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EVALUATING SMART CITY TECHNOLOGY EFFICIENCY AND CITIZEN SATISFACTION USING DATA ENVELOPMENT ANALYSIS

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Abstract. This study employs Data Envelopment Analysis (DEA) to evaluate the efficiency of the top 20 smart cities in converting Research and Development (R&D) investments into desired outcomes. Using national R&D expenditure (2015–2022) as input and ten criteria from the IMD 2024 Smart City Index report as outputs, the analysis reveals varying levels of efficiency among leading smart cities. Seven cities achieved perfect efficiency scores, while others, including some high-ranking cities, showed unexpected inefficiencies. This study provides valuable insights into resource utilization and identifies specific areas for improvement across structural and technological dimensions. The limitations include the focus on top-performing cities and the use of national R&D data as a proxy for city-specific investments. The findings of this study offer a foundation for policymakers and urban planners to optimize resource allocation and improve smart city initiatives, contributing to the ongoing development of sustainable urban environments in the face of technological advancements and urban challenges.

Keywords: smart city efficiency score, human development index, urban planning, citizen satisfaction, sustainable development, assessment method.

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1. Introduction

Conceived in the late 20th century, the smart cities concept has continued to evolve as a popular global framework to address challenges posed by rapid urbanization during the 21st century. While its initiatives are increasingly interdisciplinary, the foundation of smart cities rests on successfully implementing innovative uses of Information and Communication Technologies (ICT) to increase efficiency, enhance the quality of life, and promote sustainable growth in cities (Ahvenniemi et al., 2017; Caragliu et al., 2011; Angelidou, 2014; Bibri & Krogstie, 2017; Kramers et al., 2014; Neirotti et al., 2014; Albino et al., 2015; Yigitcanlar et al., 2019; Zanella et al., 2014). The United Nations Department of Economic and Social Affairs estimates that 68% of the world's population will reside in urban areas by 2050 (United Nations, 2019). Lessons learned from the smart city projects are crucial to addressing the complex problems accompanying rapid urban growth (Bibri & Krogstie, 2017) that will require today's cities to transform into smart urban environments (Bibri & Krogstie, 2019).

Smart city initiatives promise to offer innovative solutions to pressing urban issues such as traffic congestion, energy consumption, waste management, and public safety. By incorporating advanced technologies such as the Internet of Things (IoT), Artificial Intelligence (AI), and big data analytics, smart cities strive to create more responsive, resilient, and sustainable urban ecosystems (Allam & Dhunny, 2019). However, implementing smart technologies and initiatives does not guarantee success in achieving optimal outcomes or efficiency in addressing urban challenges (Kitchin, 2015; Vanolo, 2014). Thus, this study investigates a critical aspect of smart city development: the efficiency with which cities convert their resources into desired results. Addressing the problems that urban areas face requires optimal success in their initiatives. However, not every project or initiative a city undertakes can be assured of being a success. Present-day cities that rank high in smart city indices almost certainly are not thriving in every smart venture (Anthopoulos, 2017; Caird & Hallett, 2019; Fernandez-Anez et al., 2018; Huovila et al., 2019). In other words, a city's high ranking does not necessarily indicate that it most efficiently uses its resources to achieve smart city outcomes (Kitchin et al., 2019; Mora et al., 2019; Joss et al., 2017).

Therefore, the success of 21st-century cities in meeting the challenges of continued rapid urbanization rests not only on posing solutions, but also on how efficiently and effectively cities implement their initiatives and programs. In this context, efficiency refers to the ratio of outputs to inputs, which indicates how well a municipality or decision-maker utilizes their resources to achieve desired results. Thus, efficiency is a critical metric as it reflects a city's performance as well as performance relative to the resources at its disposal. High efficiency suggests that a city maximizes the impact of its investments and efforts in smart city initiatives. In contrast, low efficiency demonstrates the need to improve resource allocation or implementation strategies.

The main objective of this study is to gain deeper insights into smart city performance by applying DEA to evaluate the efficiency of resource utilization in smart city initiatives. DEA is a non-parametric method that empirically measures the productive efficiency of Decision-Making Units (DMUs), allows for simultaneous comparisons of multiple input and output variables (Charnes et al., 1978; Emrouznejad & Anouze, 2010; Toloo & Tichý, 2015). In this case, the smart cities are the DMUs within the DEA model, used for comparison of efficiency.

The approach of this study provides a comprehensive view of efficiency that goes beyond simple rankings or individual metrics, offering a nuanced assessment of smart city performance.

By focusing on the often-neglected aspect of efficiency, this study makes a significant contribution to the field of smart city research. The application of DEA to smart city data enables the identification of best practices, facilitates benchmarking among cities, and highlights areas where improvements can enhance overall efficiency. Moreover, by comparing efficiency levels to established smart city indices, this study has the potential to challenge existing assumptions about the relationship between perceived and actual performance in urban development.

To test DEA's utility in assessing smart city efficiency, the following research questions were posed:

1. To what extent does the efficiency of converting inputs into desired outputs reflect the efficiency of policymakers in smart city governance and development?
2. How can insights derived from DEA be used to improve smart city planning and implementation strategies?

To address the research questions, published data will be extracted and analyzed from peer-reviewed reports focusing on a select group of high-ranking smart cities. The balance of this paper is structured as follows: Section 2 provides a comprehensive literature review, examining existing research on smart city evaluation of efficiency measurement and the application of DEA in urban studies. Section 3 describes the methodology used in this study, including the selection of input and output variables, the data collection process, and the DEA model used. Section 4 presents the findings and analysis of the study, providing insights into the efficiency ratings of various smart cities and identifying patterns and trends within the data. Section 5 discusses the implications of the findings, exploring potential reasons for efficiency disparities, and suggesting strategies for improvement. The final section summarizes the key study findings, acknowledging limitations and proposing directions for future smart city efficiency evaluation research.

2. Relevant literature

The assessment of efficiency in urban development is essential for effective resource allocation and the maximization of benefits for citizens. Smart cities have become increasingly popular with rapid advances in ICT, promising to transform urban landscapes and revolutionize how people live, work, and interact. The chief characteristic of smart city initiatives is the utilization of advanced technologies such as AI, the IoT, and "big data" analytics to improve the quality of life of residents, promote sustainability, and drive economic growth (Kushwah et al., 2024; Pelton & Madry, 2024). Caragliu et al. (2011) made a significant contribution to the field of urban studies by offering a comprehensive definition of smart cities, identifying key characteristics, and analyzing these concepts within the European context. Based on Caragliu et al. (2011) study, there are six main axes that characterize smart cities include smart economy, smart mobility, smart environment, smart people, smart living, and smart governance. The six axes for smart cities offers a comprehensive and structured approach to urban development. By focusing on these key areas, cities can create more livable, efficient, and sustainable environments for their citizens. On other hand, Neirotti et al. (2014), explores the concept of smart cities and their global trends. The research aims to provide a comprehensive understanding of smart cities and investigate their diffusion patterns worldwide such as economic, urban, and geographical variables. Another example, Albino et al. (2015), aimed to clarify the concept of smart cities through an extensive literature review. Albino et al. (2015) developed a classification of smart city application domains, including natural resources, energy, transport, buildings, living, government, and economy. From Albino et al. (2015), an analysis of 70 cities implementing smart city projects and introduce a coverage index to measure the extent of smart initiatives across various domains. The study by Albino et al. (2015) investigates how economic, urban, demographic, and geographical factors influence a city's approach to becoming smarter.

This literature review provides an overview of the current research on smart city evaluation methodologies, explicitly focusing on applying DEA in urban studies and smart city contexts. As the smart city concept continues to evolve, researchers and policymakers are facing the challenge of defining, implementing, and evaluating smart city initiatives. This review explores various approaches to smart city evaluation, including the qualitative and quantitative methodologies developed to assess the performance and impact of smart city projects.

