QATAR UNIVERSITY

COLLEGE OF ENGINEERING

LINKING SUSTAINABILITY, RESILIENCE, AND LIVABILITY WITH SMART CITY DEVELOPMENT: BUILDING A NOVEL HYBRID DECISION SUPPORT MODEL FOR COMPOSITE PERFORMANCE ASSESSMENT

BY

ADEEB ALI KUNJU ABDULLA KUTTY

A Dissertation Submitted to

the Faculty of the College of Engineering

in Partial Fulfillment of the Requirements for the Degree of

Doctorate of Philosophy in Engineering Management

June 2022

© 2022 Adeeb Ali Kunju Abdulla Kutty. All Rights Reserved.

COMMITTEE PAGE

The members of the Committee approve the Dissertation of
Adeeb Ali Kunju Abdulla Kutty defended on 11/05/2022.

Dr. Murat Kucukvar
Thesis/Dissertation Supervisor

Dr. Galal M. Abdella
Co-Supervisor

Dr. Nuri Cihat Onat
Committee Member

Dr. Mohamed Kharbeche
Committee Member

Dr. Nikolai G. Bobylev
External Examiner

Approved:

Dr. Khaled Kamal Naji , Dean, College of Engineering

ABSTRACT

KUTTY, ADEEB A., Doctorate: June: 2022, Doctor of Philosophy in Engineering Management

Title: Linking Sustainability, Resilience, and Livability with Smart City Development: Building a Novel Hybrid Decision Support Model for Composite Performance Assessment

Supervisor of Dissertation: Dr. Murat M. Kucukvar.

Smartening development in cities have reinvented hopes to melt down predicaments in early 2000s'. At the embryonic stage, it is vital for cities of today to gain a more consistent understanding on how resilience, livability, and sustainability can be co-created into smart city planning models under a unified umbrella. In that respect, this dissertation attempts to understand smart city development through the lens of sustainability, urban resilience, and livability by proposing a novel hybrid decision support performance assessment model, as cities evolve to achieve the descriptive goal of "Futuristic cities".

State-of-the art contribution of this dissertation brings in-house novelty in terms of the subject handled and the approach used to solve the problem. The hybrid decision support model brings in; systems thinking, non-parametric optimization-based envelopment analysis, explainable machine learning based assessments and multi-criteria based combinatorial evaluations all under a unified frame at various levels of measurement. Systems thinking aids in understanding the complexities from a non-fragmented system-of-system perspective. A double-frontier slacks-based measure data envelopment analysis model, a true input-output desirability inclusion model under extended strong disposability assumptions is proposed to evaluate the sustainability performance of smart cities. A relative multivariate metric distance-

based approach is proposed to weight the indicators across various dimensions of resilience and livability combining machine learning techniques. Then, the extended version of the Evaluation Based on Distance from Average Solution (EDAS) method combined under a spherical fuzzy (SF) environment with the Analytic Hierarchy Process (AHP) is used to select the best performing smart city and rank them based on the triple criteria of futuristic smart cities (sustainability + resilience + livability). This marks the development of the aspiring “Futuristic Smart City” (FSC) composite index.

Data from 35 European smart cities ranked in the top 50 global best smart cities list is taken to empirically evaluate the sustainability, resilience, livability, and their unified performance. The results of the non-parametric optimization-based envelopment analysis revealed significant difference in the productivity progress values from the optimistic and pessimistic viewpoint, thus exemplifying the significance for the proposed aggregate productivity progress measurement model. The results of the machine learning based assessment revealed Gradient Boosting Machine (GBM) as the best classification and predictive model for the resilience, liveability, and aggregate performance assessment. The composite index proposed through the SF-AHP & extended EDAS method revealed London as the top ranked smart city that co-create sustainability, resilience, and livability holistically into their development model. Dusseldorf, Zurich, Munich, Oslo, Dublin, Amsterdam, Hamburg, Rome, Moscow, and Stockholm were no exemption to addressing the triple criteria. The proposed hybrid model augments planned decision making and policy constitution from a strategic level for urban planners and smart city development authorities to support the meta goal of futuristic cities in tech-driven intelligent living units. Tailored towards data-driven and intelligent system approaches, the findings of this dissertation finds applicability not only in the proposed regions as case studies, but in a global scale for any aspiring cities that intent for transition towards futuristic cities.

DEDICATION

To my beloved parents

&

My dear Aydin Zayed, Najeeba Kutty, and Wazeem Basheer K.

ACKNOWLEDGMENT

بسم الله الرحمن الرحيم

Glory be to Allah, The Benevolent, The most Merciful

Sincere gratitude to almighty Allah (سبحانه و تعالى) for all his infinite greatness and blessings bestowed upon me to successfully complete this dissertation. I sincerely thank Dr. Murat Kucukvar, my dissertation supervisor for his wonderful support and guidance throughout this journey of knowledge. I would like to extend my sincere gratitude to Dr. Galal M. Abdella (co-advisor), Dr. Nuri Cihat Onat, Dr. Muhammet Enis Bulak, Dr. Melih Bulu and Dr. Berk Ayvaz for providing me support, transferring knowledge and expertise in accomplishing high quality research outcomes and publications. Since thanks to all the panel of smart city experts who were involved in the expert-weighting process for fuzzy modelling and during the creation of rich-picture for systems modelling. Since thanks to Najeeba Kutty, architect, and urban planner, for sharing her knowledge on resilience planning and urban transformations during the initial period of this research.

In the prism of this accomplishment, I would like to stay humble and be grateful to my beloved mother and father for their similitude of encouragement, guidance, patience, and prayers throughout the entire doctoral journey, without which this achievement would not have been possible. I would also like to extend my sincere thanks to Al Anood Najeeb, and Tadesse G. Wakjira for their support in making this research journey possible.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1: INTRODUCTION

1.1. Theoretical Background

According to the statistics by United Nations, there has been an increase in the world urban population from 751 million in 1950 to 4.2 billion in 2019, which accounts for around 55% of the global population in 2019 inhabiting the urban area (United Nations, 2019). The United Nations estimate the world population occupying the urban cities to increase by 68% until 2050, thus giving rise to several challenges. Modern cities are up against frontlines of serious urban challenges, most recently, compounding environmental (urban sprawl, overpopulation, land management, waste disposal, climate change and pollution), social (poverty and suburbanization) to economic (outsourcing, unemployment, and economic globalization) challenges (Zander & Mosterman, 2013). These challenges bring the concept of cities as consumers than preservers of urbanism, distorting the ecological balance, thus posing a threat to future sustenance of cities (Shmelev and Shmeleva, 2018). These threats also raise huge concerns among public authorities and urban planners on how cities can be remodeled to stay safe and secure from unexpected predicaments.

As a response to these threats and challenges, technological advancement in cities have paved ways to smart cities, a solution to numerous unfathomable challenges (Dodgson and Gann, 2011). Nonetheless, smart cities have succeeded in bringing high standards of living to its residents (Angelidou and Mora, 2019). In other words, smart cities strive to improve city services and urban management for the citizens, by creating a socially advanced environment. Thus, smart cities are undoubtedly the engines of global prosperity and innovation (Yigitcanlar et al., 2020; Bibri, 2021a). However, in the midst of unfettered urban flux, Laissez-faire urbanization has drenched the leapfrogging possibilities of smart solutions and digital intelligent platforms to turn cities into more livable units thus, failing to offer a dignified standard of living to the urban inhabitants (Calzada, 2017; Sun et al., 2020). Thus, akin to the merits of smart cities lies a litany of prodigious challenges in bringing out an equitable balance between the production and consumption patterns, carbon neutrality goals, sustainable urban growth, and quality of life, all of which can be at stake due to the expected population growth rate by 2050 (Shamsuzzoha et al., 2021; Singh and Ohri, 2021). Expecting an increase in the urban ecological footprint has left smart cities to mobilize actions for embracing nature based solutions targeting long-term sustainability (Kutty et al., 2020; Way and Peng, 2021; D'Amico et al., 2021; Glaeser, 2021). Illuminating smart cities with global sustainability practices can help address several development challenges such as human development, pollution and climate change adaption, biodiversity, circular economy, natural calamity preparedness and energy consumption (Kutty et al., 2020; Kourtit, 2021; Elhmoud and Kutty, 2021). The "United Nations' Sustainable Development Goals (SDGs)" offer untapped opportunities for cities and urban spaces to drive powerful transformations and nullify the prevailing development challenges (Mata, 2018; Yigitcanlar, 2021). Accounting to the sustainable urbanization practices can help smart cities significantly in not only shaping their energy and resource utilization, but also tackling all the development challenges across each SDGs to bring smartness and sustainability practices under one umbrella (Yigitcanlar et al., 2019a; Repette et al., 2021). Thus, the ultimate goal of techno-centric development started to show a shift towards improving the sustainability of the city (Toppeta, 2010; Shehab et al., 2021). Nonetheless, city planners argue that the use of advanced technologies will by-nature improve the environmental outcomes of the city based on the pervasive use of real-time data and monitoring systems (Bibri, 2021b). For instance, the installation of smart trash bins that monitor real-time waste alert municipality officials in understanding the fill and assist in taking necessary actions in collecting the waste for appropriate disposal. Similarly, the self-powered smart streetlights respond to the urban density flow and illuminate in accordance so as to support the energy saving initiatives through smart practices. However, several contradictory studies (see: Kutty et al., 2020; Bibri, 2021c) in recent years show that these smart technologies require continuous communication through internet channels to acquire data to keep these smart systems running. This requires a great deal of energy usage and outweighs the potential benefits acquired through the use of smart infrastructures (Bibri, 2021d).

Furthermore, as discussed, digital solutions provide opportunities for development, at the same time pave ways for abuse (DeRolph et al., 2019). Howbeit, the use of smart technologies in cities have intensified beyond borders of utilitarianism to the extent of implying pressure on the infrastructure (Lee et al., 2021). When rethinking strategic autonomy in the digital era, smarter cities, a paradigm beyond smart cities framed to optimize challenges, present a mesmeric case in tremendously ameliorating interconnectivity with less focus on creating value for urban inhabitants (Boykova et al., 2016). These smarter cities are moving up the ladder of digital development where techno-centricity takes the driver’s seat (Yigitcanlar and Lee, 2014). Digital solutions in cities scale with users (Hatuka and Zur, 2020). However, embarking on technological development beyond a point where technology has met the user requirement, involves risk. Despite smart technologies being a prerequisite in intuitively bridging gaps and concerns of urban inhabitants, the bureaucratic barriers have led to uncoordinated drive for the technologies to scale when attempting to engage city residents for these technologies to work (Ramboll, 2020). Smart city experience of today focus on city dwellers as a means for testing smart solutions with less concern being paid on their values, beliefs, and liveability (Mouratidis , 2021). When scaling technological developments within the urban context, the concept of liveability requires special attention, as people and their interactions are the key drivers for technologies to find their application in the smart ecosystem (Sutriadi and Noviansyah, 2021). The British Standards Institute (BSI), the national standards body of the United Kingdom, supported that a smart city must include the efficient integration of physical, digital, and human systems in the built infrastructure in order to create a sustainable, prosperous, and inclusive future for its inhabitants (BSI, 2014). This emphasis on the habitability and inclusivity of the urban environments particularly underlines the social nature of smart cities. Via the use of digital intelligence, tools can be designed that save lives, prevent crime, and reduce the disease burden. These can save time, reduce waste, and even help boost social connectedness (McKinsey, 2018). To continue, without human settlements, cities don't exist and thus focusing on the concerns of city residents and including the dimensions of people and communities when addressing the concept of smart city is crucial, thus livability.

The concept of liveability can thus transform intelligent units to habitable spaces (Pan et al., 2021). However, techno-centric development must not only focus on liveability as the soul to an endurable unit, but also on the ability of a city to rebound post stress, thus offering a dignified standard of living to the urban inhabitants. Cities are often vulnerable to unexpected predicaments such as economic upheaval, anthropogenic disruptions, climate change, geopolitical instability, public health crisis, and diplomatic embargos (Pranadi et al., 2022). Smart cities of today despite realizing the importance of resilience are no exception to these uncertainties. The Covid-19 outbreak in Wuhan, central China is a classic exhibition of insufficient city resilience (Chu et al., 2021). The Covid-19 pandemic has left lime lighted questions on urban resilience and liveability of tech-driven smart cities around the globe (Feng et al., 2022). The pandemic paradigm has left opportunities for smart and mega-cities to optimize urban systems to cope with future external disruptions for a sustainable, livable, and resilient habitable unit.

The smart technologies deployed thus need to be lean, cost efficient and targeted not only in reducing the CO_2 emissions and refining the energy efficiency of the city, but also on the welfare of the city dwellers, fiscal sustainability, enhanced safety and security, adaption to stress and shocks, economic stability, quality of life, social cohesion and many more (Shmelev and Shmeleva, 2019; Alsarayreh et al., 2020). The concept of smartness and sustainability in cities can be viewed as a buildout archetype that came into practice in late 20th century in order to respond to the public needs, investigate the growth patterns in the city, to deliver sustainable and smart way of life to the inhabitants and, help cities achieve their competitive advantage (Kramers et al., 2014; Bingöl, 2022; Alagirisamy and Ramesh, 2022). Similarly, resilience planning dates back to the ancient era when flood resilient sewerage network systems were built by Romans in 4th century BC (Galderisi et al., 2020). Liveability dates back to even ancient times back during the time of Plato and Aristotle, with a plethora of conceptualization at different period of time (Yu, 2001). All these concepts are closely interrelated despite several variations in their growth patterns (Shehab et al., 2021). The consciousness of unsustainable resource usage patterns by humans in the cities integrated with advanced technologies to monitor the resource utilization, quality of growth in the urban ecosystem, knowledge of socio-economic disparities and decision support strategies that aid transformation of cities towards smart, resilient, sustainable, and livable units have all enabled these concepts to work along the same direction. For a city to embrace practices of sustainability, resilience, and engagement of urban inhabitants to live with better standards, the city must attempt to remodel its services and management infrastructure, enhance partnerships, adopt a radical reform in its production and consumption practices, generate less waste, and transform all the by-products to useful resources that can re-enter the value chain. This cannot be achieved only by using digital intelligent technologies but requires participatory governance, involvement of multifarious stakeholders and a citizen inclusive ecosystem. This integration would help us not only to attain SDG 11 proposed in the United Nations Development Programme (UNDP), which is to transform cities into being smart and sustainable living units, but also to connect the cities and communities with other SDGs to make cities resilient to shocks and stresses and, livable for present and future communities. The "Future cities we want" need to integrate resilience, liveability, and sustainability with urban smartness under a single umbrella. For the same, initially, it is important to understand how these elements interact in an urban context across several actors using an integrated system-of-system approach. Further, to make decision support effective and transform smart cities into futuristic smart cities, it is essential to have tools, techniques, and measurement systems that are custom tailored to assess sustainability, resilience, and livability individually and, under a unified frame in a composite manner.

1.2. Problem Description

Smart cities can be perceived as one that utilizes the possibilities offered by information and communication technologies (ICTs) in enhancing the local prosperity and competitiveness by adopting an integrated urban development approach that involves multiple actors, stakeholders, and multi-dimensional perspectives

(Paskaleva, 2009). Cities driven by ICT-based technocentric approaches can help in reducing the root causes associated with most of the pressing concerns (Margarita et al., 2020). However, ICT-centered approaches often face risk when attempting to stabilize unsustainable development patterns, as tech-driven smart cities often focus on smart targets which does not automatically bring sustainability, in turn makes development models obsolete over time (Yigitcanlar and Kamruzzaman, 2019). For instance, the question of sustainable accessibility of smart public transportation system in cities is a social concern due to the territorial allocation of public transit infrastructure networks and regionalized development around profitable territories paving ways to "smart territories" than smart sustainable cities (Kamruzzaman et al., 2020). On the contrary, these emergent systems prioritize development that rise to prominence by adapting to the market behavior and not evolving over time (Esmaeilpoorarabi et al., 2020; Kutty et al., 2020). However, attempting to optimize systems do not deliver complete efficiency (Mora et al., 2019; Kourtit et al., 2021). In addition, most self-designed smart cities are business-driven models that function on public-private collaboration that target the cash-cow maturity curves than equitable growth and sustainable development (Yigitcanlar et al., 2019b). Thus, smart cities are focusing more onto profit-driven strategies than extending wings to address sustainability and sustainable growth patterns. Hence, smart cities despite the sworn oath to sustainability, in reality is a zero-sum-game due to the fact that "the positive and negative impacts tend to cancel each other out". A better understanding on "how sustainable are smart cities in long-run ?" is an area of research to conquer so as to tackle the deficiencies in the existing cities to plan better for a transformation towards futuristic cities.

Furthermore, envisioned to discretely answer the call of improved local liveability and susceptance to unexpected predicaments, effective implementation of city resilience and urban liveability face numerous obstacles. A recent review published by Ramirez-Lopez and Grijalba Castro (2020) on resilience in smart cities revealed a lack of integrity in practically addressing the multi-dimensional facets of city resilience, where a biocentric vision of territorial urban planning and capacity building is undertaken than a human centric approach to better living. Similarly, a review conducted by Paul and Sen (2020) revealed that, the developed western cities that often act as benchmarks for Dickenson cities account liveability from a physical aspect (such as mobility options, transit-oriented design, and fiscal supremacies) than from a socio-economic perspective. It is to note that, shocks are meant to occur within cities that are termed smart, but to what speed can the cities rebound to its natural state is a question that institutions and policy makers must answer to better protect cities when under chaos. This requires a standardized lens for city leaders to analyze the resilience capacity to position adaptation to unexpected predicaments and liveability frame of reference to envision a human centric development targeted for better living standards.

To continue, it is seen that smart cities are complex urban ecological systems built to optimize challenges and improve the resident quality of life with the ubiquitous use of data. Future cities are insufficient and non-self-preservative without integrating the triple criteria with smartness. It is crucial to make best decisions according to different preferences in situations where multiple criteria exist (Ho, 2008). The cities we want, “Futuristic smart cities” need to integrate sustainability, resilience and, livability criteria with urban smartness under a single umbrella; a composite index. Composite indices are communication tools for benchmarking regional or institutional performance (Greco et al., 2019). Summarizing and condensing the complexity of a dynamic system, they are identified as efficient instruments for policy evaluation and communication (Mazziotta and Pareto, 2013). Such indices describe and represents the different dimensions of a concept through a precise numerical combination of multiple-criteria and sub-criteria (Saisana and Tarantola, 2002). The Smart City Environmental Sustainability Index (SCESI) developed by Singh and Ohri, (2021) monitors the progressive environmental sustainability of smart cities in India. The SCESI focuses only on the environmental sustainability of smart cities. While the comprehensive Smart City Resilience Index (SCRI) developed by Dong et al., (2020) for Chinese smart cities focuses on the resilience criteria alone. The complex smart resilience index developed to explore the territorial characteristics of Hungarian smart cities by Szép et al., (2020) measures the adaptive capacity of smart cities to external shocks. The world-renowned “IMD-STUD Smart City Index” aims to offer a balance between the economic and human dimensions of smart urban living with focus on a techno-centric development, ruling out the environmental dimensions for a smart and sustainable urban living. Similarly, the well-established ‘Global Liveable and Smart Cities Index (GL-SCI)’ addresses quality of life from a materialistic point of view, ignoring community well-being and other social cohesion aspects. In addition, the well-known indicator sets proposed by the International Trade Union (ITU) under the ‘United 4 Sustainable Smart City’ (U4SSC) initiative to shape future cities focus only on integrating sustainability with smartness under the dimensions: Economy, Environmental and, Society and Culture (ITU, 2019). Despite targeting the soul agenda of urban smartness and sustainability, the initiative promises on making future cities more resilient. However, the indicators under U4SSC fails to address urban resilience in depth across multiple dimensions of resilience. It is thus seen that studies often pursue the three principles (‘resilient +

sustainable + liveable') on independent tracks with their associated indicators, lacking a single composite index to achieve the futuristic smart city goal. It is unclear as to, 'Where does the world cities fall within the combined dimension of resilience, sustainability, and livability?'.

1.3. Research significance and Objectives

Cities reflect the inspiration and desire of humans to nurture sustainable, livable, and resilient societies (Kutty et al., 2020; Curşeu et al., 2021). "Sustainable-resilient" cities voice our need of the previous decades (Beatley and Newman, 2013). While "smart-sustainable" cities are the voice of the current decade (Kramers et al., 2014). The concept of 'Sustainability' is known to pivot the circular balance of demand, consumption, and supply while minimizing the environmental and ecological footprint (Kutty et al., 2022). Additionally, these cities ensure the continued existence in the face of natural disasters by upholding resilience through adaptability and flexibility (Tapsuwan et al., 2018). Shedding light on our ever-evolving perceptions of city qualities, a faultless question arises as, "What desires do we want to associate with the future city to ensure prosperity and quality of life?". To ensure quality of life and prosperity, the smart sustainable cities of today must re-model their development patterns adding the most indispensable concept of liveability with resilience. Recalling these qualities, integrating the triple criteria of 'Sustainability, Resilience and Livability' to support future smart cities is pivotal. Thus, the central agenda when making incremental technological improvements in smart cities must include the traditional involvement of technology, ecosystem, people, and strategies to address the challenges in an urban scale; in short, sustainability, resilience and livability. Thus, co-creating livability and resilience in cities to scale digital solutions in a sustainable manner has become a top priority, thus the underlying rationale of this dissertation. It is highly important to explore and understand on how smart cities address the concept of resilience, liveability, and sustainability and, to what extend leading smart cities address these paradigms in planning for next-generation cities.

In addition, the complex flow of materials and resources within the system has added up to the existing challenges of bringing about right decisions to maximize combinatorial performance under these paradigms. The possible interactions in these complex systems can be studied using a hybrid model that integrates a series of analytical techniques to quantitatively and qualitatively assess sustainability, resilience and livability individually and under a combined platform; a composite index. Decision support models combine data with analytical techniques for improved decision making. While several techniques exist, insufficient amount of systematic and integrated research on decision support models that address the triple criteria of futuristic cities is absent in the literature. To this end, this dissertation explores the aforementioned quandaries in smart city research and attempts to develop a novel hybrid decision-support model for smart city performance assessment, ending in a composite index, the “Futuristic Smart City (FSC)” index that brings in the criteria of sustainability, resilience, and livability with multiple sub-criteria under a unified score and ranking system. To achieve the meta goal of developing the hybrid decision-support model, the following objectives are set to be addressed, namely;

a) Discover the possible interactions of various dimensions under the resilience, livability, and sustainability criteria of futuristic cities, using a systems thinking approach.
b) Develop a novel non-parametric optimization-based benchmarking model to assess the sustainability performance of smart cities.

c) Build a novel resilience and livability performance assessment model integrating multi-variate distance based analysis with machine learning models for smart cities.

d) Advance a novel fuzzy-expert based multi-criteria assessment model for composite performance assessment integrating the criteria sustainability, resilience, and livability across multiple dimensions.

e) Implement each developed model in b), c) and d) to a case of 35 leading high-tech European smart cities to validate and identify the robustness of the proposed models in performance assessment.

1.4. Dissertation Outline

The dissertation is organized into 8 chapters. Chapter 1 gives a theoretical background on the state of the current smart cities and explains the relevance of the concept on integrating sustainability, resilience, and livability under a unified composite index for transitioning into the so called "futuristic smart cities". Problem description, research significance, and scientific objectives form a part of this chapter. Chapter 2 presents a detailed review of the prior art knowledge both from a theoretical and a methodological perspective to add novelty to the contributions presented in this dissertation. This chapter also includes a section dedicated to the state-of-the art contribution and how the dissertation will add novelty to the existing body of knowledge in terms of the techniques applied in creating the hybrid decision support model. Chapter 3 is the core of this dissertation, where the novel hybrid decision-support model is presented and the core modules of the decision-support model with the novel analytical techniques adopted in constructing these modules is presented in detail. Chapter 4, 5, 6 and 7 discusses in detail the implementation of the proposed hybrid decision support model applying the case of European smart cities.

Significance of the proposed model, objectives tailored for the model implementation, research data and other parts of the analysis form a common pattern in each of these chapters. Chapter 4 presents the results and discussions of the systems thinking module, followed by the implementation of the non-parametric optimization-based benchmarking model for the sustainability assessment of smart cities in Chapter 5. Chapter 6 discusses the implementation and results of the machine-learning module for the resilience and livability assessment. Chapter 7 implements the fuzzy-expert based multi-criteria assessment module and discusses the results in detail with a sensitivity and comparative analysis. This module delivers the output of the hybrid decision-support model in terms of the scores and ranks of the European smart cities, taken as the case and thus the composite index. Chapter 8 is the final chapter of this dissertation, summarizing the findings and opening doors for future avenues in research. Limitations are also pointed out in this section.

CHAPTER 2: REVIEW OF LITERATURE

2.1. Prior-art knowledge

This section of chapter 2 is dedicated to understanding the existing works related to the development of the hybrid decision support model. The literature review is tailored targeting both the theoretical and methodological "know-how" in the proposed research domain to identify the gaps needed to assert novelty and propose the current art contribution. Initially, the review dives into knowing a little in detail about smart cities and the current smart city initiatives. Post to knowing the smart city initiatives, the review extends its search on several recent existing decision support models developed and used in the area of smart cities. Further, we attempt to understand a little in detail about systems thinking and why systems thinking is relevant in the context of smart city research. The review further explores the area of knowledge pertaining to sustainability assessment in smart cities and a little about the well-known non-parametric optimization-based benchmarking model, the "Data Envelopment Analysis" (DEA). The review then excavates the body of knowledge in the area of resilience and livability assessment in smart cities, focusing on the studies relevant to the area, machine learning. The review is completed with knowing in detail on multi-criteria analysis and expert-based decision support models for composite indexing in the area of smart cities.

2.1.1. Smart city initiatives

The phrase "smart city" has transpired to address several challenges and possibilities in urban planning and city development for a vast majority of the population across several disciplines. The concept has also gained immense popularity all over the research community (Camero & Alba, 2019). In simple terms, cities that strive to make it "smarter" is termed as smart cities (Hamman et al., 2017;

Chourabi et al., 2012). Smart city initiatives are transformational initiatives aimed at reforming the city services to deliver a better quality of life to the citizens (Giffinger et al., 2010; Odendaal, 2003). As of 2018, estimates show that there are around 473 smart city projects (both inclusive of on-going and completed projects) in 57 countries around the globe (SCEWC, 2018). In particular, countries like South Korea and Singapore have invested huge shares of spending on IoT based solutions to digitalize and sustainably transform the nation into an intelligent nation. These smart city initiatives aim at implementing smart technologies to address the prevailing challenges in urban areas such as inaccessibility to safe and clean drinking water, lack of proper public health services, lack of employment opportunities and social prosperity, poverty, traffic congestion, global climatic changes, inadequate sustainable infrastructure, community living, etc.

Although the scope and objective of each smart city initiative vary widely, the primary objective of these initiatives is to transform cities into being smarter, greener, and sustainable. This offers a better quality of life to the citizens and increased economic opportunities. Smart city initiatives use a wide range of ICT based intelligent services to deliver comfort and efficiency at fingertips (Rodrigues & Franco, 2019), starting from capturing and disseminating information across the city through data centers to connecting people through smart apps or web-based services. According to Lava Active inflow report, several government agencies are partnering with private firms to optimize city services and develop more sustainable and intelligent solutions by adopting open data and geospatial intelligence. The anti-poverty initiative, “The Poverty in NYC’’ partnered with the Poverty Research Team, is a good example of using open data sources to tackle the social inequality problems (Murray, 2018). These deep-lobed partnerships support decision making to address the concerns of citizens. For instance, the innovative funding mechanism pictured by the municipal government in Rio De Janeiro has been initiated to tackle the funding issues to support urban development and city transformation. Statistics show that around 35% of the investments to support the city development activities are managed through private investors. The municipality has leveraged the bureaucratic restrictions imposed on private investments by certain policy reforms to encourage public-private partnerships (Srinivasan, 2017). City administrations extend the concept of Public-Private Partnerships (PPP) to invite not only foreign investments but also several service providers and asset builders who partner with the government to work on their behalf. An example of such a kind of PPP arrangement can be seen in the case of the General Outpatient Clinic PPP Programme launched in Hong Kong, 2014. In this program, all the general outpatient services are outsourced to private healthcare service providers who substitute the Hong Kong Hospital Authority (HA) in providing these services to the city residents (Onag, 2018). This initiative ensures proper health and sanitation benefits to all its citizens. Here the government acts as an enabler, policy reformer, and procurer of city services, thus stimulating economic growth.

As these examples suggest, smart city initiatives help in mitigating several urban development obstacles by utilizing data and services from intelligent technologies, like location intelligence, Geospatial technology, Internet of Things, Big data, Cloud systems, etc. thus, catering the needs of the city residents, improving city stakeholder involvement, and providing a better understanding on the city operations. Although the concept of sustainable urban development in smart cities seems very practical and viable, in reality, however, it is very complex, demanding, and context determined. Assessing the environmental sustainability performance remains a great challenge (Egilmez et al., 2015) along with several array of challenges that includes but are not limited to the inability of matching the urban sustainability demands to the real-time applicability context, lack of proper alignment in policy and technology implementation and coercion on social and regional solidarity that demand diverse governance solutions.

2.1.2. Decision Support Models for smart city research

Extending the light on decision support models from a city level perspective, we can see several scholarly works over the years have spread across this area of research. For the interconnected management of urban infrastructure assets, Wei et al., (2020) developed a knowledge based expert model using modular ontologies and rule base for sub domain interdependencies. Similarly, a smart decision support tool integrating “Building Information Modelling (BIM)” and “Geographic Information System (GIS)” was devised by Marzouk and Othman, (2020) to identify the infrastructure utility needs in an attempt to plan smart solution retrofits for traditional residential stocks. Papadopoulou and Hatzichristos, (2020) developed a “Spatial-Decision Support Model” (S-DSM) combining the “Geographic Information system” (GIS) and “Multi Criteria Decision Analysis (MCDA)” for the smart exploration of possible livable spaces in Greece. The urban space management system included an ICT support platform for effective land use management incorporating living labs and crowdsourcing in its architecture. A web-based data driven decision support model was developed by Marinakis et al., (2018) to support the management of intelligent energy services for smart cities using a cross-domain data platform encompassing high level architecture. The proposed model aids in making insightful decisions by simplifying the data gathering procedures from multiple sources relating to the cities energy performance. A model named Apus-Kul using “Simple Additive Weighting

(SAW)" algorithm was developed by Ayu, (2020) to measure the decisions related to choosing business directives and materials for food business in smart cities. The model attempted unstructured problems using the SAW algorithm to bring insightful judgements based on people's perception towards taste, food materials and ingredients for opening food and beverage industry. Hartatik et al., (2019) developed a decision-support model tailored towards smart city development through smart health planning using a naive Bayes method that detects acute skin diseases based on expert judgements. Dermatological self-diagnosis pathways and big data technology supports the Dipen-ku model. A transportation planning DSS named BISTRO was developed to support high-level regional planning, promoting smart urban mobility that act as a human intervened cyber-physical system by Feygin et al., (2020). The model used an agent-based simulation with optimization for scenario-based design of urban transportation management. D'Aniello et al., (2020) proposed an ontology-based service model for smart cities based on assertion and reasoning of processes whose information were shared by the city residents. The smart city service model aimed at delivering services to the city residents to ensure a high quality of life through service science theories. Nasution et al., (2020) devised a decision support model utilizing TOPSIS to analyze the eligibility of 10 major cities of Sumatra to becoming a smart city. The urban infrastructure, share of population, land use and economic status were the alternatives used in the assessment to rank the eligibility of the selected cities. Thus, research have spanned in the area of smart cities and decision support to model several challenges and bring about plausible recommendations to support effective decision making.

2.1.3. Smart cities and systems thinking

In order to tackle the prevailing challenges faced by cities, cities have started adopting smart initiatives (Marsal-Llacuna et al., 2015). These smart city initiatives are often assumed to be a successful approach in curbing possible city challenges. Despite this hypothesis, cities still face a tremendous deal of criticism, challenges, and difficulties when it comes to the deployment and implementation of the triple criteria of sustainability, resilience, and livability into the pre-conceptualized vision of smart city (Bibri and Krogstie, 2017). The literature investigates systems thinking in depth, keeping hold of the scope of the research. Table 1 highlights several peer-reviewed research articles published in the field of smart cities and systems thinking during the past decade. These emphasize the abundance of research works in the field of smart cities using a system-thinking approach, thus adding more quality to the research agenda of using systems thinking to link sustainability, resilience, and livability under smart city development.

Table 1. Literature review on studies using systems thinking in smart cities

No.	Article	Abstract	Source
01.	Towards a system-thinking based view for the governance of a smart city's ecosystem: A bridge to link Smart Technologies and Big Data.	The research utilizes a system-thinking approach to investigate the challenges faced in several domains of smart city and act as a guide in managing several dimensions and paths of social dynamics.	(Caputo et al., 2019)
02.	Systems thinking for developing sustainable complex smart cities-based on self-regulated agent systems and fog computing	The study adopts a system-thinking approach along with self-regulating agent systems and fog computing techniques for molding the futuristic concept of complex smart systems.	(Abbas et al., 2018)
03.	Applying System Science and Systems Thinking Techniques to BIM Management	The study adopts system science and the system-thinking to revitalize management norms on infrastructure development projects using augmented designs. A problem analysis	(Redmond and Alshawi, 2018)

No.	Article	Abstract	Source
		and interpretation method are used by the author on a construction project in the UAE to validate the strategies proposed in the study.	
04.	Functional resonance analysis method based-decision support tool for urban transport system resilience management	The research connects the Functional Resonance Analysis Method with a system-thinking approach in order to develop a Resilience Decision Support tool using smart data, thus helping to manage complex infrastructure resilience.	(Bellini et al., 2016)
05.	Case study of energy behavior: A system-thinking approach	A system-thinking approach is used in order to develop a three-tier based framework for smart city, focusing on changing the energy consumption behavior. The research outcomes focus on people who live in the greater part of New York City.	(Khansari et al., 2015)
06.	Industrial and business systems for Smart Cities	The research adopts systems thinking approach along with continuous engineering and IoT based concepts to develop an integrated set of best practices for smart cities and several industries.	(Amaba, 2014)
07.	Conceptual modeling of the impact of smart cities on household energy consumption	The impact of smart city technologies on the behavioral change of household energy consumption using systems thinking and cognitive and learning approaches is attempted in this study	(Khansari et al., 2014)
08.	Living labs, innovation districts, and information marketplaces: A systems approach for smart cities	Develops a candidate model for implementing the smart city concept into practice by incorporating systems thinking and integrating the living lab and innovation district concept.	(Cosgrave et al., 2013)

Systems thinking provides a broader understanding on how a system functions by investigating the relations and changes within the system. When understanding the concept of systems thinking vis-à-vis smart cities, city challenges are perceived as a product of structured relations between selective parameters that address the challenges, rather than just identifying causes and behavioral changes separately like the traditional linear thinking. These parameters are considered as a part of the city holistically, or pillars that address the challenges of the city, where the smart city is seen as an integration of systems (Dirks and Keeling, 2009). Any alteration to these parameters will affect the system as a whole. Thus, bringing systems thinking into the context of smart cities, we can troubleshoot flaws that affect the overall dynamics of the city with marginal effort. Systems theory has recently been used to formalize smart city visions by playing a vital role in strategic city planning. Several other tools, along with systems thinking, are used to tackle the prevailing challenges in urban planning like Kitemark recognition, Bench-learning, Progress monitoring, etc. (Pichler, 2017). System theory outweighs all other tools, because of its systematic behavior in integrating systems, the ability to predict composite changes within the system, and understanding the relevance of feasible divergence. Systems thinking addressed in context with smart cities considers socioeconomic and environmental characteristics and their dependencies with several systems and subsystems in a model that helps in strategic city planning (Shmelev & Shmeleva, 2018). This paves ways to sustainable urban development in smart cities (Pretorius et al., 2014). Systems thinking as a tool can aid cities in framing a better idea on several input-output parameters like population, urban space, air, water, waste, energy, safety, and transportation. It helps in a better understanding of how these parameters hold influence in the governance stage, like how vulnerable these parameters are to frequent changes in the pattern of development, availability, usage, and price elasticity.

2.1.4. Why systems thinking in smart cities ? and how it works.

Cities are often considered as complex systems (Mora et al., 2017; Portugali, 2016; Berkowitz, et al., 2003). These systems constitute several subsystems that are interconnected and interrelated with each other to perform specific functions (Bertalanffy, 1976). Functions are often related, and they tie-in connecting several elements within the system. Considering an example of the road as a function, we can see that the road functions to move vehicular traffic acting as a mediator for the movement- connecting people and vehicles from the source to destination. Thus, understanding these functions helps us in associating various elements and processes that are essential in filling these functions and facilitates us with a broader understanding of the results obtained when these functions are filled. Thus, applying systems thinking to understand these functions act as a potential leverage point since, systems thinking identifies necessities (Onat et al., 2017), possible knowledge gaps, correlations, and goals. Additionally, it helps in locating possible system paralysis, absent elements, inefficiencies in urban dynamics, and possible links that form a part of the function's work cycle.

Cities, when visualized as an urban ecological system, contain several subsystems (for example, but are not limited to population, urban space, air, water, energy, food, waste, safety, health, and transportation) that act as a system itself in the network of systems. A slight disruption in the functioning of either of these subsystems would result in undesirable consequences in other subsystems within the network of systems, thus affecting the overall dynamics and efficiency of the system. This can be understood by considering the following example of unoptimized resource allocation within a city. A city plans to reduce the number of medical dispensaries and healthcare centers as an effort to reallocate its budget on several other infrastructure development programs and concentrate resources. As a result, city dwellers need to consult other distant dispensaries, which requires them to travel long distances. This, in turn, increases their car trips leading to more road traffic congestions and harmful exhaust emissions at the same time. This increases several health hazards, thus affecting their health life. Thus, city challenges are often complicated and mysterious; and solving them is extremely difficult.

City officials and municipal organizations often work in silo mentality while attempting to curb several city challenges; for example, transportation and logistics-related issues are dealt with by the transportation modelers and logistics planners, while energy-related issues are handled by inspectors and energy managers. From the supplier's point of view, any water-related challenges are attempted to be solved by the water supply authority and energy-related challenges by the energy suppliers. When analyzing in-depth, the challenges faced by each department are interrelated and solving these city challenges becomes easy when attempting to adopt integrated management and thematic approach. 'Systems thinking' is thus an answer to all these questions and challenges, where systems thinking acts as a support tool in addressing complexities, uncertainties and identifying "what if" impacts (Onat et al., 2017),. Systems thinking interconnects several elements of a system to the point of interest, better identified as a purpose. For example, let us say that the traffic and transportation modelers in a city wish to redesign the transportation system that has been existing as an integral part of the city infrastructure for the past 50 years. The conventional planning model of the city's transportation network would hold 'transportation' as its prime focus. However, in a smart city, the modelers would extend their point of interest on factors such as smart mobility, zero-emission transportation alternatives, and increased connectivity for the city residents.

2.1.5. Sustainability assessment in smart cities

Despite technology playing a prominent role in transforming a city into being smart, there are several desired outcomes that need to be addressed when trying to mitigate several social, economic, and urban challenges in a city, which hinders urban development in a sustainable manner (Kamruzzaman and Giles-Corti, 2019; Bibri, 2020). Smart city concepts have been perceived as an ICT driven concept focusing on improving the quality of life of the citizens (Bibri and Krogstie, 2020). However, smart cities need to extend their focus from the perspective of sustainable urban development (Yigitcanlar et al., 2019c). Initially, the concept of smart city was regarded as a strategic tool to underline the increasing importance of ICT and social and environmental capital in sculpting the competitiveness of modern cities (Schaffers et al., 2012). Consequently, smart city definitions that encompass the environmental dimension of sustainability frequently include the social dimension. Schaffers et al. (2012) argued that this is due to the distinctive attributes that social and environmental capital can offer to smart cities compared to the "more technology laden counterparts," frequently mentioned in the literature as digital or intelligent cities. Thus, the distinction between digital or intelligent cities and smart cities appears to be the prevalence of the human element in the latter.

