx of crowdsourced data provides valuable insights into urban environments (Wu et al., 2021), (Zhou et al., 2021). These data offer perspectives from individual contributors on various platforms, capturing their views on smart city innovations (Crooks et al., 2015), (Niu & Silva, 2020). Such a rich data source is pivotal for monitoring real-time urban phenomena, ranging from traffic patterns to public sentiment. Considering these challenges and opportunities, this study aims to introduce a novel technique rooted in crowdsourced data to assess urban sustainability. This evaluation covers the triple bottom line (TBL) of sustainability: social, economic, and environmental aspects. Futhermore, this study delves deeper into the interactions of urban ecosystems, a dimension not addressed by traditional methodologies. By harnessing deep learning and big data analytics, this study seeks to provide a more comprehensive understanding of urban sustainability, thereby informing more effective policy decisions.

To this end, This article is meticulously structured for clarity and coherence. We commence with the Literature Review (Section 2), providing a deep dive into prior research on smart city assessment. In the Methods section (Section 3), we detail the methodological framework employed for assessing sustainable cities. The Results and Discussion (Section 4) present our findings, further probing the implications, particularly concerning the use of crowdsourced data in smart city evaluations. Finally, the Conclusions (Section 5) encapsulate our study, offering insights and suggestions for subsequent research.

2. Literature Review

The main objective of assessing smart cities is to provide feedback and guidance for decision-making, ensuring that the implementation of the smart city aligns with the desired direction (Ahvenniemi et al., 2017). Smart city assessments can also serve as a platform for exploring potential future developments (Sharifi, 2019). Moreover, these assessments can function as performance monitoring tools, beneficial for various stakeholders, ranging from city authorities, investors, funding institutions, researchers, to the general public (Patrão et al., 2020).

In smart city assessments, there are two primary focuses: 'smartness' and/or 'sustainability'. A study conducted by (Ozkaya & Erdin, 2020) evaluated these two aspects, utilizing primary data across six dimensions: living, economy, mobility, governance, environment, and people. The primary data were sourced from expert interviews, while the analytical approach employed the Analytic Network Process (ANP) and TOPSIS. Similarly, (Antwi-afari et al., 2021) used the same six dimensions, but their primary data came from surveys and questionnaires, leveraging Fuzzy Synthetic Evaluation (FSE) for analysis. Another study by (Akande et al., 2019) also focused on smartness and sustainability using secondary data, prioritizing the dimensions of social, economic, and environmental assessment. The secondary data were taken from the Urban Audit Data and the Eurostat Database, with hierarchical grouping and Principal Component Analysis (PCA) as the chosen analytical methods.

There are also studies specifically centered on either the smartness or sustainability aspect. A study by (Kimiya & Torabi, 2021) involved six dimensions, namely environment, living, mobility, economy, people, and governance. The data were sourced from primary data through interviews and surveys, with Multi-Attribute Decision Making (MADM) as the analysis method. Another study by (Li et al., 2019) remained focused on sustainability assessment, using secondary data with dimensions like innovation, economy, infrastructure, services, mobility, and environment. The secondary data came from the China Statistical Yearbook and the Yearbook of China Information Industry, followed by PCA and back propagation (BP) for analysis. A sustainability-focused study was also conducted by (Liu et al., 2021), using the dimensions of social, economic, and environmental, with secondary data sourced from previous city rankings. On the other hand, a study by (Shen et al., 2018) assessed the smartness focus, using dimensions like infrastructure, governance, economy, people, and environment. This study utilized secondary data from the China City Statistical Yearbook and air quality reports, with TOPSIS as the analytical approach.

From the aforementioned studies on smart city evaluations, it becomes evident that traditional data sources, such as surveys, questionnaires, and interviews for primary data, and statistical reports for secondary data, remain predominant. However, with technological advances and data evolution, there's growing potential for more dynamic evaluations using easily accessible data sources like crowdsourcing (Wu et al., 2021). Yet, this vast potential remains largely untapped due to the lack of innovative evaluation models capable of harnessing and researching this information (Sharifi, 2019), (Sharifi, 2020). It is within this context that the present study positions itself, aiming to bridge the gap between existing methodologies and the untapped potential of novel data sources. By restating the focus and contributions of this study, we seek to develop a robust framework that integrates crowdsourced data and sustainable cities assessment. In doing so, we believe this study will not only contribute to the academic discourse but will also provide practitioners with actionable insights, clearly articulating the potential value and contribution of this research to the broader field of smart city development and assessment.

3. Methods

This study adopted the “onion methodology” as a structured framework for conducting research and shaping the research design in a systematic manner (Hair et al., 2007). The selection of this research approach was guided by its inherent advantages in comprehending and analyzing complex business processes (Melnikovas, 2018). In the specific context of this investigation, the application of the onion methodology proved particularly pertinent as it facilitated the evaluation of smart cities with a specific emphasis on sustainable urban development—a realm intricately connected to urban business operations. The research process, adopted by the foundational principles of the onion methodology, is illustrated in Figure 1.

Fig. 1.Research Method Based On Onion Methodology

As depicted in Figure 1, this study methodology is a comprehensive framework that integrates a range of critical elements: from techniques and procedures to time horizons, methodological selections, strategic orientations, analytical paradigms, and foundational philosophies. Within this framework, the techniques and procedures section commands special focus, serving as the cornerstone for data collection and analysis protocols (Assadpour et al., 2023). This phase is instrumental in shaping the quality and reliability of the research findings. To enrich the data pool, this study leverages advanced crowdsourcing methods, targeting specific content from social media and reviews concerning smart city initiatives. This approach not only expands the range of data sources but also strengthens the practical relevance of the study. The data collection process is further optimized through the meticulous selection of keywords, each associated with specific indicators and dimensions. These keywords act as guideposts, facilitating a focused and streamlined data gathering process, as illustrated in Figure 2 (Ependi, Rochim, et al., 2023).