2.1. Current state of smart city evaluation research

The evaluation of smart cities has emerged as a critical area of research due to the substantial investments and high expectations associated with these initiatives worldwide. Numerous researchers have endeavored to define the concept of "smart city" in previous studies. For example, Angelidou (2014), conducted a research to address the lack of consensus on smart city definitions and the limited exploration of strategic planning in this field. Angelidou (2014) recognized the multidisciplinary nature of smart cities and sought to trace their historical development to gain a better understanding of what it means to be "smart" in an urban context. Thus, researchers have proposed various frameworks and methodologies to evaluate smart city performance, impact, and sustainability (Anthopoulos et al., 2019).

A key challenge in smart city evaluation is the lack of a universally accepted definition for a "smart city" (Albino et al., 2015). This ambiguity has resulted in diverse evaluation approaches focusing on different aspects of smart city performance. For example, Giffinger et al. (2007) proposed a framework that assesses smart cities based on six key characteristics: smart economy, smart people, smart governance, smart mobility, smart environment, and smart living. This multidimensional approach has been widely adopted and adapted in subsequent research (Lombardi et al., 2012).

Another significant area of research focuses on developing key performance indicators for smart cities. Huovila et al. (2019) conducted a comparative analysis of standardized indicators for smart sustainable cities, emphasizing the importance of selecting appropriate indicators based on each city's specific context and goals. Similarly, Sharifi (2019) critically reviewed smart city assessment tools, highlighting the need for more comprehensive and context-sensitive evaluation methodologies.

The use of big data and advanced analytics in smart city evaluations has gained prominence in recent years. Kitchin et al. (2015) explored the potential of urban indicators and city benchmarking as tools for smart city governance while cautioning against the overreliance on quantitative metrics at the expense of qualitative assessments. Batty et al. (2012) emphasized integrating diverse data sources and analytical approaches to understand smart city performance better.

Zanella et al. (2014) focuses on the application of IoT technology in urban environments to create smart cities. The researchers explore how IoT can enhance various aspects of city management and improve the quality of life for citizens.

Kitchin et al. (2019) developed a framework that integrates the concepts of citizenship, justice, and rights within the context of smart cities. The authors argue that the right to the smart city extends beyond individual rights to encompass collective or common rights. The study by Kitchin et al. (2019) critically examined the implementation of smart city technologies and their impact on urban life. It raises concerns about privacy, data collection, and the potential for surveillance in smart city environments.

Mora et al. (2019) identified key strategic principles for successful smart city development in Europe. The research employed a multiple case study approach to analyze best practices across various European cities.

Researchers have also examined the implications of smart city initiatives, emphasizing the need for evaluation frameworks that consider factors such as privacy, digital inclusion, and citizen participation (Cardullo & Kitchin, 2017; Vanolo, 2014). Hollands (2020) critiqued the technocentric approach to smart city development, advocating for a more citizen-centered evaluation that prioritizes social equity and democratic governance.

The economic impact of smart city initiatives has been another area of focus for evaluation research. Caragliu and Del Bo (2019) analyzed the relationship between smart city policies and urban wealth creation, while Neirotti et al. (2014) examined the factors influencing the development of smart city initiatives across various domains.

Out of all the approaches, one of the most debated smart city assessment frameworks is one proposed by Zhang et al. (2019), which utilized the evaluation index system with references to Maslow's hierarchy of needs. The model aimed to fulfill residents' needs on five levels: physiological, safety, love/belonging, esteem, and self-actualization (Ismagilova et al., 2022; Sharif & Pokharel, 2022; Stübinger & Schneider, 2020). Using the Fuzzy Analytical Hierarchy Process (FAHP) method and questionnaires, the weight of each index is assessed, and 29 cities in China were evaluated (Milošević et al., 2021; Ozkaya & Erdin, 2020; Simonofski et al., 2021). The K-means clustering analysis showed differences in the priorities of smart city construction from the perspective of urban residents.

Similarly, Fang and Shan (2024) further elaborated on a people-centered analysis methodology for smart city assessment. Their model aimed to maximize user experience while selecting the allocation of investments considering various aspects of smart cities (Lai et al., 2020; Neves et al., 2020; Yigitcanlar et al., 2022). The study developed efficiency evaluation and user demand models to test the analysis and determine the smart city's development direction and emphasis (Bellini et al., 2022; Guo & Zhong, 2022; Patrão et al., 2020; Sharifi, 2020). This approach focused more on the dynamic assessment of experienced cities, suggesting that indicators should be changed to consider future public demands and relevant technologies.

Huovila et al. (2019) evaluated and compared various standardized indicators used for assessing smart sustainable cities. The research aimed to provide guidance on which indicators and standards are most appropriate for different contexts and purposes.

Researchers have conducted multiple reviews of existing literature to consolidate and gain a deeper understanding of study findings. These reviews provided additional evaluation frameworks or expanded upon facets of earlier studies. For example, Yigitcanlar et al. (2018) analyzed the existing literature to identify key drivers and outcomes of smart city initiatives. Their review resulted in a multidimensional framework for understanding smart cities by intertwining development drivers with desired outcomes (Yigitcanlar et al., 2018). Similarly, Ahvenniemi et al. (2017) compared sustainable and smart city frameworks and indicators to identify critical differences in urban development approaches. This work highlighted gaps in how each approach addressed various aspects of urban sustainability.

Hodson et al. (2023) prioritized human-centered design by analyzing eight smart city projects to evaluate the social impact of smart city technologies and services. In examining smart cities' methods, challenges, and future directions, the authors' findings revealed gaps in social impact evaluation and proposed criteria for assessing smart cities' technologies and services.

Taking a broader perspective, Caird and Hallett (2019) focused on digital, human, and physical characteristics in assessing smart city progress and called for an evidential approach. They also emphasized the importance of using appropriate, valid, and credible evaluation methodologies (Kashef et al., 2021; Ninčević Pašalić et al., 2021; Tan & Taeihagh, 2020) while admitting that challenges and limitations remain in creating evaluation frameworks.

Angelidou (2015) identified four primary factors influencing smart city development: urban futures, knowledge and an innovation economy, technology push, and application pull. Similarly, Huang and Nazir (2021) focused on evaluating smart cities based on IoT use cases and the challenges posed by rapid urban population growth and increased adoption of IoT devices.

Hodson et al. (2023) examined methods, challenges, and future directions for evaluating the social impact of smart city technologies and services. They analyzed eight smart city projects prioritizing human-centered design across various contexts and development phases. This study identified gaps in social impact evaluation in smart city indices, examined projects, proposed criteria for social impact evaluation in smart cities, and suggested new research directions.

Lytras and Visvizi (2018) examined user adoption patterns in smart city services and suggested the need for sustained interdisciplinary approaches (Lytras & Visvizi, 2018). Lacson et al. (2023) also emphasized the importance of a multidisciplinary approach in future smart city evaluations. The authors identified gaps in city assessments through a scoping review, analysis, and synthesis of existing assessments of developing economies. They proposed incorporating more robust, mixed, and quantitative studies.

A longitudinal bibliometric analysis by Mora et al. (2017) revealed publication trends, influential authors, and papers in the smart city field from 1992 to 2012. In 2017, Bibri and Krogstie (2017) conducted an interdisciplinary literature review of state-of-the-art smart, sustainable cities, identified gaps, and proposed a framework that integrated the studies' strengths. Ruhlandt (2018), emphasized the role of smart cities' governance structures, processes, and challenges. After reviewing existing research, the study proposed an integrated conceptual model to assist in smart city evaluation. Fang and Shan (2024) briefly noted that despite many theoretical and methodological surveys and research, practical applications of smart city evaluations require further exploration.

A significant contribution to the field comes from Zhang et al. (2022), who evaluated new first-tier smart cities in China using the entropy method and Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS). Their study established an evaluation system with five dimensions and 30 indicators, providing insights into the varying performance of smart cities across different aspects such as infrastructure, economy, governance, and environment. This research highlights the uneven development of smart city initiatives and the need for targeted improvements in specific areas.