As an attempt to understand the methodological approaches, and tools developed to assess urban sustainability in smart cities, a review was carried out based on a series of latest research studies, and several indexing reports published in the field. The screening process of both scientific and gray literature was conducted with the aid of several search engines and Scopus online database, with a view to include a wide spectrum of journals, books, and technical reports with high relevance to smart city and urban sustainability assessment. The purpose of this bibliographical search was to identify the most well-known and widely-accepted sustainability assessment tools, indices, and methodologies used in smart cities for sustainability assessment from the last decade. We note that even though sustainability goes beyond local and urban areas, and several composite indices tackle country or global scale evaluation, we have restricted our study to urban sustainability in smart cities alone. Our research indicates that a variety of models and tools have been developed for the evaluation and comparability of sustainability in smart cities. These tools are based on composite indices that assess critical dimensions of sustainability. A good example of a composite index offered also as an interactive tool, that introduces both technology maturity and sustainability aspects in urban development is the "Networked Society City Index" (Ericsson, 2016). The Green City tool is another initiative on a European Union (EU) level and under the "European Green Capital framework" (European Green Capital, 2021), aiming to facilitate sustainable urban planning with a prime focus on offering best practices and guidance. It provides a simple, straightforward tool, limited to generic qualitative inputs of self-assessment for cities. In general, composite indices provide some key outcomes, such as ranking and benchmarking of cities, facilitating research and analysis in the urban design (Buldeo Rai et al., 2018) and assisting in sharing knowledge for the development of smart and sustainable cities (Abu-Rayash and Dincer, 2021). However, given that city sustainability entails a multitude of aspects and domains (Ali-Toudert and Ji, 2017), all these evaluation frameworks and indices present methodological gaps and conflicts, as they capitalize on different definitions of urban performance and development (Molinaro, 2020), while showing imbalance between smartness and sustainability.

Although there are many similarities among characteristics of evaluation frameworks, rating systems, or composite indices, they differ considerably in conceptualization, focus, and goals, due to the determined diverse city needs, boundaries and expected outcomes of the smart and sustainable cities under assessment, as well as the perspectives of the relevant stakeholders and experts. A majority of applications, experiments, projects, and initiatives use as a guiding principle the “triple bottom line (TBL)” in order to evaluate sustainability performance which integrates social, economic, and environmental variables (Chen and Zhang, 2020). A good illustration of this is the China’s urban sustainability indices (USI), the last version of which launched in 2016 and uses 23 indicators categorized under the 3 dimensions of TBL for ranking 185 Chinese cities of diverse sizes and development stages assessing their sustainability performance level between 2006 and 2014 (The China Urban Sustainability Index, 2016). Furthermore, some indices represent strong sustainability while others present a weak sustainability assessment. A representative index with strong sustainability criteria is the sustainable development of energy, water, and environment systems index (SDEWES) that assesses the sustainable performance of 120 cities across 7 dimensions, while identifying best practices for policy learning and adoption (Kılkış, 2016). There are also indices that primarily focus on environmental sustainability, such as the European Green City Index, grounded on 30 individual indicators to assess and compare the environmental performance of 30 big European cities from different countries (Shields et al., 2009), or indices that explore only specific urban aspects, such as urban mobility, air quality, business development, etc. (Akande et al., 2019), e.g., the index developed by Collins et al. (2019) that builds upon geographic, meteorological, and socio-economic data and k-means clustering to determine which out of 119 U.S. cities included in the analysis are bicycling-friendly cities (Collins et al., 2020).

Several indices used to assess sustainability also hold drawbacks that lie in the difference and multiplicity of the data sources used for results' comparison, owing to lack of data for some indicators or even due to inconsistency of the framework approach. In some cases, country-level data are utilized, or extrapolation techniques are implemented, while data are also obtained from other indices to calculate a number of their metrics (for example see., e.g., Cohen, 2012; Innovation Cities Index, 2019). In the case of a city evaluated by two or more different indices, results lead to diverse type of rankings, implying an indication of subjectivity. A good illustration of this is the city of London when assessed via the IESE Cities in Motion Index 2020 and the IMD Smart City Index 2020. The city ranks top in the first index and on the 15th place in the second, due to the different approaches in the smart and sustainable city concept and its dimensions, as well as the number of cities and indicators of city evaluation between the two indices, leading to extremely difficult comparison of results. In addition, it is also to note that several major differences and incoherence are observed among composite indices regarding the normalization, weighting, and aggregation methods used to evaluate sustainability performance. However, non-parametric approaches such as the Data Envelopment Analysis (DEA) uses normalized values for all the indicators from linear scaling in the min-max range. The technique allows the analyst to endogenously assign weights for the partial indicators, yielding an overall score that depicts the analyzed decision making unit in its best possible light relative to the other observations.

2.1.6. DEA models for sustainability assessment

Data Envelopment Analysis (DEA) is a non-parametric quantitative optimization-based benchmarking technique developed by Charnes, Cooper, and Rhodes, (1978) to assess the relative efficiency of productive units. In this approach, the values of the selected input and output parameters are multiplied with appropriate weights calculated to obtain the desirable efficiency scores. The proposed model by Charnes, Cooper, and Rhodes, (1978) (formally known as the CCR model) based on "constant returns to scale (CRS)" was further modified by Banker, Charnes, and Cooper, (1984) (so called BCC model) entitling "variable returns to scale (VRS)". In a classic DEA model, appropriate weights for each "Decision Making Units" (DMU) are formulated using mathematical programming. In contrast to DEA, a less frequently used non-parametric technique for efficiency calculation is the "Free disposal hull (FDH) approach" proposed by Deprins et al., (1994), which later on was modified by Lovell et al., (1994). Till date, DEA models are based on two measures, the radial DEA model proposed by Charnes, Cooper, & Rhodes, (1978) and the Slack based measure (SBM) DEA model developed by Tone, (2001).

Through the years, various DEA models have been extended from the classical CCR and BCC models to calculate the relative efficiency of the DMUs. Tayala et al., (2020) applied the BCC model with constant input to calculate the efficiency and select the most sustainable facility layout plan, combined with machine learning, K-means clustering and meta heuristics approaches. An SBM-DEA model combined with energy analysis was used to assess the urban metabolic performance of eight Chinese communities by Tang et al., (2020). The frontier approach has brought all the sustainability assessment indicators under the composite sustainability framework. A meta frontier DEA approach was used to study the territorial eco-efficiency patterns in 282 European regions for the years from 2006 till 2014 by (Bianchi et al., 2020). Yasmeen et al., (2020) used a "super-efficiency" DEA model combined with a system generalized method of moment estimator to study the ecological productivity of 30 provinces of Mainland China under the COP-21 agreement. The impact of pivotal factors contributing towards national and regional sustainability were also identified and targeted for possible improvements. A multi power system network-based DEA model was used to monitor the degree of sustainability by Tavassoli et al., (2020) within the context of Iran's electricity distribution grid. The model included several undesirable outputs, excess inputs, and system re-work indicators whose weights were assigned based on expert judgements. A similar network DEA approach was used by Wang & Song, (2020) to measure the degree of sustainable airport development for 12 Asian airports from the grey model using real time and forecasted data. Castellano et al., (2020) made use of a "multi-stage DEA" model to assess the relative environmental and economic prosperity of 24 Italian seaports. The model estimated the diligence of economic efficiency when considerable adjustments were made in the ecological costs and pro-ecological commitments. A multistage DEA-ratio data model developed by Mozaffari et al., (2020) was used to estimate the sustainable efficiency of 20 fire station supply chain (SC) based on a set of dependent variables. The model utilized the Genetic Algorithm (GA) as a means to obtain the productive weights of a multi-echelon SC model. Ibrahim & Alola, (2020) applied an "Autoregressive Distributed Lag (ARDL)" method with "Pooled Mean Group (PMG) estimation" approach to understand the non-renewable resource efficiency for a set of response variables like GDP growth rate, energy usage and aggregate natural resource rent. While a similar study was conducted using a DEA model to evaluate the efficiency for renewable energy and, socio-economic and ecological development. Thus, DEA can be seen as a powerful tool in assessing sustainable development capacity across several domains.

Progressive efficiency can be assessed by understanding the technological changes as a whole over the years. Productivity measurement is an important topic to account for when understanding sustainability. The DEA based Malmquist Productivity Index (MPI), as an effective tool has long been used to measure the productivity change in efficiencies over time for a set of representative units. A DEA-MPI model was used by Pan et al., (2021) to measure the sustainable development of electronic agriculture-based infrastructure in 31 provinces of China. The integrated approach rules out bias in estimation of production efficiency associated with the use of cross-sectional or time series data. To assess the ecological productivity of 30 Chinese cities from a time series perspective, Zhu et al., (2019) developed a common weight DEA approach combined with Biennial-MPI. Zhang et al., (2020) employed a super efficiency DEA-MPI to create an evaluation index system to understand the impact of IoT with real economy for an economic sustainability assessment. To study the productivity change in eco-efficiency and technology catch-up indices, a non-radial meta frontier Malmquist-Luenberger DEA model was used by Tang et al., (2020a) over time on 30 Chinese provinces. Double bootstrapped MPI was used by Kularatne et al., (2019) to analyze on how environmentally sustainable practices can make Sri Lankan hotel industry more efficient, by measuring productivity change over period from 2010-2014. Wang and Li, (2018) employed DEA-MPI to analyze the carbon emission performance of petrochemical producers in United States over time. Combined with super efficiency DEA-MPI and kernel density estimation, Ge et al., (2021) studied the eco-efficiency performance of 40 growing cities. DEA-Malmquist-Luenberger productivity index was used in combination with Difference in Difference-Propensity Score Matching (PSM-DID) approach to estimate the productivity progress of low-carbon emission pilot cities of China by Fu et al., (2021).

Wang, (2019) used DEA-MPI to understand the sustainability performance and productivity change of 40 world-wide cities across 6 prime dimensions.

2.1.7 DEA with undesirable factors

The literature till date provides two intuitive approaches when dealing with undesirability while calculating the efficiency performance. The most commonly employed approach is the application of suitable data transformation to the undesirable factors in the PPS to make them desirable. Non-data transformation approaches are also used to preserve the true input-output relationship of the production process. A non-parametric DEA model using the directional distance function (DDF) under the assumption of weak free disposability was proposed by Färe & Grosskopf (2004) and Yu (2004) to treat both undesirable inputs and outputs in the linear conventional BCC-DEA model. A single-process DDF approach to treat undesirable outputs in a network DEA model was proposed by Lozano et al., (2013) when computing the airport efficiency scores. Based on the classification invariance property, the performance of the inefficient DMU can be improved by maximizing the undesirable inputs and desirable outputs with minimizing the undesirable outputs and desirable inputs. This was applied by Seiford & Zhu, (2002) in understanding the performance of 30 paper production mills in the United States. The undesirable input X^{UI}_{ko} was multiplied by "-1" and then a translational vector "*w*" was added to convert the negative X^{UI}_{ko} to a positive form. Here, the undesirable input X^{UI}_{ko} is increased. A "Semi-Oriented Radial Measure DEA (SORM-DEA)" model presented by Emrouznejad (2010) dealt with negative undesirable inputs/outputs. A modified extension to the conventional SBM-DEA model proposed by Tone (2001) was used by Sharp et al., (2007) to addresses the desirability concerns in the input and output variables that are present in the technology set. A restricted DEA model using optimal shadow pricing considering the undesirability in the output was used by Guo and Wu (2013) to rank DMUs based on “Maximal Balance index”.

Several data transformational approaches exist in literature to deal with desirability concerns in inputs and/or outputs when measuring relative performance. Lovell et al., 1995 used the multiplicative inverse approach to treat the undesirable outputs (monotone decreasing transformation) to achieve the desirable state. For instance, any undesirable output can be treated in the form $f\,(\mathrm{Y}) = 1/\ \mathrm{Y}^{\mathrm{UO}}{}_{\mathrm{vj}}\ \{(v = 1,2,3,\ldots\ldots t) \in T_c\}$ to use it as a set of desirable output for the efficiency assessment. Data translations of the form $f\,(\mathrm{Y}) = -\,\mathrm{Y} + \delta$ was used in the studies conducted by Pastor (1996) and Scheel (2001) to transform undesirable outputs to their desirable forms. Reducing dimensionality of the data set to its intrinsic dimension can help in capturing the significant inputs and outputs to be included while measuring the relative efficiency scores. Liang et al., (2009) used a monotone increasing data transformation on a selected set of principal components to rule out negative undesirable outputs when attempting to understand the ecological performance of 17 Chinese cities.

2.1.8. The evolution of urban resilience and livability

Ecological modernization and socio-biophysical uncertainties in cities have raised consensus of urban planners in the opinion to include the concepts of liveability and resilience in the existing development model. Since the classical era, Aristotle in his best-known work Ēthika Nikomacheia mentions the term “Eudaimonia” which means living a reconciled life (Yu, 2001). American psychologist Carol Ryff in 1989 extended Aristotle’s Eudemonic well-being of what she regarded as psychological well-being under: autonomy, personal growth, self-acceptance, sense of purpose in life, environmental mastery and positive relations with others (Ryff, 1989). Thus, liveability is known from ancient time dating back to Plato and Aristotle, with a plethora of conceptualization at different period of time. The late 1960s and 1970s saw the emergence of liveability with The "Electors Action Movement (TEAM)" in Vancouver, as a people-centric concept to the then existing growth-centred approach on the economy. Geographer David Lay argued on the existing liveability approach of late 1970s as a discursive approach to showcase political power amidst the quality-of-life proposition (Lay, 1980). In 1981, Donald Appleyard, an American landscaper, introduced liveability in the field of urban planning and design for the first time through his book 'Liveable streets, protected neighbourhoods'. Appleyard et al., (1981) characterised liveability as an unmeasurable definition to the quality of life through urban redevelopment plans, focusing on the infrastructure and transportation sector. Appleyard mentions that cities have different stage of attractiveness and thus different stage of liveability. A Liveable city is one where people aspire to live and can afford to live (Newman, 1999). The late 1990s' in the view of scholars was an era that focused on liveability discourse as a means to address the concerns of the elite class and nobles; a neo-liberal agenda (Uitermark, 2009). The 21st century saw the use of liveability as an integrative concept that connected human values with the social environment, rather than a profit-centred development agenda. Brenner et al., (2009) in his publication 'Cities for People, Not for Profit', exemplifies liveability as "an alternative, post-capitalist form of urbanization". There are many criteria that define liveability of a city, where the criteria defining liveability is either objective or subjective to an individual's personality, culture, national background, traditions, and expectations. Dutch sociologists Tonkens and Constandse however argues on the objective notion of liveability in cities, as it rips human-centric urbanization with the division of functionalism on cities, thus tarnishing the social fabric of community-living (Kaal, 2011). Thus, liveability in modern era is a malleable concept translated into spatial levels to add quality to human lives, conceptualized under diverse contexts (Higgs et al., 2019).

Liveability is obtained by re-creating small neighbourhoods so-called new urban villages with an eye to combat unprecedented urbanization (Weichselgartner and Kelman, 2014; Benita et al., 2020). These so-called urban villages are a part of complex ecological systems that are susceptible to several shocks and operate under numerous exogenous and endogenous uncertainties. Dealing with uncertainties is crucial for cities to thrive when attempting to recover from adversity (Nitschke et al., 2021). Building resilience in ecological systems is a vital endeavour towards reducing the exposure to extreme events and peace-building in city (Sanchez et al., 2018). Etymologically the word "resilience" originates from the Latin word “resilio”, meaning “to-bounce back” (Manyena et al., 2011). Resilience planning dates back to the ancient era, long since the Romans in 4th Century BC built the *Cloaca Maxima* sewer pipeline; a flood resilient sewerage network system (Galderisi et al., 2020). Resilient studies focus on understanding a systems performance pre and post disruptive events (Hudec et al., 2018). Reggiani et al., (2015) identifies resilience as; the ability of a regional system to return to equilibria post disruption (engineering resilience), or the extent to which urban systems can handle chronic stresses and shocks (ecological resilience). Martin, (2012) recognizes adaptive resilience as the ability of a system to reorganize post stress to facilitate system operation through endless change and reduced recursion of shocks. While Lagravinese et al., (2015) defines economic resilience as an adaptive capacity of regions/local areas to resist recessionary shocks. Socio-ecological resilience as identified by Rodin, (2014), recognizes urban system as a nonlinear system susceptible to change in an evolutionary pattern. The degree of resilience can support explanations on why some regions are capable to withstand stress and the reason why some adversely affected regions recover in a relatively short period of time post disaster compared to other regions. Thus, the concept of urban resilience and liveability is multi-dimensional and does not hold a 'fixed boundary' in terms of its definition and interpretation.

2.1.9. Are smart cities addressing resilience and livability ?

Transforming a city into being smart with the use of innovative technologies is vital and inseparable to achieve better living standards for urban residents (Mdari et al., 2022). Smart cities are vessels of intelligence and an efficient incubator of empowered spaces which clearly holds tight the importance of the themes: intelligence, well-being, resilience, and spatial development (Rios, 2008). Although these concepts are of high importance, they are addressed only marginally by several authors in their proposed definitions of the smart city. Livable cities shape residents to be better citizens, intelligent scientists, potential workforce, effective policy reformers and better enablers of smart services (Kutty et al., 2020). While resilient cities act as shields against undesirable externalities by working in 'smarter ways' with relentless focus on civic life and communities' adaptive capacities (Patel and Nosal, 2016). Thus, an intimate philosophical kinship exists between these paradigms. In vain, livability and resilience paradigm have been used interchangeably in several context targeting the soul agenda; quality of life with a smart growth strategy.

Despite philosophical kinship between both the paradigms, their application has spanned across diverse dimensions specific to social needs and diverse functionalism of cities. Although the objectives remain same, i.e., to enhance quality of living and provide a sustainable way of life to the inhabitants, most cities have diversified this objective to attain city specific goals to meet the needs of city dwellers. The Russian capital city Moscow addresses the bedeviled road traffic congestion issues by initiating alternative mobility plans and implementing intelligent transport systems (a clear example of pan-city development) geared at delivering a sustainable mode of work and life to the citizens (Golubchikov and Thornbush, 2020; Danilina and Slepnev, 2018; Chudiniva and Afonina, 2018). In Jaffa-Tel Aviv, the smart city practice is viewed as an ideal strategy to tackle the prevailing challenges of education, health, sanitation, and culture to promote sustainable development and community well-being (Toch and Feder, 2016). In the case of Singapore, the smart city program focuses on big data by implementing a nationwide network of digital sensors intended to provide city officials with real-time information on the happenings of the city by gathering, allocating, analyzing, and interpreting the data with the sole objective of transforming the country into an intelligent nation (Shamsuzzoha et al., 2021). Thus, offering a dignified standard of living to the citizens through smart practices. While the Msheireb downtown smart city project in Doha, Qatar which is an urban regenerative development program built with a strong and unique Qatari identity complementing Islamic architectural language aims at delivering a better and a greener standard of living to its citizens and expat community (Sharif and Pokharel, 2021). The city intends to practice green transportation system by adopting zero emission mobility-electric tram system. In addition, it also focuses on another important goal, which is to transmit knowledge and diversify the broadband connectivity. This initiative would aid the community to attract foreign investments into their market thus helping in boosting the smart economy with a touch of livability (Ringel, 2021). To understand the vulnerability of smart city development to climate change, nature based-solutions are integrated with built-up spaces to improve livability under the Smart City Mission in Bhubaneshwar, India (Pandey, 2021). Livability conditions were assessed in the city of Bhopal, India for smart mobility services based on socio-economic profiling (Chatterjee et al., 2020). Administrators in the city of Bhopal believe smart transportation as a measure to integrate community needs for economic and social development. Thus, a smart city can be viewed as a multi-objective concept tailored to achieve livability.

Reconfiguring urban development in light of sustainability requires integrating resilient features with digitalized smart solutions. A resilience-based ontology was structured to assess and elaborate the real time data streams from smart city technologies in the city of Florence, Italy under the “RESOLUTE” project (Bellini et al., 2017). A real-time assessment of dynamic resilience of smart infrastructures was made possible through the Smart Resilience Project (SRP) by constructing a benchmarking matrix, the “resilience cube” (Jovanovic et al., 2019). The impact of critical infrastructure retrofits; smart rainwater harvesting mechanism on urban resilience was studied by Oberascher et al., (2021). To understand the impact of smart city development on urban resilience in China, Zhou et al., (2021) constructed an urban resilience model, where policy performance was assessed using the PSM-DID approach. While, based on the geomorphological characteristics, a mixed approach using machine learning (ML) classifiers and GIS was used to identify the hotspot areas prone to flood in Lisbon city, Portugal by Motta et al., (2021). A flood risk index was then constructed for the city within every 100 m^3 cell. To improve the power distribution network resilience in Milan, Italy, Bosisio et al., (2021) used ML with GIS algorithm to understand the surges in the network under variable load conditions.

2.1.10. Bringing machine learning to smart city research

Machine learning (ML) is a hypernym term that encompasses several tools and techniques to explicitly perform tasks based on self-learning and adapting to patterns on their own (Alpaydin, 2020). ML models assist in understanding system behaviours by executing functions through learned trends and patterns rather than any predefined set of procedural codes. ML algorithms act as powerful tools in decision making scenarios where knowledge execution through strict complex algorithms becomes a tedious task (Meyer, et al., 2014). Machine learning has found applications in several areas including social media platforms like Facebook that pops friend recommendations and content suggestions captured through previous user interference with the platform (Bishop, 2006). Image recognition features such as face detection has brought smart phone development to the next level (Zoph et al., 2018), which is one of the most notable ML techniques. Sentiment analysis for identifying the tone of text and content filtering for unauthenticated bank transactions (Habernal et al., 2013) are some of the common applications of ML on a day-to-day basis.

ML techniques also play a significant role in the areas that aim to foster smartness and sustainability from a city level perspective. Majumdar et al., (2021) used ML approaches to predict the congestion propagations on road networks using a LSTM network architecture based on motor vehicle speed data. A univariate and multivariate predictive model was built, and the predictive accuracy of the models were estimated. Wang and Gohary, (2017) proposed several data-driven predictive models to understand the level of building energy in terms of consumption for smart infrastructures. Here, prediction using the smart metrices from historic data, along with feature selection identifying the required data quantity were based on ML algorithms. While, LASSO algorithm dealt with feature selection, three ML techniques were used for model implementation and testing. While Nutkiewicz et al., (2017) combined data driven machine learning model with an energy simulation model to address the influence of transition spaces on building energy usage. The integrated model provided recommendations in addressing sustainable practises at the building design, management, and energy utilization phases. Li et al., (2019) developed and implemented an improved deep machine learning model by integrating "genetic algorithms (GAs)" and the "extended Kalman filter (EKF)" for effective computation, prediction, and accuracy of infrastructure smartness. This modified deep belief network (DBN) was trained using a "back-propagation algorithm (BP-DBN)", or new algorithm based on EKF. Gomez et al., (2020) used supervised modelling to develop a sustainability category forecasting framework to assess the comprehensive community perspective at micro territorial levels. The decision-making model used ML tools such as "decision trees (DT), support vector machines (SVM), and artificial neural networks (ANN)". This involved three procedures, namely, indicator depiction within study area, developing a sustainable development index (SDI) based classified labelled supervised learning model and developed machine learning models. Considering time dimensionality, Sehovac et al., (2020) developed a novel energy load forecasting method integrating RNN with "Sequence-to-Sequence (S2S) deep learning algorithm". Two S2S models namely "Gated Recurrent Unit (GRU)" and LSTM were used to test electrical data consumed by a single building level post-smart retrofits at different forecasting lengths.

Machine learning techniques have also been applied to improve medical diagnosis in smart healthcare sector such as; to estimate the adverse patient risk when administered to antibiotics (Wiens et al., 2014), accurate prediction of zoonotic disease outbreak in communities (Han et al., 2015), pattern detection-based automatic classification in radiographic imaging (Guo et al., 2015) and patient behaviour based on heart rate monitoring through wearable smart devices (Huynh-The et al., 2020) and many more. ML techniques have also been used extensively in identifying the pattern of cybercrimes in cities (Alrashdi et al., 2019) and outlining the breach patterns in the IoT network traffics (Lourenco et al., 2018).

2.1.11. Multi-criteria methods for composite indexing

MCDM is a decision-making technique that analyses (ranks, classifies, chooses) a series of potential alternatives while considering different criteria. Consequently, it is imperative to identify and understand different MCDM methods used in literature for constructing composite indices. MCDM is defined as a set of methods that facilitates a high flexibility in the process of decision making when more than one criterion is involved (Cinelli et al. 2014). Among the diverse approaches, one of the most extended categories distinguishing the MCDM approaches are the "Multi-Objective Decision-Making (MODM)" and the "Multi-Attribute Decision-Making (MADM)". The former is used in design problems with infinite alternatives, while the latter deals with a limited (discrete) number of alternatives. For simplicity and clarity, this section categorizes the MCDM methods adopted by different researchers to construct composite indices into three categories. These include: (1) the elementary methods, (2) the outranking relation approach, and (3) the distance function-based methods. The elementary methods form the base of MCDM methods, whereby simple conditions are adopted to select a preferred option by reducing the complex problem into a simple one (Lai et al., 2008). For instance, the "Simple Additive Weighting (SAW)" and the "Weighted Product (WP)" are the two most used elementary methods. Next category infuses all those methods responsible for drawing comparisons between pairs of selected alternatives, termed as the outranking relation approach. For example, this approach drives the decision-making process by determining if the "option *a* is at least as good as option *b*". Within this group, ELECTRE and PROMETHEE (“Preference Ranking Organization Method for Enrichment Evaluations”) are among the two most widely used methods (Lai et al., 2008). The third category describes the distance function-based methods, where the basic idea lies in substituting the maximization of a function by the minimization of the distance between alternative points with favorable properties (Díaz-Balteiro et al., 2017). The MCDM methods are further explored under the respective categorization as discussed:

1. Elementary methods: Using the elementary methods of weighted sum approach, a few preliminary studies successfully constructed composite indices. In this regard, notable is the Composite Environmental Index (CEI) constructed by Kang et al., (2002), where an AHP was used to assign weights to the environmental problems. Similarly, Torres-Sibille et al., (2009) assessed the impact of wind farm installations on the perceived aesthetics of landscapes using a composite indicator constructed using a weighted sum approach. The weights assigned to this indicator were decided by a panel of experts and further analyzed using AHP. The UTASTAR MCDM method was employed by Papapostolou et al., (2017) to evaluate the compliance of seven Western Balkan countries in promoting renewable energy sources while assessing the achievement of the “Directive 2009/28/EC joint project development”. Using the state-of-the art neighborhood sustainability assessment tools and expert SAW methods, Haider et al., (2018) developed a set of sustainability indicators addressing all the sustainability dimensions associated with small-sized neighborhoods.
2. Outranking relation approach: A study conducted by Petrovic et al. (2014) established a methodological framework based on ELECTRE, to assign

hierarchical ranks to European Union (EU) member states against the Digital Agenda key performance target attainment. Further, studies have employed PROMETHEE to determine the overall sustainability performance of 30 European countries through the analysis of 38 composite indicators over a duration of 10 years (2004 –2014) (Antanasijevic et al., 2017). Further, by combining an optimization procedure with normative judgements, Amado et al., (2016) proposed a methodological framework to quantify the active ageing in the European Union countries. Based on Data Envelopment Analysis (DEA) approach, the team developed a model of 22 indicators with virtual weight restrictions categorized under four main domains. Furthermore, a common weight MCDA-DEA approach was developed by Hatefi and Torabi, (2010), which was further validated by constructing two composite indicators, namely the Sustainable Energy Index and the Human Development Index. Motivated by the multi-criteria method of PROMETHEE II family, Abreu et al. (2020) utilized the LTI method to rank the overall sustainability of countries based on their CO_2 emissions against the criteria established in the Kaya identity indicator. The country rankings were determined based on the combined indicators of economic projection and energy efficiency.

3. Distance function-based methods: Adopting a Double Reference Point (DRP) based methodology, Ruiz et al., (2017) proposed a set of synthetic indicators in comparison to the Ease-of Doing-Business indicators suggested by the World Bank. Here, authors use the Fuzzy Degree of Similarity between rankings to investigate the different degrees of comparisons based on ambiguity, and uncertainty of the data. Using TOPSIS, a novel mixed model approach was developed by Wang et al., (2012) to integrate the different

indicators meticulously and objectively into a composite one. Further, the team proposed a methodological extension through a smart MCDM framework based on TOPSIS to assess the air pollutant and economic development dependent factors for the city of Wuhan in China (Wang et al., 2017). Enhancements to the TOPSIS approach in the form of fuzzy TOPSIS was adopted by Escrig-Olmedo et al., (2017) for integrating the environmental, social and governance performance criteria into social asset evaluations. Similarly, an improved hierarchical fuzzy TOPSIS model was proposed by Bao et al., (2012) to develop an overall safety performance index by combining multilayer performance indicators based on experts' knowledge. Considering the importance of MCDM techniques in the linear ordering of cities, Hajduk and Jelonek, (2021) proposed the TOPSIS method for assessing critical energy enterprise locations in smart cities. The model used 21 alternatives analyzed using 7 ISO 37120 indicators to rank 6 smart cities based on the urban energy context. Milošević et al., (2020) applied the fuzzy (Trapezoidal and Triangular) and interval grey AHP methods to assess the management of architectural heritage in smart cities from the perspectives of heritage and smart city development experts. Here, the trapezoidal AHP showed better stability, while interval grey approach ranked the heritage indicators more significantly.

4. Hybrid Approaches: Using the composite indicator of GDP per capita, Morais and Camanho, (2011) measured the effectiveness of local authorities in promoting quality of life for a given economy. Using DEA, the composite indicator combined the single indicators based on the quality of life and local management performance targets. Further, comparisons of cities and countries

were executed using goal programming. De-Mare et al., (2015) developed, tested, and validated the efficacy of using the simplified linear aggregative model, SMART and the PROMETHEE II model in expanding synthetic indexes for ranking urban development investments. Darmawan et al., (2020) carried out the critical factor investigation modelling for smart districts using the Balanced Scorecard technique combined with the hierarchy structure modelling using the Fuzzy TOPSIS approach. This hybrid model enabled in the easy mapping and validation of the associated criteria and alternatives in smart districts. A competitive evaluation framework was developed by Ozkaya and Erdin, (2020) based on the combined advantage of the "Analytical Network Process (ANP)" and the TOPSIS approach to propose smart and sustainable city planning decisions. Here, the dimensions of smart cities were weighted using the ANP, while comparison results of 44 cities were made using TOPSIS.

2.1.12. Fuzzy-based expert models for decision support

Expert-based models are models that emulate decision making skills based on judgements from field experts (Turban, 1993). These models are developed to solve complex problems with a set of rules rather than procedural codes by translating the expert thinking to reach desirable outcomes. Expert models are classified into; a) Rule-Based Expert Models (RBEM) where the knowledge base is represented by a series of "If-then" linguistic rules; b) Frame-Based Expert Models (FBEM) that utilize frames for knowledge representation (Minsky, 1974); c) Hybrid Expert Models (HEM) that makes use of integrated rule and frame approaches; d) Readymade Expert Models (RMEM) that are ready to use systems off the rack for multi-criteria assessments and; e) Real time knowledge based models that are custom made models with expert knowledge. All these categories of expert-based models are data-driven models that depend on the data collected through previous research and experimentation (Babanli, 2019). One of the prime concerns on expert-based models that deal with data include, the level of uncertainties that accompany during evaluation and unreliable or partially reliable information associated with the set of indicators. To tackle these challenges, fuzzy logic approaches are best suggested. The spectrum of fuzzy-based expert model application spans to several areas of technological development. A fuzzy expert-based evaluation technique (FET) was used by Ivanova et al., (2020) to bring out decisions in the area of cerebral palsy learning blocks using fuzzy algorithms and k-means clustering. While, Liao and Lee (2004) used an FET, to identify the power quality disturbances in the transmission system combined with a Fourier transform and physiological system analysis. Oh et al., (2012) used a fuzzy RBEM for product portfolio management applied to Korean electronics firms under uncertain conditions. The strategic bucket tool combined with portfolio matrixes and scoring models were used to build the FBEM framework. A modular indicator set for solar radiation models were proposed using expert-based fuzzy logic modelling used to assess the quality of performance by Bellocchi et al., (2002). Thus, expert-based models have been used to solve multi-attribute problems across several areas involving multiple criteria and sub-criteria.

Several studies over the years have also used fuzzy theories for decision making with expert elicitation in the field of urban and city planning as well. Among them, fuzzy set theories are the most commonly used in smart city related assessment. To accomplish certain levels of environmental sustainability, an AHP combined with Fuzzy Inference System (FIS) was designed by Kim et al., (2018). This model aided in illustrating the risk mitigation and reduction scoring measures of infrastructure projects in smart cities. Previously, researchers at the University of Columbia developed an adaptable analytical framework using fuzzy set theory to evaluate sustainable development goals with diverse indicator sets. Identified as a modifiable model with transparent assumptions, this method evaluated the progress of Canadian smart transportation systems in accomplishing social and eco-environment sustainability goals (Montemayor et al., 2018). Recently, a fuzzy expert-based model was developed by Frare et al., (2020) to characterize a decision tree for creating an urban livability and sustainability index for small sized municipalities. Here, initially a fuzzy-Delphi technique was used for the indicator selection process. Similarly, studies by Lin et al., (2020) proposed a selection and evaluation model for selecting urban inhabitants based on human development indicators. The efficiency of fuzzy systems in dealing with uncertainty was used by Cavallaro, (2020) in developing a sustainable and smart energy technology index based on an intelligent FIS. This study measured the environmental impacts due to usage of electricity power production technologies in smart cities. Fallahpour et al., (2020) integrated the "Fuzzy Preference Programming (FPP)" with the FIS to develop a MCDM model to assess the sustainability and infrastructure resilience of smart buildings in cities. By replacing the Fuzzy-AHP with FPP as a modification, the solution to the selection problem attained high reliability and robustness. While Santos et al., (2020) developed and applied an expert model based on fuzzy logic to select a single preferred solution from a set of optimized pavement maintenance and rehabilitation strategies in cities. Fuzzy expert judgements combined with blockchain protocol on EOS.IO ecosystem developed by Aguilera et al., (2021) was used to plan the optimal allocation of sensors and obtain sensor readings from infrastructures in smart networks. Thus, expert based models have been used in recent studies related to smart cities for planned composite outcomes.

2.2. Novelty and State-of-the art contribution

Several studies as observed through the umbrella review in the area of smart cities have attempted to address concerns related to city based challenges and have devised solutions by structuring several decision support models. However, from most of all the studies reviewed, it can be seen that all the developed decision support models were tailored to focus only on the inter-dimensional elements of smart cities like smart health (Hartatik et al., 2019), smart infrastructure (Wei et al., 2020; Marzouk and Othman, 2020), smart mobility (Feygin et al., 2020), smart people (Ayu, 2020) etc.,. Similarly, all the proposed decision support models for cities focused on addressing concerns from a regional perspective and not from a global perspective where the scope of applicability in a global scale is often restricted. Alternatively, among the studies that focused on sustainability and resilience planning criteria in light of smart cities often focused on SDG-11 of the UNDP 2030 agenda (building sustainable and resilient cities) alone, ruling out all other possible indicators and dimensions trivial for futuristic smart city development aligned with other sustainable development goals. The well-established U4SSC initiative is one great example with the soul agenda to achieve SDG 11: “make cities and human settlements inclusive, safe, resilient and sustainable" alone, ruling out other possible SDGs for smart city transformation. Most importantly, all the developed decision support models for smart/sustainable/resilient cities reviewed were mostly isolated stand-alone systems. While no research has yet attempted to develop a hybrid decision support model addressing the resilience, livability, and sustainability criteria of the futuristic smart cities under a unified frame of assessment to evaluate performance for informed decision making. Additionally, no hybrid decision support model powered by novel analytical methods such as a double frontier optimistic and pessimistic DEA model, multi-variate metric-distance based weighting and scoring approach combined with machine learning classifier models, systems thinking models across the SRL concept, and fuzzy multicriteria assessment techniques combined expert model have ever been employed in the past, to support the transition of smart cities to futuristic smart cities. To this end, this dissertation attempts to develop a hybrid model to base decisions at four different level of performance assessment to overcome the challenges that occur in smart cities of today. The hybrid decision support model proposed in this dissertation is novel in many important aspects:

1. The futuristic smart city (FSC) index developed as an output to the decision support model uses multiple set of indicators (118 indicators) across multiple dimensions (13 dimensions) under the triple criteria concept (sustainability + resilience + livability) of futuristic smart cities to represent the composite performance. Such a comprehensive monitoring model is unique in its design for improvement decision making and discursive transformation.
2. The hybrid decision support model design focuses on the typology of indicators namely; input-output indicators, coverage/activity based indicators and outcome indicators which are specific across each "levels of measurement". Such detailed focus in design is a least sought approach or an often ruled out scheme for computational simplicity, in previously developed models when attempting to understand the composite performance.
3. The use of novel advanced analytical techniques across each level of performance measurement in the decision support model is unique in ruling out uncertainties and vagueness associated with the use of existing methods.

4. The use of 35 top ranked European smart cities as a case to implement the proposed decision support model and, understand sustainability, resilience, liveability, and combined performance of smart cities is fairly justifiable. The selected smart cities cover nearly three-quarter of the list of top 50 leading global smart cities, making the sample size fairly large for the results to be economically extrapolated to a global level when understanding sustainability, resilience, and liveability in any current smart city development models.

The contribution of this dissertation brings in-house novelty in terms of the subject handled and the approach used to solve the problem. Thus, we further dive into explaining the novelty in terms of the methods used within the hybrid decision support model. To continue, the 2030 Agenda for Sustainable Development accentuates the importance of techno-centric development in transforming urban spaces to more smarter living units (World Urban Forum, 2018). However, it is unclear on how well these technological retrofits and advancements can bring sustainable outcomes or improve sustainability. Studies over the years have focused on attempts to transform smart cities into smarter living units in belief that technological advancements can pave ways to sustainability. Nevertheless, recent research contradicts this paradigm to support the smart sustainable city concept. This study tries to explore the true essence of the concept of sustainability (in one level of measurement) in leading European smart cities through a novel data-driven analytical approach for performance assessment. In addition, traditional production theories, as seen in our literature analysis, often ignores the presence of undesirability (undesirable input and undesirable output) in the technology set while computing relative efficiencies for representative units to rule out the computational difficulties. However, this does not reflect the true production possibility set. Studies have considered the inclusion of undesirable outputs from an efficiency frontier perspective for sustainability assessment. However, no mention on the undesirable input and simultaneous inclusion of undesirable input and output reflecting their true technology set characteristics could be seen in the literature. In the real-world scenario, the efficiency measure for each representative units or DMU depends on the presence of certain undesirable inputs and outputs in the technology set, which rarely can be ignored as it does not reflect the real situation, ending up giving bias in the results. Furthermore, most of all the studies conducted till date analyzed the relative sustainability performance based on the efficiency frontier alone, disregarding the anti-ideal frontier. Recent research has revealed the essence of simultaneous inclusion of the efficiency and anti-efficiency frontiers for the performance assessment of representative units (see Entani et al., 2002; Azizi and Ajirlu, 2010; Azizi, 2011; Azizi, 2014; Ganji and Rassafi, 2019). However, all the studies ignored the presence of undesirability (undesirable inputs and undesirable outputs) and their simultaneous inclusion while computing the pessimistic and optimistic efficiencies from the double-frontier approach. Furthermore, in some of the DEA models, optimistic and pessimistic efficiencies are used to form an interval (see Entani et al., 2002; Wang and Yang, 2007; Jahanshahloo et al., 2011). These models considered the efficiency of a DMU as the interval between the optimistic and pessimistic values. However, these DEA models for computation of the pessimistic efficiency of each DMU holds a major drawback; namely, it does not consider some of the input and output data. These methods practically consider the data of only one input and one output for the DMU under evaluation and ignores the rest of the input and output data. Similarly, these models are not able to identify DEA-inefficient DMUs adequately. In addition, our literature review reveals that existing MPIs for productivity measurement are all proposed from the optimistic DEA point of view by using optimistic DEA models. No attempt has been made to examine the MPI from the pessimistic DEA point of view with due consideration to the input-output undesirability. This inevitably ignores some very useful information on productivity changes because the MPI values measured from different points of view are hardly the same and none of them can be replaced by each other. More importantly, measuring the MPIs from both the optimistic and the pessimistic DEA points of view can provide a comprehensive assessment and panoramic view of the productivity changes over time. To this end, the sustainability assessment of smart cities from a methodological perspective targets to bridge the existing knowledge gaps identified by;

1. Proposing a novel modified DF-SBM bounded Malmquist-DEA model, extending the desirability inclusive DEA model of Liu et al., (2010) to a unified presentation of sustainability performance based on the DF-SBM approach.
2. Including desirability while considering the technology set for the sustainability assessment to simultaneously increase some selected set of input indicators (along with decreasing the desirable input indicators) and decrease selected set of output indicators (maximum value outputs included). The proposed model simultaneously considers the inclusion of undesirable factors to reflect the true production possibility set.
3. Conducting the first of its kind sustainability performance assessment of leading European smart cities in view of both the optimistic and pessimistic performances simultaneously (as bounded efficiency scores), with a true reflection of the technology set with multiple indicators across several

dimensions of sustainable development, to make the concept of smart sustainable cities actionable.