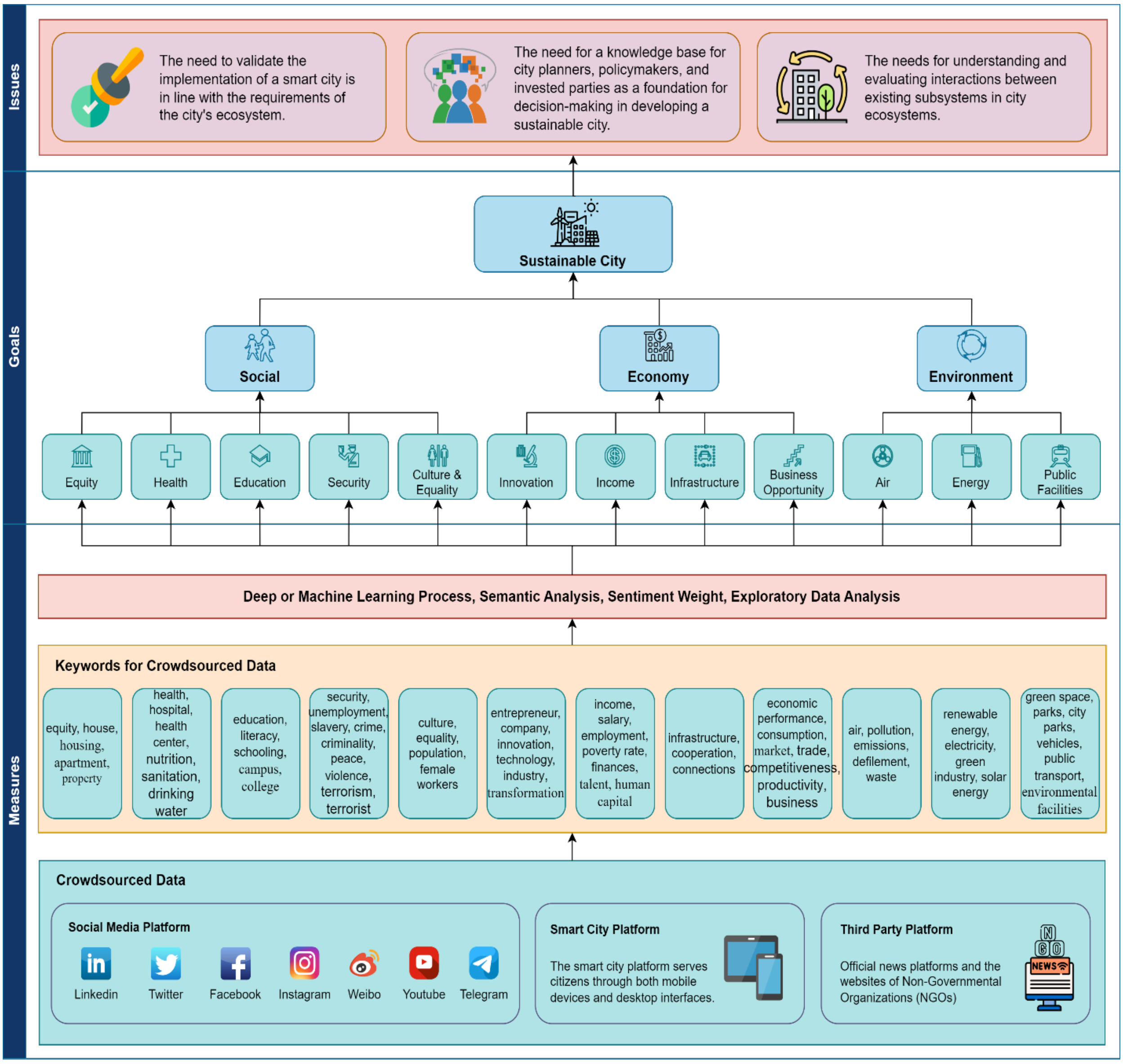

Fig. 2. Sustainable City Assessment Model Using Crowdsourced Data

The evaluation framework for sustainable cities, as illustrated in Figure 2, is built upon three fundamental dimensions of sustainability: social, economic, and environmental aspects. This multidimensional approach ensures a comprehensive assessment, capturing the intricate nature of urban ecosystems. To construct the framework, a set of carefully selected procedures were employed. These include the Design Science Methodology (vom Brocke et al., 2020), multi-criteria analysis (Ahmad et al., 2006) for creating a taxonomy of dimensions and indicators (Ahmad et al., 2006), and the Smart City Reference Architecture Framework for model development (Government Japan, 2020). Taxonomy is informed by thematic indicators from previous research. By incorporating these thematic indicators, the framework leverages the insights of prior studies, ensuring a robust and comprehensive evaluation. These indicators underwent rigorous validation by experts in the field, using a purposive sampling methodology (Helmy et al., 2017). This method allowed for the inclusion of a wide range of expert opinions, thus enhancing the reliability and validity of the framework. To further refine the selection process, statistical methods such as measures of central tendency and variability (Saihi et al., 2022) were employed. These statistical techniques ensured that the chosen indicators were both representative and diverse, capturing the various nuances of sustainability. An inclusion criterion was established with a cut-off score of 3.7 on a scale of 1 to 5 (Nordin et al., 2012). This threshold was determined to balance rigorous standards with the inclusion of a diverse set of indicators.

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After the expert validation process, a comprehensive list of twelve key indicators was identified for assessing a city's sustainability. These indicators serve as a roadmap for policymakers and urban planners in their quest for sustainable development. The social dimension includes five indicators: equity, health, education, security, and culture & equality. These indicators reflect the aspiration for a socially cohesive and inclusive urban environment. The economic dimension is covered by four indicators: innovation, income, infrastructure, and business opportunity. These economic metrics aim to capture the vitality and resilience of the urban economy. The environmental dimension is represented by three indicators: air quality, energy efficiency, and public facilities. These indicators were chosen based on the sustainable city assessment model that focuses on crowdsourced data. The ratings from this validation process are summarized in Table 1.

Table 1. Rating Value Based on Expert Judgement

Indicators	Mean	Median	Mode	SD
Equity (So1)	4,38	4	4	0,48
Health (So2)	4,63	5	5	0,48
Education (So3)	4,63	5	5	0,48
Security (So4)	4,63	5	5	0,48
Culture and equality (So5)	4,38	4	4	0,48
Innovation (Ec1)	4,63	5	5	0,48
Income (Ec2)	4,13	4,5	5	1,05
Infrastructure (Ec3)	4,63	5	5	0,48
Business opportunity (Ec4)	4,63	5	5	0,48
Air (En1)	4,75	5	5	0,43
Energy (En2)	4,75	5	5	0,43
Public facilities (En3)	4,75	5	5	0,43

The subsequent phase of the research focuses on data collection, employing a longitudinal type within a clearly defined as times horizon. In the context of this study, longitudinal data collection refers to the systematic gathering of information over predetermined intervals (Al-Ababneh, 2020). To facilitate this, advanced crowdsourcing tools, such as Rapidminer, accessed through an academic license, along with web scraping techniques, are utilized. Data sourcing from social media platforms is executed in a phased manner. This staggered approach is necessitated by the inherent constraints on the volume of data that can be extracted from these platforms. For a more localized analysis, geographical filters are applied to the social media data, restricting the search to a 20-kilometers radius from the central point of each city under study. Conversely, data collection from that review of smart cities platforms unlike the social media data, no geographical filters are applied to these review platforms, as they are intrinsically city specific. Upon completion of the data collection and subsequent filtering processes, a total of 10,381 pertinent data entries related to smart cities have been amassed. These entries are further categorized based on a set of predefined evaluation indicators, thereby enriching the depth and scope of the analysis.

The comprehensive data collection process was meticulously carried out across selected provincial capitals on Java Island, Indonesia. This effort serves as a landmark case study in evaluating the sustainability of urban landscapes. Specifically, the case study is an integral component of the broader Onion methodology, a strategic analytical framework that has garnered considerable attention in research circles (Saunders et al., 2019). Within this framework, particular attention was focused on provincial capitals located on Java Island, given that Java holds the majority of Indonesia's population. The island's dense population makes it a strategic location to observe the adoption and progression of the smart city concept. According to the National Central Bureau of Statistics' 2021 data, Java's population constitutes 56.10%, or approximately 151.59 million, of Indonesia's total population of 270.20 million. This underscores the importance of understanding the dynamics and public response to smart city initiatives in Java's major cities.

The four provincial capitals under investigation are Jakarta (DKI Jakarta), Semarang (Central Java), Bandung (West Java), and Surabaya (East Java). These cities were chosen based on their alignment with the smart city concept and their substantial population. However, two other capitals, Serang (Banten) and Yogyakarta (DI Yogyakarta), were excluded due to the absence of official smart city websites. The decision to focus solely on provincial capitals aims to ensure a uniform evaluation process for smart cities. Collectively, this selected group of cities forms the core of the case study, providing a rich and varied landscape for exploring the intricacies of sustainable urban development. To provide further context, the geographical locations of these cities are illustrated in Figure 3.

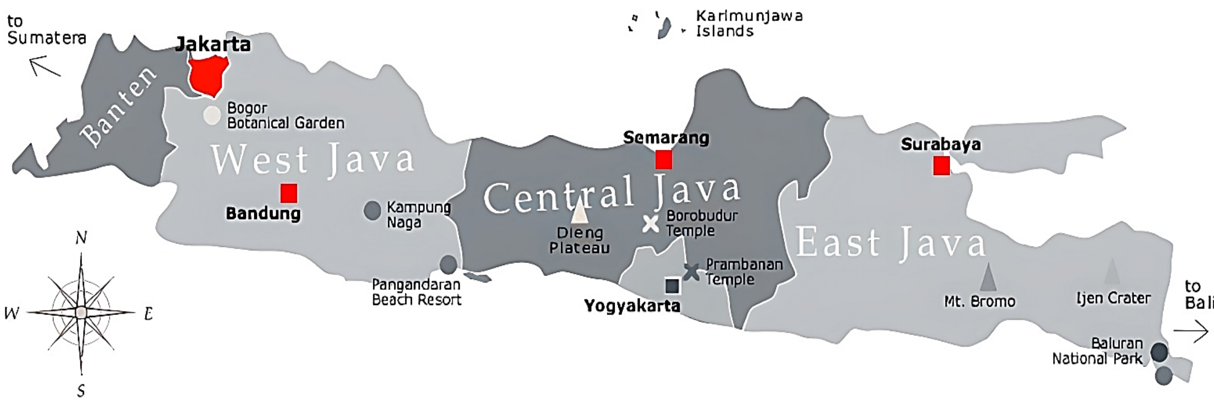

Fig. 3.Case Study Area

The subsequent phase entails the execution of value computation and weight allocation for individual indicators, leveraging sentiment analysis and exploratory data analysis methodologies. This operation aligns with the "choice method" section of the Onion Methodology framework. As delineated in Figure 4, the research employs a multi-tiered analytical approach encompassing three principal components: data compilation, data analysis and processing, and urban evaluation. Within the domain of data compilation, two sub-phases exist: acquiring crowdsourced information and the cleansing and preprocessing of data. The crowdsourced data is gleaned from social media platforms such as Twitter and various smart city platform reviews, as previously elaborated. The subsequent sub-phase involves data cleaning and preprocessing, where techniques from Natural Language Processing (NLP) are utilized.