Another significant contribution to the field comes from Makki and Alqahtani (2024), who identified and analyzed the obstacles that hinder the development of smart cities using Decision Making Trial and Evaluation Laboratory (DEMATEL) method.

Zhang et al. (2022), who evaluated new first-tier smart cities in China using the entropy method and TOPSIS.

The multifaceted nature of smart city development is further emphasized by Toli and Murtagh (2020), who delved into the concept of sustainability within smart city definitions. Their research underscores the importance of considering environmental, social, and economic dimensions in smart city evaluations. Building on this, Chen et al. (2022) focused specifically on social sustainability in smart cities, highlighting the critical role of inclusion, equity, and citizen participation as both inputs and long-term outcomes in urban development.

Kramers et al. (2014) studied the potential of ICTs in assessing energy consumption within urban environments. The study aims to develop an analytical framework that can guide city authorities and ICT companies in assessing, identifying, and implementing effective solutions for sustainable urban development.

Practical implementation challenges in smart city projects are addressed by Mosannenzadeh et al. (2017), who introduced a case-based learning methodology to predict barriers to implementing smart and sustainable urban energy projects. This approach offers valuable insights for policymakers and urban planners in anticipating and overcoming obstacles in smart city initiatives. The technological aspect of smart cities is explored by Bibri (2018), who proposed an analytical framework for leveraging IoT and big data applications to enhance environmental sustainability in urban settings. This research demonstrates the potential of advanced technologies in improving city operations and environmental performance.

Efficient planning and operation of urban logistics and mobility services are critical components of smart city development as they directly impact the accessibility, operational efficiency, and human-centric design of these evolving urban environments. A key factor in this process is the crucial role of Geographic Information System analysis, which has proven invaluable for mapping and analyzing spatial and urban patterns in the context of city and urban transport and logistics planning (Nasser et al., 2021).

Caird and Hallett (2019) developed a comprehensive framework for evaluating smart city initiatives. The researchers recognize the growing importance of smart cities and the need for effective evaluation methods to assess their impact and success. Thus, the authors proposed a structured approach to evaluate smart city projects, considering multiple dimensions such as economic, social, and environmental impacts.

Apostolopoulos and Kasselouris (2022) examined the potential of transport pooling in urban logistics, using the case study of the Thriasio Logistics Centre in Greece. Their research highlighted the importance of innovative solutions to address the challenges of urban freight transport, which is a crucial component of smart city development. Meanwhile, Liu et al. (2023) conducted a comprehensive review of GIS models for sustainable urban mobility planning, identifying the current use, future needs, and potential of these tools.

Bafail (2024) employs random forest and regression analysis, two powerful machine learning techniques, to analyze large datasets collected from various urban systems. These methods are commonly used in smart city research for their ability to handle complex, multidimensional data and provide accurate predictions. The findings from Bafail's study reveal that the human development index is a key predictor of smart city performance. Interesting study by Fernandez-Anez et al. (2018) addresses the complex nature of smart city initiatives and proposed a novel approach to understanding and implementing these strategies.

Other researchers have also used other instrument methods to evaluate industrial cities. For instance, Ye et al. (2022) focused on the methodological aspects of smart city evaluation, including the selection of criteria and the application of multi-criteria decision-making models for ranking smart cities. Kourtzanidis et al. (2021) proposed a novel comprehensive evaluation framework that assesses the impact, performance, and sustainability potential of smart city projects. The framework consists of a set of key performance indicators grouped into five dimensions: impact, efficiency, effectiveness, sustainability, and replicability. The versatility of this framework is demonstrated through its application to three distinct smart city projects, showcasing its ability to provide valuable insights for decision-makers and project managers, regardless of the specific context or focus of the initiatives.

2.2. Application of DEA in urban studies and smart cities

The DEA is a powerful tool for evaluating factors that contribute to the efficiency of urban areas. More recently, DEA has been used to evaluate the efficiency of smart cities (Shen et al., 2022). Initially developed by Charnes et al. (1978), DEA has been widely used in various fields, including urban planning, public service delivery, and environmental management.

In the realm of DEA applications to urban systems, recent studies have expanded the use of this methodology beyond traditional efficiency measurements. For instance, Romão et al. (2018) explored the concept of smart cities as common places for tourists and residents, offering a structural analysis of urban attractiveness determinants. Their work provides valuable insights into how smart city initiatives can enhance the quality of life of both permanent inhabitants and visitors.

A study by Lee et al. (2019b) evaluated the efficiency of transfer stations between bus and subway systems in Seoul using smart card data. The researchers employed DEA to estimate the relative efficiency of transfer stations and conducted Tobit regression analysis to identify factors influencing transfer efficiency. The average efficiency score for 32 major stations was 0.557, with efficiency being proportional to the number of transfer trips and transfer rates.

Another study by Lee et al. (2019a) assessed Transit-Oriented Development (TOD) efficiency in Seoul using the network slacks-based measure DEA model. The study analyzed 352 subway station areas using smartcard and socioeconomic data. The overall efficiency score average was 0.349, with transit design and efficiency scores of 0.453 and 0.245, respectively. The findings highlight the importance of balancing transit design and efficiency for optimal station performance

Worthington and Dollery (2000) applied DEA to assess the efficiency of local government service delivery in Australia, and García-Sánchez (2006) used DEA to analyze the efficiency of street cleaning services in Spanish municipalities. These studies demonstrated the versatility of DEA in handling multiple inputs and outputs, making it well-suited for evaluating complex urban systems.

Lee and Jeong (2023) evaluated the equity of vertical transport system installations in Seoul subway stations for mobility-impaired users. Using DEA and smart card data, the researchers found an average equity score of 0.48 for subway stations. Out of 257 stations, 27 were deemed equitable with a score of 1.0, while the bottom 27 stations averaged 0.19, indicating a need for significant improvement. The study suggests that targeted investments based on station-specific needs can lead to more equitable and efficient improvements.

Lee and Lee (2024) evaluated nightlife attractiveness in Seoul, focusing on Millennials and Generation Z (Gen MZ) all-nighters. Using DEA with smart card data and open data sources, the study analyzed 161 Dong unit areas in Seoul. The average attractiveness score was 0.87, suggesting room for improvement to reach maximum attractiveness. The study found that Gen MZ all-nighters from affluent suburban areas tended to frequent these nightlife hotspots, providing insights into existing and potential future hotspots.

Kourtit et al. (2021) used a highly efficient DEA methodology to establish a safety condition benchmark and rank in 57 global and 14 major European cities (Duan et al., 2020; Fan et al., 2021; Kourtit et al., 2021; Omrani et al., 2020). The analysis revealed a gap in safety data and highlighted the potential effectiveness of implementing efficient and informed safety policies in the cities studied (Manoharan et al., 2023; Van Puyenbroeck et al., 2021). The study demonstrated the possible use of DEA in informing urban planning and policy decisions by identifying the relative efficiency in specific areas.

Similarly, Kutty et al. (2022) applied DEA methodology to assess the relative sustainability performance of Europe's top 35 smart cities. Their Double-Frontier Slack-Based Measure DEA model utilized optimistic and pessimistic assumptions, resulting in a more accurate sustainability performance evaluation. The study identified Dublin, Oslo, Zurich, and Amsterdam as the four cities with the highest ratings in the overall sustainability index. The use of DEA in this study highlights its ability to evaluate the interactions between various dimensions of sustainability and smart city development.

Fancello et al. (2014) used DEA to evaluate the efficiency of smart city transportation systems in Italian cities, providing insights into the impact of smart technologies on urban mobility. Smart city DEA application has also gained attention in studies by Zhao et al. (2018) in evaluating the energy efficiency of smart grid systems in Chinese cities and by Mardani et al. (2017) through a comprehensive review of DEA applications in energy and environmental studies.