Furthermore, moving on to the resilience and livability assessment part, it is seen that urban resilience and liveability paradigms share multidimensionality (Bruzzone et al., 2021). Most of the existing resilience framework do not address socioecological and multi-dimensional facets of city resilience (Zhou et al., 2021). Indeed, most of the urban resilience assessments focus on addressing risk-specific events including natural calamities like flood, earthquake etc. with mere consideration of social connectivity, institutional resilience, and infrastructural aspects. Similarly, the current liveability indices address quality of life from a materialistic point of view, ignoring well-being and other social aspects. The well-known Economist Intelligence Unit (EIU) 'Global Liveability Index' (GLI) fails in addressing many environmental factors such as the access of green urban areas, sports, and recreational facilities, population claiming to suffer from noise pollution and, to what extend the citizens are active in the city (O'Sullivan, 2020).

In addition, most of the studies have used ML techniques to understand the smartness of cities across each Giffinger's dimensions (see Giffinger et al., 2007) with relatively no studies focusing on the use of ML techniques to understand resilience and liveability in smart cities as a joint analysis. To continue, none of the studies have attempted to capture resilience and liveability using ML techniques from a broader picture including a mix of materialistic and socio-economic conditions, political commitments, and resident engagement all under an indicandum. The use of ML classifiers in predicting the degree of resilience and liveability of smart cities across a broad spectrum of themes is unique. Furthermore, the subjective weights assigned to indicators often increases uncertainty in the scores analysed (Becker et al., 2017; Gan et al., 2017). Similarly, the use of equal weights for indicators ignores the relative importance and trade-offs between the indicators used in the assessment process (Paracchini et al., 2008; Greco et al., 2019). The current existing liveability indices such as the OECD ‘Better Life Index’ and the EIU Global Liveability Index, which act as the ‘best’ among many existing performance assessment frameworks for liveability are all based on equal weights assigned to each indicator, dimensions, and sub-dimensions. Similarly, the well-established Arup ‘City Resilience Framework’ uses expert-based weights for all the indicators, aspects, and sub-aspects within the framework to construct a composite index to quantify resilience. Thus, to this end, this research attempts to close the prevailing knowledge gaps by proposing a novel two-stage joint assessment framework for resilience and liveability assessment with several novel elements within as follows;

a) First of its kind joint analysis in smart cities using machine learning techniques that considers the intricate facet of connectivity lodged in the urban resilience and liveability concepts for smart cities.

b) The liveability assessment presented in this research includes a mix of materialistic and socio-economic conditions that intertwine each other to support the multidimensional perspective of liveability; a unique approach least applied to the current existing liveability frameworks.

c) The urban resilience indicators chosen for the assessment is unique in its ability to access the potential response capacity of city from a multi-dimensional perspective that includes political commitments and resident engagement.

d) An unbiased novel weighting scheme based on the relative metric-distance with reference to a benchmark entity being processed in the observed set is used to score and rank the performance of smart cities under multiple aspects of the resilience and liveability framework.

Now, moving on to the use of fuzzy expert-based muti-criteria assessment, we can see that the central agenda tends towards ranking and scoring the high-tech smart cities based on their performance towards addressing sustainability, resilience and liveability under a unified composite index using a novel integrated approach. When investigating prior-art from a methodological perspective, the current fuzzy extensions such as the hesitant fuzzy sets restricts the membership degrees to take values beyond the interval [0, 1], thus preventing decision makers (DM) to express preferences in a larger space. For Intuitionistic fuzzy sets (IFSs), introduced by Atanassov (1986), the sum of membership and non-membership degrees cannot exceed 1. While, “Pythagorean Fuzzy Set (PFSs)”, presented by Yager (2013), which are a generalization to the IF sets, can handle the uncertainty in some conditions better than the IF sets. In the latter case, the sum of membership and non-membership degrees can exceed 1. However, IF sets and PF sets cannot cope with inconsistency and indetermination of decision makers effectively. Several PF set extensions also fail to handle conditions such as $u_A(x) + \nu_A(x) + \pi_A(x) > 1$, in real time selection problems. Hence, “Neutrosophic Fuzzy Sets (NFSs)” are developed to complete the gaps in this area including a truth-membership, an indeterminacy-membership, and a falsity-membership function. A generalization of PFS and NFS is the Spherical Fuzzy Sets (SFSs) presented by Kutlu Gündoğdu and Kahraman, (2020). The novel concept of SFS helps in resolving the uncertainties present in the existing structures as discussed for satisfactory results in similar MCDM problems. In SFS, decision makers should define their hesitancy degrees just like other dimensions that are membership and non-membership functional parameters. The spherical representation of fuzzy sets enables decision-makers to calculate the hesitancy degrees independent of the membership and non-membership functions unlike other fuzzy set theories, such as the type-1 and type-2 FS, providing a larger preference domain. Unlike Neutrosophic or Intuitionistic-type 2 fuzzy membership functions, the squared sum of functional parameters in the membership function of SFS is somewhere between zero, and the value of each parameter can be independently defined between 0 and 1 in a non-linear 3D space. Furthermore, no research to the best of our knowledge deals with covering further uncertainties related to the AHP technique under a spherical-fuzzy (SF) environment, with no studies extending wings in the context of smart city related problems. Similarly, distance-based Multi-Criteria Assessment Techniques (MCAT) such as the EDAS approach is well-known for fewer computations while evaluating alternatives compared to methods like TOPSIS and VIKOR. Existing EDAS methodology for composite scoring and ranking in the field of smart city selection problems based on multiple criteria and sub-criteria have not been benefited with the integration of SF-AHP method to address vagueness till date. To this end, this study brings in several inventive steps to assert novelty to the prior-art knowledge by;

1. Combining the extended EDAS method under a spherical-fuzzy environment to elicit expert preference supported with AHP technique for multi-attribute composite performance monitoring.
2. Integrating SF-AHP and extended EDAS method with an unsupervised partitioning algorithm, the fuzzy c-means clustering to group the decision making entities into clusters with similar characteristics.

3. Constructing a comprehensive FSC index integrating the themes of sustainability, urban resilience and livability within the smart city context using the proposed novel approach to assess the unified performance of cities, taking high-tech European smart cities as the case.
4. Carrying out a comparative study employing different recent distance-based MCAT such as: “Operational Competitiveness Rating Analysis (OCRA)”, “Multi-Attributive Ideal-Real Comparative Analysis (MARCOS)” and “Multi-Attributive Border Approximation Area Comparison (MABAC)” combined with SF-AHP is conducted to check the validity and robustness of the results obtained through the proposed novel model (SF-AHP with extended EDAS methodology). Similarly, the extended EDAS approach is combined with several MCDM models that integrate fuzzy logic theory with AHP technique such as “Pythagorean Fuzzy-AHP (PF-AHP)”, “Intuitionistic Fuzzy-AHP (IF-AHP)”, and “Interval-Valued Neutrosophic-Fuzzy AHP (IVNF-AHP)” for a comparative analysis.

2.3. Chapter summary

This chapter conducted a detailed umbrella review to investigate the prior-art knowledge centered around the research agenda and identified the gap to assert novelty to the state-of-the art. The succeeding chapter, Chapter 3 will explain the development of the hybrid decision support model adhering to the caveats identified through the review and incorporating the aforementioned novel elements into the model for improved performance assessment.

CHAPTER 3: MODEL DEVELOPMENT

A hybrid decision support model (DSM) integrates a series of analytical techniques to perform data analysis and deliver composite information to the decision makers. The proposed hybrid data-driven model integrates four general modules namely, a systems thinking module (module 1), a sustainability assessment module (module 2), a resilience and livability assessment module (module 3) and, a multi-criteria based composite performance assessment module (module 4). In module 1, systems thinking is used to develop mental models that offer an understanding on how multiple elements interact across several actors under the sustainability (S), resilience (R) and livability (L) criteria of "futuristic cities". In module 2, a novel double frontier non-parametric quantitative optimization-based benchmarking model is proposed to understand the relative sustainability performance of smart cities. In module 3, a novel metric distance based-multivariate analysis combined with several machine learning models is proposed for the relative performance assessment of smart cities in terms of resilience and livability. In module 4, a novel fuzzy expert-based multi-criteria decision support model is proposed to assess the composite performance of smart cities, aggregating the SRL criteria with multiple sub-criteria. Accordingly, the hybrid DSM will provide a sound ground for examining the sustainability, resilience, and livability performance of smart cities both independently and under a unified umbrella, a composite index, ideally the "Futuristic Smart City (FSC)" index being the DSM output.

Systems thinking as a tool presented in module 1 will facilitate impeccable legitimacy of judgments for the intercession and a collaborative approach to support decision making in understanding the interactions of elements within the existing urban development models under the SRL criteria. These aim at providing the best possible solutions for discursive judgement making. The system thinking framework considers all the interdependencies among various subsystems and considers multiple dimensions under the SRL criteria, offering support in framing urban policies and in planning better on what indicators much be considered while constructing the comprehensive FSC index under respective dimensions of the SRL criteria. The double-frontier non-parametric optimization based benchmarking model presented in module 2 will stand as a robust assessment technique in evaluating the relative sustainability performance of decision making entities (i.e., smart cities) that utilizes a set of input and output indicators, both from the efficiency and anti-efficiency perspective. The output of module 2 will be interval-valued bounded efficiency scores across 6 dimensions of sustainability namely, Energy and Environmental Resources (ER), Governance and Institution (GI), Economic dynamism (E), Social cohesion and solidarity (SC), Climate Change (CC) and, Safety and Security (SS). Further, combining a novel metric-distance based weighting approach with machine learning algorithms in module 3 will provide advanced capabilities for the prediction and performance assessment of resilience and livability using a set of ‘coverage’ indicators. The output of module 3 will be composite scores for a selected set of decision making entities across the dimensions of resilience (social, economic, environmental, and institutional resilience) and livability (accessibility, community well-being and economic vibrancy). The novel fuzzy-based expert model using the multi-criteria analysis in module 4 will then utilize the results obtained from module 2 and module 3 as ‘outcome’ indicators, whose weights will be assigned through a panel of experts under a spherical fuzzy environment. Sustainability, resilience and livability will be the main-criteria and all the dimensions under the SRL criteria, whose results were obtained from module 2 and 3 with the sub-criteria for the multi-criteria analysis in module 4. The output of module 4 will be composite scores of the FSC index and segmented outputs based on the clustered performance with each decision making entities ranked in accordance with their comprehensive performance. Thus, the proposed hybrid DSM will aid in executing long term optimum management solutions that are effective for transformational policies to makes cities smarter, sustainable, resilient and livable. Further, the novel approaches used helps in managing uncertainties related to data and decision-making processes. Figure 1 shows the structure of the proposed hybrid DSM for smart city performance assessment. The following sections will then discuss in detail the setting and design of each module.

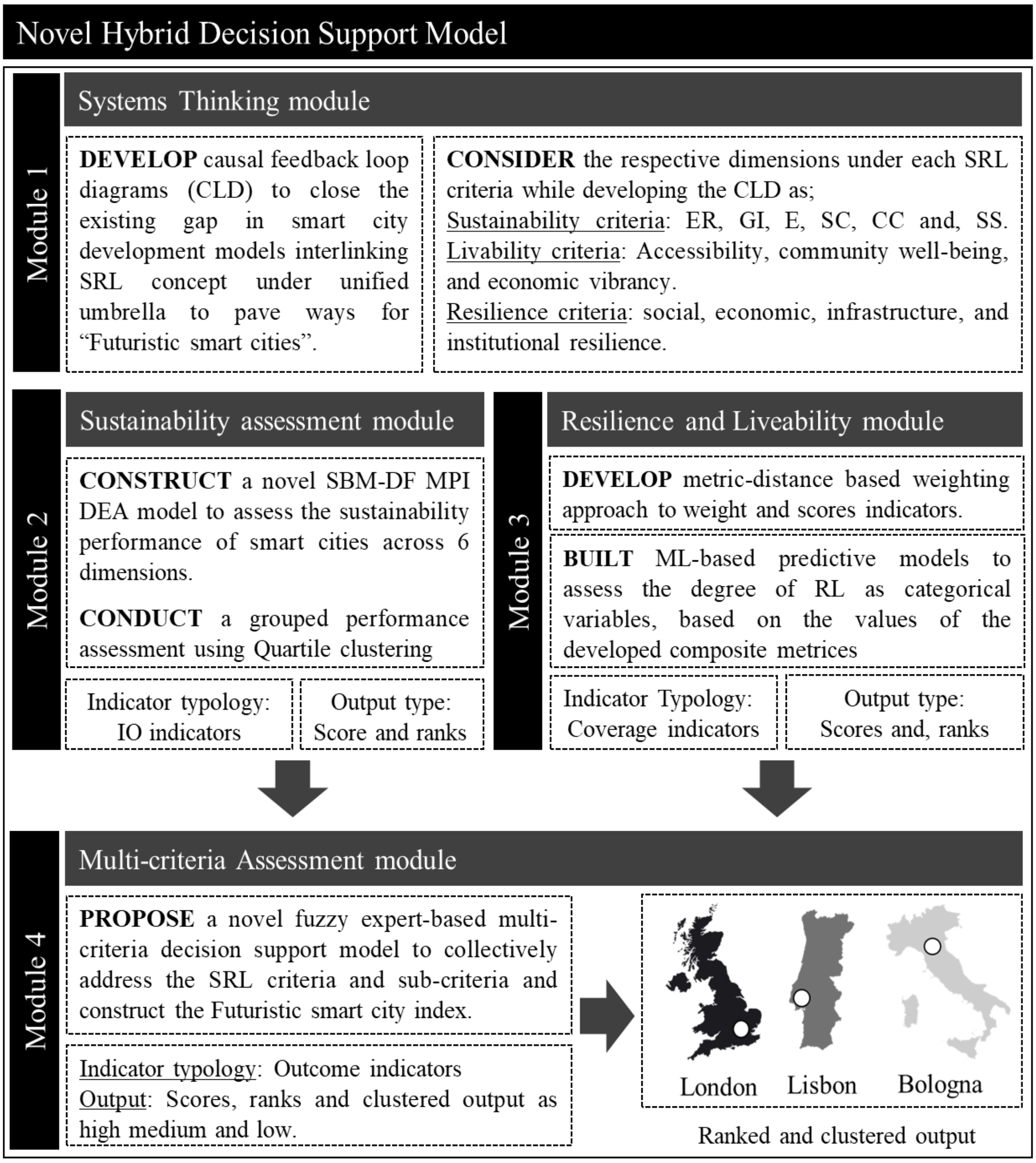


Figure 1. Schematic diagram of the proposed novel hybrid decision support model

3.1. System Thinking Module

Systems-thinking approach uses the causal loop diagram to visualize the system behavior. In this module, causal loop diagrams with feedback loops as reinforcing, denoted by **R** and balancing, denoted by **B** is constructed to capture the dynamism across each dimensions of the SRL concept. To proceed with the construction of the causal loop diagram, initially, a rich picture was used to understand the complex situation. An iterative process was conducted to re-work on the existing perceptions of each group member, who were siloed while creating the rich picture. The individual mental modals were then grouped to form a good rich picture with a better understanding of the scenario. Once the rich picture was developed and the major elements in the system identified, an interrelationship digraph (IRD) was constructed. A paper and pen were used to create the IRD. The IRD approach provides a better understanding of the key drivers in the system and helps in identifying the feedback loops. The causalities between each element in the system were backed by expert judgements, literature reviews and author's conceptualization. These diagrams were constructed with elaborate behaviors and realistic hypotheses. Finally, the IRD was converted to causal loop diagrams through an iterative process. The causal loop diagrams were built using the Vensim PLE modelling package developed by Ventana Corporation. Under the urban liveability model, the inter-dynamics between the elements in the system is understood across the dimensions of accessibility, community well-being and economic vibrancy; while for the urban resilience model, the key dimensions considered were social, economic, environmental, and institutional resilience. The dynamics of urban sustainability in smart cities were explained through the dimensions climate change, natural and energy resources, safety and security, governance and institution and, society and well-being; the key drivers in fostering a sustainable city. The causalities between the elements under various dimensions of urban liveability, resilience and sustainability model is depicted in Figure 2, Figure 3, and Figure 4 respectively. Table 2, Table 3, and Table 4 shows the respective loops and, their interconnections and feedback mechanisms for the urban liveability, resilience, and sustainability model.

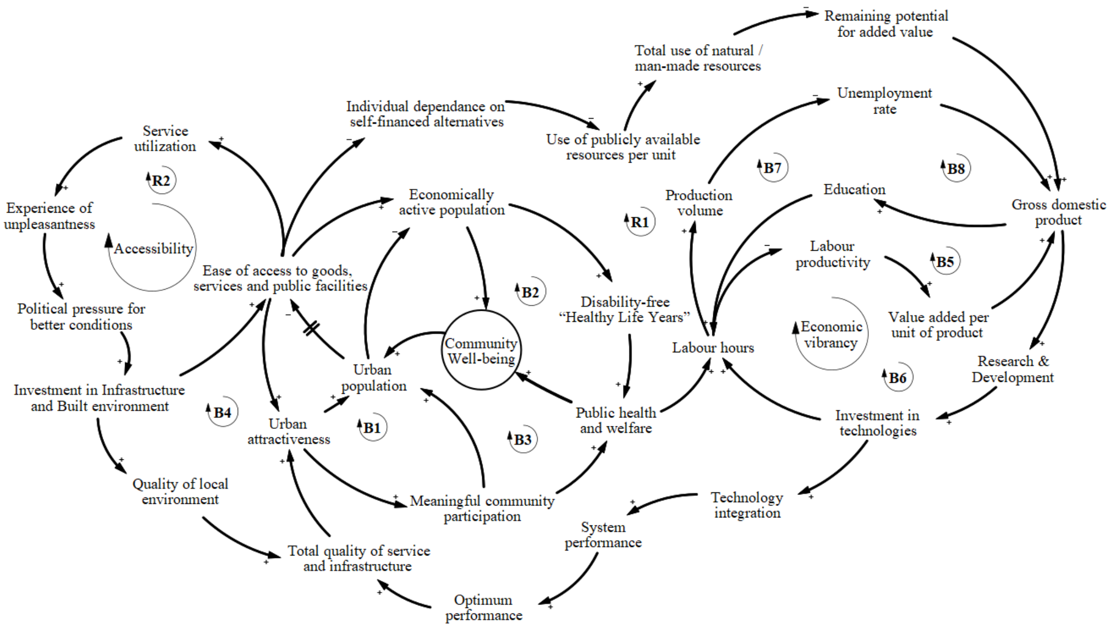


Figure 2. Causal loop diagram for the urban liveability model

Table 2. The causal loops and feedback relations for the urban liveability model

Loops	Interconnections and feedbacks
B1	Urban population – Ease of access to goods, services, and public facilities – Urban attractiveness – Meaningful community participation – Urban population.
B2	Urban population – Ease of access to goods, services, and public facilities – Economically active population – Disability-free "Healthy Life Years" – Public health and welfare – Community Well-being – Urban population.
B3	Urban population – Ease of access to goods, services, and public facilities – Urban attractiveness – Meaningful community participation – Public health and welfare – Community Well-being – Urban population.
B4	Urban population – Ease of access to goods, services, and public facilities – Service utilization – Experience of unpleasantness – Political pressure for better conditions – Investment in infrastructure and built environment – Quality of local environment – Total quality of service and infrastructure – Urban attractiveness – Urban population.
B5	Labor hours – Labor productivity – Value added per unit of product – Gross domestic product – Education – Labor hours.
B6	Labor hours – Labor productivity – Value added per unit of product – Gross domestic product – Research and development – Investment in technologies – Labor hours.
B7	Labor hours – Production volume – Unemployment rate – Gross domestic product – Education – Labor hours.

Loops	Interconnections and feedbacks
B8	Labor hours – Production volume – Unemployment rate – Gross domestic product – Research and development – Investment in technologies – Labor hours.
R1	Ease of access to goods, services, and public facilities – Individual dependance on private mode of transit – Use of publicly available resources per unit – Total use of natural/ man-made resources – Remaining potential for added value – Gross domestic product – Research and development – Investment in technologies – Technology integration – System performance – Optimum performance – Total quality of service and infrastructure – Urban attractiveness – Urban population – Ease of access to goods, services, and public facilities.
R2	Service utilization – Experience of unpleasantness – Political pressure for better conditions – Investment in infrastructure and built environment – Ease of access to goods, services, and public facilities – Service utilization

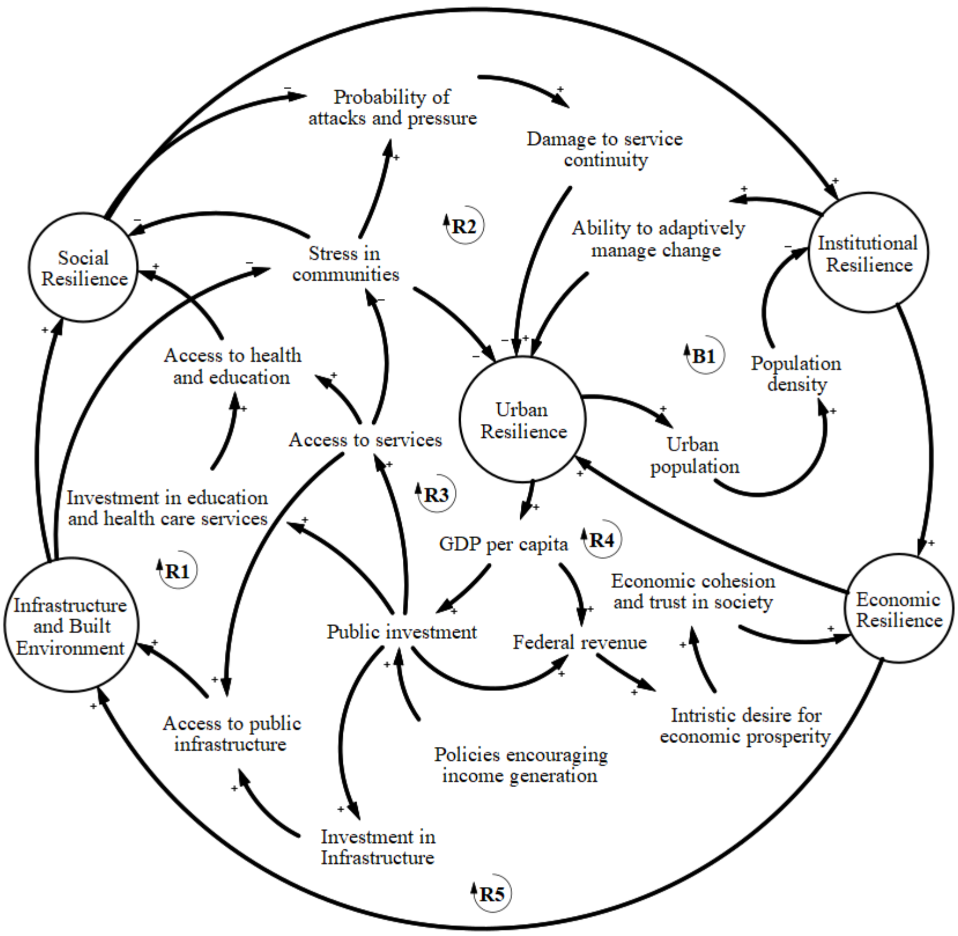


Figure 3. Causal loop diagram for the urban resilience model

Table 3. The causal loops and feedback relations for the urban resilience model

Loops	Interconnections and feedbacks
B1	Urban resilience – Urban population – Population density – Institutional resilience – Ability to adaptively manage changes – Urban resilience.
R1	Urban resilience – GDP per capita – Public investment – Investment in infrastructure – Access to public infrastructure – Infrastructure and Built environment resilience – Stress in communities – Urban resilience.
R2	Urban resilience – GDP per capita – Public investment – Investment in education and health care services – Access to health and education – Social resilience – Probability of attacks and pressure – Damage to service continuity – Urban resilience.
R3	Urban resilience – GDP per capita – Public investment – Access to services – Stress in communities – Urban resilience.
R4	Urban resilience – GDP per capita – Federal revenue – intrinsic desire for economic prosperity – Economic cohesion and trust in society – Economic resilience – Urban resilience.
R5	Economic resilience – Infrastructure and Built environment resilience – Social resilience – Institutional resilience – Economic resilience

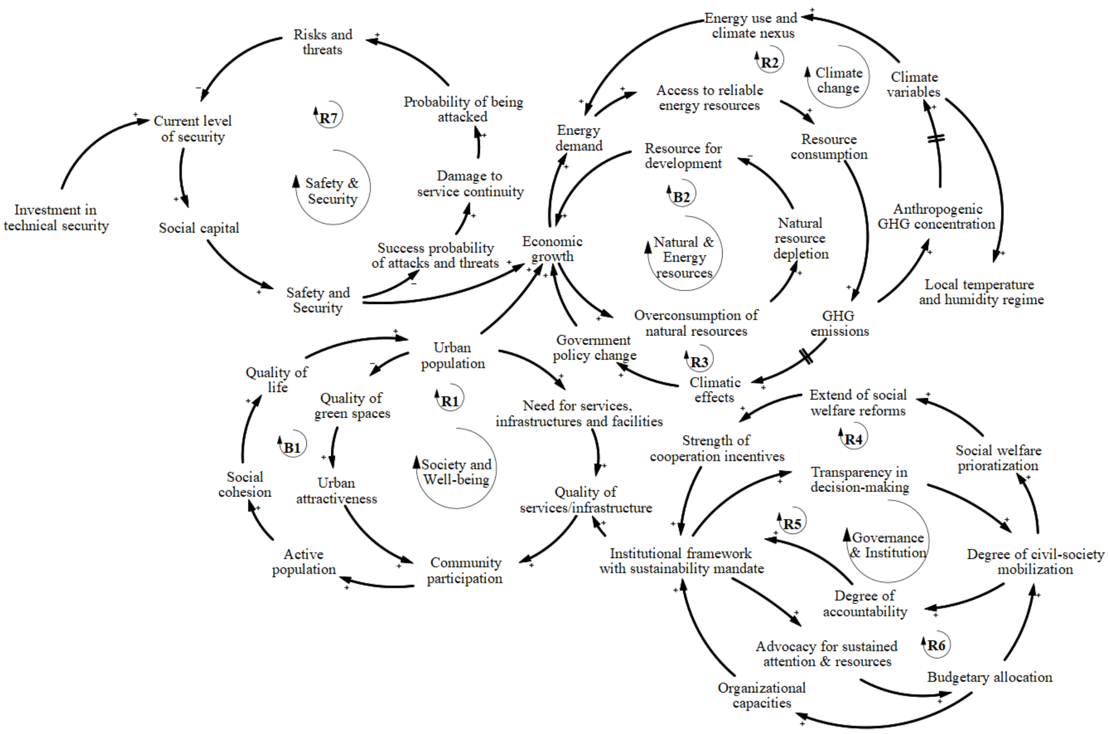


Figure 4. Causal loop diagram for the urban sustainability model

Table 4. The causal loops and feedback relations for the urban sustainability model

Loops	Interconnections and feedbacks
B1	Quality of life – Urban population – Quality of green spaces – Urban attractiveness – Community participation – Active population – Social cohesion – Quality of life.
B2	Resource for development – Economic growth – Overconsumption of natural resources – Natural resource depletion – Resource for development.
R1	Urban population – Need for services, infrastructures, and facilities – Quality of services/infrastructure – Community participation – Active population – Social cohesion – Quality of life – Urban population.
R2	Energy demand – Access to reliable energy resources – Resource consumption – GHG emissions – Anthropogenic GHG concentration – Climate variables – Energy use and climate nexus – Energy demand.
R3	Economic growth – Energy demand – Access to reliable energy resources – Resource consumption – GHG emissions – Climate effects – Government policy change – Economic growth.
R4	Institutional framework with sustainability mandate – Transparency in decision-making – Degree of civil-society mobilization – Social welfare prioritization – Extend of social welfare reforms – Strength of cooperation incentives – Institutional framework with sustainability mandate.
R5	Institutional framework with sustainability mandate – Transparency in decision-making – Degree of civil-society mobilization – Degree of accountability – Institutional framework with sustainability mandate.
R6	Institutional framework with sustainability mandate – Advocacy for sustained attention and resources – Budgetary allocation – Degree of civil-society mobilization – Degree of accountability – Institutional framework with sustainability mandate.
R7	Safety and security – Success probability of attacks and threats – Damage to service continuity – Probability of being attacked – Risks and threats – Current level of security – Social capital – Safety and security.

3.2. Sustainability Assessment Module

In this module, a novel double frontier optimistic and pessimistic Slack Based Measure (SBM) Data Envelopment Analysis (DEA) model to assess the relative sustainability performance of smart cities is proposed. The bounded aggregate sustainability performance assessment model is further proposed and a modified double frontier Malmquist Productivity Index model to assess the progressive performance is developed.

3.2.1. Double Frontier SBM (DF-SBM) approach

The model assumes to evaluate ***n*** smart cities, represented by the response unit DMU_j (j = 1,2,3,.….*n*) were each DMU consumes ***m*** desirable inputs $X^{DI}{}_{ij}$ (i = 1,2,3,….....m) ϵ *T* and ***p*** undesirable inputs $X^{UI}{}_{kj}$ (k = 1,2,3,.…...p) ϵ *T* to produce ***s*** desirable outputs $Y^{DO}{}_{rj}$ (r = 1,2,3,…...s) ϵ *T* and ***t*** undesirable outputs $Y^{UO}{}_{vj}$ (v = 1,2,3,.…...t) ϵ *T*.

Assuming extended strong disposability and convexity, the technology set $T_{optimistic} \subseteq T$, for the optimistic SBM (represented by OSBM) reads as presented in Eq. (1):

$$T_{optimistic} = \Big\{ (X^{UI}{}_k , X^{DI}{}_i , Y^{UO}{}_v , Y^{DO}{}_r) : X^{UI}{}_k \leq \sum_{j=1}^{n} X_{kj}^{UI}\lambda_j, X^{DI}{}_i \geq \sum_{j=1}^{n} X_{ij}^{DI}\lambda_j,$$

$$Y^{UO}{}_v \geq \sum_{j=1}^{n} Y_{vj}^{UO}\lambda_j , Y^{DO}{}_r \leq \sum_{j=1}^{n} Y_{rj}^{DO}\lambda_j , \sum_{j=1}^{n} \lambda_j=1, \lambda_j \geq 0; \forall \text{ j, k, i, r, } v\Big\} \tag{1}$$

The OSBM approach to find whether the response unit DMU_j lies in the efficient frontier or not can be achieved through the fractional programming model presented in as:

$$\text{Minimize } \boldsymbol{\Gamma}_{optimistic} = \frac{1 - \left(\frac{1}{|m| + |t|}\right)\left(\sum_{i=1}^{m} s_i^{XD-} / X_{io}^{DI} + \sum_{v=1}^{t} s_v^{YU-} / Y_{vo}^{UO}\right)}{1 + \left(\frac{1}{|s| + |p|}\right)\left(\sum_{r=1}^{s} s_r^{YD+} / Y_{ro}^{DO} + \sum_{k=1}^{p} s_k^{XU+} / X_{ko}^{UI}\right)} \tag{2}$$

Subject to

$$\sum_{j=1}^{n} X_{kj}^{UI}\lambda_j - s_k{}^{XU+} = X_{ko}{}^{UI} \tag{3}$$

$$\sum_{j=1}^{n} X_{ij}^{DI}\lambda_j + s_i{}^{XD-} = X_{io}{}^{DI} \tag{4}$$

$$\sum_{j=1}^{n} Y_{rj}^{DO}\lambda_j - s_r{}^{YD+} = Y_{ro}{}^{DO} \tag{5}$$

$\sum_{j=1}^{n} \lambda_j = 1$ for Variable Returns to Scale (VRS) (6)

$\Lambda_j, s_k^{XU+}, s_i^{XD-}, s_r^{YD+}, s_v^{YU-} \geq 0; \forall j, k, i, r, v$ (7)

Were,

X^{DI}_{ij} = The i^{th} desirable input of DMU_j

Y^{DO}_{rj} = The r^{th} desirable output of DMU_j

X^{UI}_{kj} = The k^{th} undesirable input of DMU_j

Y^{UO}_{vj} = The v^{th} undesirable output of DMU_j

λ_j = weights of efficient DMU

s_k^{XU+} = slack variable for the undesirable input

s_i^{XD-} = slack variable for the desirable input

s_r^{YD+} = slack variable for the desirable output

s_v^{YU-} = slack variable for the undesirable output

The proposed OSBM-DEA model (Eqs. 2-7) simultaneously minimizes the input and output inefficiencies. The mean rate of input minimization and the inverted mean rate of output maximization can be defined through the equations $(1/|m|+|t|) [\sum_{i=1}^{m} (X_{io}^{DI} - s_i^{XD-}) / X_{io}^{DI} + \sum_{v=1}^{t} \left(Y_{vo}^{UO} - s_v^{YU-} \right) / Y_{vo}^{UO}]$ and, $[(1/|s|+|p|) \{\sum_{r=1}^{s} (Y_{ro}^{DO} + s_r^{YD+}) / Y_{ro}^{DO} + \sum_{k=1}^{p} \left(X_{ko}^{UI} + s_k^{XU+} \right) / X_{ko}^{UI}\}]^{-1}$ respectively. The fractional programming model (Eqs. 2-7) can be converted into a linear programming (LP) model (Eqs. 8-15) by multiplying both the numerator and denominator of model (8) using a positive scalar variable $f > 0$ to form:

$$\text{Minimize } \boldsymbol{\eta}_{\textit{optimistic}} = f - [\left(\frac{1}{|m| + |t|}\right) \left(\sum_{i=1}^{m} \mathbf{S_I^{XD-}} / X_{io}^{DI} + \sum_{v=1}^{t} \mathbf{S_v^{YU-}} / Y_{vo}^{UO}\right)] \quad (8)$$

Subject to

$$1 = f + [\left(\frac{1}{|s| + |p|}\right) \left(\sum_{r=1}^{s} \mathbf{S_r^{YD+}} / Y_{ro}^{DO} + \sum_{k=1}^{p} \mathbf{S_k^{XU+}} / X_{ko}^{UI}\right)] \quad (9)$$

$$\sum_{j=1}^{n} X_{kj}^{UI} \Lambda_j - \mathbf{S}_{\mathbf{k}}^{\mathbf{XU+}} = f\, X_{ko}{}^{UI} \tag{10}$$

$$\sum_{j=1}^{n} X_{ij}^{DI} \Lambda_j + \mathbf{S}_{\mathbf{I}}^{\mathbf{XD-}} = f X_{io}{}^{DI} \tag{11}$$

$$\sum_{j=1}^{n} Y_{rj}^{DO} \Lambda_j - \mathbf{S}_{\mathbf{r}}^{\mathbf{YD+}} = f Y_{ro}{}^{DO} \tag{12}$$

$$\sum_{j=1}^{n} Y_{vj}^{UO} \Lambda_j + \mathbf{S}_{\mathbf{v}}^{\mathbf{YU-}} = f Y_{vo}{}^{UO} \tag{13}$$

$$\sum_{j=1}^{n} \Lambda_j = 1 \text{ for Variable Returns to Scale (VRS)} \tag{14}$$

$$\Lambda_j, \mathbf{S}_{\mathbf{k}}^{\mathbf{XU+}}, \mathbf{S}_{\mathbf{I}}^{\mathbf{XD-}}, \mathbf{S}_{\mathbf{r}}^{\mathbf{YD+}}, \mathbf{S}_{\mathbf{v}}^{\mathbf{YU-}} \geq 0;\ \forall\ j, k, i, r, v \text{ and } f > 0 \tag{15}$$

where $\Lambda_j = f\, \lambda_j$, $\mathbf{S}_{\mathbf{I}}^{\mathbf{XD-}} = f\, s_I^{XD-}$, $\mathbf{S}_{\mathbf{v}}^{\mathbf{YU-}} = f s_v^{YU-}$, $\mathbf{S}_{\mathbf{r}}^{\mathbf{YD+}} = f\, s_r^{YD+}$, $\mathbf{S}_{\mathbf{k}}^{\mathbf{XU+}} = f\, s_k^{XU+}$. The index η ***optimistic*** and $\Gamma_{optimistic}$ ranges between a value from 0 to 1. Greater the value of the index, greater the performance of each smart city towards sustainable development. The optimal solutions for model (2) and model (8) are ($\eta^* = \Gamma^*$, $\Lambda_j{}^*$, f^*, $\mathbf{S}_{\mathbf{I}}^{\mathbf{XD-*}}$, $\mathbf{S}_{\mathbf{v}}^{\mathbf{YU-*}}$, $\mathbf{S}_{\mathbf{r}}^{\mathbf{YD+*}}$, $\mathbf{S}_{\mathbf{k}}^{\mathbf{XU+*}}$) and ($\Gamma^* = \eta^*$; $\lambda_j{}^* = \Lambda_j{}^*/ f^*$; $s_k{}^{XU\ *+} = \mathbf{S}_{\mathbf{k}}^{\mathbf{XU+*}}/ f^*$; $s_i{}^{XD\ *-} = \mathbf{S}_{\mathbf{I}}^{\mathbf{XD-*}}/ f^*$; $s_r{}^{YD\ *+} = \mathbf{S}_{\mathbf{r}}^{\mathbf{YD+*}}/ f^*$, $s_v{}^{YU\ *-} = \mathbf{S}_{\mathbf{v}}^{\mathbf{YU-*}} / f^*$) respectively. The DMU is termed to be efficient when, $\eta^*_{optimistic} = \Gamma^*_{optimistic} = 1$. Here, the input excess: $s_k{}^{XU\ +}$, $s_i{}^{XD\ -}$ and, the output shortfall: $s_r{}^{YD\ +}$, $s_v{}^{YU\ -}$ should be equal to zero. In other case, the DMU is termed to be inefficient.