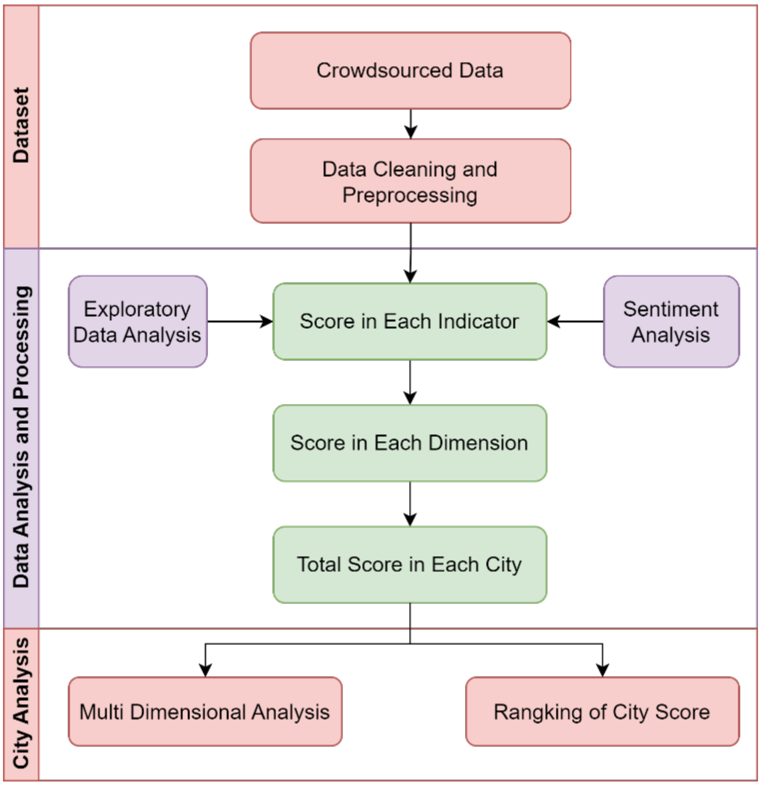

Fig. 4. The Proposed Analytical Method

Natural Language Processing (NLP) was employed in the data cleaning and preprocessing stage to achieve highly accurate results, highlighting its essential role in enabling computers to interpret data (Macrohon et al., 2022). During this phase, an array of libraries such as Google Colab, nltk, pandas, spacy, and the Indonesian Sastrawi library were leveraged for the preprocessing tasks. Notably, the Indonesian Sastrawi library facilitated the conversion of affixed words in the Indonesian language into their root forms (Widiantoro et al., 2021). The preprocessing stage was broken down into several key components, elaborated as follows: (1) Tag replacement: This step removed extraneous elements from the raw data, including introductory elements, tabs, URLs, usernames, numerals, excess spaces, and special characters. (2) Case folding: This involved converting all uppercase letters to lowercase to establish uniformity across the dataset. For example, both “Saya” and “saya” were treated as identical. This aimed to minimize discrepancies between different case forms during vectorization (Macrohon et al., 2022). (3) Stop-word removal: Meaningless words were purged using the stopwords() function offered by NLTK via the Sastrawi tool. (4) Stemming: This process turned affixed words into their root forms, conducted with the help of the Sastrawi library. (5) Normalization: Non-standard words were standardized or converted to their correct spelling. This was vital due to the diverse data sourced from Twitter and smart city platforms, which included various slang terms. An Indonesian dictionary containing 17,321 texts was employed for this purpose. (6) Tokenization: This split sentences into individual words, punctuation, and other meaningful units. The nltk library's word_tokenize() function was used for this step (Ependi; et al., 2023).

The data analysis and processing encompasses a crucial process of assigning weights to individual indicators. In order to fathom the societal perspective concerning the urban ecosystem, the exploration of data is undertaken utilizing the exploratory data analysis (EDA) method. EDA, being an evaluative endeavor, aims to unveil insights from a given dataset (Panigrahi et al., 2022). It could also be perceived as the art of deciphering a dataset that requires comprehension (Pearson, 2018). The use of EDA aims to understand the assessment data, examining the distribution of sentiments, dimensions, indicators, and frequently occurring words for each city. To enrich the EDA, data classification targeting dimensions, indicators, and sentiments was also conducted using Long Short-Term Memory (LSTM). LSTM was chosen due to its proven capability to achieve optimal results in text classification. Compared to Recurrent Neural Networks (RNN), LSTM demonstrates superior performance in text classification tasks (Kowsari et al., 2019). According to (Bhavani & Santhosh Kumar, 2021), LSTM also excels in classifying educational, English-language, and news texts. Additionally, LSTM has been tested and shown to be optimal in classifying smart city assessment dimensions derived from crowdsourced data (Ependi; et al., 2023).

Simultaneously, the allocation of weightages to indicators is facilitated through sentiment analysis. The sentiment-driven weighting technique involves the computation of row data, extrapolated from sentiment calculations grounded in specific words (Zhou et al., 2021). The determination of whether the sentiment expressed within the row data is positive or negative is accomplished using the lexicon approach. The lexicon of choice in this context is the inSet lexicon (Ependi, Aliya, et al., 2023). The detailed procedure for sentiment weight assignment as shown in Figure 5.

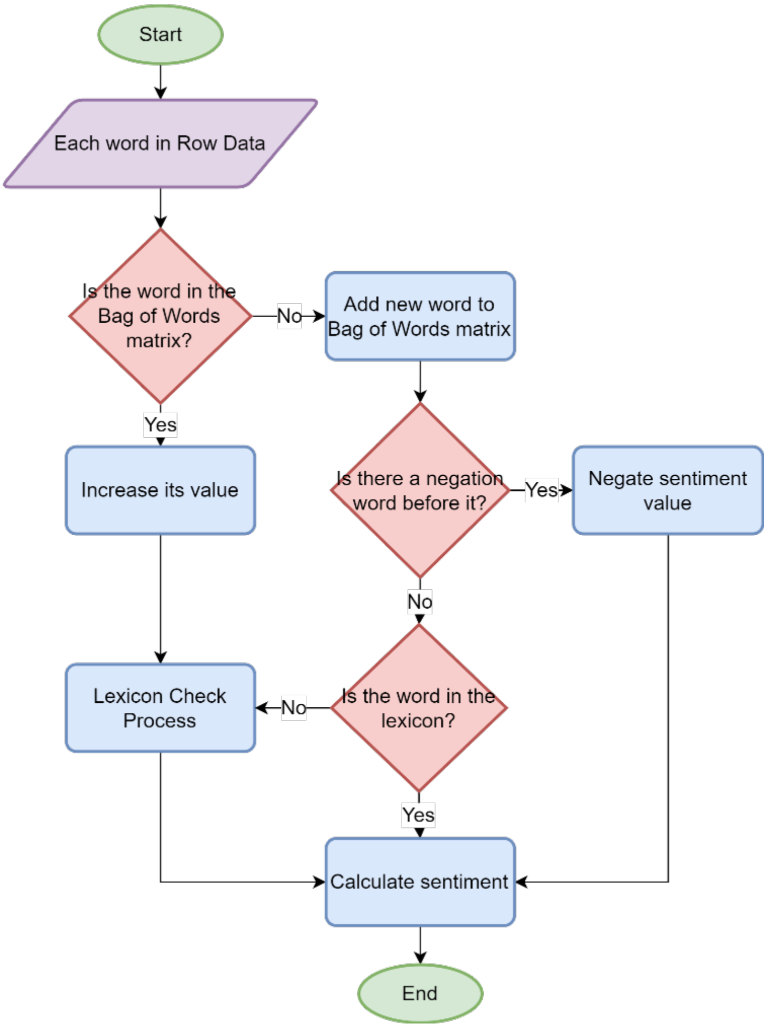

Fig. 5.Flowchart of Assigning Sentiment Weight

Subsequent computations for each indicator, spanning across social, economic, and environmental dimensions, adhere to the computational methodologies that is aligned with the sentiment weighting procedures executed through a lexicon-based approach, as detailed in Figure 5. Specifically, the scoring metrics for the social dimension are computed using Equations 1 and 2.