In contrast, Dyson et al. (2001) pointed out challenges in applying DEA to selecting appropriate input and output variables and interpreting results. Dyson et al. (2001) noted that such caution is especially relevant in smart cities, where careful consideration is required in choosing relevant indicators and interpreting efficiency scores. Despite these challenges, the use of DEA for smart city evaluation continues to evolve and grow. Recent advancements in DEA methodologies, such as network DEA (Dyson et al., 2001) and dynamic DEA (Tone & Tsutsui, 2010), offer new opportunities to capture complex relationships and temporal aspects of smart city systems.

Keles and Alptekin (2023) maintains that DEA offers various benefits in assessing smart cities. Firstly, it provides a comparative efficiency score, enabling cities to be ranked and compared for progress (Mao et al., 2023). Secondly, DEA is flexible regarding the number of inputs and outputs involved, making it possible to evaluate a wide range of factors that define smart city performance. Thirdly, DEA does not limit researchers in terms of the functional form of the production process to estimate the production frontier.

In general, the use of DEA in urban studies and smart cities holds promise for evaluating the efficiency and effectiveness of smart city initiatives. Combining DEA with other analytical techniques such as machine learning and big data analytics promises even more powerful tools for evaluation and decision-making in the future.

The extensive literature review on smart city assessment and the use of DEA in urban studies reveals a dynamic and growing research field. It also highlights significant gaps and opportunities that underscore the importance of this study. While most evaluation systems focus on infrastructure capabilities and service delivery, there is a lack of comprehensive approaches considering citizens' feedback and perceptions about the services provided (Javed et al., 2022; Kirimtat et al., 2020; Singh et al., 2023).

In addition, the literature shows that while DEA has been successfully applied in various urban contexts, its application to smart city assessment is still developing. This study directly addresses this concern by focusing on the efficiency of smart city performance, providing valuable insights beyond traditional rankings.

The significance of this study is further highlighted by its potential to inform evidence-based decision-making in urban planning and innovative city development. By identifying efficiency frontiers and best practices, this study can guide policymakers and urban planners in optimizing resource allocation and enhancing the overall efficiency of smart city initiatives. In addition, this study contributes significantly to the literature on smart cities and policy effectiveness by introducing a methodological approach to analyze the IMD 2024 report data. By applying efficiency analysis to the IMD 2024 report dataset, this study offers a fresh perspective on smart city performance that has not been previously explored. Furthermore, this study addresses a critical gap in the literature by establishing a direct link between national R&D investment (as a percentage of GDP) and citizen feedback on smart city indicators, creating a unique input-output relationship. This approach provides a nuanced evaluation of the efficiency of smart city initiatives. Moreover, this study focuses on policymakers' efficiency in converting inputs to desired outputs to yield actionable insights that can inform and enhance decision-making processes. Additionally, the utilization of 40 structure and technology indicators derived from citizen feedback as output measures from the IMD 2024 report dataset adds depth to the assessment of smart city performance, transcending traditional metrics. Consequently, this study not only advances the theoretical understanding of smart city development but also provides practical tools for policymakers to optimize the impact of their investments and strategies in fostering more responsive and efficient urban environments.

3. Methodology

This study utilized the DEA method to evaluate the efficiency of smart cities in converting their resources into the desired outcomes. As a non-parametric linear programming model well-suited for this evaluation, the DEA can handle multiple inputs and outputs simultaneously without specifying their functional relationships (Charnes et al., 1978). The methodology of this study involves eight steps as shown in Figure 1. The study encompasses a sample of 20 cities worldwide, chosen based on their inclusion in reputable smart city rankings and consistent data availability for all selected variables. The data for the analysis primarily come from the IMD Smart City Index 2024 Report (IMD World Competitveness Center, 2024), and are supplemented by other urban databases and official city statistics to ensure comprehensive coverage of input and output factors.

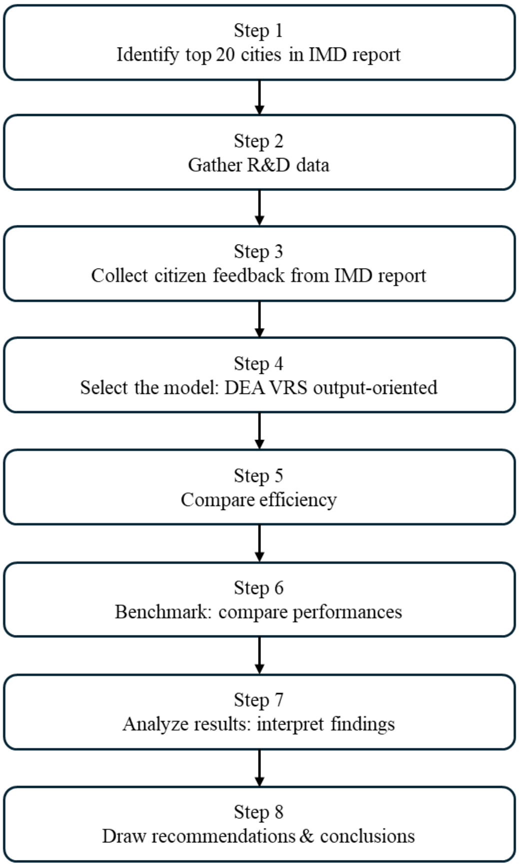

Figure 1. Methodology for the assessment of smart city efficiency using the DEA model

The methodology of this study is a structured eight-step process. Initially, the top 20 cities from the IMD Smart City Index 2024 report were identified as the units for the analysis. The next step involves gathering data on R&D expenditure, specifically the average percentage of gross domestic product (GDP) spent on R&D from 2015–2022 for the countries whose cities are identified as the top 20 ranking in the IMD 2024 report. This was followed by collecting citizen feedback data from the IMD 2024 report, focusing on two main criteria: structure and technology. These criteria are further broken down into sub-criteria, including Health & Safety, Mobility, Activities, Opportunities, and Governance, with the average of these sub-criteria being used for analysis. Each of these sub-criteria is composed of several indicators that provide a more detailed assessment of a smart city's performance in that area. In this study, the average values of these indicators within each sub-criterion were calculated to obtain a comprehensive score for each sub-criterion. These averaged sub-criteria scores were then used as outputs in the DEA model. For instance, the Health & Safety sub-criterion in the structural part includes six indicators such as basic sanitation of the poorest areas, recycling services, public safety, air pollution, medical services provision, and finding housing with rent less or equal than 30% of monthly salary. By averaging these indicator values, a single representative score for each sub-criterion was obtained, providing a balanced view of a city's performance in that particular aspect.

It is important to note that while multiple outputs were considered in the form of these averaged sub-criteria scores, only one input was used in the model. This input was the average R&D expenditure as a percentage of GDP for countries whose cities were included in the top 20 ranks in the IMD 2024 report. This approach allows for an evaluation of how efficiently cities convert their country's R&D investments into tangible improvements across various aspects of urban life and smart city development.

The study then proceeds to select the DEA output-oriented Variable Returns to Scale (VRS) model for efficiency computation. After calculating the efficiency scores, a benchmarking process conducts to compare the performances of the cities. The results are then thoroughly analyzed, and the findings are interpreted in the context of smart city efficiency. Finally, conclusions are drawn from the analysis, and recommendations are formulated based on the insights gained from the study. This comprehensive methodology allows for a systematic evaluation of how efficiently smart cities utilize their resources to achieve desired outcomes in various aspects of urban life and governance.

3.1. Data collection

The data collection for this study draws upon the comprehensive IMD 2024 Smart City Index report (IMD World Competitveness Center, 2024), a publicly available resource that offers valuable insights into urban development and citizen satisfaction. The IMD report covers various aspects, and this study primarily focuses on the structural and technological dimensions of smart cities. The IMD 2024 report is structured into four key sections: background information, priority areas, attitudes, and response scores from citizens. The fourth section, which forms the core of this analysis, presents response scores across 40 factors, categorized into two main sections: structures and technologies. These sections are further divided into five sub-sections each: health & safety, mobility, activities, opportunities, and governance. Each sub-section contains specific indicators, as detailed in Table 1. These indicators are scored on a scale from 0 to 100, based on comprehensive surveys that capture citizens' feedback on both structural and technological aspects of their urban environment. These data provide a nuanced and citizen-centric perspective on smart city performance, enabling a robust evaluation of urban development initiatives and their impact on residents' quality of life through the lens of structural and technological advancements.