Considering the pessimistic SBM (represented by PSBM) DEA model, the technology set $T_{pessimistic} \subseteq T$ for the model reads as in Eq. (16) as:

$$T_{pessimistic} = \Big\{ (X^{UI}{}_k , X^{DI}{}_i , Y^{UO}{}_v , Y^{DO}{}_r) : X^{UI}{}_k \geq \sum_{j=1}^{n} X_{kj}^{UI}\lambda_j,\ X^{DI}{}_i \leq \sum_{j=1}^{n} X_{ij}^{DI}\lambda_j, \tag{16}$$
$$Y^{UO}{}_v \leq \sum_{j=1}^{n} Y_{vj}^{UO}\lambda_j ,\ Y^{DO}{}_r \geq \sum_{j=1}^{n} Y_{rj}^{DO}\lambda_j ,\ \sum_{j=1}^{n} \lambda_j = 1,\ \lambda_j \geq 0;\ \forall\ j, k, i, r, v \Big\}$$

The fractional programming model to calculate the anti-efficiency for each DMU can be achieved using Eqs. (17-23) as:

$$\text{Maximize } \mathbf{\Gamma_{pessimistic}} = \frac{1 + \left(\frac{1}{|m| + |t|}\right)\left(\sum_{i=1}^{m} s_i^{XD+} / X_{io}^{DI} + \sum_{v=1}^{t} s_v^{YU+} / Y_{vo}^{UO}\right)}{1 - \left(\frac{1}{|s| + |p|}\right)\left(\sum_{r=1}^{s} s_r^{YD-} / Y_{ro}^{DO} + \sum_{k=1}^{p} s_k^{XU-} / X_{ko}^{UI}\right)} \tag{17}$$

Subject to

$\sum_{j=1}^{n} X_{kj}^{UI}\lambda_j + s_k^{XU-} = X_{ko}^{UI}$ (18)

$\sum_{j=1}^{n} X_{ij}^{DI}\lambda_j - s_i^{XD+} = X_{io}^{DI}$ (19)

$\sum_{j=1}^{n} Y_{rj}^{DO}\lambda_j + s_r^{YD-} = Y_{ro}^{DO}$ (20)

$\sum_{j=1}^{n} Y_{vj}^{UO}\lambda_j - s_v^{YU+} = Y_{vo}^{UO}$ (21)

$\sum_{j=1}^{n} \lambda_j = 1$ for Variable Returns to Scale (VRS) (22)

$\Lambda_j, s_k^{XU-}, s_i^{XD+}, s_r^{YD-}, s_v^{YU+} \geq 0; \forall$ j, k, i, r, v (23)

The proposed PSBM model (Eqs. 17-23) maximizes the mean rate of input expansion as well as the inverted mean rate of output reduction through (1/|m|+|t|) $[\sum_{i=1}^{m} (X_{io}^{DI} + s_i^{XD+}) / X_{io}^{DI} + \sum_{v=1}^{t} \left(Y_{vo}^{UO} + s_v^{YU+} \right) / Y_{vo}^{UO}]$ and, [(1/|s|+|p|) $\{\sum_{r=1}^{s} (Y_{ro}^{DO} - s_r^{YD-}) / Y_{ro}^{DO} + \sum_{k=1}^{p} \left(X_{ko}^{UI} - s_k^{XU-} \right) / X_{ko}^{UI}\}]^{-1}$ respectively. The fractional programming PSBM model can be converted into the LP model (Eqs. 24-31) by multiplying both the numerator and denominator using a positive scalar variable $f > 0$, similar to the OSBM to form:

Maximize $\boldsymbol{\eta}_{\boldsymbol{pessimistic}} = f + [\left(\frac{1}{|m| + |t|}\right) \left(\sum_{i=1}^{m} \mathbf{S_I^{XD+}} / X_{io}^{DI} + \sum_{v=1}^{t} \mathbf{S_v^{YU+}} / Y_{vo}^{UO}\right)]$ (24)

Subject to

$1 = f - [\left(\frac{1}{|s| + |p|}\right) \left(\sum_{r=1}^{s} \mathbf{S_r^{YD-}} / Y_{ro}^{DO} + \sum_{k=1}^{p} \mathbf{S_k^{XU-}} / X_{ko}^{UI}\right)]$ (25)

$\sum_{j=1}^{n} X_{kj}^{UI}\Lambda_j + \mathbf{S_k^{XU-}} = f\, X_{ko}^{UI}$ (26)

$\sum_{j=1}^{n} X_{ij}^{DI}\Lambda_j - \mathbf{S_I^{XD+}} = f\, X_{io}^{DI}$ (27)

$\sum_{j=1}^{n} Y_{rj}^{DO}\Lambda_j + \mathbf{S_r^{YD-}} = f\, Y_{ro}^{DO}$ (28)

$\sum_{j=1}^{n} Y_{vj}^{UO}\Lambda_j - \mathbf{S_v^{YU+}} = f Y_{vo}^{UO}$ (29)

$\sum_{j=1}^{n} \Lambda_j = 1$ for Variable Returns to Scale (VRS) (30)

$\Lambda_j, \mathbf{S_k^{XU\,-}}, \mathbf{S_I^{XD\,+}}, \mathbf{S_r^{YD\,-}}, \mathbf{S_v^{YU\,+}} \geq 0; \forall$ j, k, i, r, v and $\theta > 0$ (31)

where $\Lambda_j = f\grave{}\lambda_j$, $\mathbf{S_I^{XD+}} = fs_I^{XD+}$, $\mathbf{S_v^{YU+}} = fs_v^{YU\,+}$, $\mathbf{S_r^{YD\,-}} = fs_r^{YD\,-}$, $\mathbf{S_k^{XU\,-}} = fs_k^{XU-}$. All the optimality conditions for the PSBM approach is equivalent to that of the optimistic SBM model. The DMU is termed to be anti-efficient when, $\eta^{*}_{\textit{pessimistic}} = \Gamma^{*}_{\textit{pessimistic}} = 1$. This highlights the fact that the corresponding DMU lies on the anti-efficient frontier. Such a condition should have all the slack variables $s_I^{XD\,+}$, $s_v^{YU\,+}$, $s_r^{YD\,-}$ and $s_k^{XU\,-} = 0$. To measure the relative sustainable development capacity of ***n*** European smart cities over time *t*, *t+1*,…*t+n*, refer the optimistic and pessimistic SBM in time (see Appendix A).

3.2.2. Bounded model for aggregate sustainability performance

The aggregate sustainability performance of each smart city will be studied using Azizi, (2011)'s bounded-DEA model, which is modified further to include undesirable factors both in the inputs and outputs. Both the pessimistic and optimistic efficiency scores are represented within an interval, after considerable modifications to the pessimistic efficiency scores. The modified pessimistic efficiency is $\tilde{\varphi}_j^{*} = \alpha \times \eta_{\text{pessimistic}}^{*}$. φ_{vj}^{*} is the pessimistic efficiency of the virtual (*v*) DMU 'j', where φ_{vj}^{*} is obtained using the LP model applying Charnes and Cooper, (1962)'s transformation. The model is presented in Eqs. (32-40) which reads as follows;

$$\text{Min } \varphi_{vj*} = 1 + \left(\sum_{i=1}^{m} X_{io}^{min}\lambda_i + \sum_{v=1}^{t} Y_{vo}^{min}\lambda_v\right)\left(\sum_{r=1}^{s} Y_{ro}^{max}\lambda_r + \sum_{k=1}^{p} X_{ko}^{max}\lambda_k\right) \quad (32)$$

Subject to

$$\left(\sum_{i=1}^{m} X_{ij}^{DI}\lambda_{ij} + \sum_{v=1}^{t} Y_{vj}^{UO}\lambda_{vj}\right) - \left(\sum_{r=1}^{s} Y_{rj}^{DO}\lambda_{rj} + \sum_{k=1}^{p} X_{kj}^{UI}\lambda_{kj}\right) \geq 0; \quad (33)$$

$$\left(\sum_{r=1}^{s} Y_{ro}^{max}\lambda_r + \sum_{k=1}^{p} X_{ko}^{max}\lambda_k\right) \leq \left(\frac{1}{|m| + |t|}\right); \quad (34)$$

$$\left(\sum_{i=1}^{m} X_{io}^{min}\lambda_i + \sum_{v=1}^{t} Y_{vo}^{min}\lambda_v\right) \leq \left(\frac{1}{|s| + |p|}\right)[1 + \left(\sum_{i=1}^{m} X_{io}^{min}\lambda_I + \sum_{v=1}^{t} Y_{vo}^{min}\lambda_v\right) -$$

$\left(\sum_{r=1}^{s} Y_{ro}^{max}\lambda_r + \sum_{k=1}^{p} X_{ko}^{max}\lambda_k\right)];$ (35)

For $\lambda_I, \lambda_v, \lambda_r, \lambda_k \geq \varepsilon; \forall$ k, i, r, v (36)

Were,

$X_i^{min} = \min_j\{X_{ij}^{DI}\}$, For i = 1,2,3,…....m; (37)

$X_k^{max} = \max_j\{X_{kj}^{UI}\}$, Fork k = 1,2,3,.…...p; (38)

$Y_r^{max} = \max_j\{Y_{rj}^{DO}\}$, For r = 1,2,3,.…...s; (39)

$Y_v^{min} = \min_j\{Y_{vj}^{UO}\}$, For v = 1,2,3,.…...t; (40)

The value of α is determined as $\alpha = \theta_{min}^{*}/\varphi_{vj}^{*}$, where the aggregate sustainability performance score is represented within an interval of [α, 1]. It is to note that the estimate value "α" must satisfy the criterion $\alpha\eta_{pessimistic}^{*} \leq \theta_{min}^{*}$ $\forall$ $[\alpha\eta_{pessimistic}^{*}, \theta_j^{*}]$ (j= 1,2,3…***n***).

We have, $\theta_{min}^{*} = \min\{\eta_{optimistic}\}\forall$ j = 1,2,3...***n*** and $\varphi_{vj}^{*} \geq \max\{\eta_{pessimistic}\}\forall$ (j = 1,2,3...***n***. The interval efficiency is represented as $[\alpha\eta_{pessimistic}^{*}, \theta_j^{*}] = [\tilde{\varphi}_j^{*}, \theta_j^{*}] = [\eta_o^{L*}, \eta_o^{U*}]$ where L = lower bound efficiency and U = upper bound efficiency measured from the pessimistic and optimistic perspective respectively.

To rank each smart city based on the interval efficiency score, the midpoint $m(A_i)$ and range $w(A_i)$ of each interval efficiency score obtained using model presented in Eqs. (32-40) is calculated. Smart cities are then ranked in the ascending order based on the midpoint values. The smart city with the largest $m(A_i)$ value is ranked 1 followed by other smart cities in the descending order of their $m(A_i)$ values. The $m(A_i)$ and $w(A_i)$ are calculated using Eq. (41) as;

$m(A_i) = \frac{1}{2}(\eta_o^{L*} + \eta_o^{U*})$ and $w(A_i) = \frac{1}{2}(\eta_o^{U*} - \eta_o^{L*})$ (41)

3.2.3. Malmquist Productivity Index

Smart cities are often driven by technology and their progressive efficiency can be assessed by understanding the technological changes as a whole over the years. The MPI $_{optimistic}$ for each smart city represented by DMU_j for optimistic efficiencies can be calculated using the following formulation in Eq. (42) as;

MPI $_{optimistic}$ =

$$\left[\frac{\alpha_0^t (w^{t+1}_{io}, x^{t+1}_{ko}, y^{t+1}_{ro}, z^{t+1}_{vo})}{\alpha_0^t (w^{t}_{io}, x^{t}_{ko}, y^{t}_{ro}, z^{t}_{vo})} \cdot \frac{\alpha_0^{t+1} (w^{t+1}_{io}, x^{t+1}_{ko}, y^{t+1}_{ro}, z^{t+1}_{vo})}{\alpha_0^{t+1} (w^{t}_{io}, x^{t}_{ko}, y^{t}_{ro}, z^{t}_{vo})}\right]^{1/2} \tag{42}$$

Where, $\alpha_0^t (w^{t}_{io}, x^{t}_{ko}, y^{t}_{ro}, z^{t}_{vo})$ is the OSBM in time t;and $\alpha_0^{t+1} (w^{t+1}_{io}, x^{t+1}_{ko}, y^{t+1}_{ro}, z^{t+1}_{vo})$ is the OSBM in time t +1. Similarly, $\alpha_0^t (w^{t+1}_{io}, x^{t+1}_{ko}, y^{t+1}_{ro}, z^{t+1}_{vo})$ calculates the optimistic efficiency in time t+1 utilizing the technology in time t; and $\alpha_0^{t+1} (w^{t}_{io}, x^{t}_{ko}, y^{t}_{ro}, z^{t}_{vo})$ evaluates the optimistic efficiency in time t, making use of the technology in time t+1. To better understand on the growth index for productivity change measurement, see Sueyoshi, (1998).

Model (42) measures the productivity change in efficiencies for smart cities from time t *to* t+1. A progress is marked in productivity when MPI $_{optimistic} > 1$, while if MPI $_{optimistic} = 1$, then there is no change in the level of productivity, and an MPI $_{optimistic} < 1$ indicates a decrease in the productivity level from time t *to* t+1 (Färe et al., 1992).

Similarly, from a pessimistic point of view, the productivity change in efficiencies can be calculated taking the geometric mean of the pessimistic efficiencies, $\alpha_0^t (w^{t+1}_{io}, x^{t+1}_{ko}, y^{t+1}_{ro}, z^{t+1}_{vo}) / \alpha_0^t (w^{t}_{io}, x^{t}_{ko}, y^{t}_{ro}, z^{t}_{vo})$ and $\alpha_0^{t+1} (w^{t+1}_{io}, x^{t+1}_{ko}, y^{t+1}_{ro}, z^{t+1}_{vo}) / \alpha_0^{t+1} (w^{t}_{io}, x^{t}_{ko}, y^{t}_{ro}, z^{t}_{vo})$. The MPI $_{pessimistic}$ for each smart city in time t *to* t+1 can be calculated using Eq. (43) as:

MPI $_{\textit{pessimistic}}$

$$= \left[\frac{\alpha_0^{t}\,(w^{t+1}_{io}, x^{t+1}_{ko}, y^{t+1}_{ro}, z^{t+1}_{vo})}{\alpha_0^{t}\,(w^{t}_{io}, x^{t}_{ko}, y^{t}_{ro}, z^{t}_{vo})} \cdot \frac{\alpha_0^{t+1}(w^{t+1}_{io}, x^{t+1}_{ko}, y^{t+1}_{ro}, z^{t+1}_{vo})}{\alpha_0^{t+1}(w^{t}_{io}, x^{t}_{ko}, y^{t}_{ro}, z^{t}_{vo})}\right]^{1/2} \tag{43}$$

Where, $\alpha_0^{t}\,(w^{t}_{io}, x^{t}_{ko}, y^{t}_{ro}, z^{t}_{vo})$ is the PSBM in time *t;*and $\alpha_0^{t+1}\,(w^{t+1}_{io}, x^{t+1}_{ko}, y^{t+1}_{ro}, z^{t+1}_{vo})$ is the PSBM in time t +1. Similarly, here $\alpha_0^{t}\,(w^{t+1}_{io}, x^{t+1}_{ko}, y^{t+1}_{ro}, z^{t+1}_{vo})$ calculates the pessimistic efficiency in time t+1 utilizing the technology in time t; and $\alpha_0^{t+1}(w^{t}_{io}, x^{t}_{ko}, y^{t}_{ro}, z^{t}_{vo})$ evaluates the pessimistic efficiency in time t, making use of the technology in time t+1.

Similar to the MPI $_{\text{optimistic}}$ based on to Färe et al., (1992) assumptions, an increase in the productivity level is noticed when MPI $_{\textit{pessimistic}} > 1$. A regression over time *t to t*+1 is when MPI $_{\textit{pessimistic}} < 1$. There is no noticeable change in the productivity over time when MPI $_{\textit{pessimistic}} = 1$.

To achieve consistency in the evaluation of the Malmquist productivity index and arrive at concrete conclusions, it is essential to integrate the proposed point of views to accurately understand the productivity changes for each smart city under selected dimensions over time. Thus, combining the geometric means of Eq. (42) and (43), we obtain the Double Frontier Malmquist productivity index (DF-MPI) for the j^{th} smart city, which is presented in Eq. (44) as follows;

$$\text{DF-MPIj} = \left[\text{MPI}_{\text{optimistic}} \cdot \text{MPI}_{\text{pessimistic}}\right]^{1/2} \tag{44}$$

Table 5. Pseudo code for the proposed novel DF-SBM MPI based DEA model

DF-SBM MPI-DEA

For a $\text{DMU}_j \in j = 1,2, 3\ldots.\ n$

Stage 1: // Optimistic and pessimistic efficiency evaluation

1. Solve model (8) to obtain $\eta_{\text{optimistic}}$ with optimal solutions η_o^{*}; λ_j^{*}, $s_k^{XU\,*+}$, $s_i^{XD\,*-}$, $s_r^{YD\,*+}$ and $s_v^{YU\,*-}$
2. Solve model (24) to obtain $\eta_{\text{pessimistic}}$ with optimal solutions η_p^{*}; λ_j^{*}, $s_k^{XU\,*-}$, $s_i^{XD\,*+}$, $s_r^{YD\,*-}$ and $s_v^{YU\,*+}$

DF-SBM MPI-DEA

3. **if** $\eta^*_{optimistic} = \Gamma^*_{optimistic} = 1$ for model (8) **then**
4. DMU_j is optimistic efficient $\forall\ s_k^{XU+}, s_i^{XD-}, s_r^{YD+}, s_v^{YU-} = 0$
5. **else**
6. DMU_j is optimistic non-efficient $\forall\ s_k^{XU+}, s_i^{XD-}, s_r^{YD+}, s_v^{YU-} \neq 0$
7. **if** $\eta^*_{pessimistic} = \Gamma^*_{pessimistic} = 1$ for model (24) **then**
8. DMU_j is pessimistic inefficient $\forall\ s_k^{XU-}, s_i^{XD+}, s_r^{YD-}, s_v^{YU+} = 0$
9. **else**
10. DMU_j is pessimistic non-inefficient $\forall\ s_k^{XU-}, s_i^{XD+}, s_r^{YD-}, s_v^{YU+} \neq 0$
11. **end if**
12. **end if**

Stage 2: // Bounded interval efficiency calculation for integrated sustainability performance

13. Find: $X_i^{min} = \min_j\{X_{ij}^{DI}\}$, i = 1,2,3,…....m; //min value for the set of desirable inputs of DMU_j
    $X_k^{max} = \max_j\{X_{kj}^{UI}\}$, k = 1,2,3,…....p; //max value for the set of undesirable inputs of DMU_j
    $Y_r^{max} = \max_j\{Y_{rj}^{DO}\}$, r = 1,2,3,...s; //max value for the set of desirable outputs of DMU_j
    $Y_v^{min} = \min_j\{Y_{vj}^{UO}\}$, v = 1,2,3,.....t; // min value for the set of undesirable outputs of DMU_j
14. Solve model (32) to find φ_{vj}^* //pessimistic efficiency of virtual DMU_{vj}
15. **if** $\theta_{min}^* = \min\{\eta_{optimistic}\}$; $\varphi_{vj}^* \geq \max\ \{\eta_{pessimistic}\} \forall$ j= 1,2,3...n **then**
16. estimate $\alpha = \theta_{min}^*/\varphi_{vj}^*$
17. **end if**
18. Calculate η-bounded as $[\alpha\eta_{pessimistic}^*, \theta_j^*] = [\tilde{\varphi}_j^*, \theta_j^*]\ \forall\ \alpha\eta_{pessimistic}^* \leq \theta_{min}^*$

Stage 3: // productivity change using DF-Malmquist index model

19. Solve model (42) to obtain MPI $_{\textit{optimistic}}$ and model (43) to obtain MPI $_{\textit{pessimistic}}$ $\forall$ time t *to* t+1 **then**
20. Calculate $DF-MPI_j = \left[MPI_{\textit{optimistic}}\ .\ MPI_{\textit{pessimistic}}\right]^{1/2} \epsilon$ j = 1,2, 3…. n
21. **if** $DF\text{-}MPI_j > 1$ **then** //same applies for $MPI_{optimistic}$ and $MPI_{pessimistic}$
22. DMU_j has a productivity progress across time t to t+1
23. **else if**
24. $DF\text{-}MPI_j < 1$ **then** //same applies for $MPI_{optimistic}$ and $MPI_{pessimistic}$
25. DMU_j has a decline in productive performance across time t to t+1
26. **else**
27. DMU_j has no productivity progress/regress across time t to t+1
28. **end else if**
29. **end if**

End Loop

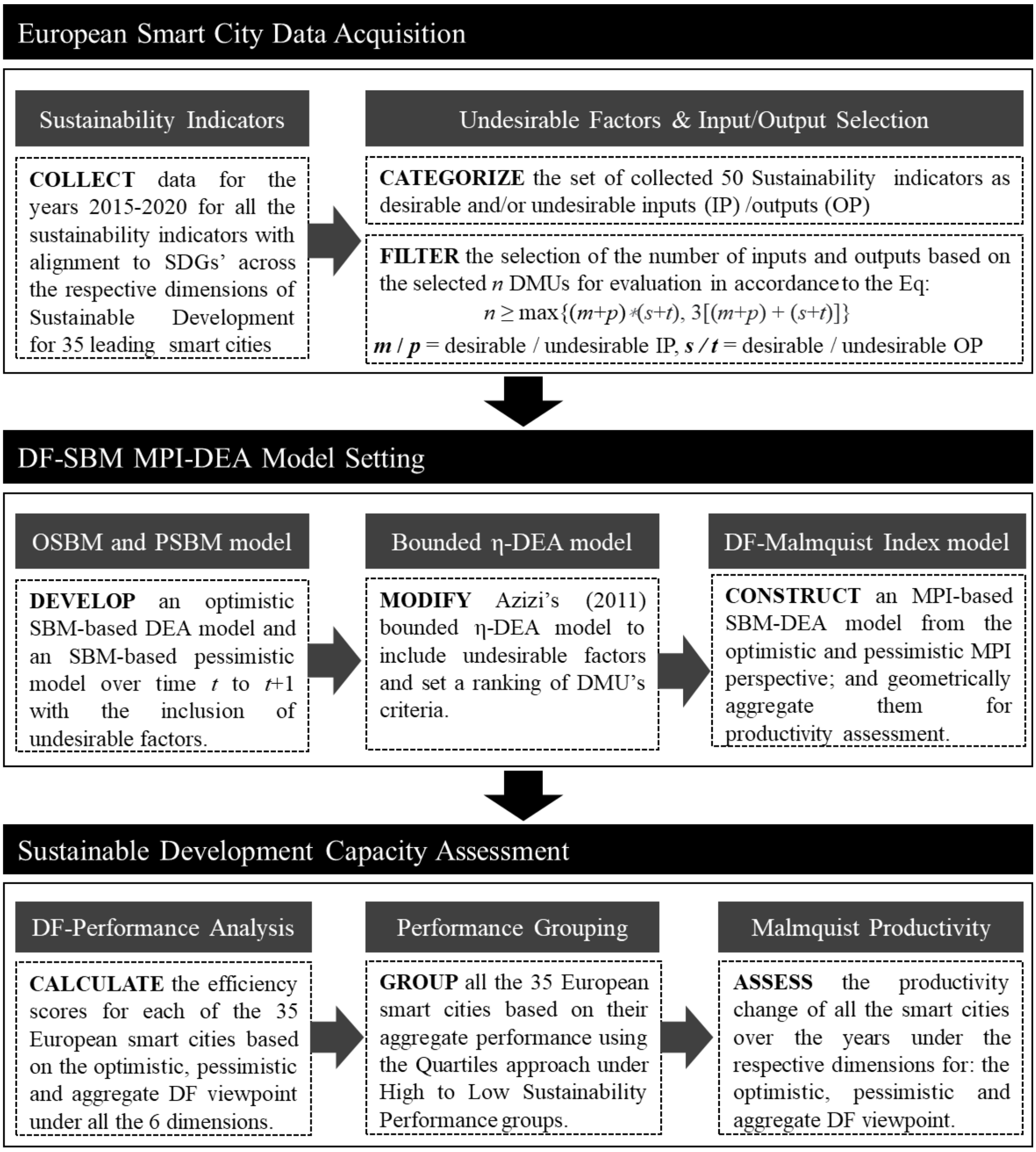


Figure 5. Schematics of research flow

3.3. Resilience and Livability Module

In this module, a novel two-stage assessment approach combining multivariate analysis and various machine learning models is proposed to thoroughly investigate the resilience and livability of smart cities over time using a set of indicators. In stage 1, a novel metric-distance based weighting and scoring approach is used initially to assign weights to all the indicators and obtain desired scores across each dimension under resilience (social, economic, infrastructure and built environment and, institutional resilience) and liveability (accessibility, community well-being and economic vibrancy) criteria. In stage 2, two types of data-driven analysis are performed namely; clustering as one of the unsupervised machine learning technique and classification, a supervised ML technique. The Fuzzy c-means clustering algorithm as a simple clustering technique is used to identify the optimum number of clusters and label the smart cities to different clusters based on their performance as high, medium, and low. The classification techniques, “Naïve Bayes, k-nearest neighbor (kNN), Support Vector Machine (SVM), Classification and regression tree (CART), Random Forest (RF), and Gradient Boosting Machine (GBM)” are used to predict the level of liveability and resilience of smart cities, as categorical variables, based on the values of the indicators under each dimension of resilience and livability.

3.3.1. Metric-distance based weighting and scoring

Multi-criteria performance assessment combines numerous heterogenous indicators across several aspects in a standardized manner to a single synthetic score that explains the behavior of the phenomenon to be measured. In this stage, we propose a novel three-step multivariate metric-distance based approach to weight the indicators and obtain a homogenized score for each dimension under resilience and liveability criteria.

Multi-criteria performance indicators have different measuring units (Abdella et al., 2019). To remove the variability and achieve dimensional consistency, all these compound indicators must be normalized (Abdella et al., 2017). Besides, normalization helps in improving the training stability and performance of the model (Quackenbush, 2002). As a data pre-processing step, prior to weighting and scoring, the linear min-max scaling, a common data normalization technique is used. The overall indicator-matrix in time t, t+1…, t+N, denoted by $X^k_{ijt,t+1\ldots t+N}$, when considering the i^th indicator column under the k^th dimension for the j^th smart city under study is as shown below:

$$X^k_{ijt,t+1\ldots t+N} =$$

$$\begin{bmatrix} X^k_{11t} & X^k_{11t+1} & \cdots & X^k_{11t+N} & X^k_{21t} & X^k_{21t+1} & \cdots & X^k_{21t+N} & \cdots & X^k_{m1t} & X^k_{m1t+1} & \cdots & X^k_{m1t+N} \\ X^k_{12t} & X^k_{12t+1} & \cdots & X^k_{12t+N} & X^k_{22t} & X^k_{22t+1} & \cdots & X^k_{22t+N} & \cdots & X^k_{m2t} & X^k_{m2t+1} & \cdots & X^k_{m2t+N} \\ X^k_{13t} & X^k_{13t+1} & \cdots & X^k_{13t+N} & X^k_{23t} & X^k_{23t+1} & \cdots & X^k_{23t+N} & \cdots & X^k_{m3t} & X^k_{m3t+1} & \cdots & X^k_{m3t+N} \\ \vdots & \vdots & \cdots & \vdots & \vdots & \vdots & \cdots & \vdots & \cdots & \vdots & \vdots & \cdots & \vdots \\ X^k_{1\mathbf{n}t} & X^k_{1\mathbf{n}t+1} & \cdots & X^k_{1\mathbf{n}t+N} & X^k_{2\mathbf{n}t} & X^k_{2\mathbf{n}t+1} & \cdots & X^k_{2\mathbf{n}t+N} & \cdots & X^k_{m\mathbf{n}t} & X^k_{m\mathbf{n}t+1} & \cdots & X^k_{m\mathbf{n}t+N} \end{bmatrix}$$

where i = 1,2,3…. m; j = 1,2,3…***n*** and; X^k_{ijt} , $X^k_{ijt+1,}$ and X^k_{ijt+N} represent the i^th indicator column under the k^th dimension over time t, t+1, and t+N, respectively for the j^th smart city considered for the assessment. Initially, the indicators are categorized based on the degree of desirability i.e., on how an indicator would contribute to the outcome of the phenomenon to be estimated (see Appendix B. Table B1 and Table B2). If the indicator value contributes in a positive manner to the desired outcome, it is ascribed as a positive-indicator (e.g., in the selected city resilience indicators, the indicator "span of bicycle network per km^2" has 'positive' desirability). Other else, the indicator is attributed as a negative-indicator (e.g., the indicator "Percentage of population with no access to health insurance coverage " has 'negative' desirability among the other urban liveability indicators).

The normalized scores for the positive-indicators are calculated using Eq. (45):

$$X^k_{ijs} = k + \frac{\left(X^k_{ijs} - \mathrm{Min}^k_{js}\right)(K_1 - k_0)}{\left(\mathrm{Max}^k_{js} - \mathrm{Min}^k_{js}\right)} \;;\forall\ s = t, t+1\ldots, t+N \tag{45}$$

where Min^k_{js} and Max^k_{js} are the minimum and maximum values of the j^th smart city under the k^th aspect for over the respective time 's'. Eq. (45) is further modified to Eq. (46) to find the normalized scores of the negative-indicators (i.e., to reverse the desirability on the normalized score) as follows;

$$X^{k}_{ijs} = k + \frac{\left(Min^{k}_{js} - X^{k}_{ijs}\right)(k_0 - K_1)}{\left(Max^{k}_{js} - Min^{k}_{js}\right)} \;;\forall\ s = t, t+1\ldots, t+N \tag{46}$$

K_1 with an assigned value of 1 is the upper bound, while k_0 with an assigned value of 0 is the lower bound of the normalized data set. Assigning 1 and 0 to the upper and lower bound respectively can give a range of unit length to the resulting normalized scores.

Post data normalization, the novel three-step multivariate metric-distance based approach is used to weight the indicators and obtain a homogenized score for each dimension under city resilience and liveability. The steps involved in the metric-distance based approach is detailed as follows;

Step 1: For a selected set of standardized indicators, $X^{k}_{ij} = [X^{k}_{1j}, X^{k}_{2j}, \cdots X^{k}_{mj}]$ determined to represent the decision-making entities (in this case, European smart cities), the metric distance of a homogenous decision-making entity $\boldsymbol{e_u} = (X^{k}_{1u}, X^{k}_{2u}, \cdots X^{k}_{mu})$ with respect to a benchmark entity $\boldsymbol{e_v} = (X^{k}_{1v}, X^{k}_{2v}, \cdots, X^{k}_{mv})$ is calculated using Eq. (47) as:

$$D(v, u) = \sum_{i=1}^{m} \frac{|d_i\,(v, u)|}{\sigma(X^{k}_{i})} \prod_{\hat{j}=1}^{i-1} \left(1 - R_{\hat{j}i.\,12\ldots\,\hat{j}-1}\right) \tag{47}$$

where, $R_{\hat{j}i}$ is the partial correlation coefficient between X^{k}_{i} and $X^{k}_{\hat{j}} \mid (i > \hat{j})$; $\sigma(X^{k}_{i})$ is the standard deviation of X^{k}_{i} and, $d_i\,(v, u)$ is the distance between the values of indicator X^{k}_{iu} and X^{k}_{iv} (i.e., discriminate effect), which is obtained using Eq. (48) as:

$$d_i\,(v, u) = x^{k}_{iv} - x^{k}_{iu}, i \in \{1,2,\cdots m\} \tag{48}$$

To rule out the presence of negative correlation and negative partial correlation coefficient, Eq. (47) is further modified as;

$$D^2(v, u) = \sum_{i=1}^{m} \frac{\left|d_i^2\ (v,\ u)\right|}{Var\ (X^k{}_i)} \prod_{\hat{j}=1}^{i-1} \left(1 - R^2_{ji.}\right) \tag{49}$$

Step 2: Adequate weights are assigned to each independent variable (indicators). For the same, the stability of each indicator in the overall-indicator matrix is looked into by determining the Pearson correlation (r) between the calculated metric distances and the indicators. The proposed metric-distance approach assigns importance to each indicator based on the empirical Pearson's correlation, rather than subjective weights. Furthermore, the calculated metric-distance values and each indicator in the overall-indicator matrix are continuous variables, thus making bivariate correlation a suitable approach for the analysis. In this step, the new weight (w_i) is assigned to each indicator (using Eq. 50) established by weighting the Pearson's r, i.e., the correlation coefficient values are divided by the aggregate correlations; where $\sum w_i = 1$.

$$w_i = \frac{r_i}{\sum_{\hat{j}=1}^{m} r_{\hat{j}}} \quad \forall\ i = 1,2,3 \cdots\cdots m \tag{50}$$

r_i is the bivariate correlation between the calculated metric-distance value and the value of the i^{th} indicator. It is to note that, to calculate the metric-distance, a fictive decision-making entity with minimum values for each of the indicators in the indicator-matrix is utilized as the benchmark entity, since the metric-distance values in the "n-dimensional space" for other entities is calculated based on the distance from the benchmark entity.

Step 3: Composite score (S_j) for each entity (i.e., smart city) under the respective dimension is obtained by following the aggregation process as in Eq. (51):

$$S_j = \sum_{i=1}^{m} w_i \cdot x_{ij}^{k} \tag{51}$$

3.3.2. Machine learning based-assessment

In this stage, two machine learning based data analytics is carried out namely; clustering as one of the unsupervised partitioning technique and classification, a supervised machine learning technique. The machine learning-based assessment is carried out to predict the degree of liveability and resilience, as categorical variables, based on the values of the indicators under each dimension. For the same, Fuzzy c-means algorithm is used as the first step to partition the composite scores obtained from each dimensions of resilience and livability into high, medium and low performance category and in the second step, six classification algorithms are tested to propose the best predictive model for livability and resilience assessment. Both these steps are discussed in detail in the succeeding paragraphs.

Step 1: Fuzzy c-means algorithm is an unsupervised fuzzy partitioning technique used first by Dunn, (1973) to partition a dataset X into fuzzy groups as outputs with a certain degree of membership. The membership matrix $[Y_{jk}]_{(c \cdot n)}$ indicates the degree of membership of the j^{th} smart city to the k^{th} fuzzy cluster as in Eq. (52), where $Y_{jk} \in [0,1]$.

$$M_f(Y) = \begin{Bmatrix} Y \in R^{c.n} \mid \sum_{k=1}^{c} Y_{jk} = 1;\ 0 < \sum_{j=1}^{n} Y_{jk} < n \\ Y_{jk} \in [0,1];\ 1 \le k \le c;\ 1 \le j \le n \end{Bmatrix} \tag{52}$$

Accordingly, with random value initialization of Y_{jk}, Eq. (53) iteratively minimizes the objective function:

$$K_w = \sum_{k=1}^{c} \sum_{j=1}^{n} Y_{jk}^{w} \| x_j - c_k \|^2 \tag{53}$$

where, $\{c_k\}_{k=1}^{c}$ represents the centroids of 'c' fuzzy clusters, w is a weighting exponent on the membership matrix highlighting the degree of fuzziness in the classification output with $1 < w < \cdot\infty$, and $\|\cdot\|$ is the Euclidean p-norm of x_j and c_k in $\mathbb{R}^n$.

The degree of fuzzy membership attributed to each cluster, at every iteration, starting from random 'c' cluster centroids is calculated using Eq. (54) as follows;

$$Y_{jk} = \frac{1}{\sum_{p=1}^{c}\left(\frac{\|x_j - c_k\|}{\|x_j - c_p\|}\right)^{\frac{2}{w-1}}} \tag{54}$$

According to the fuzzy membership values, the centroid of each cluster is then computed using Eq. (55) as follows;

$$C_k = \frac{\sum_{j=1}^{n} Y_{jk}^{w} \cdot x_j}{\sum_{j=1}^{n} Y_{jk}^{w}} \tag{55}$$

The iterative optimization is terminated on satisfying the condition in Eq. (56) i.e., when the centroid of each cluster remains the same.

$$\text{abs}\ |K_w^t - K_w^{t-1}| < \varepsilon \tag{56}$$

Step 2: In this step, a total of six classification algorithms are examined to arrive at the best predictive model with the highest predictive performance/accuracy for resilience, liveability, and aggregate performance of smart cities. The six classification algorithms used are namely; Naïve Bayes classifier, kNN, SVM classifier, CART, RF classifier, and GBM classifier. The graphical outline of the proposed machine learning techniques and model deployment is presented in Figure 6. Some basic definitions and mathematical operations related to the classification algorithm used in this research are stated here in as;

Definition 1. Naïve Bayes classifier is a supervised learning algorithm that is based on Bayes' theorem with a strong (naïve) independence assumption between the input features. This assumption enables the multiplication of the conditional probabilities to determine the response variable. Given a class variable y based on n input features $\{x_I\}_{i=1}^{n}$, the Bayes' theorem states as (see Eq. 57):

$$P(y|x_1, x_2,\ldots,x_n)=\frac{P(y)P(x_1, x_2,\ldots,x_n|y)}{P(x_1, x_2,\ldots,x_n)}=\frac{P(y)\prod_{i=1}^{n} P(x_i|y)}{P(x_1, x_2,\ldots,x_n)} \tag{57}$$

Definition 2. K-nearest neighbors (KNN) is a non-parametric machine learning algorithm that uses the observations of K nearest neighbors to make predictions. It can be used for both regression and classification problems. Given a training dataset $(X,Y)=\{(x_I, y_I)\}_{i=1}^{n}$, where X is the input variables and Y is a class label, kNN estimates the conditional probability of Y given X and groups an observation to the class with the highest probability. Given a positive integer k, the KNN algorithm first identifies k observations that are closest to a test observation x and estimates the conditional probability of observation x to be in class m as presented in Eq. (58):

$$p_k(X)=P_r(Y = m / X = x) = \frac{1}{k}\sum_{i \in N_k} I\left(y_i = m\right) \tag{58}$$

where N_k is the set of k observations closest to a test observation and $I\left(y_i = m\right)$ is an indicator variable equal to unity if a given observation $\left(x_I, y_I\right)$ is in class m and zero otherwise.

Definition 3. Support vector machine (SVM) is a popular supervised ML algorithm that can be used for classification as well as regression problems. The goal of SVM is to map the input data into high-dimensional space where they can be linearly separable by implementing kernel function. Given a training dataset $\{(x_I, y_I)\}_{i=1}^{n}$, the objective of SVM is to find a classification rule to predict the label of the response variable by solving the optimization problem in Eq. (59):

$$\min_{w, b,\xi} \frac{1}{2}||w||^2 + C\sum_{i=1}^{N} \xi_i \tag{59}$$

Subject to

$$y_i\ (w^T\ \phi\ (x_i) + b) \geq 1\text{-}\xi_i,\ \forall i \quad (60)$$

$$\xi_i \geq 0, \forall i \quad (61)$$

where $C > 0$ is a regularization parameter introduced to penalize the misclassified points via the slack variables ξ_I, b is the intercept, and *w* is the weight.

The solution to the above optimization problem is given by Eq. (62):

$$\sum_{i\epsilon\ SV} y_i \alpha_i K(x_i,\ x)+b \quad (62)$$

where $K(x_I,\ x)$ is the kernel function, SV denotes support vectors, which are subsets of training data points, and α_I is the Lagrange multiplier. The four popular kernel types include linear kernel, polynomial kernel, hyperbolic tangent (sigmoid) kernel, and radial basis function (RBF).

Definition 4. Classification and regression tree (CART) also referred to as decision tree is a set of non-parametric supervised learning algorithms that can be used for both classification and regression predictive modelling problems by learning a simple tree model (Breiman et al., 1984). The CART method splits the feature space into multiple smaller disjoint regions with similar response values using a set of rules to predict a class label (in classification) and value (in regression) of the response variable. Each internal node in CART specifies a test on an attribute of the data, while each branch represents the test output. The root node, which is the topmost node in CART denotes the most relevant feature, while the leaf node or terminal node provides the predicted class label. Given training dataset of *N* size, the algorithm firstly partitions the predictors space into *D* disjoint regions: $\{R_1, R_2, \ldots, R_D\}$ based on the Gini Index (Alpaydin, 2020). In the next step, tree pruning is performed to reduce overfitting. The performance of the CART model can be optimized by tuning its hyperparameters including the maximum depth of the tree, minimum number of samples required to split an internal node, and minimum number of samples required to be at a leaf/terminal node.