$$Soi^n = \frac{\sum Soi^n {}_m^+}{\sum MSoi^n = \sum Soi^n {}_m^- + \sum Soi^n {}_m^+} \; x\ 100 \quad (1)$$

$$So = (Soi^1 + Soi^2 + Soi^n) / \sum Soi \quad (2)$$

Where, Soi^n represents the score of indicator n in the social dimension. $\sum Soi^n {}_m^-$ represents the total number of negative row data for indicator n in the social dimension. $\sum Soi^n {}_m^+$ represents the total number of positive row data for indicator n in the social dimension. $\sum MSoi^n$ represents the total number of row data for indicator n in the social dimension. So represents the score of the social dimension. Meanwhile, $\sum Soi$ represents the total number of indicators in the social dimension. Furthermore, The calculation of weight scores for the economic dimension is performed using Equations 3 and 4.

$$Eci^n = \frac{\sum Eci^n {}_m^+}{\sum MEci^n = \sum Eci^n {}_m^- + \sum Eci^n {}_m^+} \; x\ 100 \quad (3)$$

$$Ec = (Eci^1 + Eci^2 + Eci^n) / \sum Eci \quad (4)$$

Where is the Eci^n for the indicator score to n within the economic dimension. $\sum Eci^n {}_m^-$ represents the sum of negative row data for indicator n within the economic dimension. $\sum Eci^n {}_m^+$ represents the sum of positive row data for indicator n within the economic dimension. $\sum MEci^n$ represents the sum of row data for indicator n within the economic dimension. Ec stands for the score of the economic dimension. Meanwhile, $\sum Eci$ represents the total number of indicators in the economic dimension. Furthermore, the computation of weight scores for the environmental dimension is conducted utilizing Equations 5 and 6.

$$Eni^n = \frac{\sum Eni^n {}_m^+}{\sum MEni^n = \sum Eni^n {}_m^- + \sum Eni^n {}_m^+} \; x\ 100 \quad (5)$$

$$En = (Eni^1 + Eni^2 + Eni^n) / \sum Eni \quad (6)$$

Whereas, Eni^n represents the score of indicator to n within the environmental dimension. $\sum Eni^n {}_m^-$ stands for the sum of negative row data for indicator n within the environmental dimension. $\sum Eni^n {}_m^+$ stands for the sum of positive row data for indicator n within the environmental dimension. $\sum MEni^n$ represents the sum of row data scores for indicator n within the environmental dimension. En represents the score of the environmental dimension. Meanwhile, $\sum Eni$ represents the total number of indicators within the environmental dimension.

In the field of urban planning, the city analysis phase serves a critical role as the conduit for presenting comprehensive evaluation results of sustainable cities. This pivotal stage is deeply embedded within the framework of Onion Methodology, a well-respected approach that combines both theoretical and practical perspectives on city development. The methodology prioritizes factual rigor, ensuring that data-driven insights form the backbone of any subsequent conclusions. During this analysis phase, the presentation of results is not merely an informational exercise but serves as empirical evidence that grounds the study's conclusions. The analytical process adheres to the principles of deductive reasoning, systematically deriving specific outcomes from a general theory or hypothesis. This lends both credibility and scholarly rigor to the findings, ensuring they stand up to critical scrutiny. For the sake of transparency and comprehensiveness, all detailed explanations of the evaluation outcomes, as well as the derived conclusions, will be elaborately discussed in subsequent sections of the article, specifically under “Results & Discussion” and “Conclusion.” Here, stakeholders can expect a nuanced dissection of the data, offering a holistic view that goes beyond mere numerical values to include social, economic, and environmental dimensions.

4. Results and Discussion

4.1. Exploratory Data Analysis

The collected data is labeled with various attributes such as indicators, dimensions, cities, and sentiment. The keywords for indicators and dimensions are predetermined at the time of data collection, and the same applies to the cities involved. Sentiment is assigned based on lexicon weight scores, as illustrated in Figure 4. The lexicon weight scores are further categorized into three groups: (1) Negative sentiment if the score is less than zero. (2) Neutral sentiment if the score is zero. (3) Positive sentiment if the score is greater than zero. Based on these criteria, the data distribution for each city is shown in Figure 6.

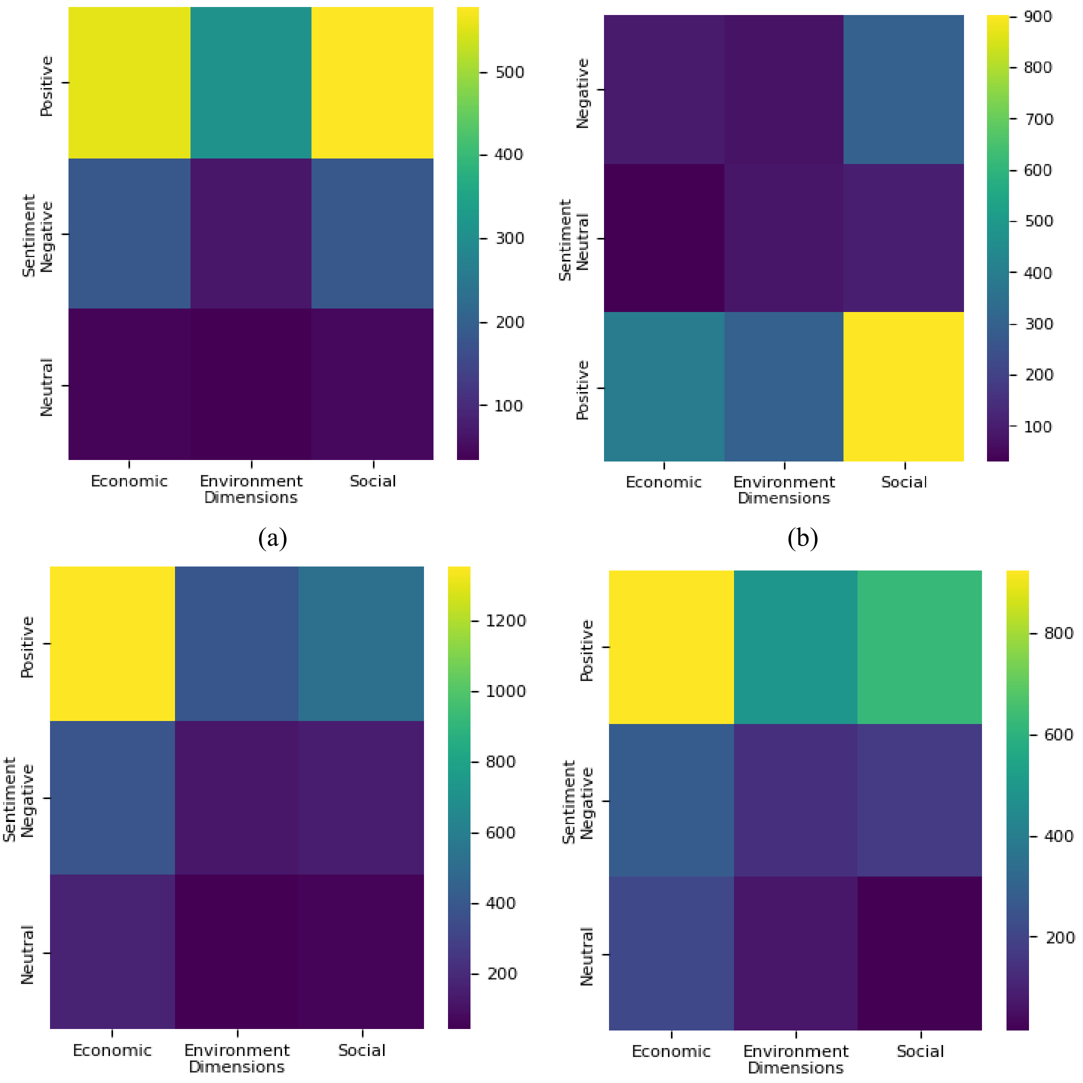

Fig. 6. Data Distribution: (a) Surabaya, (b) Semarang, (c) Bandung, and (d) Jakarta