As presented in Table 1, the structure pillar measures the quality of a city's infrastructure, while the technology pillar evaluates the availability and use of technological solutions. This index incorporates feedback from 120 residents per city to reflect recent developments.

The key indicators in the IMD 2024 report include digital equity, affordable housing, environmental sustainability,

Table 1. Input and outputs criteria for smart city DEA model

Indicator	Main criteria	Sub criteria	Feature
Average R&D expenditure as a percentage of GDP (2015–2022)	Economic	Economic	Input 1
Basic sanitation meets the needs of the poorest areas	Structure	Health & safety	Output 1
Recycling services are satisfactory			
Public safety is not a problem			
Air pollution is not a problem			
Medical services provision is satisfactory			
Finding housing with rent ≤30% of a monthly salary is not a problem			
Traffic congestion is not a problem	Structure	Mobility	Output 2
Public transport is satisfactory			
Green spaces are satisfactory	Structure	Activates	Output 3
Cultural actives (shows, bars, and museums) are satisfactory			
Employment finding services are readily available	Structure	Opportunities	Output 4
Most children have access to a good school			
Lifelong learning opportunities are provided by local institutions			
Businesses are creating new jobs			
Minorities feel welcome			
Information on local government decision are easily accessible	Structure	Governance	Output 5
Corruption of city officials is not an issue of concern			
Residents contribute to decision making of local government			
Residents provide feedback on local government projects			
Online reporting of city maintenance problems provides a speedy solution	Technology	Health & safety	Output 6
A website or app allows residents to give away unwanted items easily			
Free public Wi-Fi has improved access to city services			
CCTV cameras have made residents feel safer			
A website or app allows residents to monitor air pollution effectively			
Arranging medical appointments online has improved access			
Car-sharing apps have reduced congestion	Technology	Mobility	Output 7
Apps that direct you to an available parking space have reduced journey time			
Bicycle hiring has reduced congestion			
Online scheduling and ticket sales have made public transport more accessible to use			
The city provides information on traffic congestion through mobile phones			
Online purchasing of tickets to shows and museums has made it easier to attend	Technology	Activates	Output 8
Online access to job listings has made it easier to find work	Technology	Opportunities	Output 9
IT skills are taught well in school			
Online services provided by the city have made it easier to start a new business			
The current internet speed and reliability meet connectivity needs			
Online public access to city finances has reduced corruption	Technology	Governance	Output 10
Online voting has increased participation			
An online platform where residents can propose ideas has improved city life			
Processing identification documents online has reduced waiting times			

security, road congestion, and trust in governance. The index also highlights the growing significance of AI in urban planning and management, emphasizing how smart technologies shape various aspects of urban life, from safety and efficiency to inclusivity and overall quality of life.

This study focuses on the top 20 cities ranked in the report, providing a more in-depth analysis of their performance and characteristics. These leading smart cities, which are presented in Table 2. As shown in Table 2, Zurich tops the list with the highest ranking and an impressive HDI score of 0.989, closely followed by Oslo and Canberra, both sharing the second-highest HDI of 0.980. Interestingly, while Singapore ranks 5th overall, it has a lower HDI (0.939) compared to some lower-ranked cities, such as London (8th) and Stockholm (11th), which boast HDI scores of 0.973 and 0.972, respectively. This suggests that factors beyond the HDI influence the overall ranking. At the lower end of the ranking are cities such as Shanghai (19th) and

Table 2. Population, GNI per capita data for the analyzed cities, and HDI scores with their descriptive statistics

City	Ranking (DMU)	Population	GNI per capita (PPP $) in 2022	HDI score
Zurich	1	410,000	69,433	0.989
Oslo	2	1,040,000	69,190	0.980
Canberra	3	400,000	49,257	0.980
Geneva	4	200,000	69,433	0.966
Singapore	5	5,940,000	88,761	0.939
Copenhagen	6	1,350,000	62,019	0.967
Lausanne	7	140,000	69,433	0.966
London	8	8,870,000	46,624	0.973
Helsinki	9	650,000	49,522	0.960
Abu Dhabi	10	1,480,000	74,104	0.911
Stockholm	11	950,000	56,996	0.972
Dubai	12	2,880,000	74,104	0.911
Beijing	13	20,460,000	18,025	0.907
Hamburg	14	1,850,000	55,340	0.972
Prague	15	1,320,000	39,945	0.960
Taipei City	16	2,720,000	44,057	0.916
Seoul	17	9,960,000	46,026	0.952
Amsterdam	18	1,000,000	57,278	0.962
Shanghai	19	27,060,000	18,025	0.880
Hong Kong	20	7,550,000	62,486	0.949

Hong Kong (20th), despite Hong Kong having a relatively high HDI of 0.949. The data in Table 2 reveal that a high HDI does not always correlate directly with a higher overall ranking, indicating the complexity of factors involved in urban development and quality of life assessments.

Table 3 presents a comprehensive overview of the economic indicators for countries with cities ranked highly in the IMD 2024 Smart City Index. Table 3 displays the GDP figures for 2015 to 2022, providing a year-by-year breakdown of countries' economic performance. The values in Table 3 were obtained from the International Monetary Fund (2025). Additionally, the table includes the average GDP for this eight-year period, offering insights into each country's overall economic stability and growth. A key feature of the table is the inclusion of average R&D expenditure as a percentage of GDP for the same timeframe. The data for R&D values were collected from the Organization for Economic Co-operation and Development report (OECD, 2025). This metric is particularly relevant as it reflects each nation's commitment to innovation and technological advancement, factors that are crucial in developing smart cities. The data allow for easy comparison between these countries, highlighting their economic trajectories and investment priorities in research and development, which are fundamental to their success in smart city initiatives.

Outputs dataset for this study were meticulously collected from the IMD, ensuring a reliable and authoritative

Table 3. Economic indicators of smart city leaders: GDP and R&D expenditure (2015–2022)

City	Country	GDP								Avg. GDP	Avg. R&D % (2015–2022)	Avg. R&D expenditure (2015–2022)
		2015	2016	2017	2018	2019	2020	2021	2022			
Zurich	Switzerland	542	558	577	602	633	630	711	786	630	3.18%	20
Oslo	Norway	320	327	341	373	379	361	482	532	390	1.97%	8
Canberra	Australia	1129	1171	1220	1290	1368	1381	1557	1733	1356	2%	24
Geneva	Switzerland	542	558	577	602	633	630	711	786	630	3.18%	20
Singapore	Singapore	482	504	537	586	602	578	719	800	601	2.01%	12
Copenhagen	Denmark	292	304	319	332	352	366	412	448	353	2.96%	10
Lausanne	Switzerland	542	558	577	602	633	630	711	786	630	3.18%	20
London	United Kingdom	2829	2911	3042	3130	3336	3219	3544	3980	3249	2.58%	84
Helsinki	Finland	239	247	260	272	289	295	318	345	283	2.85%	8
Abu Dhabi	United Arab Emirates	574	612	628	702	726	614	645	743	656	1.22%	8
Stockholm	Sweden	483	499	518	541	586	595	657	715	574	3.35%	19
Dubai	United Arab Emirates	574	612	628	702	726	614	645	743	656	1.22%	8
Beijing	China	17474	18849	20519	22368	24404	25547	28722	31678	23695	2.25%	533
Hamburg	Germany	4143	4278	4473	4665	4925	4880	5237	5687	4786	3.05%	146
Prague	Czech Republic	376	389	417	443	487	480	525	579	462	1.89%	9
Taipei City	Taiwan	1065	1098	1155	1180	1238	1359	1505	1654	1282	3.10%	40
Seoul	South Korea	2021	2105	2217	2348	2408	2482	2686	2956	2403	4.53%	109
Amsterdam	Netherlands	887	918	960	1014	1081	1092	1215	1367	1067	2.21%	24
Shanghai	China	17474	18849	20519	22368	24404	25547	28722	31678	23695	2.25%	533
Hong Kong	China	17474	18849	20519	22368	24404	25547	28722	31678	23695	2.25%	533

Note: Figures are in billions of U.S. dollars. Avg. = Average.