Definition 5. Ensemble models are supervised machine learning paradigm that integrate multiple single learners (a.k.a. base learners or weak learners) into one model to reduce variance error, bias, and produce a strong model with enhanced generalization capability and superior performance (Breiman et al., 1984). The most popular type of meta-algorithms that combine base learners are bootstrap aggregation (bagging) (Breiman, 1996) and boosting (Sutton, 2005) ensembles. In bagging ensemble (e.g., random forest), multiple base learners are trained independently in parallel on a different bootstrap sample, while in boosting ensemble (e.g., gradient boosting) the base models are trained sequentially.

As its name suggests, random forest (RF) is a forest of randomly created CART models. Each decision tree predictor in the RF algorithm uses bootstrap samples, which are samples drawn from the original dataset with replacement. Moreover, random subsets of input features are considered when splitting nodes in the decision tree on the best split among a random subset of the features selected at every node (Svetnik et al., 2003). The split at each node is performed in two steps. Firstly, a random subset of input features is selected from the bootstrap sample (Svetnik et al., 2003). The best subset feature is then selected to perform the decision split at each node of a decision tree (Svetnik et al., 2003). Each tree predictor outputs a class prediction, then the final prediction of the RF classifier is taken as the class with the most votes. Similarly, Gradient boosting machine (GBM) is a powerful boosting algorithm, which combines a sequence of weak learners to generate an additive model whose performance is significantly enhanced compared to the base learners (Bishop, 2006). In the first step, equal weight is assigned to each data point. In the subsequent steps, the model is retrained by assigning more weight to the observations that were incorrectly classified by the base learner in the previous step. In each step, the GBM introduces a base learner (decision tree) to overcome the shortcomings of the existing base learner(s). The learning rate controls how hard each base learner attempts to correct the errors of the previous learner in the sequence.

Definition 6. The predictive performance of the ML model is highly dependent on the values of its hyperparameters which are the parameters that control the learning process of the model (Abdella et al., 2020a). Hence, it is crucial to explore the combination of the hyperparameters that produce the best model. In the current study, a tuning technique known as grid search, that exhaustively searches the optimum values of hyperparameters considering all possible combinations of user-specified hyperparameters was used to optimize the hyperparameters. Besides, standard k-fold cross-validation is used to overcome the problem of overfitting (Abdella and Shaaban, 2021). The k-fold cross-validation is performed in the following procedures: (a) split the training dataset into k equal parts, (b) use $k-1$ parts to train the model and the remaining one part to validate the model, (c) repeat step (b) until each part is used for both the training and validation set, and (d) finally compute the performance of the model as the average performance of the k estimations. Grid search is combined with 10-fold cross-validation (k =10) in this study to optimize the hyperparameters of the classification algorithms.

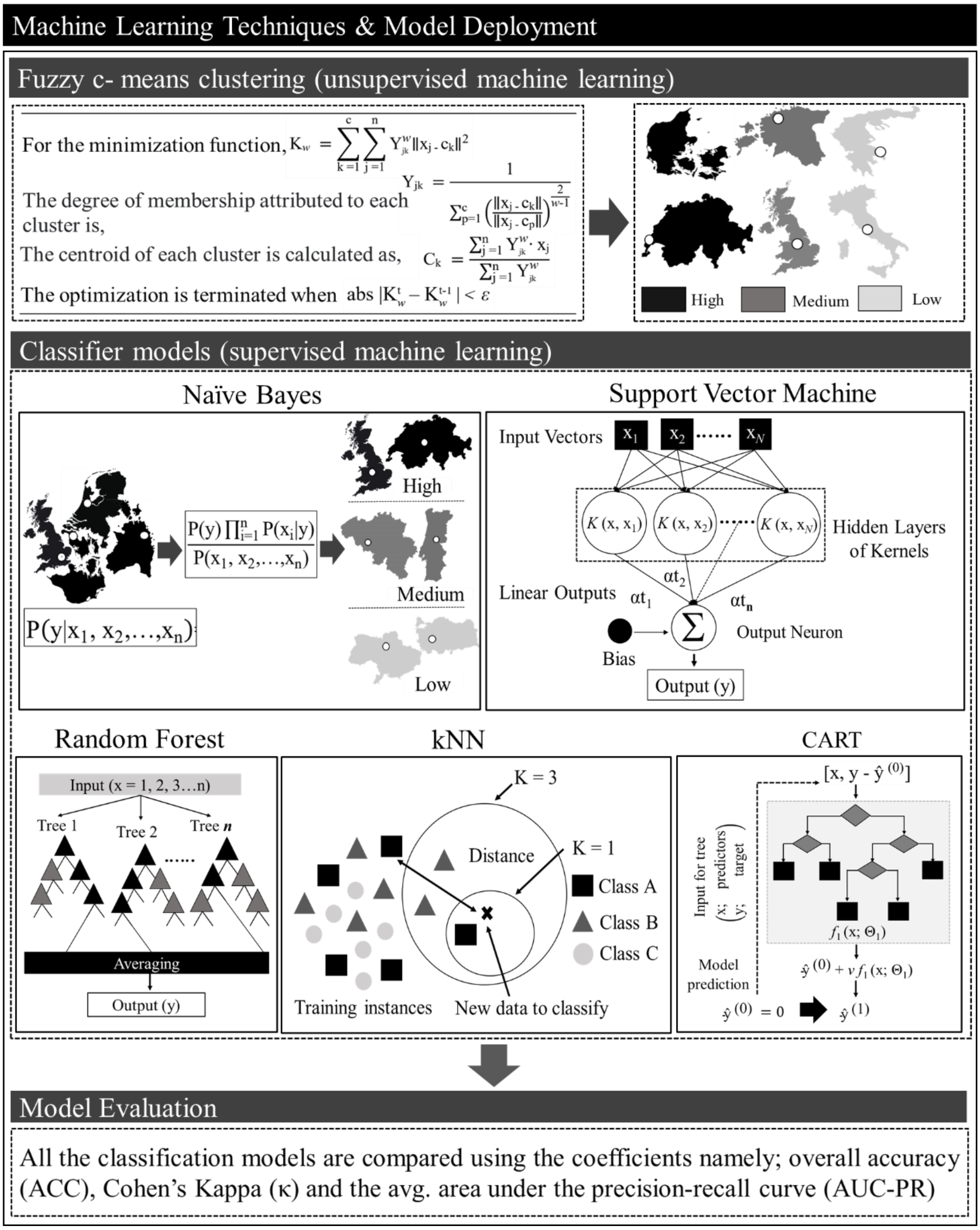


Figure 6. Graphical outline of the proposed machine learning approach

3.4. Multi-Criteria Assessment Module

In this module, a novel fuzzy expert-based multi-criteria decision support model is proposed to assess the composite performance of a group of DMU and rank them based on the composite score. The proposed model encompasses a 3-stage integrated approach, where stage 1 uses the SF-AHP method to assign weights to each main-criteria and sub-criteria based on expert elicitation. Hierarchical comparison of the criteria and sub-criteria (dimensions) is conducted through comparison matrices based on the provided linguistic scale and their spherical fuzzy equivalence. Weight matrices based on spherical fuzzy criterion are obtained which then are aggregated through the weighted geometric and arithmetic mean operators. Based on the assigned weights using SF-AHP to each criteria and dimensions with appropriate aggregation techniques, the extended EDAS methodology proposed by Keshavarz-Ghorabaee, (2021) is then used in stage 2 to rank each DMU. The extended EDAS method uses both the positive and negative distances from the average solution to obtain composite score for each alternative, with the ability to cope with negative element and zero value in the average solution through simple data transformation. The DMUs are ranked in the decreasing order of their composite performance. In stage-3, Fuzzy c-means clustering algorithm as a simple clustering technique is used to identify the optimum number of clusters and label the DMUs to different clusters based on their performance as high, medium, and low. Further, a comparative study employing several fuzzy-based weighting approaches with the extended EDAS method, and the proposed integrated expert-based multi-criteria decision support model is conducted. Alternatively, a comparative study with several distance-based MCAT and SF-AHP is carried out to validate the use of spherical sets in fuzzy environment. Further, two different sensitivity analysis is conducted to validate the result of the proposed SF-AHP and extended EDAS method by changing the threshold parameter (λ).

3.4.1 Concepts and definitions of spherical fuzzy sets

First introduced by Zadeh (1965), the Fuzzy Sets (FS) quantitatively characterize the ambiguity and vagueness in decision making with multiple goals and criteria. The traditional FS have been extended later on to Type-n FS by Zadeh (1975) that considers further uncertainties associated with the membership functions. Later on, Zadeh (1975) presented the interval-valued fuzzy set (IVFS). To accommodate the concept of hesitation margin in a fuzzy set, Atanassov (1986) introduced the Intuitionistic fuzzy sets (IFS). A general extension to the FS, the hesitant fuzzy set was later on proposed by Torra, (2010), where membership degrees take interval values than crip numbers. Atanassov, (1999) developed intuitionistic type- 2 FS (IT2FS). While Yager, (2013) presented Pythagorean fuzzy sets (PFS), a generalization of IFS to address the vagueness and complexity in defining membership grades in fuzzy-based MCDM problems. The Spherical Fuzzy Sets (SFSs) developed by Kutlu Gündoğdu and Kahraman in (2019) are an extended form of PFS and picture fuzzy sets satisfying the condition $0 \leqslant u_A^2(x) + v_A^2(x) + \pi_A^2(x) \leqslant 1$. The squared sum of functional parameters in the membership function of SFS is somewhere between zero, and the value of each parameter can be independently defined between 0 and 1 in a non-linear 3D space, where the squared sum is at most equal to 1 (Kutlu Gündoğdu and Kahraman, 2019; Kutlu Gündoğdu and Kahraman, 2020). This provides a larger preference domain for decision makers when using the novel concept of SFS (Kutlu Gündoğdu and Kahraman, 2020). For instance, a decision maker may assign his/her preference for an alternative with respect to a criterion with (0.5, 0.4, 0.6). It is clearly seen that the sum of the parameters is larger than 1 whereas the squared sum is 0.77. In SFS, decision makers should define their hesitancy degrees just like other dimensions that are membership and non-membership.

In the following section, we provide the review of basic definitions and notations for the linguistic variables of SFS and its operations (Kutlu Gündoğdu and

Kahraman, 2019; Kutlu Gündoğdu and Kahraman, 2020):

Definition 7. The spherical fuzzy set $\widetilde{A}_s$ of a universal set "U" is defined by the following expression (see Eq. 63-65)

$$u_{\widetilde{A}_s}: U \rightarrow [0,1],\ v_{\widetilde{A}_s}: U \rightarrow [0,1],\ \pi_{\widetilde{A}_s}: U \rightarrow [0,1] \tag{63}$$

and

$$0 \leq u^2_{\widetilde{A}_s}(u) + v^2_{\widetilde{A}_s}(u) + \pi^2_{\widetilde{A}_s}(u) \leq 1 \quad (u \in U) \tag{64}$$

$$\widetilde{A}_s = \left\{ \langle u, \left(u_{\widetilde{A}_s}(u), v_{\widetilde{A}_s}(u), \pi_{\widetilde{A}_s}(u) \right) \rangle \mid u \in U \right\} \tag{65}$$

For each u , the value $u_{\widetilde{A}_s}(u), v_{\widetilde{A}_s}(u)$, and $\pi_{\widetilde{A}_s}(u)$ are the degree of membership, non-membership, and hesitancy of u to $\widetilde{A}_s$, respectively.

Definition 8. Let U1 and U2 be two universes. Let two spherical fuzzy sets $\widetilde{A}_s$ and $\widetilde{B}_s$ of the universe of discourse U1 and U2. Geometrical representation of SFS and distances between $\widetilde{A}_s$ and $\widetilde{B}_s$ economics illustrated in

Figure 7 (Antonov, 1995; Yang and Chiclana, 2009).

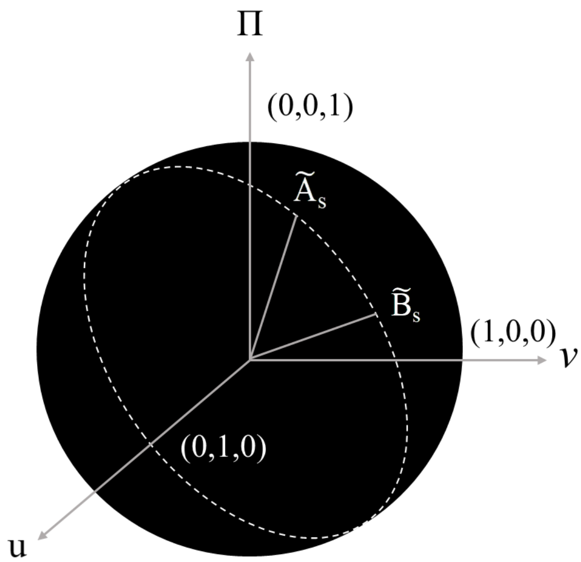


Figure 7. 3D geometrical representation of Spherical Fuzzy Sets

$$D(\widetilde{A}_s, \widetilde{B}_s) = \frac{2}{\pi} \sum_{i:1}^{n} \arccos\left(1 - 0.5 \times \left[\left(u_{\widetilde{A}_s} - u_{\widetilde{B}_s}\right)^2 + \left(v_{\widetilde{A}_s} - v_{\widetilde{B}_s}\right)^2 + \left(\pi_{\widetilde{A}_s} - \pi_{\widetilde{B}_s}\right)^2 \right]\right) \tag{66}$$

were, $0 \leq D(\widetilde{A}_s, \widetilde{B}_s) \leq n$;

Using $u_{\widetilde{A}}^2 + v_{\widetilde{A}}^2 + \pi_{\widetilde{A}}^2 = 1$, we obtain the normalized distances between $\widetilde{A}_s$ and $\widetilde{B}_s$ is presented in Eq. (67) as follows:

$D_n(\widetilde{A}_s, \widetilde{B}_s) =$

$$\frac{2}{n\pi}\sum_{i:1}^{n} \arccos\left(u_{\widetilde{A}_s}(u_i) \times u_{\widetilde{B}_s}(u_i) + v_{\widetilde{A}_s}(u_i) \times v_{\widetilde{B}_s}(u_i) + \pi_{\widetilde{A}_s}(u_i) \times \pi_{\widetilde{B}_s}(u_i)\right) \tag{67}$$

where, $0 \leq D_n(\widetilde{A}_s, \widetilde{B}_s) \leq 1$

Definition 9. Operators

a) Addition

$$\widetilde{A}_s \oplus \widetilde{B}_s = \left\{\sqrt{u_{\widetilde{A}_s}^2 + u_{\widetilde{B}_s}^2 - u_{\widetilde{A}_s}^2 . u_{\widetilde{B}_s}^2},\right.$$

$$\left. v_{\widetilde{A}_s}^2 . v_{\widetilde{B}_s}^2, \sqrt{\left(\left(1 - u_{\widetilde{B}_s}^2\right)\pi_{\widetilde{A}_s}^2 + \left(1 - u_{\widetilde{A}_s}^2\right)\pi_{\widetilde{B}_s}^2 - \pi_{\widetilde{A}_s}^2 . \pi_{\widetilde{B}_s}^2\right)}\right\} \tag{68}$$

b) Multiplication

$$\widetilde{A}_s \otimes \widetilde{B}_s = \left\{u_{\widetilde{A}_s}^2 . u_{\widetilde{B}_s}^2, \sqrt{v_{\widetilde{A}_s}^2 + v_{\widetilde{B}_s}^2 - v_{\widetilde{A}_s}^2 . v_{\widetilde{B}_s}^2},\right.$$

$$\left.\sqrt{\left(\left(1 - v_{\widetilde{B}_s}^2\right)\pi_{\widetilde{A}_s}^2 + \left(1 - v_{\widetilde{A}_s}^2\right)\pi_{\widetilde{B}_s}^2 - \pi_{\widetilde{A}_s}^2 . \pi_{\widetilde{B}_s}^2\right)}\right\} \tag{69}$$

c) Multiplication by a scalar

$$\widetilde{A}_s \otimes x = \left\{\sqrt{1\text{-}\left(1\text{-}u_{\widetilde{A}_s}^2\right)^x}, v_{\widetilde{A}_s}^x, \sqrt{\left(1\text{-}u_{\widetilde{A}_s}^2\right)^x \text{-} \left(1\text{-}u_{\widetilde{A}_s}^2 \text{-}\pi_{\widetilde{A}_s}^2\right)^x}\right\} \tag{70}$$

d) Power of $\widetilde{A}_s$

$$\widetilde{A}_s^x = \left\{u_{\widetilde{A}_s}^x, \sqrt{1 - \left(1 - v_{\widetilde{A}_s}^2\right)^x}, \sqrt{\left(1\text{-}v_{\widetilde{A}_s}^2\right)^x - \left(1 - v_{\widetilde{A}_s}^2 - \pi_{\widetilde{A}_s}^2\right)^x}\right\} \tag{71}$$

e) Union

$$\widetilde{A}_s \cup \widetilde{B}_s = \left\{\max\left(u_{\widetilde{A}_s}^2, u_{\widetilde{B}_s}^2\right), \min\left(v_{\widetilde{A}_s}^2 . v_{\widetilde{B}_s}^2\right), \min\left(1 - \left(\left(\max\left(u_{\widetilde{A}_s}^2, u_{\widetilde{B}_s}^2\right)\right)^2 + \right.\right.\right.$$

$$\left(\min\left(v^2_{\widetilde{A}_s}, v^2_{\widetilde{B}_s}\right)\right)^2\right), \max\left(\pi^2_{\widetilde{A}_s}, \pi^2_{\widetilde{B}_s}\right)\right)\Big\} \tag{72}$$

f) Intersection

$$\widetilde{A}_s \cap \widetilde{B}_s = \Big\{\min(u^2_{\widetilde{A}_s}, u^2_{\widetilde{B}_s}), \max(v^2_{\widetilde{A}_s}.v^2_{\widetilde{B}_s}), \min\Big(1$$

$$-\left(\left(\min\left(u^2_{\widetilde{A}_s}, u^2_{\widetilde{B}_s}\right)\right)^2 + \left(\max\left(v^2_{\widetilde{A}_s}, v^2_{\widetilde{B}_s}\right)\right)^2\right), \min(\pi^2_{\widetilde{A}_s}, \pi^2_{\widetilde{B}_s})\Big)\Big\} \tag{73}$$

Definition 10.

$$\widetilde{A}_s \oplus \widetilde{B}_s = \widetilde{B}_s \oplus \widetilde{A}_s \tag{74}$$

$$\widetilde{A}_s \otimes \widetilde{B}_s = \widetilde{B}_s \otimes \widetilde{A}_s \tag{75}$$

$$X\left(\widetilde{A}_s \oplus \widetilde{B}_s\right) = x.\widetilde{A}_s \oplus x.\widetilde{B}_s \tag{76}$$

$$x_1.\widetilde{A}_s \oplus x_2.\widetilde{A}_s = (x_1+x_2)\,\widetilde{A}_s \tag{77}$$

$$\left(\widetilde{A}_s \otimes \widetilde{B}_s\right)^x = \widetilde{A}_s^{\,x}.\widetilde{B}_s^{x} \tag{78}$$

$$\widetilde{A}_s^{-x} \otimes \widetilde{A}_s^{-y} = \widetilde{A}_s^{-x-y} \tag{79}$$

Definition 11. "Spherical Weighted Arithmetic Mean (SWAM)" with respect to, $w = (w_1, w_2, \ldots\ldots, w_n)$; $\sum_{i:1}^{n} w_i = 1$ SWAM is defined as follows (Eq. 80):

$$SWAM_w(\widetilde{A}_{s1}, \widetilde{A}_{s2}, \ldots, \widetilde{A}_{sn}) = w_1\widetilde{A}_{s1} + w_2\widetilde{A}_{s2} + \ldots + w_n\widetilde{A}_{sn} = \tag{80}$$

$$\left\{\sqrt{1-\prod_{i:1}^{n}\left(1-u^2_{\widetilde{A}_{si}}\right)^{w_i}}, \prod_{i:1}^{n} v^{w_i}_{\widetilde{A}_{si}}, \sqrt{\prod_{i:1}^{n}\left(1-u^2_{\widetilde{A}_{si}}\right)^{w_i} - \prod_{i:1}^{n}\left(1-u^2_{\widetilde{A}_{si}}-\pi^2_{\widetilde{A}_{si}}\right)^{w_i}}\right\}$$

Definition 12. "Spherical Weighted Geometric Mean (SWGM)" with respect to, $w = (w_1, w_2, \ldots\ldots, w_n)$; $\sum_{i:1}^{n} w_i = 1$ SWGM is defined as follows (Eq. 81):

$$SWGM_w(\widetilde{A}_{s1}, \widetilde{A}_{s2}, \ldots, \widetilde{A}_{sn}) = \widetilde{A}_{s1}^{w_1} + \widetilde{A}_{s2}^{w_2} + \ldots + \widetilde{A}_{sn}^{w_n} \tag{81}$$

$$= \left\{\prod_{i:1}^{n} u^{w_i}_{\widetilde{A}_{si}}, \sqrt{1-\prod_{i:1}^{n}\left(1-v^2_{\widetilde{A}_{si}}\right)^{w_i}}, \sqrt{\prod_{i:1}^{n}\left(1-v^2_{\widetilde{A}_{si}}\right)^{w_i} - \prod_{i:1}^{n}\left(1\text{-}v^2_{\widetilde{A}_{si}}-\pi^2_{\widetilde{A}_{si}}\right)^{w_i}}\right\}$$

Definition 13. Score functions and Accuracy functions of sorting SFS are defined using Eq. (82) and Eq. (83) respectively;

$$\text{Score}\ (\tilde{A}_s) = \left(u_{\tilde{A}_s} - \pi_{\tilde{A}_s}\right)^2 - \left(v_{\tilde{A}_s} - \pi_{\tilde{A}_s}\right)^2 \tag{82}$$

$$\text{Accuracy}\ (\tilde{A}_s) = u^2_{\tilde{A}s} + v^2_{\tilde{A}s} + \pi^2_{\tilde{A}s} \tag{83}$$

Note: $\tilde{A}_s < \tilde{B}_s \iff \text{Score}\left(\tilde{A}_s\right) < \text{Score}\left(\tilde{B}_s\right)$ or $\text{Score}\left(\tilde{A}_s\right) = \text{Score}\left(\tilde{B}_s\right)$ and Score $\left(\tilde{A}_s\right) < \text{Score}\left(\tilde{B}_s\right)$.

3.4.2. Fuzzy expert-based multi-criteria decision support

In this section, we present the integrated SF-AHP and extended EDAS method with Fuzzy c-means clustering approach. As highlighted previously, in Stage 1, we determine the weights of each criteria and sub-criteria (dimensions) using the SF-AHP technique. In Stage 2, the total alternatives are ranked based on the composite score obtained using the extended EDAS approach. In Stage 3, fuzzy c-means algorithm, an unsupervised partitioning approach is used to segregate the alternatives with similar characteristics and group them into clusters. The detailed steps involved in executing each stages of the proposed model is explained below;

Stage 1: Determine the weights of each main-criteria and sub-criteria using spherical fuzzy AHP.

The steps involved in the SF-AHP method are as follows:

Step 1. Establish the hierarchical structure of the model, specifying the main-criteria and sub-criteria.

Step 2. Constitute pairwise comparison matrices utilizing spherical fuzzy judgment matrices based on the linguistic terms given in Table 1. Eq. (84) and (85) are used to obtain the Score Indices (SI). The SI values corresponding to each linguistic scale is presented in Table 6.

Table 6. Linguistic scale, Score Index, and the corresponding SF Sets

Linguistic scale	Abbreviation	Score Index	(u, v, π)
Absolutely more importance	AMI	9	(0.9,0.1,0.0)
Very high importance	VHI	7	(0.8,0.2,0.1)
High importance	HI	5	(0.7,0.3,0.2)
Slightly more importance	SMI	3	(0.6,0.4,0.3)
Equally importance	EI	1	(0.5,0.4,0.4)
Slightly low importance	SLI	1/3	(0.4,0.6,0.3)
Low importance	LI	1/5	(0.3,0.7,0.2)
Very low importance	VLI	1/7	(0.2,0.8,0.1)
Absolutely low importance	ALI	1/9	(0.1,0.9,0.0)

For AMI, VHI, HI, SMI, and EI

$$SI = \sqrt{\left|100\times\left(\left(u_{\tilde{A}_s}-\pi_{\tilde{A}_s}\right)^2-\left(v_{\tilde{A}_s}-\pi_{\tilde{A}_s}\right)^2\right)\right|} \quad (84)$$

For EI; SLI; LI; VLI; and ALI;

$$SI^{-1} = 1 \Big/ \sqrt{\left|100\times\left(\left(u_{\tilde{A}_s}-\pi_{\tilde{A}_s}\right)^2-\left(v_{\tilde{A}_s}-\pi_{\tilde{A}_s}\right)^2\right)\right|} \quad (85)$$

Step 3. Calculate the global and local weights, under a spherical fuzzy environment using SWAM and SWAG operators as per Eq. (80) and Eq. (81) respectively with respect to each main and sub-criterion.

Stage 2: The extended EDAS method

Consider a decision making problem with ***u*** alternatives/DMU (A_1, A_2, A_3….A_u), ***v*** criteria (C_1, C_2, C_3….C_v) and $\boldsymbol{w_j}$ being the weight of the respective criteria. The computing steps of the basic EDAS algorithm to evaluate the selected set of alternatives for the given criterions are stated as below:

Step 1: Define the evaluation matrix (Y), as shown in Eq. (86):

$$Y = [\alpha_{ij}]_{u\cdot v} = \begin{bmatrix} \alpha_{11} & \alpha_{12} & \cdots & \alpha_{1j} & \cdots & \alpha_{1v} \\ \alpha_{21} & \alpha_{22} & \cdots & \alpha_{2j} & \cdots & \alpha_{2v} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \alpha_{i1} & \alpha_{i2} & \cdots & \alpha_{ij} & \cdots & \alpha_{iv} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \alpha_{u1} & \alpha_{u2} & \cdots & \alpha_{uj} & \cdots & \alpha_{uv} \end{bmatrix} \quad (86)$$

Compared to the conventional EDAS approach Keshavarz-Ghorabaee, (2021) added a transformation, $\acute{\alpha}_{ij} = \alpha_{ij} - \min_j \alpha_{ij}$ to the decision matrix Y in Eq. 87, to cope with the negative and zero element in the average solution. The transformed decision matrix $\acute{Y}$ is defined as follows;

$$\acute{Y} = [\,\acute{\alpha}_{ij}]_{u \cdot v} = \begin{bmatrix} \acute{\alpha}_{11} & \acute{\alpha}_{12} & \cdots & \acute{\alpha}_{1j} & \cdots & \acute{\alpha}_{1v} \\ \acute{\alpha}_{21} & \acute{\alpha}_{22} & \cdots & \acute{\alpha}_{2j} & \cdots & \acute{\alpha}_{2v} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \acute{\alpha}_{i1} & \acute{\alpha}_{i2} & \cdots & \acute{\alpha}_{ij} & \cdots & \acute{\alpha}_{iv} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \acute{\alpha}_{u1} & \acute{\alpha}_{u2} & \cdots & \acute{\alpha}_{uj} & \cdots & \acute{\alpha}_{uv} \end{bmatrix} \tag{87}$$

We now use the transformed decision matrix ($\acute{Y}$) and the value of $\acute{\alpha}_{ij}$ in the succeeding steps to arrive at the composite score.

Step 2: Calculate the average solution ($\bar{x}_j$) for the selected set of attributes using Eq. (88).

$$\bar{x}_j = \frac{\sum_{i=1}^{u} \acute{\alpha}_{ij}}{u} \tag{88}$$

Step 3: Determine the positive (P^{+}_{ij}) and negative (N^{-}_{ij}) distance based on the cost ($\overline{C}$) and benefit ($\overline{B}$) criteria using Eq. (89) and Eq. (90) respectively as;

$$P^{+}_{ij} = \begin{cases} \dfrac{\max(0, \acute{\alpha}_{ij} - \bar{x}_j)}{\bar{x}_j} & \forall\, j \in \overline{B} \\ \dfrac{\max(0, \bar{x}_j - \acute{\alpha}_{ij})}{\bar{x}_j} & \forall\, j \in \overline{C} \end{cases} \tag{89}$$

$$N^{-}_{ij} = \begin{cases} \dfrac{\max(0, \bar{x}_j - \acute{\alpha}_{ij})}{\bar{x}_j} & \forall\, j \in \overline{B} \\ \dfrac{\max(0, \acute{\alpha}_{ij} - \bar{x}_j)}{\bar{x}_j} & \forall\, j \in \overline{C} \end{cases} \tag{90}$$

Step 4: Calculate the additive weights of P^{+}_{ij} and N^{-}_{ij} for all the alternatives, as per Eq. (91) and Eq. (92) respectively as;

$$P^{w}_{i} = \sum_{j=1}^{u} w_j \; P^{+}_{ij} \tag{91}$$

$$N_i^w = \sum_{j=1}^{u} w_j \, N_{ij}^- \tag{92}$$

Step 5: Regularize the results of P_i^w and N_i^w for each alternative following Eq. (93) and Eq. (94)

$$P_i^r = \frac{P_i^w}{\max_i (P_i^w)} \tag{93}$$

$$N_i^r = 1 - \frac{N_i^w}{\max_i (N_i^w)} \tag{94}$$

Step 6: Calculate the composite Score (CS) for each alternative as in Eq. (95):

$$CS_i = \frac{1}{2} \left(P_i^r + N_i^r \right) \tag{95}$$

Step 7: Rank the alternatives in the descending order of the composite score (CS). The decision making entity with the highest CS value is termed as the best performing alternative.

Stage 3: Fuzzy c-means clustering

In this stage, we use "Fuzzy c-means clustering technique" to segment the composite scores obtained from stage 2, for each DMU and categorize them into respective clusters. The steps enumerated through the Eq. (52) till Eq. (56) is repeated post the results obtained from Eq. (95) to find the optimal number of clusters and perform the clustering process. A comprehensive outline of the proposed novel integrated approach is presented in Figure 8.

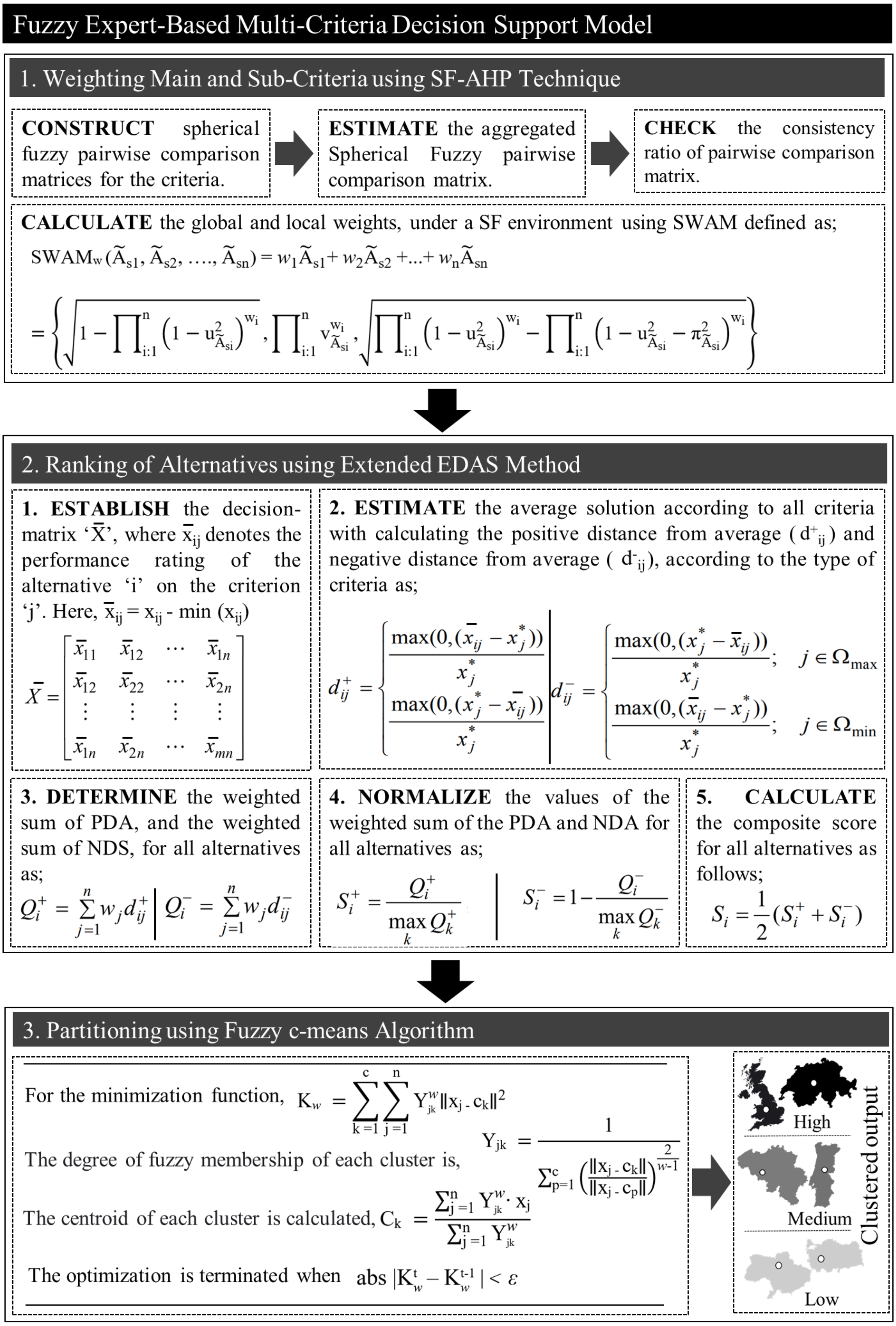


Figure 8. The proposed SF-AHP & extended EDAS Model with Fuzzy partitioning technique

CHAPTER 4: MODELING INTERCONNECTIONS USING SYSTEMS APPROACH

4.1. General Remarks

Systems thinking acts as a support tool in addressing complexities, uncertainties and identifying “what if” impacts. Systems thinking in smart cities can interlink the concepts of production and consumption patterns for a sustained future (sustainable development), while delivering quality of life to the urban dwellers of the present (urban livability), unparalleled by the smooth operating systems that form the nervous system of urban development that can resistant and rebound to shocks with minimal recovery time (urban resilience). This chapter discusses in detail the results of the causal feedback loop diagrams developed in chapter 3 under the systems thinking module (module 1), an integral part of the proposed hybrid decision support model. Causal feedback loop diagrams (CLD) are used to understand the interrelations between several elements that operate in the system across multiple dimensions that define the corner stones of SRL concepts.

4.2. Motivation and objectives

Smart cities are complex urban systems built to offer a dignified standard of living to all its denizens (Mukhlis, 2021). However, smart cities of today pose an enigmatic nature in addressing people concern (Rosati and Conti, 2016). Being platforms to multi-billion investments, smart cities of today lack cohesion due to its silo mode of functioning for business benefits rather than ensuring safety, security, livability, and inclusive growth in its development. Such business-centered development patterns have ruptured the smart city fabric in delivering the true essence of sustainable development. Pinning patches on the urban fabric to render quality of life with touches of sustainability, urban resilience and livability requires adopting the idea of having an interconnected nature throughout the city. This can be achieved through a system-of-system approach, where systems thinking helps in identifying leverage points within the complex urban network. To this end, system thinking approach as a tool is used to close the existing gap in smart city development models from a mere techno-centric perspective to interlinking sustainability (S), resilience (R) and livability (L), collectively termed as the SRL concepts under a unified umbrella to pave ways for “Futuristic Cities”. The interactions are studied using the balancing and reinforcing mechanisms and are explained further in the succeeding section.

4.3. Results and Discussion

The dynamics of urban livability in smart cities is explained through accessibility, community well-being and economic vibrancy; the key drivers in fostering a livable city (see Figure 2). Ideating public participation into the urban planning model fosters sociability when urban attractiveness is made apparent in the design conditions of the city (Guedoudj et al., 2020). Ease of socio-cultural and economic pursuits in urban areas spur urban attractiveness (Correia et al., 2020), which results in people moving into cities. Such ease of access to services and public facilities create a “Disability-free community” comprised of active population with sound health and welfare, a key driver to community well-being (Buch et al., 2014). Enhanced urban attractiveness is a key determinant for migrants moving into cities (Stead, 2003). The community well-being dynamics is captured well in the balancing loops **B1**, **B2**, and **B3**. Do, (2008) identifies a positive correlation between the ease of access to available services in cities with service utilization. However, as services become easily accessible to anyone-anytime-anywhere, an experience of unpleasantness creep as an enduring problem (Di et al., 2021). This can cause pressure to the municipal planning authorities to bring better conditions into the city, thus demanding further investments in the area of infrastructure and built-environment. Such investments can boost the quality of dwelling units, which in turn increases the urban attractiveness, leading to migrant in-flow (see loop **R2** and **B4** in Figure 2). To continue, a vibrant economy is a productive, progressive, and prosperous economy with successful value addition to the services offered to its inhabitants. Loops **B5** through **B8** captures the dynamics of economic vibrancy. As the economy booms, a change in the volume of production in goods and services is seen to meet the growing population demands (Li, 1996). This in turn has a direct influence on the unemployment rates. Studies show a significant decline in unemployment rate as production volume increases (Kreishan, 2011). Furthermore, an economy that aspires to deliver better health and welfare conditions to its labor force produces a productive work force with efficient use of labor hours (Tsoukatou, 2019). Labor productivity is closely linked with value addition per unit of goods produced which holds a positive impact on the GDP growth rate (Mourre, 2009). In addition, education, and investment in alternative technologies through R&D initiatives increases economic growth, henceforth leading to a stable economy. Similarly, the accessibility-economic vibrancy nexus is captured in the reinforcing loop **R1** (see Figure 2).

While understanding urban resilience through systems thinking (see Figure 3), it is seen that an increase in per capita GDP increases the aggregate demand which holds a positive impact on the citizen spending and federal revenue through increased taxes in the latter case and better employment opportunities in the former (Yin, 2009). Public investments provide access to multitude of services to urban inhabitants which impacts the quality and standard of living (Chakraborty and Dabla-Norris, 2011), thus alleviating urban stress and improving product level accessibility. This is evident from the reinforcing loop **R3** in Figure 3. Public investments have enormous potential to bring prolonged benefits to the cities and urban inhabitants (Czudec and Zając, 2021). With public policies encouraging income generation, investments in education, health care services, public infrastructure, capacity building, carbon-neutral transition and investments tailored to harmonize socio-economic growth in an inclusive manner can shield cities from possible socio-environmental threats and improve service continuity (loops **R1** and **R2**). This can support the social system to collectively built tolerance, adaptively manage to change, and sustainably cope with unplanned stress and shocks accompanied by urban sprawl (loop **B1**). Furthermore, a possible impact on the annual revenue levels can exert an upward push to the economy, leading towards prosperity, thus bringing in an economic upheaval and a path for higher economic growth (Abdel-Razek, 2021). Economists identify such growth in the size of economy as a "long-term phenomenon" due to its ability to suppress challenges and return to a stable operating state (Mele, 2021), thus leading to urban resilience due to a strengthened crisis repellent economy (**R4**).