Data distribution presented in Figure 6 offers a nuanced understanding of sustainability issues across four Indonesian cities: Surabaya, Semarang, Bandung, and Jakarta. These cities are evaluated on three critical dimensions of sustainability: Social, Economic, and Environmental. Moreover, the data is finely categorized based on sentiment—Positive, Neutral, or Negative—to provide a more granular understanding of public opinion. Bandung takes the lead with a remarkable 3,191 rows of data, strongly suggesting that the city is either a focal point of active civic engagement or perhaps grappling with numerous issues that demand public attention. Jakarta is a close second, with a total of 2,931 rows, underlining its status as the country's bustling capital. Semarang and Surabaya trail behind with 2,271 and 1,988 rows respectively, which may imply either less public interest or fewer concerns in these cities.

When dissecting the data by dimensions, intriguing patterns emerge. Semarang stands out for its concentration on social issues, accounting for 1,305 rows. This focus could indicate that social welfare or community-based initiatives are of paramount importance for the city. In a striking contrast, Bandung's data is heavily skewed towards economic issues, amassing an impressive 1,904 rows. This suggests that the city may be at a pivotal point economically, possibly in the midst of significant growth or facing economic challenges. Jakarta, on the other hand, presents a well-rounded profile but leans towards environmental concerns with 703 rows. Given Jakarta's status as the capital, this could signify a growing awareness or policy emphasis on environmental sustainability at a national level. Surabaya offers the most balanced spread across all dimensions, although it has fewer data points overall. This could indicate a holistic approach to city management but may also signify room for improvement in public engagement.

From a sentiment analysis standpoint, Bandung exhibits a strong presence in both positive and negative categories, with 2,267 and 653 rows respectively. This dual nature suggests that Bandung is a city of contrasts: one that is both experiencing promising advancements and facing considerable challenges. Jakarta mirrors this pattern but with a slight emphasis on positive sentiment, as indicated by 2,042 positive rows and 591 negative ones. Both Semarang and Surabaya have fewer rows, yet they maintain a comparable trend of higher positive sentiment and fewer negative or neutral impacts. This could imply a generally favorable public view of city management, albeit with some areas of concern.

All things considered, the data provides a rich tapestry of public sentiment and priorities across these four cities. Bandung emerges as a hub of economic discourse, with a wealth of both positive and negative insights. Semarang, with its focus on social issues, maybe a case study in community-led development or social welfare programs. Jakarta, the nation's capital, exhibits a balanced but expansive dataset, with a significant skew towards environmental sustainability. Lastly, Surabaya presents a balanced but less voluminous dataset, suggesting a need for increased public engagement across multiple dimensions of sustainability.

Pivoting to the qualitative nuances of the data, distinct thematic trends emerge in public conversations and opinions associated with each city. These trends are vividly highlighted by the most frequently appearing words in the crowdsourced data, serving as focal points that likely resonate with the communities involved. In Surabaya, the salient terms are "education, economy, and salary". Interestingly, these terms align well with the city's lower volume of crowdsourced data compared to others. The focus on "education and economy" could imply that while there might be less overall public participation, the concerns raised are fundamental and directly tied to long-term wellbeing and economic prosperity.

Semarang's public discourse revolves around "hospitals, education, and security", which intriguingly complements its data distribution that emphasized social issues. This could indicate a strong community focus on health and safety, perhaps signaling that social welfare initiatives are not only prevalent but also a top concern for residents. For Bandung, the frequently mentioned terms are "salary, fuel, and income". Given that Bandung had the highest number of data rows, especially in economic dimensions, these terms underscore a heightened public interest or concern in economic stability and living costs. The high frequency of these terms could be a manifestation of the city's vibrant public engagement around economic challenges or opportunities.

Jakarta stands out with terms like "salary, fuel, and security", which coalesce intriguingly with its balanced but extensive dataset and particular attention to environmental issues. The prevalence of "security" alongside economic terms could imply a complex interplay of economic and safety concerns, perhaps reflecting the multifaceted challenges of managing a bustling capital city. These commonly mentioned terms are not only textual data points but are also visually encapsulated in a word cloud, as depicted in Figure 7.

(a) (b)

(c) (d)

Fig. 7. Data Wordcloud (in Indonesia): (a) Surabaya, (b) Semarang, (c) Bandung, and (d) Jakarta

In order to rigorously evaluate how well the collected data aligns with each defined indicator, dimension, and sentiment, we employ a comprehensive classification methodology. The objective of this classification is twofold: first, to scrutinize the influence of specific keywords in the data gathering process; and second, to assess the suitability of lexicon-based sentiment analysis in this context. To achieve these ends, we utilize the Long Short-Term Memory (LSTM) algorithm, a state-of-the-art technique for sequence modeling. Addressing the issue of data imbalance is crucial for obtaining reliable classification results. To mitigate this, a hybrid data-level technique that merges Random Over Sampling (ROS) with the Neighbourhood Cleaning Rule (NCL) (Ependi; et al., 2023). This innovative approach significantly improves the distribution of the dataset across different classes.

The experimental setup is robust, comprising 10 training epochs with a dropout rate set at 0.2 to mitigate overfitting. The experiment utilizes a batch size of 64 to optimize both the efficiency and effectiveness of the training process. Upon evaluating the model's performance using various indicators, it boasts an exceptionally high level of accuracy, recording validation and testing scores of 99% and 99.17%, respectively. These stellar achievements are further corroborated by the accompanying metrics for precision, recall, and F1-score, all elaborated in Table 2.

Table 2. Precision, Recall, and F1 Score of Indicators (%)

Indicators	Precision	Recall	F1-Score
Equity (So1)	100	100	100
Health (So2)	99	99	99
Education (So3)	98	100	99
Security (So4)	99	99	99
Culture and equality (So5)	99	100	100
Innovation (Ec1)	99	100	99
Income (Ec2)	100	100	100
Infrastructure (Ec3)	100	85	92
Business opportunity (Ec4)	100	100	100
Air (En1)	98	100	99
Energy (En2)	99	100	99
Public facilities (En3)	99	098	98

Table 2 offers a comprehensive breakdown of the model's performance metrics, showcasing its consistently robust results across the tested indicators. Remarkably, the metrics for precision, recall, and F1-score often meet or even surpass the 98% benchmark. The sole exception is the "Ec3" indicator, which pertains to infrastructure, where the recall rate dips to 85% and the F1-score registers at 92%. Grouping by target dimensions reveals minor performance fluctuations, but the results remain laudable, hovering between 96% and 98%. The model's dependability is further underscored by validation and testing accuracies of 96% and 96.57%, respectively. Such unwavering performance underscores the model's resilience and its alignment with the predefined dimensions.

In the intricate realm of sentiment classification, the model excels. For positive sentiments, it consistently registers an impressive 98% for precision, recall, and F1-score, indicating near-flawless categorization. Neutral sentiments are characterized by a 96% precision, bolstered by an impeccable 100% recall, which elevates the F1-score to 98%. Even with negative sentiments, the model stands firm with a 98% precision, slightly tempered by a 93% recall, culminating in an F1-score of 95%. The model's credibility is further enhanced with sentiment-based classification accuracies of 98% and 97.52% for validation and testing, respectively. Such outstanding accuracy across diverse sentiment categories solidifies the model's trustworthiness and underscores the significance of sentiment-annotated data for in-depth urban sustainability assessments. Based on the performance metrics gleaned from crowdsourced data, it's evident that there's a high degree of alignment, whether viewed from the lens of indicators, dimensions, or sentiments. Consequently, it can be inferred that the utilized crowdsourced data is both apt and appropriate for sustainable city evaluations.