Table 4. Smart city performance outputs dataset

City	Ranking	Output 1	Output 2	Output 3	Output 4	Output 5
Zurich	1	71	68	85	72	72
Oslo	2	60	54	79	72	60
Canberra	3	64	60	81	75	59
Geneva	4	64	56	82	69	66
Singapore	5	71	64	77	74	69
Copenhagen	6	61	49	78	72	63
Lausanne	7	60	49	80	70	62
London	8	43	42	73	62	49
Helsinki	9	57	59	78	68	58
Abu Dhabi	10	71	68	85	72	72
Stockholm	11	52	40	76	65	55
Dubai	12	70	60	84	73	73
Beijing	13	70	50	82	76	67
Hamburg	14	54	43	73	62	53
Prague	15	53	46	64	66	53
Taipei City	16	66	41	67	66	59
Seoul	17	55	47	61	51	48
Amsterdam	18	47	43	68	66	53
Shanghai	19	73	55	83	79	71
Hong Kong	20	49	47	55	61	50
City	Ranking	Output 6	Output 7	Output 8	Output 9	Output 10
Zurich	1	78	73	89	80	76
Oslo	2	54	52	81	61	45
Canberra	3	58	39	78	60	43
Geneva	4	59	55	81	64	55
Singapore	5	72	59	82	75	64
Copenhagen	6	54	46	79	62	48
Lausanne	7	53	51	78	63	50
London	8	55	57	75	65	54
Helsinki	9	54	50	73	63	50
Abu Dhabi	10	78	73	89	80	76
Stockholm	11	52	48	74	58	45
Dubai	12	78	72	90	80	73
Beijing	13	79	78	88	81	76
Hamburg	14	49	50	77	55	45
Prague	15	57	50	76	60	51
Taipei City	16	71	65	83	67	67
Seoul	17	71	59	80	59	59
Amsterdam	18	53	54	77	61	51
Shanghai	19	83	83	91	85	81
Hong Kong	20	60	55	76	69	58

source for the analysis. As previously detailed in Table 1, the study encompasses a comprehensive set of 40 output indicators, each carefully selected to measure various aspects of smart city performance. These indicators provide a multifaceted view of urban development and technological integration across the cities under examination. Table 4 displays the specific outcome data for the cities under study. The average scores for each sub-criterion were also calculated. For example, the first output includes the average scores for residents' feedback on health and safety for the structural criterion.

3.2. Data envelopment analysis

This study employs the Banker, Charnes, and Cooper (BCC) model (Banker, 1984), which allows variable returns to scale to account for the diverse sizes and contexts of the cities in the sample. This model allows for a more nuanced assessment of efficiency, considering that smart cities may operate at varying scales of development. DEA has various models. The two most common are the BCC mentioned above and the Charnes-Cooper-Rhodes (CCR). The CCR model assumes Constant Returns to Scale (CRS) (Alidrisi, 2021; Balubaid et al., 2023; Dellnitz & Rödder, 2021; Ebrahimzade Adimi et al., 2021; Kohl & Brunner, 2020), meaning that any input change results in proportional output changes (Amiri et al., 2023; Cooper et al., 2007; Kraidi et al., 2024; Moghaddas et al., 2023; Sarparast et al., 2022; Xiong et al., 2024). For instance, in the case of smart city energy management, if the input is the number of smart matters installed and the output is the energy savings in kilowatt-hours (kWh), then,

- Installing 1,000 smart meters results in 100,000 kWh of energy savings;
- Installing 2,000 smart meters results in 200,000 kWh of energy savings;
- Installing 3,000 smart meters results in 300,000 kWh of energy savings.

The above example indicates that when the number of smart meters increases by two or three times, the energy savings will also increase proportionally. This ratio of input to output remains consistent regardless of the scale of operation. However, complex systems, such as urban environments, do not always exhibit such perfect proportionality. Therefore, the BCC model with VRS is often more suitable for analyzing smart cities.

The VRS indicates that the relationships between inputs and outputs may not be proportional (Mahajan et al., 2024; Tone & Tsutsui, 2010; Zarrin & Brunner, 2023). As the scale of operations changes, the efficiency or productivity may increase, decrease, or remain constant. The concept acknowledges that not all DMUs operate optimally due to imperfect competition, resource constraints, or other external influences. There are three types of VRS:

- Increasing Returns to Scale (IRS): Output increases by a more significant proportion than the input increase;
- Constant Returns to Scale (CRS): Output increases by the same proportion as the input increases;
- Decreasing Returns to Scale (DRS): Output increases by a smaller proportion than the input increase.

To illustrate the differences between the three VRS types, consider a smart city app for citizen engagement. In this scenario, the input is a \$10,000 investment in app development and marketing, and the output is the number of active users in thousands. The VRS scenario is:

- \$10,000 investment results in 5,000 active users (0.5 users per \$);
- \$20,000 investment results in 15,000 active users (0.75 users per \$) – IRS;
- \$30,000 investment results in 20,000 active users (0.67 users per \$) – DRS.

This example shows increasing returns initially as the app gains popularity, followed by decreasing returns as the market becomes saturated. This demonstrates that the relationship between inputs and outputs is not constant in real-world situations, especially in complex systems such as smart cities (Bartolacci et al., 2025; Raith et al., 2022). The BCC model, which considers the VRS, can accurately assess the efficiency and provide a more realistic performance evaluation across different scales of operation. Additionally, input-oriented models in DEA aim to minimize inputs while keeping outputs constant (Moradi et al., 2025; Toloo et al., 2022; Zubir et al., 2024), while output-oriented models in DEA seek maximum outputs while maintaining constant inputs (Alves & Meza, 2023; Liu & Chen, 2022; Moradi et al., 2025). The choice between input and output orientations depends on the DMUs' control over their inputs and outputs (Zubir et al., 2024). The input-oriented model is suitable for cities with more control over its inputs. By comparison, the output-oriented model is applicable if cities have more control over their outputs, such as services and outcomes.

This study used an output-oriented DEA model over an input-oriented approach due to the nature of the variables being considered. The input variable is defined as the average R&D expenditure as a percentage of GDP for the period 2015–2022, specifically for countries whose cities rank in the top 20 of the IMD Smart City Index 2024. On the other hand, the output variables, which include citizen-evaluated service quality metrics, are more susceptible to policy interventions and managerial decisions. This scenario aligns with the fundamental premise of output-oriented DEA models that seek to maximize outputs while keeping inputs constant.

The output-oriented for the BCC model can be viewed in Equation (1) as:

$$Max \sum_{i=1}^{m} u_i \cdot y_{i0} + w \tag{1}$$

subject to:

$$\sum_{j=1}^{n} v_j \cdot x_{j0} = 1;$$

$$\sum_{i=1}^{m} u_i \cdot y_{ik} - \sum_{j=1}^{n} v_j \cdot x_{jk} + w \le 0,$$

where: u_i represents the weight of output i for the DMU under analysis; y_{i0} represents the amount of output i of the DMU under analysis; v_j represents the weight of input j for the DMU under analysis; x_{j0} represents the amount of input j of the DMU under analysis; u_i represents the weight of output i for the DMU under analysis; y_{ik} represents the amount of output i of the other DMUs; x_{jk} represents the amount of input j of the other DMUs; m represents the number of outputs analyzed; n represents the number of inputs analyzed; w represents the scalar variable; k represents the comparisons across different DMUs.