Moving on, we attempt to understand the dynamic interactions of all the elements under various dimensions of urban sustainability through the causal loop diagram presented in Figure 4. Smart cities of today are criticized for their ambiguous growth patterns that lack cohesion between entrepreneurial mind-sets and social progress (Jonek-Kowalska, and Wolniak, 2021). However, smart cities are no exception in providing a dignified standard of living to all the inhabitants including migrants that seek quality in life. Enhanced quality of life boosts the inflow of working-age immigrants to cities in search of jobs (Mubangizi, 2021). As the urban population increases, there is a huge market for the economy to progress in terms of innovation and technological advancements, thus increasing competition at the same time risk of security (Abdella et al., 2019; Ullah et al., 2021; Abdella and Shaaban, 2021). Such breach in security levels can damage the service continuity in smart cities that are driven on ubiquitous data from sensors and tech-driven platforms. Investments in technical safety can increase the social capital, thus increasing resilience to threats and adaption capacity to insecurities (Andrade et al., 2020). The dynamics is represented in the reinforcing loop **R7**. When exploring the society and well-being dynamics (loops **R1** and **B1**), an increase in population can trigger a demand for better services, infrastructures and facilities in cities which hold a positive impact on quality of service to be offered (Kutty et al., 2020a; Kutty et al., 2020b). Howard-Grabman et al., (2017) using the “Research Evidence framework” identified service quality as a key facilitator for effective community participation, which in turn generates an active and socially cohesive society. Factors that seek to enhance social cohesion hold a positive correlation on the quality of life (Paramita et al., 2021). Furthermore, as population increases, the physical and physiological accessibility to green urban areas are compromised, which hinders community participation (Menconi et al., 2021). Community participation positively predicted better quality of life when a pool of active population in a socially cohesive environment was put under study by Chen and Zhang, (2021). When understanding the dynamics of natural and energy resources in smart cities, studies over the years show a significant correlation between economic growth and energy demand (see **B2-R3** in Figure 3) . A positive impact is observed on the variables ‘access to reliable energy resources’ due to the demand generated, which in turn affects the consumption of available resources. Excess consumption can result in depleting the current sources, that are the anticipated resources for future developments in cities (Kucukvar et al., 2016; Kucukvar et al., 2019). The natural and energy resource utilization dynamics is depicted in loops **B2** and **R3**. While, over resource consumption leads to resource depletion, an optimal amount to meet the increasing demand can also lead to emissions related to the use of resources (Abdella et al., 2020; Abdella et al., 2021). This can create a concern for the government to instill sustainable behavior in the consumption and resource utilization patterns for the economy to thrive. At the same time, if unattended, this can result in climatic changes that can alter the balance in the energy-climate nexus as in loop **R2** (Kucukvar et al., 2016; Kucukvar et al., 2018). Smart cities of today are power houses of greenhouse gas (GHG) emissions due to the increased energy consumption while assimilating data from sensors that run 24/7 to improve its core functions, including reducing the environmental impacts of our cities. An increase in urban population can actually create the possibility for a better quality life and a lower carbon footprint through more efficient infrastructure and planning (loop **R1**) (Spanos et al., 2021). An equitable balance needs to be maintained in terms of the resources available for consumption, as smart cities of today face numerous sustainability challenges along with climate change (Kucukvar et al., 2021). For the same, an 'institutional framework with sustainability mandate' is essential for transparent decision making in civil society, which prioritizes social welfare through strengthened cooperation incentives (see loop **R4**). Such frameworks hold potential in harnessing the growing power of "social mobilization", an important means to bring responsiveness and accountability when addressing people concern (loop **R5**).

4.4. Chapter synopsis

This chapter investigations the possible interactions in cities through the lens of sustainability, urban resilience, and liveability, for the causal feedback loop models proposed in Chapter 3, so as to broaden the concept of the existing smart cities to a sustainable, resilient, and livable dwelling unit. Possible elements of importance based on the extensive conceptualizations conducted have resulted in a base to understand the prime actors across the sustainability, resilience, and livability assessment models. These support in selecting possible indicators in the data collection process while implementing and validating the succeeding modules of the hybrid DSM and, thus the indicator system for the FSC index.

CHAPTER 5: A NOVEL DOUBLE-FRONTIER DATA ENVELOPMENT ANALYSIS-BASED SUSTAINABILITY ASSESSMENT

5.1. General outline

The urban revolution in smart cities needs to be backed by sustainability, since smart cities are the epicentre of untapped opportunities for the future generation. This chapter presents a numerical solution to the proposed Double Frontier (DF) Slacks-Based Measure (SBM) Data Envelopment Analysis (DEA) model, the module 2 in the hybrid decision support model, taking the case of 35 high-tech smart cities in Europe. A grouped performance assessment is then carried out using the quartile clustering technique to classify smart cities in accordance with their performance. A progressive productivity performance assessment is conducted using the novel double-frontier Malmquist productivity index backed by a comparative analysis from both the optimistic and pessimistic viewpoint. This chapter starts by presenting the significance of the research, highlighting the essentiality in conducting relative sustainability assessment in smart cities using non-parametric techniques and the true essence of the proposed model in light of sustainable development capacity assessment.

5.2. Significance and Objectives

At urban scale, functions and environments are more consistent, with input and output variables designed with the coverage of considerations of economic, environmental, and societal aspects (Kucukvar et al., 2021). Assessing the sustainability performance of smart cities is often crucial when planning development strategies. The insurmountable challenges of smart cities can reach better conclusions when assessed through the lens of sustainable development goals. For the same, several approaches are being used to understand the sustainable development capacity of smart cities. Till date, the literature contains two assessment techniques namely the parametric and non-parametric approach for the sustainability performance assessment, in general efficiency assessment. The frequently applied non-parametric linear programming-based performance assessment technique is the "Data Envelopment Analysis" (DEA). DEA is one of the mainstream methods for evaluating sustainability performance of cities; during the infancy of this method, the DEA method was considered suitable for studying economically complex cities, and it was also used to evaluate twenty-eight major cities in China by the pioneer of the method (Charnes et al., 1989). Zhu, (1996) built on this research and compared the results of the DEA method with those obtained using other contemporary methods and provided evidence for the effectiveness of this method. These studies were focused on evaluating the economic output of cities, and it was only later when the DEA method was used to evaluate the environment and sustainability of Chinese cities. Yuan et al., (2015) used the DEA method to study the ability of sixty-five cities to respond to natural disasters, while Yang et al., (2016) used this method to evaluate the sustainability of cities in Taiwan. However, no comprehensive assessment of the sustainable development ability of European smart cities has been performed. The reason for the low frequency of usage of the DEA method, as noted by Li et al. (2005), is the limited availability of statistical data at the city level. In reality, the DEA method is perfectly suitable for comprehensive evaluation of a city's efficiency, and several case studies that have already been performed abroad using this method (Honma and Hu, 2008; Storto, 2016). In addition to a comprehensive assessment, as noted by Mega (1996), an increasing number of researchers has regarded sustainability in cities as a process rather than as an endpoint.

The use of DEA to assess the sustainability of smart cities hold the ability to include multiple inputs and outputs without defining any functional forms to these input and output variables. These inputs and outputs can be both desirable and undesirable. Several approaches exist when dealing with undesirable factors in DEA (see Koopmans, 1951; Golany and Roll, 1989; Ali and Seiford 1990; Seiford & Zhu, 2002). Most tend to ignore these undesirable factors from the "production possibility set" (PPS), while others undergo treatment and case-dependent transformations. However, a true reflection of the production process is often lost when desirability is not accounted while calculating the relative performance. This is the case of many of the existing approaches in the literature. Furthermore, it is essential to understand the relative sustainability performance considering both the efficiency and anti-efficiency frontiers of decision-making units to arrive at better understanding while framing policies. Smart cities of today need to steer away from a capitalism-centric approach to a holistic approach, which encompasses environmental concerns, energy needs, standard of living and economic growth in order to ensure sustainable development. At present, the problem confronting the policy makers of all smart cities is on how to formulate a set of effective policies regarding the impacts of global warming potential on weather patterns, environmental protection, energy conservation, people-centric governance all in the pursuit of economic development. However, this involves a wide range of decision-support variables such as climate change adaption, geo-political stability, environmental and energy resource utilization, societal well-being concerns which significantly increases the complexity of policy making. Understanding the performance of cities based on these decision-support variables often tend to be from the optimistic point of view that inevitably ignores some extremely useful information compared to their performance measured from different points of view. This fails to cover the panoramic view of sustainable outcomes leading to hindering the policy making process in smart cities. Here lies the rationale in undertaking this research which intends to quantify the sustainability performance of smart cities from multiple points of view by using a double frontier non-parametric approach. To this end, this chapter, dedicated to module 2 of the proposed hybrid decision support model, the sustainability assessment module attempts to address the aforementioned concerns by accomplishing the following objectives namely;

a) Assess the overall sustainable development capacity of leading European smart cities using the proposed DF-SBM DEA model over time.
b) Understand the grouped sustainability performance of smart cities under the double-frontier approach to identify the best and worst performing smart city in terms of sustainable development in Europe.
c) Evaluate the change in productivity and sustainable capacity over time using an aggregate-DF-Malmquist productivity index (MPI) based DEA model from pessimistic, optimistic, and double-frontier perspective.

5.3. Numerical solution

5.3.1. Research Data and description

Despite the pervasive use of technology, the steep growth in urban population and the subsequent increase in resource consumption has inevitably created numerous challenges for smart cities. This fact highlights the importance of shifting paradigms in the way cities work in terms of sustainability. For the purpose of the present study, it is important to establish a working definition of sustainability in the context of smart cities. Allen and Hoekstra (1993) highlight the importance of establishing the scale on which a system is being assessed in terms of its progress towards sustainability. Achieving sustainability on a global scale requires different type of actions than on a city level. There is no single best-established definition in terms of sustainability in the regional scale nevertheless there is a commonly-used set of characteristics of urban sustainability (Kutty and Abdella, 2020; Abdella et al., 2021). These include intergenerational equity, intra-generational equity (social, geographical, and governance and institutional equity), conservation of the natural and built environment, significant reduction of the use of non-renewable energy and resources, climate change, economic vitality and diversity, autonomy in communities, citizen well-being, gratification of fundamental human needs and secure living (Maclaren, 1996). For the context of this research an urban space can be sustainable when adaption to climatic changes, social equity, conservation of the natural environment and energy resources, economic dynamism, Social cohesion and solidarity, and quality of life are achieved. Urban sustainability appears to be one of the prevailing themes in smart city literature, but to what extent is the concept embedded in the understanding of smart cities and how comprehensively is it addressed, is what this study investigates. Thus, to better understand on whether smart cities address sustainability and principles of sustainable urban development? the proposed desirability inclusive DF-SBM DEA approach is used to study the performance of 35 leading European smart cities over time from 2015 till 2020. The smart cities were selected based on the ranks assigned to these cities by the Smart City Index 2020, categorizing them as the top ranked smart cities in Europe. The rationale behind selecting top ranked smart cities is to capture better the idea of whether these tech-driven cities that promise sustainability and smartness are truly sustainable or not. In addition, the European smart cities cover nearly 3/4th of the list of major smart cities in the world with 28 European cities included in the top 50 global smart cities. It is well evident that the sample size is large enough for the results to be extrapolated to a global level in terms of the sustainability performance of smart cities. A comprehensive assessment is carried out using 50 sustainability input-output indicators under 6 dimensions of sustainable urban development, based on the proposed working definition of sustainability, namely; Energy and Environmental Resources (ER), Governance and Institution (GI), Economic dynamism (E), Social cohesion and solidarity (SC), Climate Change (CC) and, Safety and Security (SS). For this purpose, this paper uses the longitudinal time-series data extracted from the European data portal (https://data.europa.eu/en) and EU city data statistics from 2015-2020. The indicators under each dimension are aligned to the 17 SDGs. The indicators were then categorized according to their desirability to be increased or decreased simultaneously based on managerial and computational reasoning. To understand better on preparing data for DEA assessment see Sarkis, (2007). Some selected set of input indicators were maximized (undesirable) along with simultaneously decreasing the desirable inputs and, some output indicators were minimized (undesirable) with maximum value outputs included. The input-output indicators used for the sustainability performance assessment under all the six dimensions of sustainable urban development can be seen in Table B3 (Appendix B). The selection of input and output indicators based on the number of smart cities chosen for the study satisfied by the Eq. (96).

$$n \geq \max\{(m+p)*(s+t), 3[(m+p) + (s+t)]\} \tag{96}$$

Where $\boldsymbol{n}$ is the number of smart cities, $\boldsymbol{m}$ is the number of desirable inputs, $\boldsymbol{p}$ is the number of undesirable inputs, $\boldsymbol{s}$ is the number of desirable outputs and $\boldsymbol{t}$ is the number of undesirable outputs.

5.3.2. Sustainable development capacity assessment

This section evaluates and presents the sustainability performance of the 35 smart cities from the optimistic, pessimistic, and aggregate double frontier perspectives. According to the results in Table 7, under the climate change dimension, it is evident that the smart cities, namely Brussels, Copenhagen, Tallinn, Dublin, Athens, Lyon, Dusseldorf, Hamburg, Merseille, Geneva, Manchester, Amsterdam, Vienna, Lisbon, Helsinki, Stockholm, Oslo, and Zurich are optimistic-efficient ($\eta_{optimistic}$ = 1.00) based on model (8). These smart cities all-together make the efficiency frontier. All the other smart cities considered in the study are optimistic non-efficient ($\eta_{optimistic}$ < 1.000) under the climate change dimension. It is found that Kyiv, with an efficiency score, $\eta_{optimistic}$ = 0.5022 is the most optimistic non-efficient smart city for all the inputs and outputs considered for the study under the climate change dimension. Considering the pessimistic viewpoint, it is identified that Bilbao, Bologna, Warsaw, Bratislava, Zaragoza, Kyiv, and Ankara are pessimistic inefficient with $\eta_{pessimistic}$ = 1.000. The other smart cities ($\eta_{pessimistic}$ < 1.000) are less worse performing under the climate change dimension than the DEA-inefficient smart cities. Similarly, Zurich with $\eta_{pessimistic}$ = 0.1044 is the least worst performing (pessimistic non-inefficient) smart city in Europe in terms of climate change and mitigation strategies. Contrastingly, under the integrated DF DEA-model, when observing the interval efficiencies, it is seen that Geneva is the most sustainably performing smart city under the climate change dimension. Without no surprise, Lyon, Vienna, and Bologna backs the 1st, 2nd, and 3rd runner up positions in addressing climate change concerns under the bounded model. It is evident from the interval efficiency scores [0.2362, 0.5022] and an $m(A_i)$ value of 0.3692 that, Kyiv is the least relatively sustainable smart city under the climate change dimension over time from 2015 till

2020. However, while measuring the best relative-efficiency for all the 35 European smart cities under the “Governance and institution” dimension (see Table 8), it is found that Brussels, Dusseldorf, Manchester, Helsinki, Stockholm, Oslo, and Zurich have retained their position of being on the top list as in the climate change dimension ($\eta_{pessimistic}$ = 1.000). The smart cities namely, St. Petersburg, Bucharest, Krakow, and London were new add-ons to the list of the best relatively efficient smart cities under the “Governance and Institution” dimension. Nevertheless, Prague with an efficiency score of $\eta_{optimistic}$ = 0.2090 was the most optimistic non-efficient smart city under this dimension. When analyzing from the pessimistic viewpoint under the Governance and Institution dimension, it can be noticed that 6 smart cities, i.e., Sofia, Prague, Munich, Tallinn, Lisbon, and Kyiv are pessimistic inefficient with worse performance ($\eta_{pessimistic}$ = 1.000). It is seen that Manchester with $\eta_{pessimistic}$ = 0.1583 is the least DEA-non-inefficient smart city when compared to all the other worst performing smart cities. Oslo with an interval efficiency of [0.1026, 1.0000] followed by London (η bounded = [0.1020, 1.0000]; Rank 2) and Stockholm (η bounded = [0.0920, 1.0000]; Rank 3) are the best performing smart cities in Europe under the dimension “governance and institution” from the bounded DEA perspective.

Similarly, when comparing the efficiency scores from the optimistic and pessimistic perspective, it can be found that under the dimension “economic dynamism,” smart cities namely, Sofia, Athens, Geneva, Manchester, and Zurich are optimistic efficient (see Table 9). While Brussels, Tallinn, Bologna, Kyiv, and Ankara are pessimistic inefficient smart cities with $\eta_{pessimistic}$ = 1.000. Kyiv with an efficiency score, $\eta_{optimistic}$ = 0.2380 is the most optimistic non-efficient smart city when compared with its peers. On the contrary, Sofia with $\eta_{pessimistic}$ = 0.1522 has the least relative pessimistic performance under “economic dynamism.” Under the bounded model for aggregate sustainability performance measurement, Oslo ranks 1st with an η bounded interval value [0.1491, 0.9910]. While Kyiv ranks as the least sustainable smart city under the economic dynamism dimension with a bounded interval score [0.1846, 0.2380].

Table 7. Sustainability performance, efficiency scores and relative ranks for the 35 European smart cities from 2015-2020 under the climate change dimension

Smart cities	SBM Optimistic		SBM Pessimistic		DF-SBM Bounded η	
	$\eta_{optimistic}$	Rank	$\eta_{pessimistic}$	Rank	$[\alpha_1\eta_{pessimistic}^{*}, \theta_j^{*}]$	Rank
Brussels	1.0000	1	0.6697	20	[0.1582, 1.0000]	7
Sofia	0.7923	27	0.3808	10	[0.0899, 0.7923]	32
Prague	0.7991	26	0.5331	15	[0.1259, 0.7991]	28
Copenhagen	1.0000	1	0.2876	5	[0.0679, 1.0000]	18
Munich	0.9570	20	0.4264	13	[0.1007, 0.9570]	20
Tallinn	1.0000	1	0.7377	24	[0.1742, 1.0000]	5
Dublin	1.0000	1	0.5036	14	[0.1189, 1.0000]	11
Athens	1.0000	1	0.3219	7	[0.0760, 1.0000]	16
Bilbao	0.7660	30	1.0000	35	[0.2362, 0.7660]	25
Lyon	1.0000	1	0.9112	27	[0.2152, 1.0000]	2
Dusseldorf	1.0000	1	0.6680	19	[0.1578, 1.0000]	8
Bologna	0.9493	21	1.0000	35	[0.2362, 0.9493]	4
Hamburg	1.0000	1	0.6778	21	[0.1601, 1.0000]	6
St. Petersburg	0.8390	25	0.7132	22	[0.1685, 0.8390]	24
Marseille	1.0000	1	0.4211	12	[0.0995, 1.0000]	12
Geneva	1.0000	1	0.9359	28	[0.2211, 1.0000]	1
Budapest	0.7782	29	0.5740	17	[0.1356, 0.7782]	29
Manchester	1.0000	1	0.3811	11	[0.0900, 1.0000]	13
Amsterdam	1.0000	1	0.5955	18	[0.1407, 1.0000]	9
Vienna	1.0000	1	0.8443	26	[0.1994, 1.0000]	3
Warsaw	0.8492	24	1.0000	35	[0.2362, 0.8492]	14
Lisbon	1.0000	1	0.2627	3	[0.0620, 1.0000]	19
Bucharest	0.9645	19	0.7298	23	[0.1724, 0.9645]	10
Krakow	0.7900	28	0.8100	25	[0.1913, 0.7900]	26
Bratislava	0.7156	31	1.0000	35	[0.2362, 0.7156]	27
Helsinki	1.0000	1	0.3036	6	[0.0717, 1.0000]	17
Stockholm	1.0000	1	0.3526	9	[0.0833, 1.0000]	15
London	0.8500	23	0.2661	4	[0.0629, 0.8500]	30
Zaragoza	0.6094	34	1.0000	35	[0.2362, 0.6094]	33
Oslo	1.0000	1	0.1938	2	[0.0458, 1.0000]	21
Zurich	1.0000	1	0.1044	1	[0.0247, 1.0000]	22
Moscow	0.6836	32	0.3482	8	[0.0822, 0.6836]	34
Kiev	0.5022	35	1.0000	35	[0.2362, 0.5022]	35
Rome	0.8913	22	0.5565	16	[0.1314, 0.8913]	23
Ankara	0.6617	33	1.0000	35	[0.2362, 0.6617]	31

φ_{vj}^{*}: 2.1262, θ_j^{*} : 0.5022, α_1 : 0.2362

Table 8. Sustainability performance, efficiency scores and relative ranks for 35 smart cities from 2015-2020 under the Governance and institution dimension

Smart cities	SBM Optimistic		SBM Pessimistic		DF-SBM Bounded η	
	$\eta_{optimistic}$	Rank	$\eta_{pessimistic}$	Rank	$[\alpha_2\eta_{pessimistic}^*, \theta_j^*]$	Rank
Brussels	1.0000	1	0.4079	11	[0.0591, 1.0000]	6
Sofia	0.4420	33	1.0000	35	[0.1449, 0.4420]	31
Prague	0.2090	35	1.0000	35	[0.1449, 0.2090]	35
Copenhagen	0.7130	19	0.6749	26	[0.0978, 0.7130]	18
Munich	0.4590	32	1.0000	35	[0.1449, 0.4590]	30
Tallinn	0.5490	29	1.0000	35	[0.1449, 0.5490]	25
Dublin	0.8840	15	0.4762	17	[0.0690, 0.8840]	15
Athens	0.9010	14	0.3837	10	[0.0556, 0.9010]	14
Bilbao	0.4980	31	0.2041	3	[0.0296, 0.4980]	34
Lyon	0.5780	26	0.4323	13	[0.0627, 0.5780]	28
Dusseldorf	1.0000	1	0.3043	8	[0.0441, 1.0000]	8
Bologna	0.7270	18	0.6715	25	[0.0973, 0.7270]	17
Hamburg	0.9550	13	0.3288	9	[0.0477, 0.9550]	13
St. Petersburg	1.0000	1	0.4123	12	[0.0598, 1.0000]	5
Marseille	0.5960	24	0.4956	18	[0.0718, 0.5960]	27
Geneva	0.6230	22	0.5718	21	[0.0829, 0.6230]	22
Budapest	0.6000	23	0.5784	22	[0.0838, 0.6000]	26
Manchester	1.0000	1	0.1583	1	[0.0229, 1.0000]	12
Amsterdam	0.8260	16	0.2669	6	[0.0387, 0.8260]	16
Vienna	0.5110	30	0.5065	19	[0.0734, 0.5110]	32
Warsaw	0.7420	17	0.2964	7	[0.0430, 0.7420]	19
Lisbon	0.5530	28	1.0000	35	[0.1449, 0.5530]	23
Bucharest	1.0000	1	0.2198	5	[0.0319, 1.0000]	9
Krakow	1.0000	1	0.1794	2	[0.0260, 1.0000]	11
Bratislava	0.9730	12	0.5466	20	[0.0792, 0.9730]	7
Helsinki	1.0000	1	0.5938	23	[0.0861, 1.0000]	4
Stockholm	1.0000	1	0.6345	24	[0.0920, 1.0000]	3
London	1.0000	1	0.7034	28	[0.1020, 1.0000]	2
Zaragoza	0.6620	21	0.4541	14	[0.0658, 0.6620]	21
Oslo	1.0000	1	0.7080	29	[0.1026, 1.0000]	1
Zurich	1.0000	1	0.2111	4	[0.0306, 1.0000]	10
Moscow	0.5540	27	0.4688	15	[0.0680, 0.5540]	29
Kiev	0.3910	34	1.0000	35	[0.1449, 0.3910]	33
Rome	0.6760	20	0.4711	16	[0.0683, 0.6760]	20
Ankara	0.5940	25	0.7008	27	[0.1016, 0.5940]	24

φ_{vj}^*: 1.4419, θ_j^* : 0.2090, α_2 : 0.14495

Table 9. Sustainability performance, efficiency scores and relative ranks for the 35 European smart cities from 2015-2020 under the dimension economic dynamism

Smart cities	SBM Optimistic		SBM Pessimistic		DF-SBM Bounded η	
	$\eta_{optimistic}$	Rank	$\eta_{pessimistic}$	Rank	$[\alpha_3\eta_{pessimistic}{}^{*}, \theta_j^{*}]$	Rank
Brussels	0.570	32	1.0000	35	[0.1846, 0.5700]	27
Sofia	1.000	1	0.1522	1	[0.0281, 1.0000]	12
Prague	0.544	33	0.4378	5	[0.0808, 0.5440]	34
Copenhagen	0.651	19	0.5817	11	[0.1074, 0.6510]	24
Munich	0.651	19	0.3661	3	[0.0676, 0.6510]	31
Tallinn	0.571	31	1.0000	35	[0.1846, 0.5710]	26
Dublin	0.961	9	0.8694	28	[0.1605, 0.9610]	3
Athens	1.000	1	0.6065	13	[0.1119, 1.0000]	4
Bilbao	0.606	25	0.4898	6	[0.0904, 0.6060]	32
Lyon	0.775	16	0.6996	20	[0.1291, 0.7750]	16
Dusseldorf	0.903	13	0.3882	4	[0.0716, 0.9030]	13
Bologna	0.591	29	1.0000	35	[0.1846, 0.5910]	22
Hamburg	0.850	14	0.5139	8	[0.0948, 0.8500]	14
St. Petersburg	0.932	10	0.6860	18	[0.1266, 0.9320]	9
Marseille	0.838	15	0.4918	7	[0.0908, 0.8380]	15
Geneva	1.000	1	0.2062	2	[0.0381, 1.0000]	10
Budapest	0.909	12	0.6524	16	[0.1204, 0.9090]	11
Manchester	1.000	1	0.5341	10	[0.0986, 1.0000]	6
Amsterdam	0.596	28	0.9787	29	[0.1806, 0.5960]	21
Vienna	0.530	34	0.6708	17	[0.1238, 0.5300]	33
Warsaw	0.639	22	0.5909	12	[0.1091, 0.6390]	28
Lisbon	0.703	17	0.6393	15	[0.1180, 0.7030]	17
Bucharest	0.625	23	0.5229	9	[0.0965, 0.6250]	30
Krakow	0.929	11	0.8467	27	[0.1563, 0.9290]	8
Bratislava	0.672	18	0.7014	21	[0.1295, 0.6720]	20
Helsinki	0.598	27	0.7561	23	[0.1396, 0.5980]	29
Stockholm	0.579	30	0.9886	30	[0.1825, 0.5790]	23
London	0.605	26	0.8284	25	[0.1529, 0.6050]	25
Zaragoza	0.651	19	0.8433	26	[0.1556, 0.6510]	19
Oslo	0.991	6	0.8081	24	[0.1491, 0.9910]	1
Zurich	1.000	1	0.7455	22	[0.1376, 1.0000]	2
Moscow	0.984	7	0.6118	14	[0.1129, 0.9840]	7
Kiev	0.238	35	1.0000	35	[0.1846, 0.2380]	35
Rome	0.980	8	0.6949	19	[0.1283, 0.9800]	5
Ankara	0.625	23	1.0000	35	[0.1846, 0.6250]	18

φ_{vj}^{*}: 1.2895, θ_j^{*} : 0.2380, α_3 : 0.18457

Table 10. Sustainability performance, efficiency scores and relative ranks for 35 smart cities from 2015-2020 under the energy and environmental resource dimension

Smart cities	SBM Optimistic		SBM Pessimistic		DF-SBM Bounded η	
	$\eta_{optimistic}$	Rank	$\eta_{pessimistic}$	Rank	$[\alpha_4\eta_{pessimistic}{}^*, \theta_j{}^*]$	Rank
Brussels	0.5507	25	0.3731	8	[0.0724, 0.5507]	26
Sofia	0.4154	33	0.3411	7	[0.0662, 0.4154]	34
Prague	0.3995	34	1.0000	35	[0.1939, 0.3995]	29
Copenhagen	1.0000	1	0.8603	26	[0.1668, 1.0000]	7
Munich	1.0000	1	0.9104	29	[0.1766, 1.0000]	4
Tallinn	0.3844	35	1.0000	35	[0.1939, 0.3844]	32
Dublin	1.0000	1	0.9065	28	[0.1758, 1.0000]	5
Athens	0.4178	32	0.2209	5	[0.0428, 0.4178]	35
Bilbao	0.4829	30	0.3807	9	[0.0738, 0.4829]	33
Lyon	0.7190	17	0.6413	20	[0.1244, 0.7190]	17
Dusseldorf	0.7779	14	0.6568	21	[0.1274, 0.7779]	14
Bologna	1.0000	1	0.1995	4	[0.0387, 1.0000]	10
Hamburg	0.7587	15	0.6318	18	[0.1225, 0.7587]	16
St. Petersburg	1.0000	1	0.1988	3	[0.0386, 1.0000]	11
Marseille	0.6370	21	0.5493	17	[0.1065, 0.6370]	21
Geneva	1.0000	1	0.9788	32	[0.1898, 1.0000]	1
Budapest	0.6118	23	0.4477	13	[0.0868, 0.6118]	24
Manchester	1.0000	1	0.1294	2	[0.0251, 1.0000]	12
Amsterdam	0.6494	20	0.7427	24	[0.1440, 0.6494]	18
Vienna	1.0000	1	0.9646	31	[0.1871, 1.0000]	2
Warsaw	0.5088	29	0.3931	10	[0.0762, 0.5088]	31
Lisbon	0.4686	31	1.0000	35	[0.1939, 0.4686]	25
Bucharest	0.5220	28	0.4755	15	[0.0922, 0.5220]	28
Krakow	0.5305	27	0.4516	14	[0.0876, 0.5305]	27
Bratislava	0.6674	18	0.4130	11	[0.0801, 0.6674]	20
Helsinki	1.0000	1	0.9206	30	[0.1785, 1.0000]	3
Stockholm	0.6589	19	0.6373	19	[0.1236, 0.6589]	19
London	1.0000	1	0.8005	25	[0.1552, 1.0000]	8
Zaragoza	1.0000	1	0.6969	22	[0.1352, 1.0000]	9
Oslo	1.0000	1	0.9033	27	[0.1752, 1.0000]	6
Zurich	0.7507	16	0.7265	23	[0.1409, 0.7507]	15
Moscow	1.0000	1	0.1099	1	[0.0213, 1.0000]	13
Kiev	0.6326	22	0.4328	12	[0.0839, 0.6326]	22
Rome	0.6033	24	0.5368	16	[0.1041, 0.6033]	23
Ankara	0.5427	26	0.2605	6	[0.0505, 0.5427]	30

$\varphi_{vj}{}^*$: 1.9821, $\theta_j{}^*$: 0.3844, α_4 : 0.19394

Table 11. Sustainability performance, efficiency scores and relative ranks for the 35 European smart cities from 2015-2020 under the safety and security dimension

Smart cities	SBM Optimistic		SBM Pessimistic		DF-SBM Bounded η	
	$\eta_{optimistic}$	Rank	$\eta_{pessimistic}$	Rank	$[\alpha_5\eta_{pessimistic}{}^*, \theta_j{}^*]$	Rank
Brussels	0.7277	29	0.4864	23	[0.1524, 0.7277]	6
Sofia	1.0000	14	0.1939	7	[0.0607, 1.0000]	17
Prague	1.0000	1	0.2308	13	[0.0723, 1.0000]	22
Copenhagen	0.7371	28	0.2266	10	[0.0710, 0.7371]	4
Munich	0.6227	34	0.1208	4	[0.0378, 0.6227]	1
Tallinn	1.0000	1	0.2219	9	[0.0695, 1.0000]	19
Dublin	0.7979	25	0.4897	24	[0.1534, 0.7979]	8
Athens	0.8854	22	0.7058	27	[0.2211, 0.8854]	28
Bilbao	0.6808	31	1.0000	35	[0.3133, 0.6808]	11
Lyon	0.9999	16	0.2996	17	[0.0939, 0.9999]	24
Dusseldorf	1.0000	1	0.1849	6	[0.0579, 1.0000]	16
Bologna	0.7837	26	1.0000	35	[0.3133, 0.7837]	26
Hamburg	1.0000	1	0.1066	2	[0.0334, 1.0000]	13
St. Petersburg	1.0000	1	0.2508	14	[0.0786, 1.0000]	23
Marseille	1.0000	1	0.2303	12	[0.0722, 1.0000]	21
Geneva	0.8937	21	0.7155	28	[0.2242, 0.8937]	29
Budapest	0.9793	17	0.7278	29	[0.2280, 0.9793]	34
Manchester	1.0000	15	0.2996	17	[0.0939, 1.0000]	25
Amsterdam	0.6874	30	0.0983	1	[0.0308, 0.6874]	2
Vienna	0.7480	27	0.2512	15	[0.0787, 0.7480]	5
Warsaw	1.0000	1	0.1114	3	[0.0349, 1.0000]	14
Lisbon	0.7979	24	0.5291	25	[0.1658, 0.7979]	10
Bucharest	1.0000	1	0.3206	19	[0.1004, 1.0000]	27
Krakow	0.8694	23	0.4493	22	[0.1408, 0.8694]	12
Bratislava	1.0000	1	0.3939	20	[0.1234, 1.0000]	30
Helsinki	1.0000	1	0.1366	5	[0.0428, 1.0000]	15
Stockholm	0.6728	32	0.2783	16	[0.0872, 0.6728]	3
London	0.5876	35	1.0000	35	[0.3133, 0.5876]	7
Zaragoza	1.0000	1	0.2302	11	[0.0721, 1.0000]	20
Oslo	0.9197	20	0.6623	26	[0.2075, 0.9197]	31
Zurich	0.6469	33	1.0000	35	[0.3133, 0.6469]	9
Moscow	1.0000	1	0.2016	8	[0.0632, 1.0000]	18
Kiev	0.9785	18	0.7439	30	[0.2331, 0.9785]	35
Rome	0.9591	19	0.7628	31	[0.2390, 0.9591]	33
Ankara	1.0000	1	0.4403	21	[0.1379, 1.0000]	32

$\varphi_{vj}{}^*$: 1.8755, $\theta_j{}^*$: 0.5876, α_5 : 0.3133

Table 12. Sustainability performance, efficiency scores and relative ranks for the smart cities from 2015-2020 under the social cohesion and solidarity dimension

Smart cities	SBM Optimistic		SBM Pessimistic		DF-SBM Bounded η	
	$\eta_{optimistic}$	Rank	$\eta_{pessimistic}$	Rank	$[\alpha_6\eta_{pessimistic}{}^*, \theta_j{}^*]$	Rank
Brussels	1.0000	1	0.2203	8	[0.0168, 1.0000]	13
Sofia	0.5695	33	1.0000	35	[0.0761, 0.5695]	33
Prague	1.0000	1	0.3087	12	[0.0235, 1.0000]	9
Copenhagen	0.7958	26	0.6258	18	[0.0477, 0.7958]	26
Munich	1.0000	1	0.8183	27	[0.0623, 1.0000]	3
Tallinn	0.8119	23	0.6704	21	[0.0510, 0.8119]	23
Dublin	1.0000	1	0.2022	7	[0.0154, 1.0000]	14
Athens	0.8742	21	0.7332	26	[0.0558, 0.8742]	21
Bilbao	1.0000	1	0.2394	9	[0.0182, 1.0000]	12
Lyon	0.8054	25	0.6304	19	[0.0480, 0.8054]	25
Dusseldorf	1.0000	1	0.1098	3	[0.0084, 1.0000]	18
Bologna	1.0000	1	0.1997	6	[0.0152, 1.0000]	15
Hamburg	1.0000	1	0.1897	4	[0.0144, 1.0000]	17
St. Petersburg	1.0000	1	0.2988	11	[0.0228, 1.0000]	10
Marseille	1.0000	1	0.2969	10	[0.0226, 1.0000]	11
Geneva	1.0000	1	0.6211	17	[0.0473, 1.0000]	6
Budapest	0.7031	28	0.6878	23	[0.0524, 0.7031]	29
Manchester	1.0000	1	0.5199	15	[0.0396, 1.0000]	7
Amsterdam	1.0000	1	0.9801	29	[0.0746, 1.0000]	1
Vienna	0.8054	24	0.6651	20	[0.0506, 0.8054]	24
Warsaw	0.7901	27	0.6833	22	[0.0520, 0.7901]	27
Lisbon	1.0000	1	0.3443	13	[0.0262, 1.0000]	8
Bucharest	0.5883	32	1.0000	35	[0.0761, 0.5883]	32
Krakow	0.5602	34	1.0000	35	[0.0761, 0.5602]	34
Bratislava	0.6946	29	0.4195	14	[0.0319, 0.6946]	31
Helsinki	1.0000	1	0.7205	25	[0.0549, 1.0000]	4
Stockholm	0.8327	22	0.6130	16	[0.0467, 0.8327]	22
London	1.0000	1	0.0492	2	[0.0037, 1.0000]	19
Zaragoza	1.0000	1	0.1903	5	[0.0145, 1.0000]	16
Oslo	1.0000	1	0.9399	28	[0.0716, 1.0000]	2
Zurich	1.0000	1	0.7121	24	[0.0542, 1.0000]	5
Moscow	0.6602	31	1.0000	35	[0.0761, 0.6602]	30
Kiev	0.2034	35	1.0000	35	[0.0761, 0.2034]	35
Rome	1.0000	1	0.0113	1	[0.0009, 1.0000]	20
Ankara	0.6811	30	1.0000	35	[0.0761, 0.6811]	28

$\varphi_{vj}{}^*$: 2.6712, $\theta_j{}^*$: 0.2034, α_6 : 0.07615

When considering smart cities under the dimension "energy and environmental resource" for the optimistic scenario, we can see that Copenhagen, Munich, Dublin, Bologna, St. Petersburg, Geneva, Manchester, Vienna, Helsinki, London, Zaragoza, Oslo, and Moscow perform relatively efficient with a score $\eta_{optimistic} = 1.00$. While Tallinn ($\eta_{optimistic} = 0.238$) is the most optimistic non-efficient smart city under the respective dimension. On the other hand, Moscow with $\eta_{pessimistic} = 0.1099$ lies farthest away from the anti-efficiency frontier. Smart cities like Prague, Tallinn and Lisbon lies on the anti-efficient frontier, thus branded as the "anti-ideal" smart city with relatively worst efficiency performance (Table 10). While, considering the bounded sustainability performance under the double frontier approach; Geneva, Vienna and Helsinki rank 1st, 2nd, and 3rd respectively in terms of its performance under the energy and environmental resource dimension across the years from 2015 till 2020. It is seen those smart cities namely, Bilbao, Sofia and Athens perform relatively worse under the aggregated performance with ranks 33, 34 and 35 among all the European smart cities.

Based on the set of input and output indicators chosen under the "safety and security" dimension (Table 11), it is found that the cities that show relatively best performance under the optimistic scenario are namely, Sofia, Prague, Tallinn, Dusseldorf, Hamburg, St. Petersburg, Merseille, Manchester, Warsaw, Bucharest, Bratislava, Helsinki, Zaragoza, Moscow, and Ankara. It is noticed that Amsterdam is pessimistically non-inefficient ($\eta_{pessimistic} = 0.0983$); while Bilbao, Bologna, London, and Zurich are pessimistic inefficient smart cities with a score $\eta_{pessimistic} = 1.000$. However, the results from the aggregate performance ranks Munich, Amsterdam and Stockholm as 1st, 2nd and 3rd best smart city that is safe and secure for the citizens and tourists visiting them. While smart cities namely, Rome (rank: 33), Budapest (rank:

34) and Kyiv (rank: 35) are ranked as the least sustainably performing smart city from the "safety and security" perspective. Under the "society and well-being" dimension (Table 12), it is found that Sofia, Copenhagen, Tallinn, Athens, Lyon, Budapest, Vienna, Warsaw, Bucharest, Bratislava, Krakow, Stockholm, Moscow, Kyiv, and Ankara are optimistic non-efficient smart cities. These smart cities lie outside the efficiency frontier ($\eta_{pessimistic} < 1.000$). While, among all the optimistic non-efficient smart cities, Kyiv with an $\eta_{optimistic} = 0.2034$ performs as the most inefficient smart city under the optimistic scenario. The double frontier bounded model for aggregate performance assessment reveals, Amsterdam (η bounded = [0.0746, 1.0000]; Rank 1), Oslo (η bounded = [0.0716, 1.0000]; Rank 2) and Munich (η bounded = [0.0623, 1.0000]; Rank 3), as the best performing smart cities. On the other hand, Kyiv, Krakow, and Sofia ranks 35th, 34th and 33rd with bounded DEA scores [0.0761, 0.2034], [0.0761, 0.5602] and [0.0761, 0.5695] respectively.