4.2. Sustainability City Assessment

Building upon the data that has been previously elaborated, this study undertakes a comprehensive exploration of the multifaceted issues facing four principal cities on Indonesia's Java Island—Surabaya, Semarang, Bandung, and Jakarta. Designed with meticulous care, this assessment ventures into three fundamental realms that define these urban centers: social, economic, and environmental factors. The overarching aspiration is to glean profound insights into these cities, thus paving the way for more informed policy decisions and strategic interventions by local authorities and other stakeholders. This investigation commences with an in-depth focus on the social fabric of these communities—a cornerstone for their overall well-being and prosperity. To capture the nuances in this area, the study uses five key indicators, which are presented in Table 1: equity (So1), health (So2), education (So3), security (So4), and cultural and equality (So5).

Equity (So1): This gauge serves to measure the accessibility and fairness associated with asset ownership among the populace. Health (So2): This indicator provides an overview of the community's general health and evaluates the accessibility and quality of healthcare services. Education (So3): This indicator serves to evaluate the caliber and availability of educational facilities and programs, offering a snapshot of the cities' intellectual reservoir and developmental prospects. Security (So4): This yardstick provides insights into the effectiveness of law enforcement and gauges the overall safety levels within these urban centers. Cultural and Equality (So5): This measure scrutinizes the cities' cultural mosaic and inclusivity, shedding light on the social harmony and integration within these communities.

Through a rigorous analysis of these key indicators in the social dimension, this study aims to present a holistic view of the targeted cities. This will not only contribute to a more nuanced understanding of the specific challenges and strengths unique to each city but also serve as an invaluable resource in understanding the social dimension. The detailed outcomes of this assessment are conveniently encapsulated in Figure 8, offering a visual presentation of the findings.

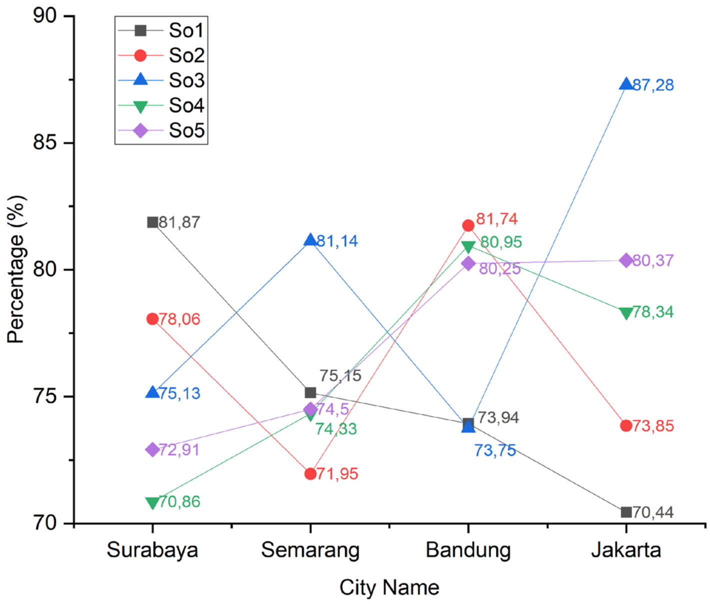

Fig. 8. Score of Social Dimension

Based on the assessment results depicted in Figure 8, Surabaya emerges as the frontrunner among the four cities in terms of asset ownership equity. This finding implies that Surabaya boasts a more balanced distribution of resources and opportunities when it comes to asset ownership. The city's policies and governance likely play a crucial role in achieving this favorable outcome. Following Surabaya, we have Semarang, Bandung, and Jakarta, in that order. This trend suggests that Jakarta may encounter challenges related to asset ownership and calls for increased attention from city authorities. It also implies the existence of income disparities or unequal access to services between Jakarta and Surabaya. Consequently, officials in Jakarta should consider revisiting their urban planning and social welfare strategies to effectively address these issues.

In terms of health indicators, Bandung garners the highest score, indicating a high level of public satisfaction with the city's healthcare services or community health programs. This exceptional score could also reflect Bandung's commitment to healthcare innovation and the delivery of quality services. On the other hand, Semarang scores the lowest in this area, highlighting the need for improvements. The city would benefit from a review of its healthcare policies and possibly a restructuring of its healthcare services. While Surabaya and Jakarta fare better than Semarang, all three cities should prioritize enhancements, improvements, and public awareness in healthcare services. Public-private partnerships could be a viable solution to expedite these improvements.

Jakarta, the capital of Indonesia, leads the pack in educational indicators, outshining other major cities like Surabaya, Semarang, and Bandung. The capital's educational prowess can be attributed to substantial investments in educational infrastructure and programs, along with a rich array of higher learning institutions and research centers. On the other end of the spectrum, Bandung lags behind, signaling the need for targeted interventions to bolster its educational landscape. Despite Bandung's lower ranking, it's worth acknowledging that all four cities fare well overall in educational metrics, given their status as sought-after destinations for students across different regions of Indonesia. This underscores the importance for these urban centers to sustain and even increase their educational investments to cater to a multifaceted student population.

In addition to health, Bandung also excels in security indicators, closely followed by Jakarta. This suggests that both cities are relatively safe and have effective measures in place to maintain public order. Technological innovations such as smart surveillance may be aiding these cities in their safety measures. Meanwhile, Surabaya ranks at the bottom, highlighting the need for enhancements in safety protocols. This also suggests that Surabaya should focus on strengthening its urban security system, perhaps through increased police visibility and community engagement programs. On the other hand, Semarang performs better than Surabaya in terms of city safety but still has room for improvement, particularly in implementing advanced security systems.

Regarding cultural and equality indicators, Jakarta and Bandung claim the top positions. This signifies that both cities are more progressive in promoting cultural activities and fostering social equality. The rich cultural heritage and diverse population in these cities are likely contributing factors. Surabaya and Semarang, however, lag behind, indicating potential disparities in cultural and social initiatives. This trend underscores the need for Surabaya and Semarang to invest more in these areas. Community outreach and the development of cultural centers could be steps in the right direction for these cities.

The next dimension to assess is the economic dimension. This dimension is crucial as it provides a holistic view of the economic vitality and sustainability of a city. It is particularly important in an era of rapid globalization and technological change, where cities must continually adapt to remain competitive. The dimension focuses on public perceptions concerning the economic conditions of a city, an important aspect given that perception often drives investment and community engagement. It centers on four key indicators that are deeply interconnected, each influencing and being influenced by the others. These indicators are not just metrics; they serve as a compass that guides policy decisions and public opinion. They also help local governments and businesses identify strengths and weaknesses, thereby informing strategies for economic development and social welfare programs. The indicators include: Innovation (Ec1), Income (Ec2), Infrastructure (Ec3), and Business Opportunity (Ec4). By paying close attention to these indicators, cities can better position themselves for long-term growth and prosperity.

Innovation (Ec1) assesses the extent to which a city is innovative in the field of technology within the context of entrepreneurship. This is an important indicator as cities with high levels of innovation are often more resilient to economic downturns and are better positioned for future growth. Income (Ec2) measures the level of income or economic prosperity in the city. A high income level often correlates with a higher standard of living and greater access to services and opportunities, which in turn attracts more talent and investment to the city. Infrastructure (Ec3) evaluates the quality and availability of essential infrastructure facilities, such as transportation, utilities, and both national and international economic collaborations. Good infrastructure is the backbone of any thriving city, facilitating the efficient movement of people, goods, and information. Business Opportunity (Ec4) gauges how much the city offers in terms of business opportunities. This indicator can encompass factors like economic performance, regulations, market conditions, and access to capital. Cities that score high in business opportunity are generally more attractive to investors and entrepreneurs, thereby fostering a dynamic and competitive economic. The asssesment results of ecocomic dimension as shows in Figure 9.