In the scope of DEA, Overall Technical Efficiency (OTE) and Pure Technical Efficiency (PTE) provide distinct perspectives on a city's performance. OTE, derived from the CCR model, evaluates a city's efficiency without considering its size by comparing it to the best-performing cities regardless of their size. For example, OTE might indicate that a large metropolis with advanced smart infrastructure is 100% efficient in delivering services to citizens, setting a benchmark for other cities to strive towards. In contrast, PTE, calculated from the BCC model, considers the effects of size and assesses a city's efficiency relative to cities of similar size. For instance, PTE might reveal that a medium-sized city, while not as efficient as a large metropolis in absolute terms, operates at 100% efficiency compared to cities of similar scale and resources. This distinction is crucial in analyzing smart cities, as it enables fairer comparisons and helps to identify whether inefficiencies stem from suboptimal scales, as indicated by OTE and PTE, or by managerial and operational factors, as indicated by PTE alone. By examining both OTE and PTE, policymakers can gain a more comprehensive understanding of their cities' performance and identify potential areas for enhancement in the delivery of smart services.

4. Result and analysis

When evaluating the efficiency of smart cities using a DEA model, it is crucial to consider both input and output factors to measure the success of different cities. All indicators are listed in the previous section of this paper in Tables 1–4.

In DEA, different inputs and outputs are often measured in various units (e.g., dollars, hours, and quantities). The use of different measurement units without adjustments can lead to biased or misleading results. Therefore, all data points were normalized before performing the DEA efficiency scores.

Table 5. DEA efficiency scores for smart cities

City	DMU (Rank)	Efficiency score	Status
Zurich	1	1	Efficient
Oslo	2	1	Efficient
Canberra	3	1	Efficient
Geneva	4	0.890	Inefficient
Singapore	5	1	Efficient
Copenhagen	6	0.913	Inefficient
Lausanne	7	0.848	Efficient
London	8	0.599	Inefficient
Helsinki	9	0.770	Inefficient
Abu Dhabi	10	1	Efficient
Stockholm	11	0.697	Inefficient
Dubai	12	1	Efficient
Beijing	13	0.952	Inefficient
Hamburg	14	0.592	Inefficient
Prague	15	0.686	Inefficient
Taipei City	16	0.808	Inefficient
Seoul	17	0.739	Inefficient
Amsterdam	18	0.634	Inefficient
Shanghai	19	1	Efficient
Hong Kong	20	0.479	Inefficient

The DEA-based efficiency scores were used to assess the performance of each city. Table 5 presents the DEA efficiency scores for the top 20 smart cities in the IMD 2024 report. The DEA defines a DMU as efficient when it can produce the maximum output with its available inputs compared to other DMUs in the same group. The efficiency frontier consists of the top-performing DMUs. These DMUs have a perfect efficiency score of 1 (or 100%) and are benchmarks for less efficient DMUs. Less efficient DMUs fall below the efficiency frontier and have an efficiency score of less than 1 (or less than 100%), indicating room for improvement through increased outputs, decreased inputs, or both. Certain cities have demonstrated higher efficiency in converting inputs into valuable outputs, as measured by citizen surveys across multiple factors.

The DEA results reveal that several cities demonstrate optimal efficiency in converting their inputs into desired smart city outcomes. Zurich, Oslo, Canberra, Singapore, Abu Dhabi, Dubai, and Shanghai all achieved an efficiency score of 1, indicating that these cities are operating at the efficiency frontier. These efficient cities span diverse geographical regions, including Europe, Asia, Oceania, and the Middle East, suggesting that smart city excellence is not confined to a particular continent or economic bloc. Notably, these cities have successfully leveraged their resources to maximize their smart city performance, as reflected in their top rankings in the IMD 2024 Smart City Index. Their achievement of perfect efficiency scores underscores their ability to optimally utilize inputs, including R&D expenditures, to produce superior smart city outcomes across various indicators.

Conversely, the analysis identifies several cities that exhibit inefficiencies in their smart city operations. Cities such as Geneva, Copenhagen, London, Helsinki, Stockholm, Beijing, Hamburg, Prague, Taipei City, Seoul, Amsterdam, and Hong Kong demonstrate efficiency scores below 1, indicating suboptimal conversion of inputs to smart city outputs. The degree of inefficiency varies considerably, with efficiency scores ranging from 0.479 (Hong Kong) to 0.952 (Beijing). This variation suggests diverse challenges and opportunities for improvement across these cities. Interestingly, some high-ranking cities in the IMD Smart City Index, such as Geneva (rank 4) and Copenhagen (rank 6), show inefficiencies despite their overall strong performance, highlighting that even top-performing smart cities have room for enhancing their resource utilization. The identification of these inefficiencies provides valuable insights for policymakers and urban planners, pointing to areas where strategic interventions could yield significant improvements in smart city performance.

As indicated earlier, the DEA measures cities' efficiency by comparing them with other cities. Based on the output-oriented model of BCC, outputs are maximized while inputs are kept constant, and for DMUs with low efficiency, the model determines how outputs must be increased in

Table 6. Output slack values in smart city DEA analysis: potential for additional performance improvements

City	Output									
	1	2	3	4	5	6	7	8	9	10
Zurich	0	0	0	0	0	0	0	0	0	0
Oslo	0	0	0	0	0	0	0	0	0	0
Canberra	0	0	0	0	0	0	0	0	0	0
Geneva	0.147	0.368	0	0	0.140	0.495	0.38	0.381	0.486	0.520
Singapore	0	0	0	0	0	0	0	0	0	0
Copenhagen	0.263	0.454	0	0	0.234	0.567	0.39	0.322	0.493	0.510
Lausanne	0.236	0.408	0	0	0.321	0.705	0.438	0.611	0.53	0.603
London	0.960	0.937	0	0.081	0.925	0.548	0.116	0.733	0.244	0.417
Helsinki	0.303	0	0	0	0.465	0.626	0.436	0.914	0.490	0.593
Abu Dhabi	0	0	0	0	0	0	0	0	0	0
Stockholm	0.530	0.998	0	0	0.594	0.71	0.511	0.798	0.689	0.826
Dubai	0	0	0	0	0	0	0	0	0	0
Beijing	0.042	0.233	0	0	0.133	0.045	0.022	0.055	0.045	0.051
Hamburg	0.363	0.852	0	0.066	0.656	0.835	0.389	0.537	0.833	0.784
Prague	0.418	0.427	0.484	0	0.705	0.448	0.329	0.589	0.544	0.444
Taipei City	0	0.955	0.515	0.068	0.416	0.049	0.057	0.213	0.32	0.098
Seoul	0.372	0.372	0.678	0.835	0.984	0	0.201	0.441	0.655	0.255
Amsterdam	0.734	0.661	0.127	0	0.550	0.544	0	0.314	0.406	0.295
Shanghai	0	0	0	0	0	0	0	0	0	0
Hong Kong	0.599	0.017	0.924	0.231	0.728	0.310	0.238	0.616	0	0.181

order to reach the efficiency frontier. An inefficient DEA result indicates that the city is not producing the maximum amount of outputs given its inputs in comparison with other cities in the analysis group. For example, Geneva, has an efficiency score of 0.890, which is equivalent to 89%, meaning that it needs to increase its output by 12.3% (1/0.890 = 1.123) to be efficient. Another example, Copenhagen has an efficiency score of 0.913, which indicates it needs to increase outputs by 9.5% (1/0.913 = 1.095) while maintaining its inputs constant in order to achieve efficiency. However, this does not mean Geneva or Copenhagen perform poorly overall but this suggests that there is room for improvement in terms of efficiency compared with the most efficient cities.

While Geneva and Copenhagen may excel in many aspects of being smart cities, the DEA results indicate the possibility of enhancing resource utilization and maximizing output. This insight applies not only to Geneva or Copenhagen but also to all cities found to be inefficient.