5.3.3. Sustainability performance clustering

This section uses the Quartile clustering method to group the efficiency scores for each smart city under all the 6 dimensions of sustainable development depending on their performance. The method partitions the data set into 4 equal clusters (groups), where each cluster has 25% of the data. The semantics for each group is represented on a scale from High to Low sustainability performance (SP). Performance grouping helps in understanding the impact of having certain undesirable parameters in the production set on the total sustainability performance. Once the data set is divided into 4 equal intervals, each smart city is placed in appropriate quartile based on their efficiency scores to better understand the standing of each smart city relative to one another under respective viewpoints namely; optimistic, pessimistic, and aggregate double frontier perspective.

Figure 9 shows the group-based sustainability performance along with their respective ranks for each smart city under the optimistic scenario. To better visualize the sustainability performance, conditional formatting is used to assign position-dependent color gradience to each cluster relative to the smart city performance. Manchester ranks No.1 as the relatively best performing smart city in terms of sustainable development among all the 35 leading European smart cities under the optimistic scenario. Oslo, St. Petersburg, and Dusseldorf backed the 1st, 2nd and 3rd runner up positions falling under the high sustainability performance cluster. It is seen that Kyiv is the most under-performing smart city in terms of addressing sustainable development from the optimistic viewpoint, falling under the Low SP cluster. Smart cities namely; Brussels, Amsterdam, Stockholm, Bratislava, Bucharest, Munich, Krakow, Vienna, and Budapest show a medium-to-low SP.

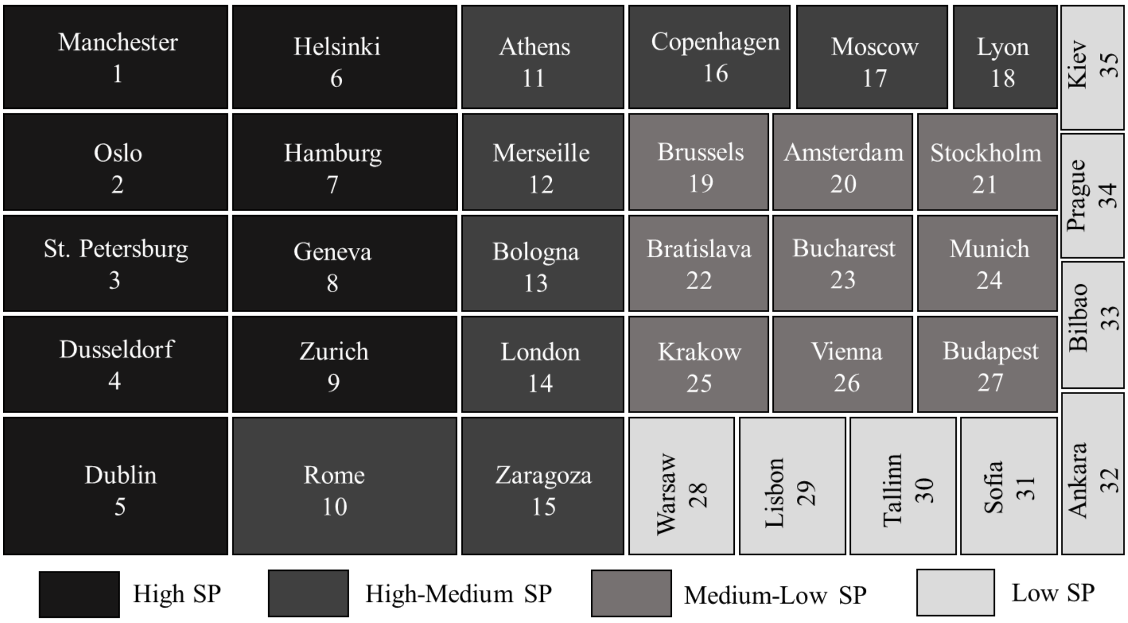


Figure 9. Grouped optimistic sustainability performance of smart cities

Figure 10 reveals Kyiv, Tallinn, Ankara, Oslo, Bologna, Geneva, Vienna, Lisbon, and Krakow as pessimistic inefficient smart cities with a relatively low sustainability performance from the pessimistic viewpoint. Oslo, Dublin, Geneva, and

Zurich which were grouped under the High SP category from the optimistic viewpoint were replaced by Rome, Moscow, Merseille and Athens in the High SP category under the pessimistic viewpoint. These smart cities show less relatively worse performance or better termed less pessimistic non-inefficiency when compared to its peers in other clusters. It is seen that Manchester is ranked 35th under the High SP cluster and Kyiv ranked 1st, falling under the Low SP cluster under the pessimistic scenario.

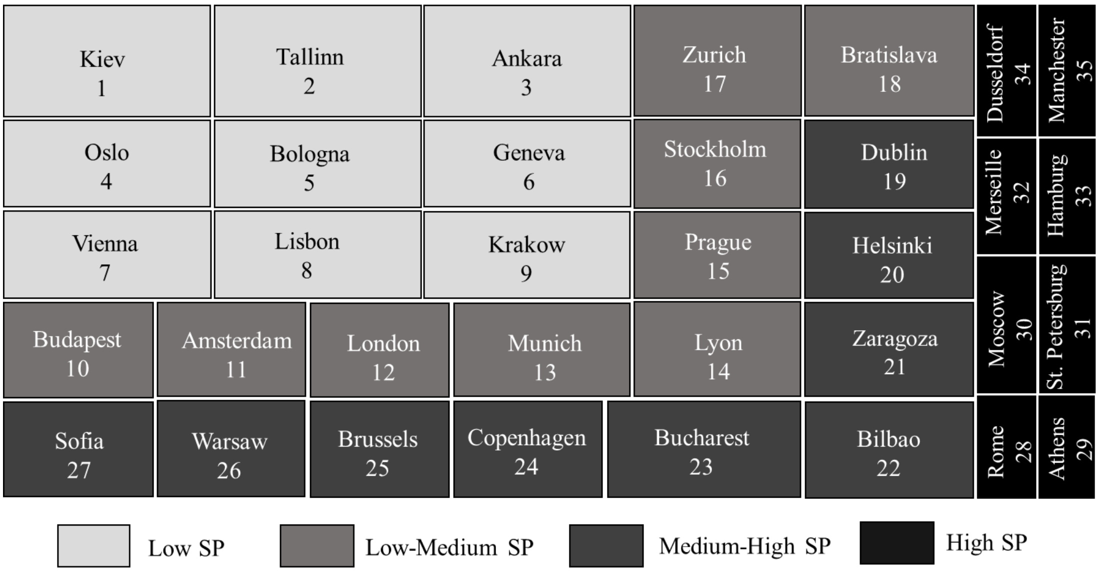


Figure 10. Grouped sustainability performance under the pessimistic scenario

Figure 11 shows the performance grouping of smart cities from High SP to Low SP under the double frontier approach. Kyiv remains the least sustainably performing smart city under all the viewpoints including the double frontier point of view (Fig. 4). It is seen that Dublin (ranked 1st) is the most smart and sustainable European city under all the dimensions of sustainable development. Along with Dublin in the High SP cluster lies Oslo, Zurich, Amsterdam, Geneva, Helsinki, Manchester, Dusseldorf, and Hamburg. St. Petersburg that made itself into the High SP cluster under both the optimistic and pessimistic viewpoint is grouped under the

High-Medium SP cluster under the DF scenario. It is surprising to see the position of Amsterdam pushed to the High SP cluster under the DF approach from the Medium-Low SP/Low-Medium SP cluster under the optimistic and pessimistic viewpoint, respectively. Kyiv, Ankara, Sofia, and Prague that were grouped under the Low SP cluster from the optimistic point of view remained within the Low SP cluster under the aggregate DF scenario along with Budapest, Bilbao, Bucharest, and Bratislava.

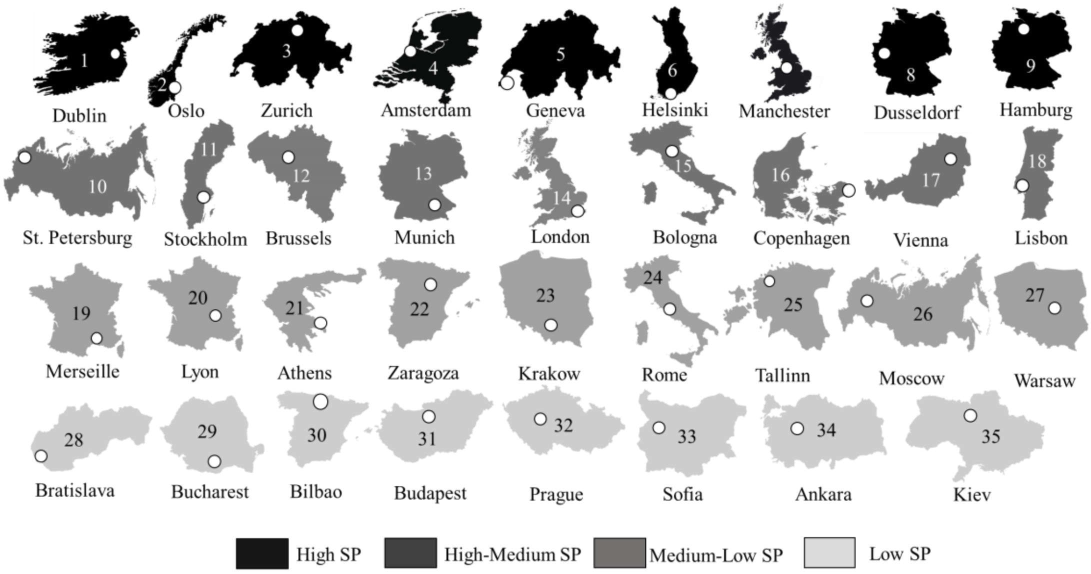


Figure 11. Grouped sustainability performance of smart cities under the DF approach

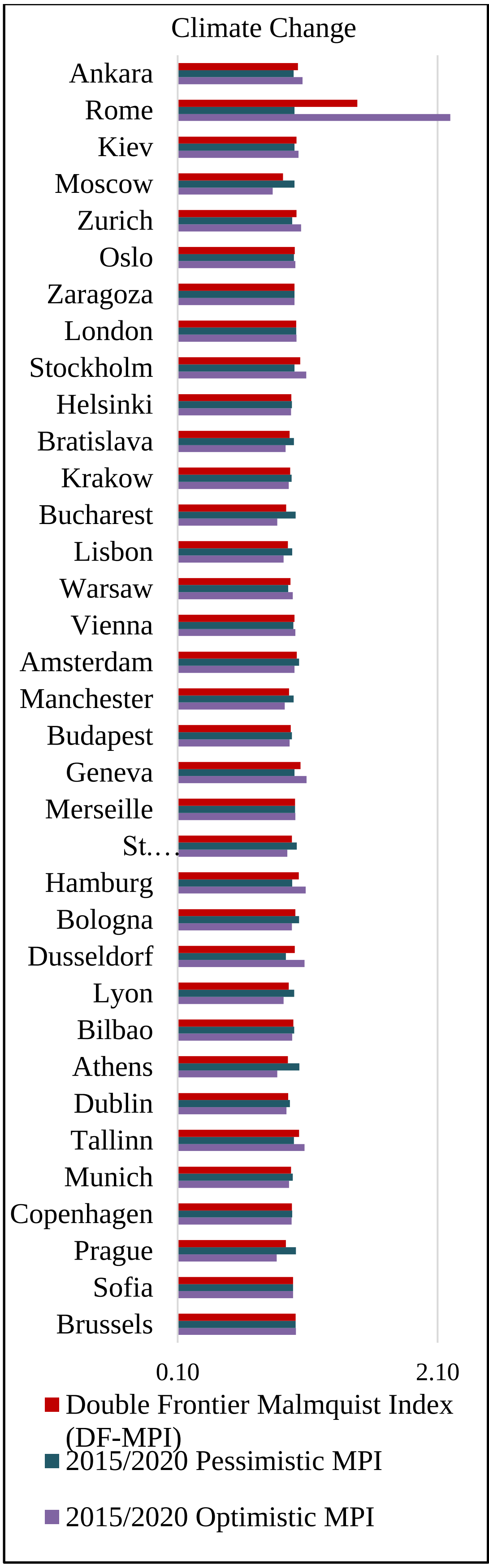
5.3.4. Productive performance through novel Malmquist Index

In this section, the relative productivity change of each smart city over different period of time from 2015 till 2020 is presented under the Double-Frontier approach using an aggregate DEA-SBM Malmquist index (model 44). To discuss the change in the sustainability performance for all the smart cities under study, the MPI's were measured from different viewpoints: optimistic (model 42) and pessimistic (model 43) point of view under the dimensions; climate change, economic dynamism, governance and institution, social cohesion and solidarity, energy, and environmental resource and, safety and security. A productivity progress is indicated when the DF-

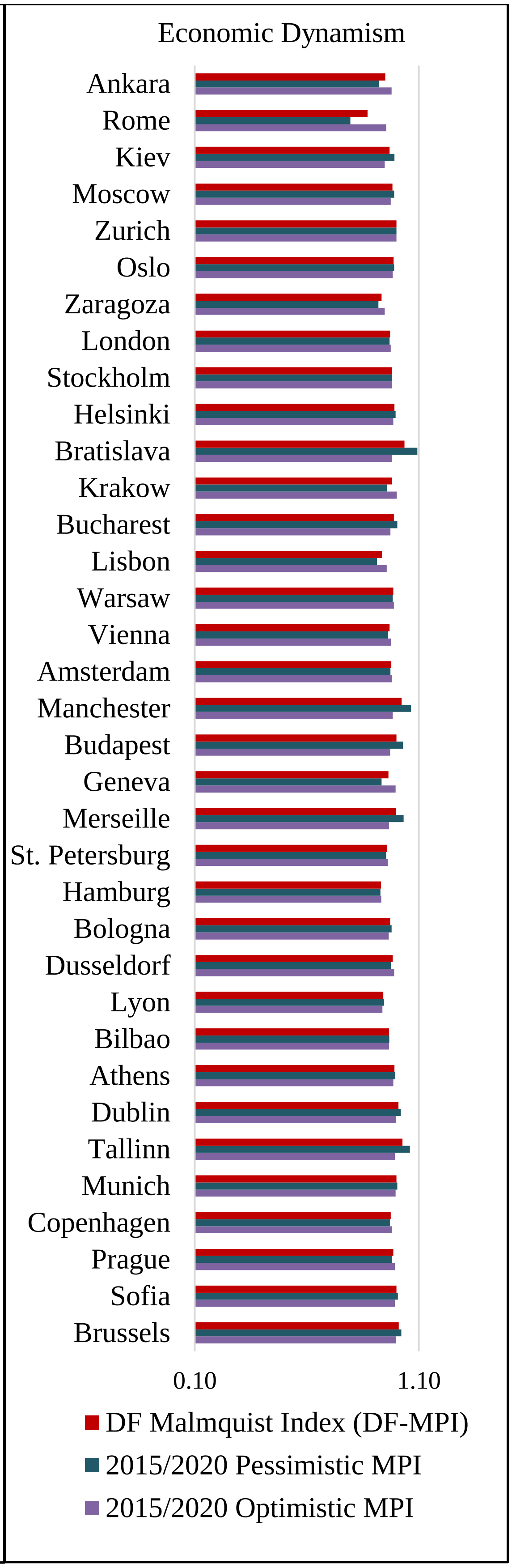
MPI >1. It is seen from Figure 12(a) under the climate change dimension that, Rome (DF-MPI =1.4827), Geneva (DF-MPI =1.0444), Stockholm (DF-MPI =1.0437), Tallinn (DF-MPI =1.0342) and Hamburg (DF-MPI =1.0326) showed the greatest positive productivity change from 2015 to 2020. The most decline in productivity is seen for Moscow (DF-MPI =0.9114), Prague (DF-MPI =0.9334), Bucharest (DF-MPI =0.9345), Athens (DF-MPI =0.9473), Lisbon (DF-MPI =0.9480) and Dublin (DF-MPI =0.9507). However, under the optimistic MPI (Table B6(a), Table B6(b) in Appendix B), Stockholm made the most cumulative productivity progress of 89.77%. While Manchester experienced the most regress in productivity with -54.26%. It is to note that, Athens failed to achieve productive progress under the double frontier integrated approach, while under the optimistic MPI, Athens achieved a progress in productivity by 68.98%. However, it is surprising to note that for the smart cities namely, Geneva, Stockholm, Zaragoza, Moscow, Kyiv and Rome, there is no noticeable change in productivity during the years from 2015 till 2020 with $MPI_{pessimistic} = 1$. While, Zaragoza with $MPI_{optimistic} = 1$ and $MPI_{pessimistic} = 1$ has not achieved any progress under both the optimistic and pessimistic MPI scenarios. Similarly, under the dimension "economic dynamism" (see Table B7(a), Table B7(b) in Appendix B), from the optimistic perspective, it is seen that Bratislava has made the greatest progress by 20.563% in terms of productivity followed by Kyiv (7.274%), Athens (3.088%), Geneva (1.739%) and Hamburg (1.323%). All the other smart cities showed a regress in productive performance with Manchester showing a steady decline in productivity by -32.926% followed by Munich (-32.91%), Helsinki (-32.56%) and Bilbao (-20.63%). Contrastingly, from the pessimistic viewpoint, it is seen that Rome with a productivity regress of 54.21% ranks as the least productive smart city in terms of its progress towards achieving sustainable development across the years. Contrarily, Rome ranks 35th under the aggregate double frontier approach with a DF-MPI index that equals 0.87099 (Figure 12b) for lowest productivity progress over the years, followed by Hamburg (DF-MPI =0.9309), Zaragoza (DF-MPI =0.93373), Lisbon (DF-MPI =0.93478) and Lyon (DF-MPI =0.94166). Figure 13(a-f) shows the productivity change for the 35 European smart cities over the years from 2015 till 2020 under respective dimensions of sustainable development from the optimistic viewpoint. Figure 14(a-f) shows the change in productivity from the pessimistic viewpoint over time for the smart cities under various dimensions.

While, investigating the productivity changes of all the European smart cities over the years, it is seen that St. Petersburg has made noteworthy progress in terms of productivity under the governance and institution dimension from the optimistic viewpoint ($MPI_{\textit{optimistic}}$ = 1.2949). An average productivity increase of 91.86% is seen under the optimistic viewpoint from 2015-2020 while, under the pessimistic viewpoint, a decline of 13.604% over the years is seen ($MPI_{\textit{pessimistic}}$ = 0.9924). However, the integrated DF-MPI value for St. Petersburg show an overall productivity progress (DF-MPI =1.1336) and ranks 1st as the smart city that achieved best productivity growth in terms of addressing the essence of the governance and institution theme from 2015-2020 (Figure 12c). On the contrary, Zaragoza experienced a decline in productivity under both the optimistic and pessimistic scenarios with an average productivity regress rate of 18.41% and 15.45% respectively (Table B8(a), Table B8(b) in Appendix B). However, under the integrated DF-MPI, Ankara stands as the first runner up (DF-MPI =1.0645) followed by Merseille (DF-MPI =1.0467), Bucharest (DF-MPI =1.0413) and Helsinki (DF-MPI =1.0143) in terms of its progressive performance growth under the governance and institution dimension of sustainable development. A distinct evaluation to understand the productivity progress under the “society and well-being” dimension was carried out using models from 6-8 for the smart cities under study. No noticeable change in the productivity over time was investigated under the pessimistic scenario for Munich, Merseille, Lisbon, Zaragoza, Oslo, and Moscow Table B9(a), Table B9(b) in Appendix B). This is evident from the $MPI_{pessimistic}$ value of 1.000. Paradoxically, a decline in productivity was noticed for all these smart cities under the optimistic scenario except for Munich with a progress of 0.522% over the years. Smart cities that showed rapid productivity growth under the aggregate pessimistic MPI values from 2015-2020 where; Dublin ($MPI_{\textit{pessimistic}}$ = 1.0255), Lyon ($MPI_{\textit{pessimistic}}$ = 1.0035), Geneva ($MPI_{\textit{pessimistic}}$ = 1.011), Amsterdam ($MPI_{\textit{pessimistic}}$ = 1.0304), Warsaw ($MPI_{\textit{pessimistic}}$ =1.0034), Helsinki ($MPI_{\textit{pessimistic}}$ =1.0158), London ($MPI_{\textit{pessimistic}}$ =1.0068) and Zurich ($MPI_{\textit{pessimistic}}$ =1.0037). Under the MPI based on double frontier, Brussels achieved the least productivity growth with a DF-MPI value of 0.93243.

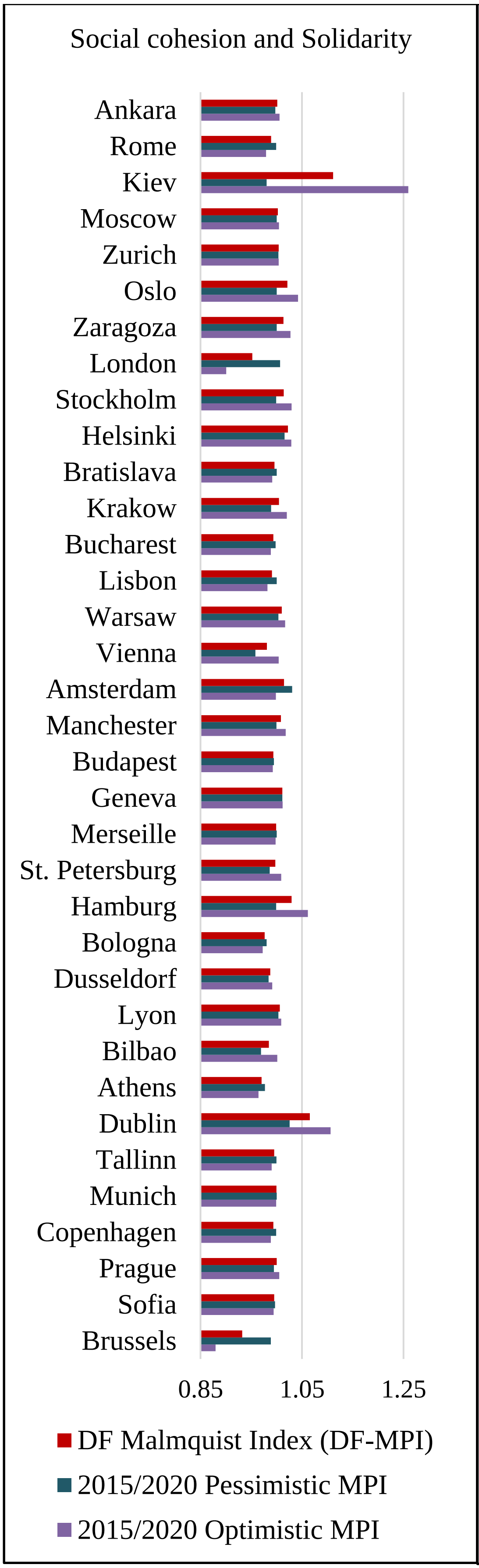
When analyzing the MPI values for the European smart cities under the “energy and environmental resource” dimension, it is found that the smart cities that show the highest amount of increase in productivity under the integrated double frontier approach are namely; London (DF-MPI =1.2945; Rank: 1), Helsinki (DF-MPI =1.0681; Rank: 2), Oslo (DF-MPI =1.0656; Rank: 3), Manchester (DF-MPI =1.0311, Rank: 4), and Dublin (DF-MPI =1.0304, Rank: 5). A decline in productive performance over time was found for Geneva (DF-MPI =0.9578; Rank: 35), Moscow (DF-MPI =0.96686; Rank: 34), Hamburg (DF-MPI = 0.9737; Rank: 33), Munich (DF-MPI = 0.9895; Rank: 32) and St. Petersburg (DF-MPI = 0.9902; Rank: 31). However, Geneva shows a noteworthy progress in terms of productivity by 30.517% under the optimistic viewpoint Table B10(a), Table B10(b). While a regress in productivity of 26.7% is found that has resulted in the overall productivity decline under the DF-MPI approach. Furthermore, London (progress rate: 62.73%, Rank: 1), Helsinki (progress rate: 43.90%, Rank: 2), St. Petersburg (progress rate: 28.45%, Rank: 4) and Zurich (progress rate: 10.91%, Rank: 5) exhibits a cumulative productive progress under the optimistic viewpoint. Howbeit, smart cities namely; Zaragoza (progress rate: 13.45%, Rank: 1), Brussels (progress rate: 7.584%, Rank: 2), Zurich (progress rate: 5.69%, Rank: 3), Helsinki (progress rate: 4.76%, Rank: 4) and Kyiv (progress rate: 4.484%, Rank: 5) show improved productivity under the pessimistic scenario. Whilst, under the "safety and security" dimension (Table B11 (a)-Table B11 (b), Merseille (progress rate: 29.7%), Dusseldorf (progress rate: 29.49%) and Lisbon (progress rate: 19.803%) ranks 1st , 2nd, and 3rd in terms of aggregate productive progress over time under the optimistic MPI scenario. However, a dip in productivity is shown most in the case of Moscow by 24.052%, Hamburg by 19.6% and Zaragoza by 17.764% under the optimistic MPI, while a productivity regress by 47.57%, 29.74% and 24.53% is shown under the pessimistic viewpoint by Geneva, Zurich, and St. Petersburg respectively. For a change index of DF-MPI =0.8846, Bologna indicates the highest decrease in productivity level from 2015 till 2020 while, the greatest progress in productivity is marked for Kyiv with a DF-MPI index of 1.0477 for the study duration. Furthermore, it is to note that, St. Petersburg under the optimistic scenario and Moscow under the pessimistic scenario show no change in productivity with MPI index values equal to 1.000. Productivity change for all the 35 European smart cities over the years from 2015 till 2020 under the 6 dimensions of sustainable urban development are shown in Table B6(a)-Table B9(a). Figure 12(a-f) shows the cumulative MPI values for all the 35 smart cities under the optimistic, pessimistic, and pessimistic and double frontier approach over time.


Climate Change
Ankara
Rome
Kiev
Moscow
Zurich
Oslo
Zaragoza
London
Stockholm
Helsinki
Bratislava
Krakow
Bucharest
Lisbon
Warsaw
Vienna
Amsterdam
Manchester
Budapest
Geneva
Merseille
St.…
Hamburg
Bologna
Dusseldorf
Lyon
Bilbao
Athens
Dublin
Tallinn
Munich
Copenhagen
Prague
Sofia
Brussels
0.10
2.10
Double Frontier Malmquist Index (DF-MPI)
2015/2020 Pessimistic MPI
2015/2020 Optimistic MPI

a)

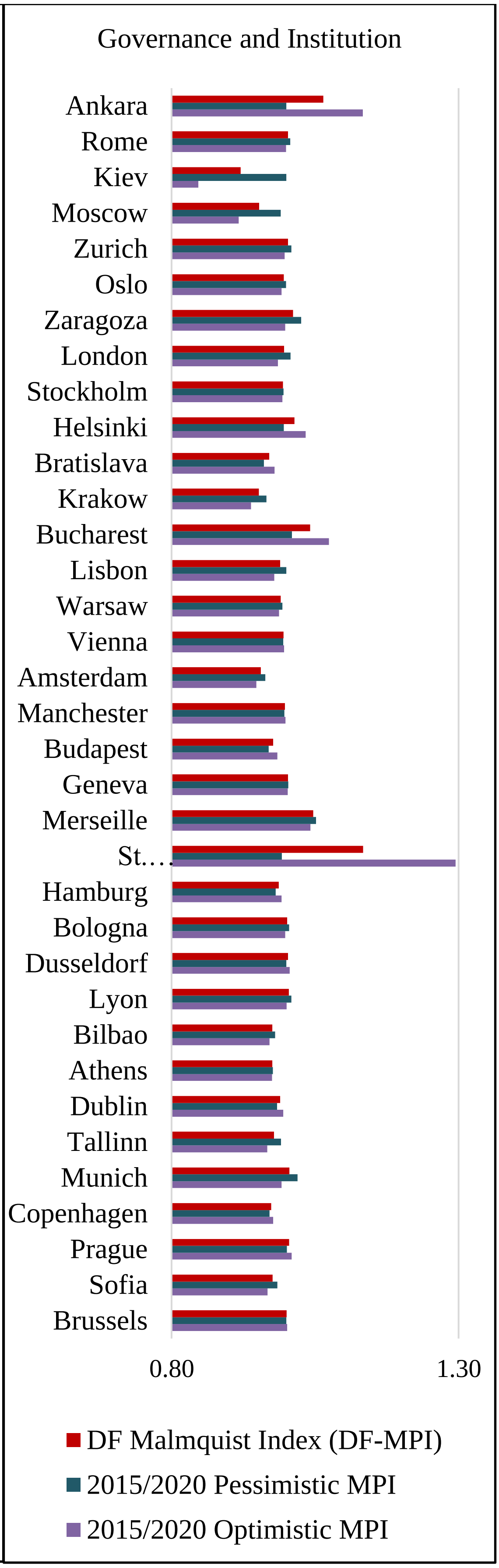

Economic Dynamism
Ankara
Rome
Kiev
Moscow
Zurich
Oslo
Zaragoza
London
Stockholm
Helsinki
Bratislava
Krakow
Bucharest
Lisbon
Warsaw
Vienna
Amsterdam
Manchester
Budapest
Geneva
Merseille
St. Petersburg
Hamburg
Bologna
Dusseldorf
Lyon
Bilbao
Athens
Dublin
Tallinn
Munich
Copenhagen
Prague
Sofia
Brussels
0.10
1.10
DF Malmquist Index (DF-MPI)
2015/2020 Pessimistic MPI
2015/2020 Optimistic MPI

b)



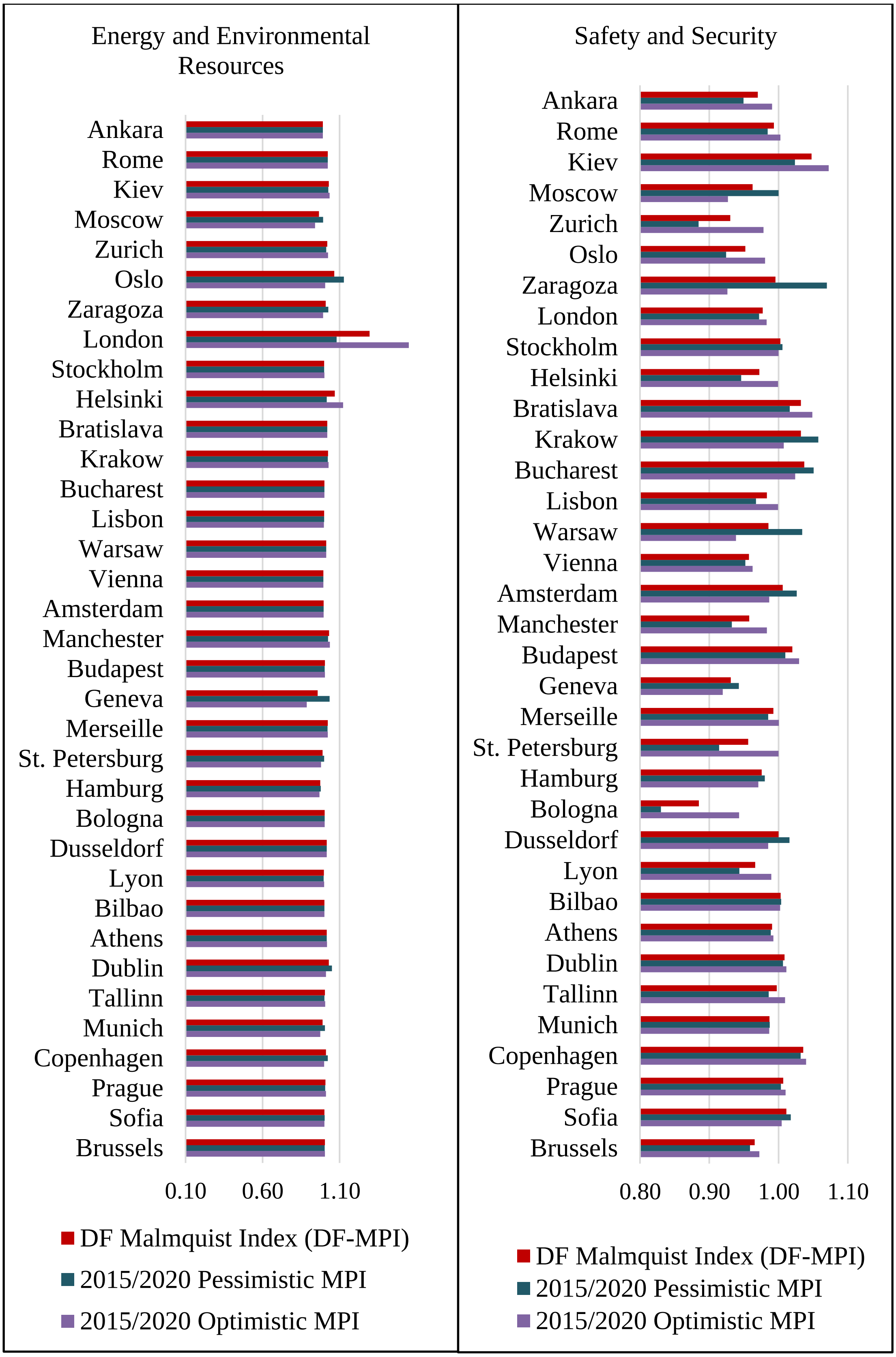
Social cohesion and Solidarity
Ankara
Rome
Kiev
Moscow
Zurich
Oslo
Zaragoza
London
Stockholm
Helsinki
Bratislava
Krakow
Bucharest
Lisbon
Warsaw
Vienna
Amsterdam
Manchester
Budapest
Geneva
Merseille
St. Petersburg
Hamburg
Bologna
Dusseldorf
Lyon
Bilbao
Athens
Dublin
Tallinn
Munich
Copenhagen
Prague
Sofia
Brussels
0.85
1.05
1.25
DF Malmquist Index (DF-MPI)
2015/2020 Pessimistic MPI
2015/2020 Optimistic MPI

c)



Governance and Institution
Ankara
Rome
Kiev
Moscow
Zurich
Oslo
Zaragoza
London
Stockholm
Helsinki
Bratislava
Krakow
Bucharest
Lisbon
Warsaw
Vienna
Amsterdam
Manchester
Budapest
Geneva
Merseille
St.…
Hamburg
Bologna
Dusseldorf
Lyon
Bilbao
Athens
Dublin
Tallinn
Munich
Copenhagen
Prague
Sofia
Brussels
0.80
1.30
DF Malmquist Index (DF-MPI)
2015/2020 Pessimistic MPI
2015/2020 Optimistic MPI

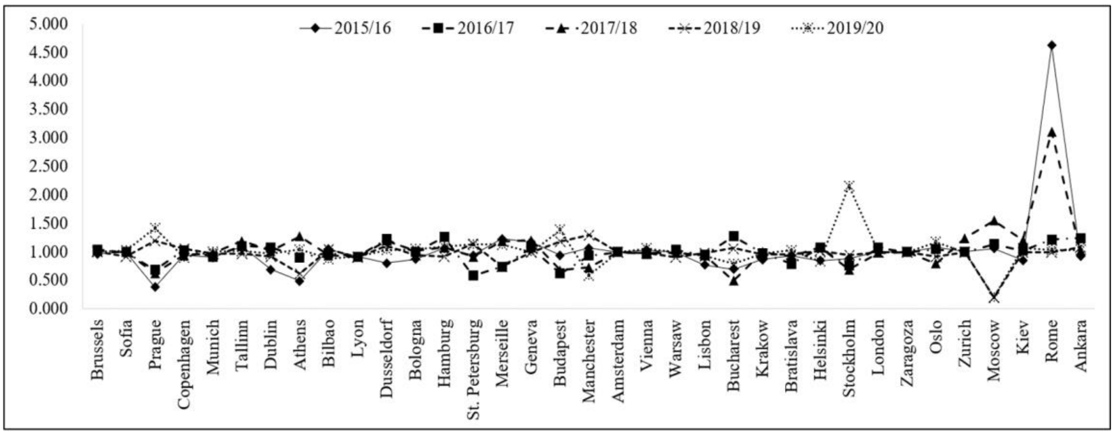
d)



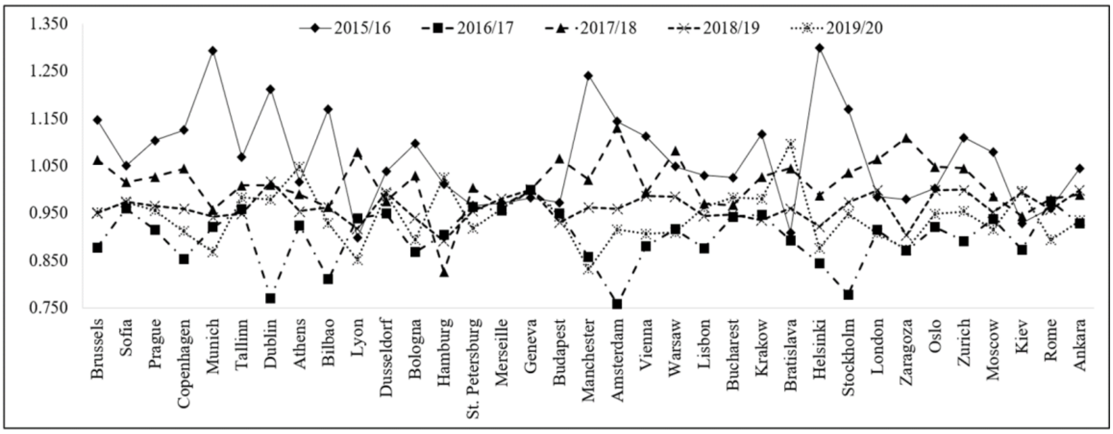
e) f)

Figure 12. Sustainable productivity comparison for 35 European smart cities from pessimistic, optimistic, and double frontier perspective under a) Climate change b)

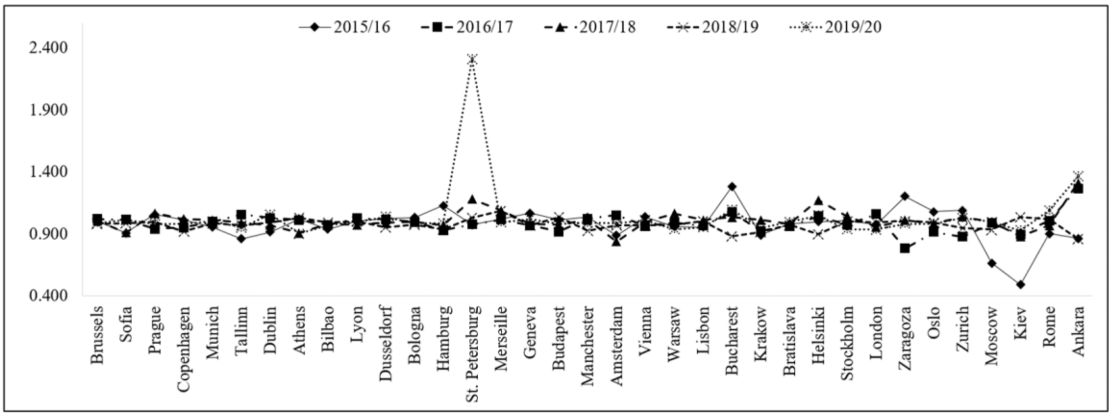
Economic dynamism c) Governance and Institution d) Social cohesion and solidarity e) Energy and environmental resources f) Safety and security