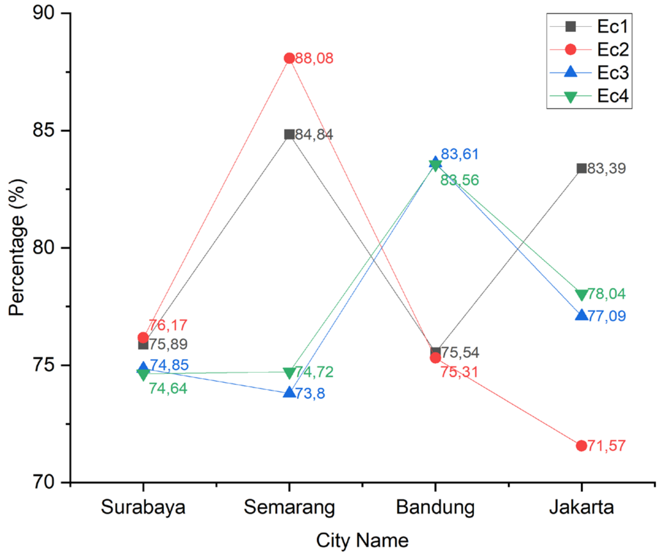

Fig. 9. Score of Economic Dimension

Semarang stands out as a leader in the innovation indicator compared to other cities. The city's high level of innovation signals a robust ecosystem for technology startups, research, and development, positioning it as an attractive location for knowledge-based investments. It is followed by Jakarta, which takes the second position in this metric. Jakarta's vibrant startup ecosystem, bolstered by easy access to capital and high-quality human resources, indicates a significant potential for innovation. Both Bandung and Surabaya exhibit comparable levels of innovation; while Bandung has promise in the technology sector, it requires additional investments to enhance its innovation capabilities. Surabaya, although not a leader, performs reasonably well, with an environment conducive to research and development—likely facilitated by educational institutions or research centers—but there's room for improvement.

Additionally, Semarang tops the list in terms of income compared to other cities, signifying a higher level of prosperity and quality of life. This advantage also makes Semarang an appealing place for business activities. Next is Surabaya, showcasing a balanced economy with stable income levels. However, income in Surabaya has not yet peaked, indicating potential for further economic growth. Bandung, strong in innovation, shows relatively lower income levels, suggesting that the city's innovative potential has not yet been fully converted into economic wealth. Lastly, Jakarta, despite excelling in innovation, has lower income levels compared to other cities, possibly due to income disparities or the high cost of living affecting the average income in Jakarta.

Bandung emerges as the city with the best infrastructure among the four, likely reflecting sound investments in public transportation, utilities, and other facilities that support economic and social activities. Jakarta takes the second position, with infrastructure that outperforms its income levels. This suggests that significant investments have been made in public facilities and transportation, although there's still room for improvement. Surabaya, despite having adequate infrastructure, is not a leader in this aspect. Its existing infrastructure sufficiently supports economic activities, but there is potential for further enhancements. Lastly, although Semarang excels in other aspects, its infrastructure lags behind, indicating a need for more attention and investment to sustain growth.

In terms of business opportunities, Bandung ranks highest among the four cities, possibly due to a combination of strong infrastructure and a burgeoning innovation ecosystem. This makes Bandung a highly attractive location for investors and entrepreneurs. Jakarta follows Bandung, displaying fairly high business opportunities as well. This advantage is supported by good access to markets and capital, although there are areas that need improvement to increase its competitiveness. Surabaya and Semarang are nearly on par in business opportunities, albeit with their strengths in other areas. Surabaya shows decent prospects but has room for improvement, especially in regulations and access to capital. Meanwhile, Semarang, while leading in innovation and income, still needs to adjust other aspects to enhance its appeal for business.

The final dimension to examine is the Environmental Dimension, a critical cornerstone that defines the livability and resilience of urban areas. This aspect is of paramount importance as it offers a comprehensive view of a city's environmental vitality and sustainability. It serves as a lens through which we can evaluate a city's efforts in combating climate change and ensuring public health. In today's fast-paced era of technological advancements and globalization, cities are compelled to continually adapt to stay ahead of the curve. This dimension places particular emphasis on how the public perceives the environmental state of a city. Such perceptions are crucial as they often serve as catalysts for both community engagement and investment. Moreover, public opinion can shape policy agendas and accelerate the implementation of green initiatives. The dimension revolves around three key, interrelated indicators: Air (En1), Energy (En2), and Public Facilities (En3).

Air Quality (En1) gauges how well a city maintains good air standards, particularly in the context of environmental sustainability. This indicator is noteworthy since cities that excel in air quality are often deeply committed to environmental policies. Furthermore, good air quality has a ripple effect, positively impacting not just health but also the economy by reducing healthcare costs. Energy (En2) assesses a city's efficiency and sustainability in energy utilization. High energy efficiency and the use of renewable energy sources are hallmarks of environmental responsibility and sustainability. Cities that prioritize energy efficiency are often more resilient to energy price fluctuations and are better prepared for the challenges posed by climate change. Public Facilities (En3) evaluates the quality and availability of essential community amenities such as waste management, public parks, public transportation, and other communal facilities. Effective management of public facilities indicates a city’s commitment to improving the quality of life for its residents while also minimizing its ecological footprint. The assessment results for the Environmental Dimension are as illustrated in Figure 10.

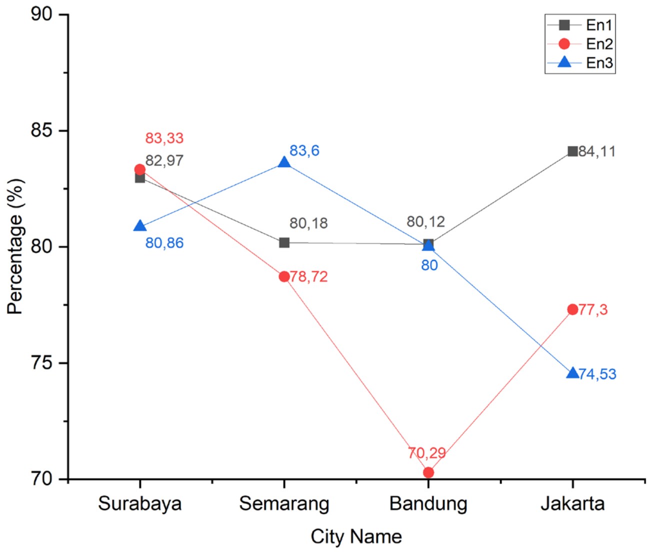

Fig. 10. Score of Environment Dimension

According to the data presented in Figure 10, Jakarta stands out with the highest scores in air quality indicators. This performance is a testament to the city's robust commitment to environmental stewardship. It positions Jakarta as an appealing destination for residents and investors who place a premium on sustainable living and well-being. However, it's worth considering that these high scores could partially be attributed to reduced urban activities spurred by the COVID-19 pandemic. This raises questions about the sustainability of these improvements as normal activities resume. In contrast, Surabaya also garnered positive perceptions, marking the effectiveness of its local environmental policies. This suggests that localized initiatives can be remarkably effective in boosting air quality. As for Semarang and Bandung, their scores were fairly close, indicating that both cities have potential but require targeted interventions to reach established air quality standards.

In the realm of energy sustainability, Surabaya led the pack with the highest scores. The city's community demonstrates a strong adherence to responsible energy policies, be it in terms of fuel consumption or other energy-related practices. This makes Surabaya a lucrative hub for investments focusing on sustainability and renewable energy. Semarang, although trailing behind Surabaya, showed promising performance. However, there remains an opportunity for Semarang to accelerate its transition towards renewable energy sources, aligning itself more closely with global sustainability goals. On the other hand, Jakarta and Bandung exhibited areas for improvement in their energy policies. Bandung, in particular, calls for immediate attention and could benefit from initiatives such as public awareness campaigns, policy reforms, or partnerships with sustainability-focused organizations.

Semarang took the lead in the public facilities indicator, reflecting an exceptional level of availability and management of public amenities. This performance indicates that the city's residents are generally satisfied with the public facilities, a key metric in assessing the effectiveness of urban governance. Surabaya and Bandung scored similarly in this sector, hinting at a level of parity but also revealing room for growth. Targeted investments in public transportation, parks, and community centers could further elevate their standings. Conversely, Jakarta's low score in this sector is a paradox. Despite boasting a more extensive range of public facilities than other cities, it falls short of meeting the general expectations of its diverse and growing population. This underscores the need for the Jakarta city authorities to not only invest in infrastructure but also focus on the quality and accessibility of these public services.