Further insights into these inefficiencies can be gleaned through slack analysis in DEA, which provides a more granular view of potential enhancements beyond basic efficiency scores. Slack analysis identifies both input and output slacks, with output slacks being particularly relevant in the context of smart cities as they quantify the potential for increased outputs while maintaining constant inputs. Table 6, which presents output slack values, offers valuable information for policymakers and urban planners by quantifying the additional improvements required in specific smart city outcomes. High output slack values indicate significant potential for enhancement in particular areas, providing a roadmap for targeted interventions to optimize smart city performance across all dimensions, even for top-ranked cities such as Geneva and Copenhagen.

5. Discussion

The DEA of smart cities, using R&D expenditure as a percentage of GDP (2015–2022) as input, reveals significant insights into the efficiency of various urban centers in converting R&D investments into tangible smart city outcomes. The output slack values presented in Table 6 offer a nuanced view of potential improvements across ten critical smart city criteria. This analysis provides valuable insights for policymakers and urban planners, highlighting areas in which strategic interventions could yield substantial benefits.

Structure Health & Safety criterion (Output 1): the analysis reveals varying levels of efficiency across cities in translating R&D investments into structural health and safety improvements. Cities such as Zurich, Oslo, and Canberra demonstrate optimal efficiency with zero slack, indicating their success in this domain. However, cities such as London (0.960) and Amsterdam (0.734) showed significant room for improvement. This suggests that these cities could potentially enhance their health and safety infrastructure without additional R&D investment, perhaps by adopting best practices from more efficient counterparts or by reallocating resources more effectively within this sector.

Structure Mobility criterion (Output 2): in the realm of structural mobility, several cities exhibit substantial potential for improvement. Stockholm (0.998) and London (0.937) showed the highest slack values, indicating significant opportunities to enhance their mobility infrastructure. This could involve improving public transportation systems, implementing smart traffic management solutions, or developing more efficient urban planning strategies. Cities with zero slack, such as Zurich and Singapore, could serve as benchmarks for best practices in this area.

Structure Activities criterion (Output 3): the slack values for this criterion are notably lower across most cities, with many showing zero slack. However, cities like Seoul (0.678) and Taipei City (0.515) demonstrate room for improvement in providing structural support for urban activities. This might involve enhancing public spaces, cultural facilities, or recreational areas to better serve the population's needs and improve the overall quality of life.

Structure Opportunities criterion (Output 4): most cities show minimal slack in this area, suggesting generally efficient conversion of R&D investments into structural opportunities. However, Seoul (0.835) stands out with a high slack value, indicating the potential for significant improvement in creating structural foundations for economic and social opportunities. This could involve developing better educational facilities, business incubators, or job training centers.

Structure Governance criterion (Output 5): the analysis reveals varied performance in governance structures. Cities like Helsinki (0.465) and Stockholm (0.594) show moderate room for improvement, suggesting potential enhancements in e-governance systems, citizen engagement platforms, or administrative efficiency. Cities with zero slack, such as Zurich and Singapore, could offer valuable insights into effective governance structures that maximize R&D investments.

Technology Health & Safety criterion (Output 6): this area shows significant variation across cities. Lausanne (0.705) and Stockholm (0.71) exhibit the highest slack values, indicating substantial potential for technological improvements in health and safety. This could involve the implementation of advanced emergency response systems, health monitoring technologies, or smart surveillance for public safety. Cities such as Zurich and Dubai, with zero slack, may serve as exemplars in this domain.

Technology Mobility criterion (Output 7): the slack values for technological mobility solutions are generally lower, suggesting relatively efficient R&D utilization in this area. However, cities like Stockholm (0.511) and Lausanne (0.438) show room for improvement. This could involve enhancing smart traffic systems, developing more sophisticated public transport applications, or implementing advanced ride-sharing platforms to improve urban mobility.

Technology Activities criterion (Output 8): several cities show significant potential for improvement in this area, with Helsinki (0.914) and Stockholm (0.798) having the highest slack values. This suggests opportunities to better leverage technology to enhance urban activities, possibly through improved digital platforms for cultural events, smart tourism solutions, or advanced systems for managing public spaces and recreational facilities.

Technology Opportunities criterion (Output 9): the analysis reveals varied performance in creating technological opportunities. Cities like Hamburg (0.833) and Stockholm (0.689) show substantial room for improvement. This could involve developing more advanced digital skills training programs, creating better online platforms for job matching, or implementing more sophisticated systems to support entrepreneurship and innovation.

Technology Governance criterion (Output 10): in the realm of technological governance solutions, several cities demonstrate significant potential for enhancement. Stockholm (0.826) and Hamburg (0.784) show the highest slack values, indicating opportunities to improve e-governance platforms, digital citizen engagement tools, or data-driven decision-making systems in urban management.

In conclusion, this DEA analysis provides a comprehensive overview of how effectively cities convert R&D investments into smart city outcomes across various structural and technological domains. While some cities, such as Zurich and Singapore, consistently demonstrate high efficiency, others show varying degrees of potential for improvement. These findings underscore the importance of not only increasing R&D investments but also ensuring their efficient utilization across all aspects of smart city development. Policymakers and urban planners should focus on learning from high-performance cities and adapting successful strategies to their local contexts. Furthermore, cities with high slack values in specific areas should prioritize these domains for targeted interventions and resource reallocation to maximize the impact of their R&D investments on smart city outcomes.

6. Conclusions

This study employed DEA to evaluate the efficiency of the top 20 smart cities in converting their resources into desired outcomes. The input variable was the average R&D expenditure as a percentage of GDP for the period 2015–2022, while the outputs were derived from the IMD 2024 Smart City Index report, encompassing ten criteria across structure and technology dimensions.

The analysis revealed that seven cities – Zurich, Oslo, Canberra, Singapore, Abu Dhabi, Dubai, and Shanghai – achieved perfect efficiency scores, demonstrating optimal utilization of their R&D investments in producing smart city outcomes. Surprisingly, some high-ranking cities in the overall IMD Smart City Index, such as Geneva (4th) and Copenhagen (6th), showed inefficiencies despite their strong performance, highlighting the complexity of smart city development.

Data for this study were collected from reputable sources, including national statistics for R&D expenditure and the IMD Smart City Index 2024 for output measures. The DEA methodology provides valuable insights into the relative efficiencies of these cities and identifies specific areas for potential improvement through slack analysis.

However, this study has several limitations that should be acknowledged. Firstly, the focus on the top 20 smart cities limits the generalizability of findings to a broader range of urban environments. Secondly, the use of national R&D expenditure as an input may not fully capture city-specific investments in smart initiatives. Thus, one of the primary limitations is the difficulty in obtaining reliable and consistent data on city-specific investments in R&D for smart initiatives. Many cities do not have uniform methods for reporting their R&D expenditures specifically related to smart city initiatives. Detailed city-level data on R&D investments in smart technologies are often not publicly accessible or may be incomplete. Due to these constraints in acquiring reliable city-specific data, this study utilized national R&D expenditure as a percentage of GDP as a proxy input variable. While this approach provides a broader context for a country's commitment to innovation and technological advancement, it is important to acknowledge that it may not fully capture the nuanced investments made specifically for smart city initiatives at the municipal level.

It is important to note that this study is specifically based on data from the IMD Smart City Index 2024. This temporal specificity is a crucial aspect of the research and has implications for the interpretation and application of the results. The smart city landscape is dynamic and rapidly evolving, with cities constantly implementing new initiatives and technologies. Consequently, the efficiency scores and rankings derived from this analysis are a snapshot of the performance at a particular point in time.

Moreover, the use of data from a single year (2024) implies that the results are sensitive to the specific conditions, achievements, and challenges faced by cities during that period. Any changes in the underlying data, whether due to updated measurements, revised methodologies, or actual changes in city performance, could potentially alter the efficiency scores and rankings.

Future studies could benefit from a longitudinal approach, analyzing data over multiple years to identify trends and the impact of sustained smart city investments. This would provide a more comprehensive understanding of how cities' efficiencies evolve over time and how they respond to various interventions and global challenges.

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