After a comprehensive assessment across multiple dimensions—ranging from social, economic to environmental sustainability—the data has been synthesized to form clusters that categorize the cities in the context of their overall sustainable development. These clusters offer a nuanced understanding of how each city ranks in its pursuit of balanced growth and well-being. Figure 11 visually encapsulates these findings.

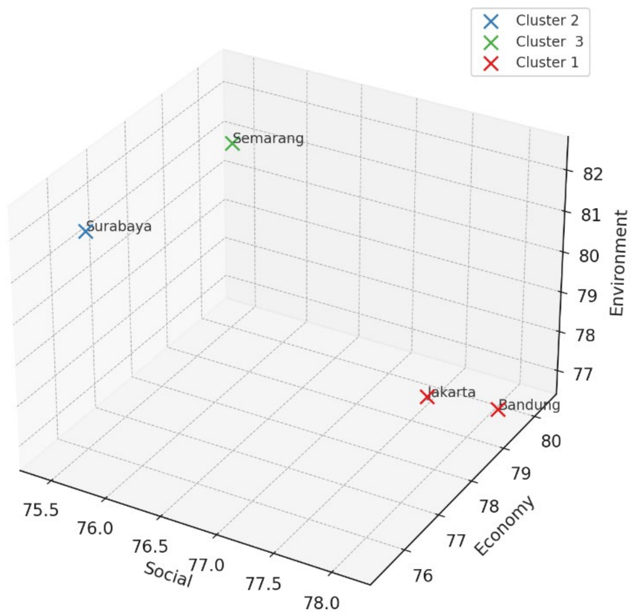

Fig. 11. City Cluster Based on Dimension Score

The clustering reveals three distinct groupings. The first cluster comprises Bandung and Jakarta. These cities excel in areas like healthcare, education, and cultural inclusivity but face challenges in equitable asset distribution and income levels. Their robust infrastructures and strong emphasis on innovation and business opportunities make them magnets for investment, yet there is a pressing need for these cities to address social inequalities. The second cluster is represented solely by Surabaya. Despite leading in asset ownership equity and energy sustainability, Surabaya needs to make strides in healthcare, safety, and particularly in its urban security systems. The city's moderate income levels and adequate infrastructure serve as a strong foundation for future growth, but targeted investments in these lagging areas could propel Surabaya to the forefront of sustainable urban development. The third cluster includes Semarang. This city stands out for its leadership in innovation and income indicators, reflecting a prosperous and future-ready environment. However, its relatively lower performance in healthcare and infrastructure suggests that for sustained growth, a balanced focus across all dimensions is required.

These clusters serve as a roadmap for policymakers, offering targeted insights into the areas each city should focus on for holistic development. For instance, Jakarta may need to prioritize asset ownership and income equality, while Bandung might need to divert more resources to educational and healthcare reforms. Surabaya's focus could be on ramping up healthcare services and urban safety measures, aligning them with its already strong asset ownership equity and energy sustainability. Semarang, on the other hand, should consider bolstering its infrastructure to match its high levels of innovation and income. By categorizing these cities into clusters, we can better understand their unique strengths and challenges in the multi-faceted landscape of sustainable urban development. It underscores the imperative for each city to adopt a balanced approach, taking cues from their cluster characteristics to inform future policy and investment decisions.

4.3. Discussion

This study's findings offer a persuasive argument for the utility of crowdsourced data as a robust alternative to traditional urban sustainability assessment methods. Through an integrated framework that combines real-time assessment models with contemporary analytical techniques, the study provides a comprehensive understanding of urban ecosystems across three core dimensions: social, economic, and environmental. Each dimension is evaluated using a set of twelve key indicators. For instance, the social dimension encompasses indicators such as equity (So1), health (So2), education (So3), security (So4), and cultural equality (So5), while the economic dimension includes indicators like innovation (Ec1), income (Ec2), infrastructure (Ec3), and business opportunities (Ec4). Finally, the environmental dimension covers indicators like air quality (En1), energy usage (En2), and the availability of public facilities (En3).

To better understand the efficacy of using crowdsourced data in this context, the comparison as shown in Table 3. Table 3 delineates how this study uniquely contributes to the existing body of work by prioritizing crowdsourced data gathered from social media platforms and smart city platform. In contrast, comparable studies such as (Wu et al., 2021) focus on intelligent cities through differing sets of dimensions and indicators, while (Zhou et al., 2021) relies on data sourced from statistical year reports and provincial message boards. In summary, this study provides a novel and robust alternative for evaluating urban sustainability, centering exclusively on the rich, real-time data that crowdsourcing affords. This approach not only validates the use of crowdsourced data in sustainability assessments but also enriches the collective understanding of what makes a city sustainable from multiple perspectives.

Table 3. Smart City Assessment Using Crowdsourced Data

Ref	Domain	Data	Indicators
(Wu et al., 2021)	Smartness	Crowdsourced (Sosial media)	20

(Zhou et al., 2021)	Sustainabl e	Multi driven (Statistical year book and provicial message board)	24
This study	Sustainabl e	Crowdsourced (Social media and smart city platform)	12

This study presents an innovative angle to urban sustainability assessment. Drawing data from a myriad of platforms, including social media and review platforms, the study sought to gauge the sustainability index of urban environments. The selection of Indonesian cities as its subjects provided a unique setting, given Indonesia's rapid urbanization. The differentiation in the sustainability profiles of these cities illuminated the heterogeneity in their developmental trajectories. Furthermore, the study's validation of crowdsourced data cements its position as an invaluable tool for policymakers, emphasizing its timeliness and depth. Historically, urban sustainability assessments leaned heavily on government data, surveys, and periodic censuses. However, this study underscores a shift towards more dynamic, real-time data sources. While some previous studies have dabbled in using alternative data sources, none have placed as much emphasis on crowdsourced data as this one. However, it's essential to note that despite its novelty, there exists a faction of researchers skeptical about the reliability and consistency of crowdsourced data, given its inherent volatility and potential biases.

The study's reliance on crowdsourced data, though pioneering, introduces a set of challenges. Crowdsourced data can be influenced by several factors, including platform algorithms, user demographics, and even current events. For instance, a city's perceived sustainability on a review platform might be temporarily skewed after a major event or campaign. Furthermore, the selected cities, while diverse, represent only a fraction of Indonesia's urban landscape. As such, findings might require calibration when extrapolating to other Indonesian cities or globally. This study represents more than just another investigation; it's a clarion call for a paradigm shift in how urban sustainability assessments are approached. The real-time nature of crowdsourced data allows for a more nuanced, timely understanding of urban challenges and successes. For policymakers, this represents a treasure trove of insights, enabling them to make informed decisions that can have immediate, tangible impacts. It also hints at the potential of integrating technology and urban planning in unprecedented ways.

In the grand tapestry of urban sustainability literature, this study stands out as a vibrant thread. Traditional models and assessments, while robust, often lack the immediacy that today's dynamic urban environments demand. By comparing this study with previous works, a narrative of evolution emerges – from static, periodic assessments to dynamic, real-time insights. While the study heralds a new era in data sources for urban assessment, it's essential to tread with caution. Crowdsourced data, for all its merits, is fraught with challenges – from data verification to representativeness. The study's analytical techniques, while state-of-the-art, might not account for all the nuances and idiosyncrasies of such a diverse dataset. Moreover, while the focus on Indonesian cities provides depth, it also narrows the study's scope, potentially limiting its global applicability.

5. Conclusion

This study demonstrates a new data-driven approach for assessing urban sustainability using crowdsourced data. The findings reveal comparative strengths and weaknesses across multiple Indonesian cities based on 12 social, economic, and environmental indicators. The results showcase crowdsourced data as a valuable alternative to traditional data sources, enabling real-time sustainability monitoring. However, limitations exist regarding data reliability and model generalizability. Further research should investigate sustainability perceptions across wider demographic and geographic scopes. Overall, by categorizing cities into tailored clusters, this study provides actionable and nuanced insights to inform smart city development policies that meet the unique needs of each urban ecosystem.

Acknowledgements

We express our sincere gratitude to Universitas Diponegoro for providing the essential facilities and resources that significantly contributed to this study's completion. We also extend heartfelt appreciation to Universitas Bina Darma for their funding support in publishing this article. Both institutions have played pivotal roles, and we are deeply grateful for their unwavering commitment to excellence.

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