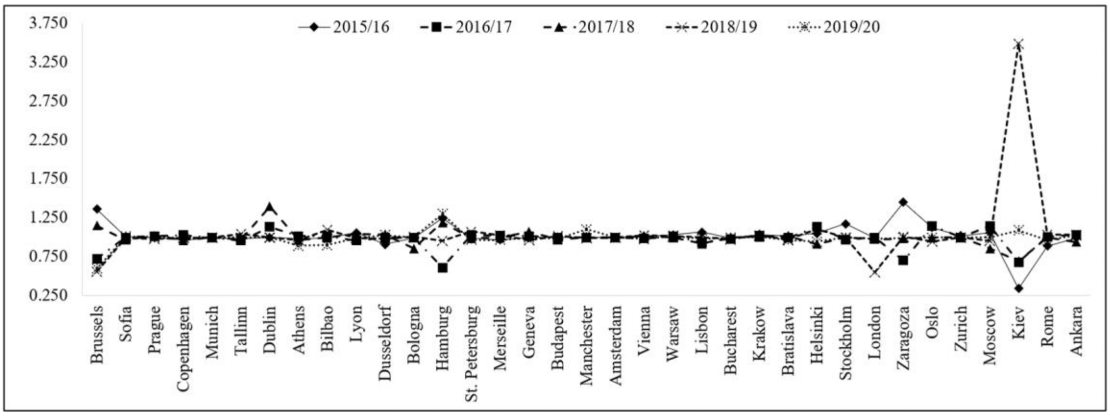
(a)



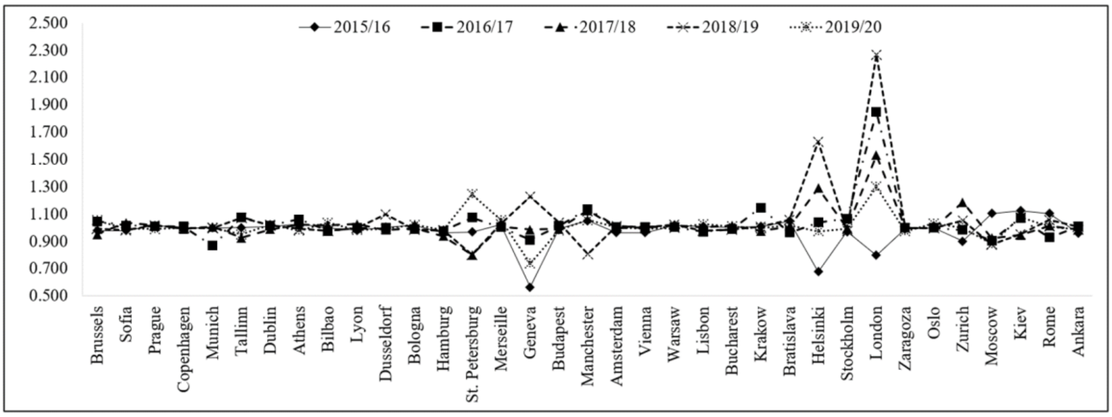
(b)



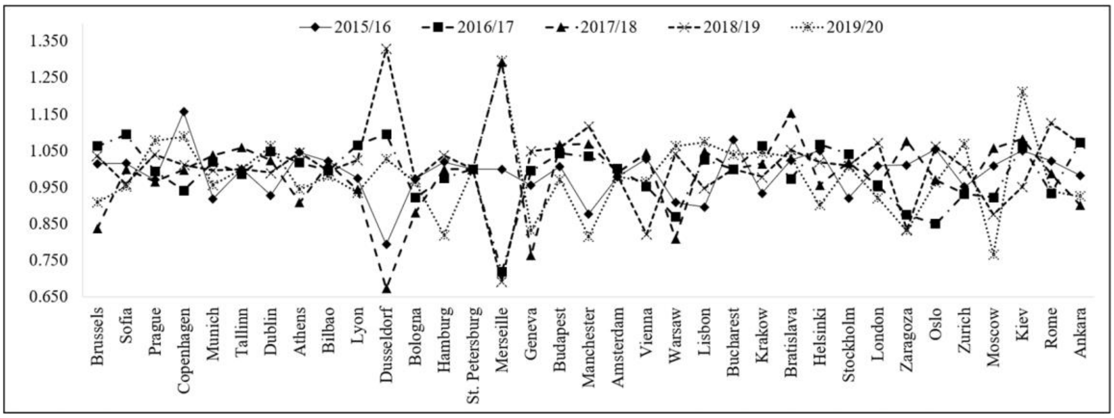
(c)



(d)

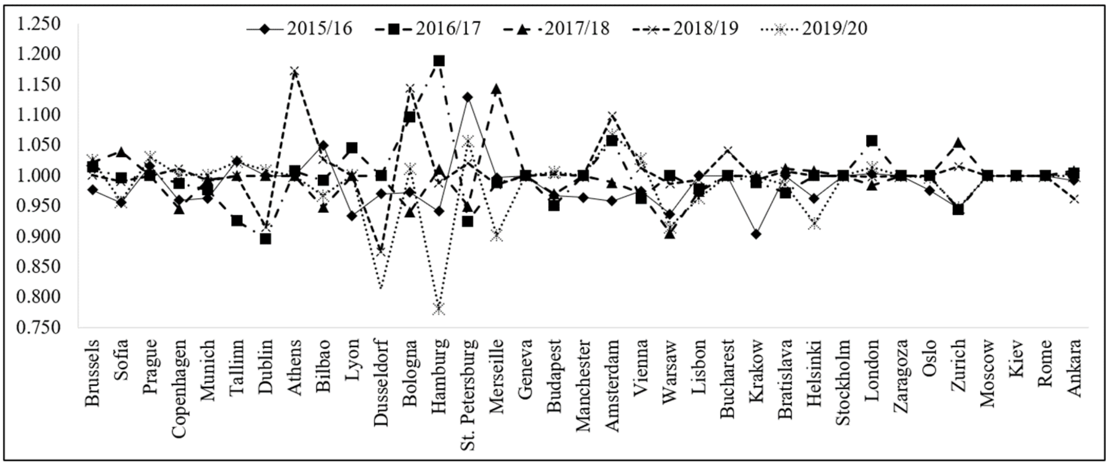


(e)

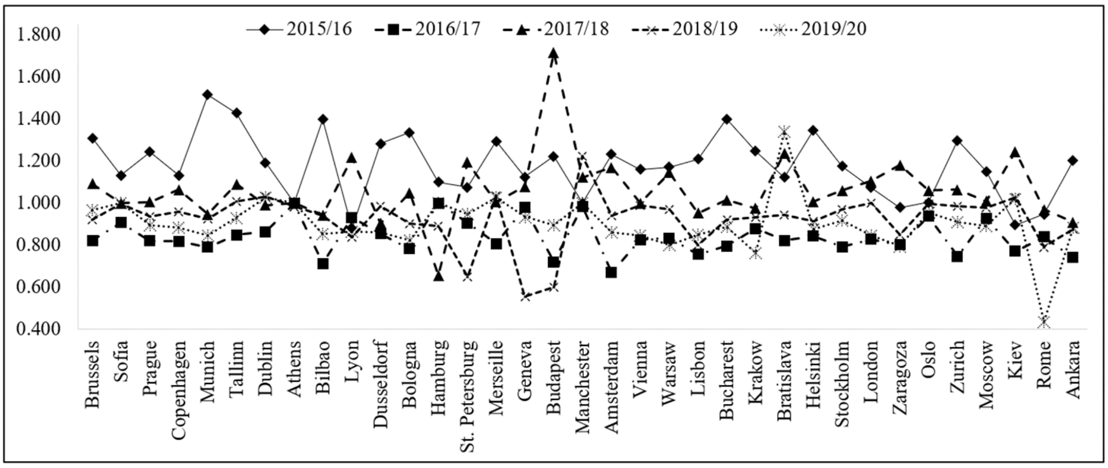


(f)

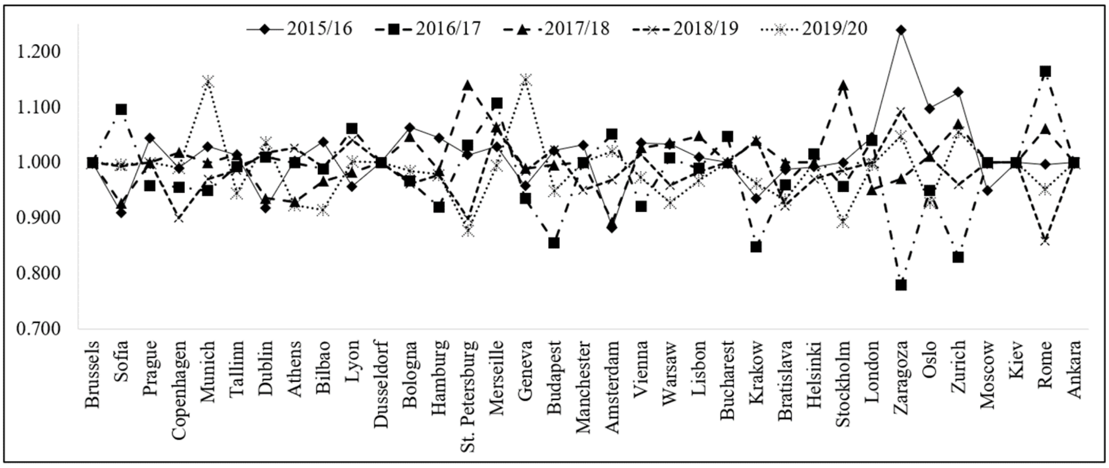
Figure 13. Productive performance from optimistic viewpoint from 2015-2020 under the dimensions a) climate change b) economic dynamism c) governance & institution d) social cohesion & solidarity e) energy & environmental resource f) safety & security


2015/16
2016/17
2017/18
2018/19
2019/20
1.250
1.200
1.150
1.100
1.050
1.000
0.950
0.900
0.850
0.800
0.750
Brussels Sofia Prague Copenhagen Munich Tallinn Dublin Athens Bilbao Lyon Dusseldorf Bologna Hamburg St. Petersburg Merseille Geneva Budapest Manchester Amsterdam Vienna Warsaw Lisbon Bucharest Krakow Bratislava Helsinki Stockholm London Zaragoza Oslo Zurich Moscow Kiev Rome Ankara

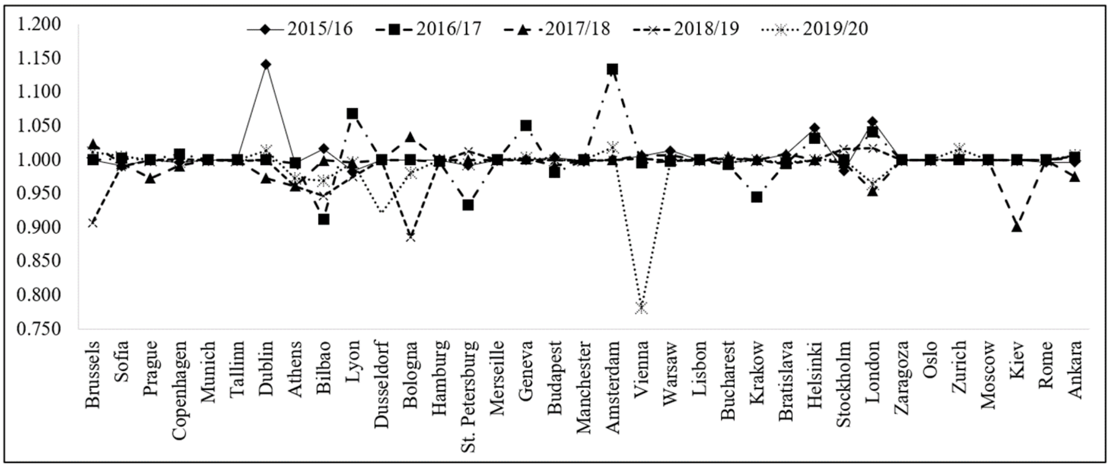
(a)


2015/16
2016/17
2017/18
2018/19
2019/20
1.800
1.600
1.400
1.200
1.000
0.800
0.600
0.400
Brussels Sofia Prague Copenhagen Munich Tallinn Dublin Athens Bilbao Lyon Dusseldorf Bologna Hamburg St. Petersburg Merseille Geneva Budapest Manchester Amsterdam Vienna Warsaw Lisbon Bucharest Krakow Bratislava Helsinki Stockholm London Zaragoza Oslo Zurich Moscow Kiev Rome Ankara

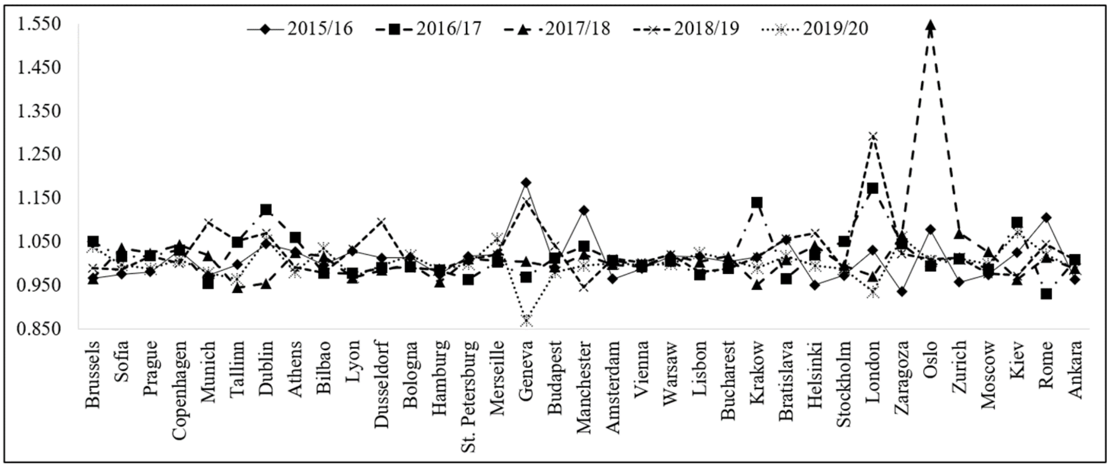
(b)


2015/16
2016/17
2017/18
2018/19
2019/20
1.200
1.100
1.000
0.900
0.800
0.700
Brussels Sofia Prague Copenhagen Munich Tallinn Dublin Athens Bilbao Lyon Dusseldorf Bologna Hamburg St. Petersburg Merseille Geneva Budapest Manchester Amsterdam Vienna Warsaw Lisbon Bucharest Krakow Bratislava Helsinki Stockholm London Zaragoza Oslo Zurich Moscow Kiev Rome Ankara

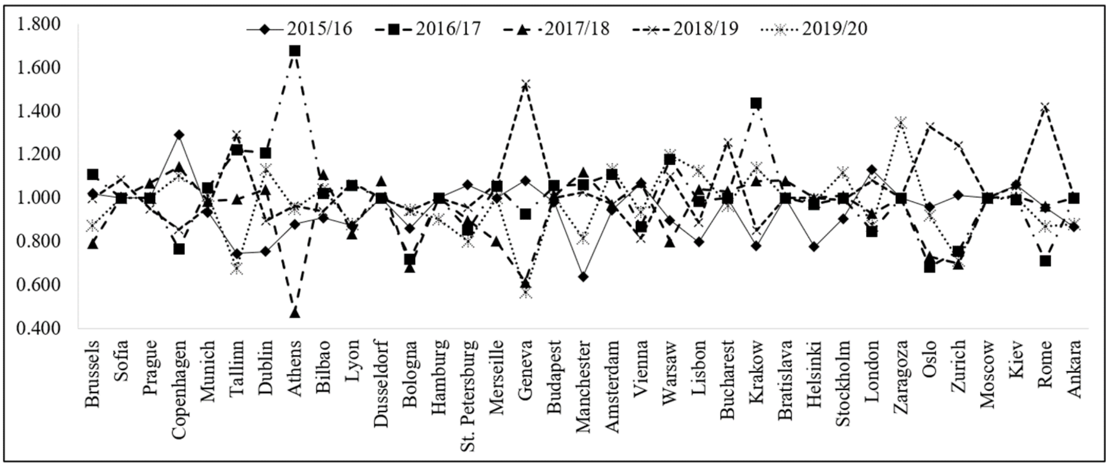
(c)



(d)



(e)



(f)

Figure 14. Productive performance from pessimistic viewpoint of 35 European smart cities over time from 2015 till 2020 under the dimensions a) climate change b) economic dynamism c) governance and institution d) social cohesion and solidarity e) energy and environmental resource f) safety and security.

5.4. Chapter synopsis

Sustainability is the crux of urban renaissance. Imbibed with utopian technological planning, understanding the convergence between smart development and sustainable practices for city development is necessary. Smart cities have succeeded in bringing high standards of living to its residents. This chapter evaluated the long-term sustainability performance of 35 leading European smart cities over time from 2015 till 2020 by implementing module 2 of the proposed hybrid decision support model, to understand on how these cities address sustainability to make the concept of smart sustainable cities more actionable. The proposed novel Double-Frontier Slack Based Measure Data Envelopment Analysis (DFSBM-DEA) model considering undesirable factors in the technology set is used in assessment. An integrated relative sustainability performance assessment model considering both the optimistic and pessimistic viewpoint simultaneously, in terms of interval efficiency is used to determine the most efficient smart city under 6 various dimensions of sustainable development. These key dimensions include; Energy and Environmental Resource, Governance and Institution, Economic dynamism, Social cohesion and solidarity, Climate Change and, Safety and Security. A productivity progress assessment from a double frontier perspective using a modified Malmquist-DEA model is then used to capture the response of each smart city in terms of their productivity growth towards achieving sustainable development. Results show Dublin (ranked 1st) as the most smart and sustainable European city under all the proposed dimensions of sustainable development from the double-frontier perspective. Along with Dublin lies Oslo, Zurich, and Amsterdam as the cities with high aggregate sustainability performance. The results also revealed significant difference in the productivity progress values from the optimistic and pessimistic viewpoint, thus exemplifying the significance for the proposed aggregate productivity progress measurement model. The findings of the present study contribute to knowledge and practice for smart city modellers, decision makers and urban planners, by aiding methodological clarity in assessing sustainable capacity of cities from a double frontier perspective and, in particular, by drawing attention to underlying assumptions about the role of sustainability in smart city development. The research finds of this chapter stands as a breakthrough in the field of relative sustainability assessment using non-parametric approaches and a benchmark for global smart cities to shape their development in light of sustainability.

CHAPTER 6: A NOVEL EXPLAINABLE MACHINE LEARNING BASED URBAN RESILIENCE AND LIVABILITY ASSESSMENT

6.1 General outline

Livability and resilience paradigm have been used interchangeably in several context targeting the soul agenda; quality of life with a smart growth strategy to rebound post stress. This chapter presents an empirical solution taking the case of 35 tech-driven European cities, to the proposed novel two-stage model combining metric-distance based multivariate analysis with machine learning techniques for the assessment of urban livability and resilience of smart cities based on various influential indicators. This chapter is a practical implementation and validation of module 3 in the proposed hybrid decision support model. A step forward is taken to aggregate the performance and develop an aggregate model to understand the co-creation of resilience and livability under the smart city paradigm. Clustering and classification algorithms form the base of the assessment, with scores and ranks of smart cities based on their resilience and livability performance. All the predictive classification models were tested and validated for performance based on the parameters; accuracy, Cohen's Kappa (κ) and average area under the precision-recall curve (AUC-PR).

6.2 Significance and objective

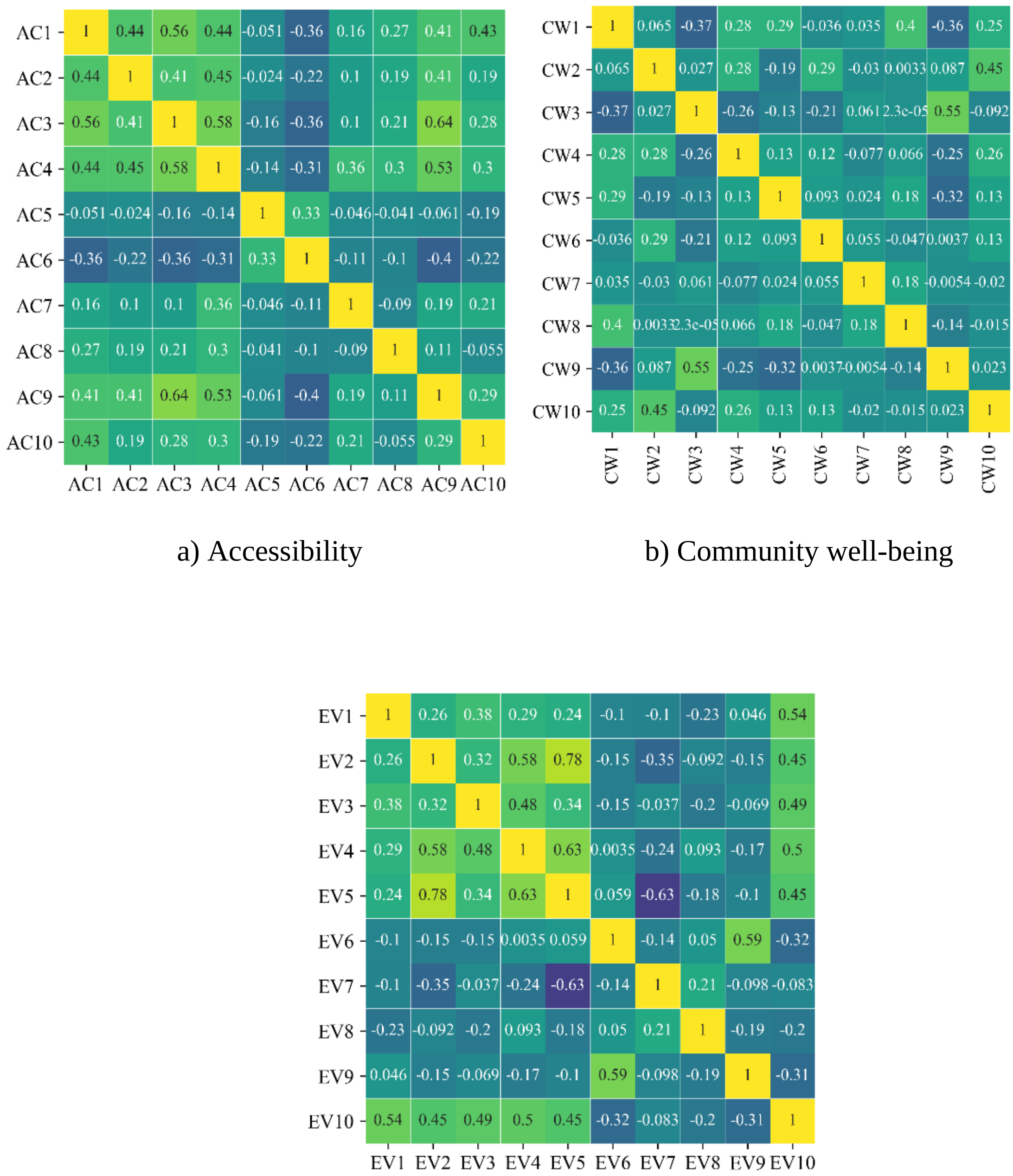
Given the intrinsic element of kinship between urban resilience and livability, it is crucial for planners and policy makers to analyze these paradigms under a generalized frame of reference tailored across multiple dimensions. Thus, investigating smart city development from a broader strategic vision in light of resilience capacity and livability is crucial. For the same, several assessment approaches exist such as the non-parametric optimization based techniques like the data envelopment analysis, composite index based scoring, GIS and remote sensing based assessments and many more. Machine learning, a subset of artificial intelligence (AI) is one such, that has recently gained immense attention owing to its ability to effectively determine the relationship between the input features and the response variable (s) in a complex system. Despite their great capability, machine learning models are rarely applied in the field of resilience and livability assessments in an urban scale. In this research, a large dataset of smart cities has been collected and used to propose a novel machine learning based framework, as presented in Chapter 3. Several machine learning models have been investigated to propose the best model for predicting the livability and resilience level of smart cities. To this end, this chapter, dedicated to module 3 of the proposed hybrid decision support model, the resilience and liveability assessment module, targets to achieve the following objectives through the development of the 2-stage novel approach, as to;

a) Conduct a comprehensive assessment of city resilience and livability of 35 leading European smart cities as the case using the proposed novel two-stage model (see Chapter 3 for the developed model) based on machine learning, to identify their coping capacities based on their clustered performance as high, medium, and low.
b) Predict the degree of livability and resilience, as categorical variables, based on the values of the indicators under each dimension of resilience and livability using machine learning classifiers.
c) Compare and select the best classifiers based on coefficients such as model accuracy and precision to predict the degree of aggregate performance as the classification output.

6.3. Numerical solution

6.3.1. Research data

In this study, 35 High-tech and top ranked European smart cities as per the ranks published in the 2020 IMD Smart City Index were chosen to understand the resilience and liveability of smart cities. Due to these cities covering nearly three-quarter of the list of top 50 leading global smart cities, the sample size is fairly large for the results to be economically extrapolated to a global level when understanding resilience and liveability in the current smart city development models. Indicators were selected across multiple dimensions from the existing literature on resilience and liveability criteria. A total of 68 indicators (30 liveability indicators and 38 resilience indicators) were used in computing the aggregate performance and building predictive models. All the data for each indicator across years from 2015 till 2020 were collected from European Commission's Urban Audit survey (https://ec.europa.eu/eurostat/data/database) and OECD regional and cities statistics (https://stats.oecd.org/). City resilience considers four broad dimensions namely; social resilience (Säumel et al., 2019; Copeland et al., 2020), economic resilience (Williams and Vorley, 2014; Bastaminia et al., 2017), infrastructure and built environment (Masoomi, and van de Lindt, 2019), and institutional resilience (Guiraudon, 2014). While urban liveability is addressed under three prime dimensions namely; accessibility (Lotfi and Koohsari, 2009; Ziemke et al., 2018), community well-being (Phillips et al., 2014; Chao et al., 2017), and economic vibrancy. The indicators and dimensions selected for urban liveability and city resilience along with their desirability values are presented in Table B1 and Table B2, respectively in the Appendix B. The correlation matrix for all the indicators under various dimensions of urban liveability and city resilience used in the study is shown in Figure 15 and Figure 16 respectively.

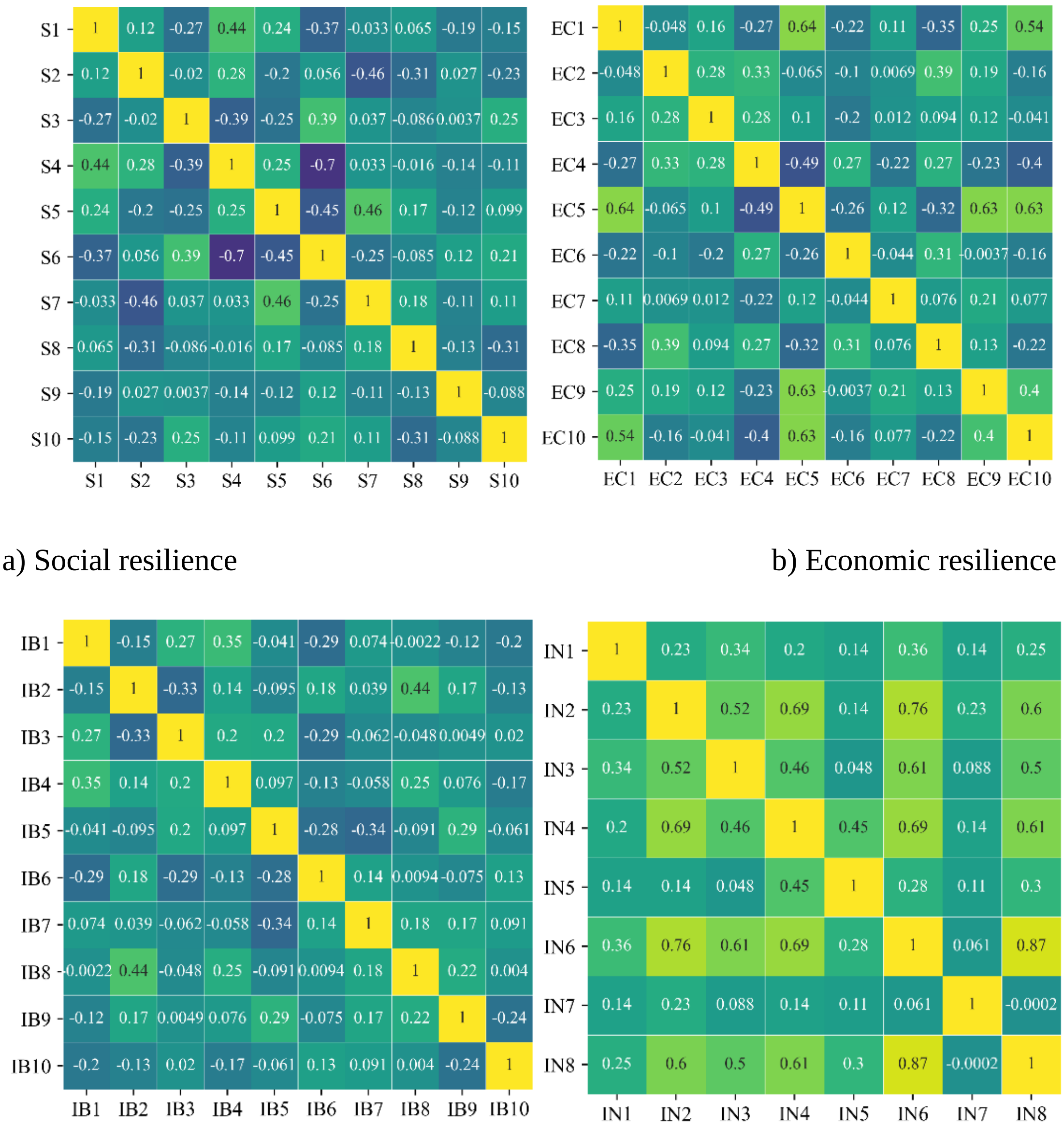


a) Accessibility

b) Community well-being

c) Economic vibrancy

Figure 15. Correlation matrix for all the indicators under each aspect of urban liveability



a) Social resilience b) Economic resilience

c) Infrastructure and built environment resilience d) Institutional resilience

Figure 16. Correlation matrix for all the indicators under each aspect of urban resilience

6.3.2. Scoring and performance assessment

In this section, we assess the resilience capacity, liveability, and then estimate the aggregate performance of all the 35 European smart cities to address the research question on to what level the smart cities of today co-create resilience and liveability in their development model. For the same, scores across each dimension under resilience and liveability were calculated and presented in Table 13 and Table 14, respectively. It is seen that, when understanding social resilience, Amsterdam is the most socially resilient smart city with a performance score (S_s) of 0.8965, followed by Zurich (S_s = 0. 8873) and London (S_s = 0. 8757) in the 2nd and 3rd place, respectively. However, Kiev, Ankara, and Athens are most vulnerable to social upheavals in city, which is evident from the significantly low social resilience performance of 0.0978 (rank = 35), 0.1529 (rank = 34) and, 0.2534 (rank = 33), respectively. Under economic resilience, Stockholm, Oslo, and Copenhagen with a score of 1.0009, 0.9826, and 0.9754 perform significantly well and are ranked 1st , 2nd, and 3rd, respectively in the order of their economic resilience. While the least resilient smart city to economic shocks is the Ukrainian city of Kiev (S_{EC} = 0.2879). The second to the least resilient city is Ankara (S_{EC} = 0.3669, rank = 34) followed by Moscow (S_{EC} = 0.4339, rank = 33). Kiev still remains the least resilient city under the infrastructure and build environment dimension with a score (S_{IB}) of 0.2841. This translates the fact that, Kiev despite being a well-established east European smart city, the ability to absorb, and recover from the escalating climate change, disaster and environment related risks is relatively low. The same is true in the case of Ankara (S_{IB} = 0.3172, rank = 34) and Warsaw (S_{IB} = 0.4679, rank 33) as well. On the contrary, the capital of Denmark, Copenhagen has well designed infrastructural resilience in their planning model, which is well reflected in their performance (S_{IB} = 0.9554, rank = 1). Along with Copenhagen stands Geneva and Amsterdam are in the 2nd and 3rd place, respectively under the same dimension. It is seen that Oslo is the most efficient smart city in terms of enforcing normative practices in adverse operating environments with an institutional resilience score (S_{IN}) of 0.8924. While Copenhagen with a score of 0.8224 and the English city of London (S_{IN} = 0.8184) also adopt well to changing conditions and thus, institutionally resilient with ranks 2nd and 3rd, respectively. On the other hand, Ankara (S_{IN} = 0.1120, rank = 35), Bucharest (S_{IN} = 0.2253, rank = 34), and Kiev (S_{IN} = 0.2518, rank = 33) pose insufficient institutional resilience relative to the existing smart cities.

Table 13. Resilience performance for all the 35 smart cities across each dimension of urban resilience for the average data over time 2015-2020.

Smart Cities	S[1]	Rank	EC[2]	Rank	IB[3]	Rank	IN[4]	Rank
Brussels	0.7190	13	0.7469	19	0.6268	19	0.6490	13
Sofia	0.4215	31	0.6144	28	0.5665	25	0.2782	32
Prague	0.6951	15	0.8338	14	0.6928	13	0.4078	27
Copenhagen	0.8258	8	0.9754	3	0.9554	1	0.8224	2
Munich	0.7469	10	0.8937	8	0.7168	8	0.5941	17
Tallinn	0.7414	11	0.8700	9	0.6575	16	0.6215	15
Dublin	0.6158	19	0.5958	32	0.6840	15	0.6956	9
Athens	0.2534	33	0.6114	29	0.5872	21	0.5633	18
Bilbao	0.6491	18	0.6421	25	0.6962	9	0.5497	19
Lyon	0.5846	20	0.7783	18	0.6961	10	0.6610	11
Dusseldorf	0.4961	26	0.7122	23	0.5092	28	0.3881	30
Bologna	0.5437	23	0.6053	31	0.4949	32	0.3292	31
Hamburg	0.6979	14	0.7003	24	0.5019	29	0.6506	12
St. Petersburg	0.4545	27	0.7883	17	0.6293	18	0.5463	20
Marseille	0.5460	22	0.8040	16	0.6437	17	0.5974	16
Geneva	0.8376	7	0.8274	15	0.8698	2	0.8136	5
Budapest	0.5662	21	0.7422	20	0.6010	20	0.4833	24
Manchester	0.8748	4	0.7242	22	0.6892	14	0.5049	22
Amsterdam	0.8965	1	0.9459	4	0.8388	3	0.7907	6
Vienna	0.8586	6	0.8431	12	0.7860	4	0.6467	14
Warsaw	0.5163	25	0.8384	13	0.4679	33	0.4495	25
Lisbon	0.4402	30	0.7280	21	0.5678	24	0.4449	26
Bucharest	0.4534	28	0.6320	26	0.4979	30	0.2253	34
Krakow	0.6574	17	0.9099	5	0.4954	31	0.4955	23
Bratislava	0.5275	24	0.6106	30	0.5862	22	0.3914	29
Helsinki	0.6749	16	0.9033	6	0.7820	5	0.6883	10
Stockholm	0.8634	5	1.0009	1	0.7511	6	0.8171	4
London	0.8757	3	0.8562	11	0.6960	11	0.8184	3
Zaragoza	0.7200	12	0.8563	10	0.7341	7	0.7257	8
Oslo	0.7992	9	0.9826	2	0.5791	23	0.8924	1
Zurich	0.8873	2	0.9019	7	0.6956	12	0.7901	7
Moscow	0.3697	32	0.4339	33	0.5313	27	0.4015	28
Kiev	0.0978	35	0.2879	35	0.2841	35	0.2518	33
Rome	0.4418	29	0.6197	27	0.5404	26	0.5443	21
Ankara	0.1529	34	0.3669	34	0.3172	34	0.1120	35

S[1]: Social; EC[2]: Economic; IB[3]: Infrastructure and Built Environment; IN[4]: Institutional

When studying urban liveability of smart cities, it is seen that Geneva follows an inclusive urban development pattern with better access to facilities for its people. This is well evident when observing the accessibility score (S_{AC} = 1.0721) of the ‘peace capital’ of world under the said dimension. London (S_{AC} = 1.0271, rank = 2) and Stockholm (S_{AC} = 0.9807, rank = 3) are no exception for people to get around and live in the city. On the contrary, Athens with a score of 0.2344 is ranked the least accessible smart city followed by Bucharest (S_{AC} = 0.3394, rank = 34) and the Turkish city of Ankara (S_{AC} = 0.3659, rank = 33). Under the community well-being dimension, the north central Swiss state of Zurich is the best performing smart city with a score S_{CWB} = 0.6867. London continues its reign as the 2nd best liveable smart city (S_{CWB} = 0.6389) committed to build a community with lifelong wellness along with Kiev ranked the 3rd (S_{CWB} = 0.6047). However, Ankara (S_{CWB} = 0.1241) remains the least liveable city followed by Bucharest (S_{CWB} = 0.1393) and St. Petersburg (S_{CWB} = 0.1469) under the community well-being dimension. A well-orchestrated response towards economic vibrancy is seen in the case of Munich with a score (S_{EV}) of 0.8656. London (S_{EV} = 0.7699; rank = 2) and Zurich (S_{EV} = 0.7220; rank = 3) are no far behind in realizing urban vibrancy in their planning model. While Kiev with a performance score of 0.0823 is ranked the least economically vibrant smart city, followed by Athens (S_{EV} = 0.1204; rank = 34) and Rome (S_{EV} = 0.1976; rank = 33).

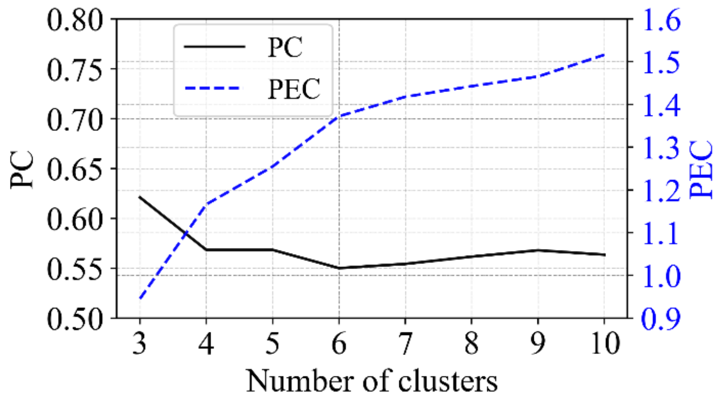
Table 14. Liveability performance for all the 35 smart cities across each dimension of urban liveability for the average data over time 2015-2020.

Smart Cities	AC[1]	Rank	CWB[2]	Rank	EV[3]	Rank
Brussels	0.8187	15	0.3404	17	0.4963	18
Sofia	0.4115	32	0.3585	15	0.3558	29
Prague	0.6835	21	0.3836	12	0.5506	13
Copenhagen	0.9416	8	0.3588	14	0.6308	9
Munich	0.9508	6	0.3382	18	0.8656	1
Tallinn	0.5179	30	0.2349	28	0.4911	19
Dublin	0.8671	11	0.4511	8	0.4660	21
Athens	0.2344	35	0.1672	31	0.1204	34
Bilbao	0.8172	16	0.3186	22	0.4575	23
Lyon	0.8339	14	0.3899	11	0.5363	14
Dusseldorf	0.6874	20	0.3976	10	0.2740	31
Bologna	0.6150	26	0.2452	27	0.3249	30
Hamburg	0.8149	17	0.2178	29	0.4342	25
St. Petersburg	0.6044	27	0.1469	33	0.4634	22
Marseille	0.6286	25	0.1683	30	0.4793	20
Geneva	1.0721	1	0.3012	25	0.6195	10
Budapest	0.6814	22	0.3285	20	0.4966	17
Manchester	0.9429	7	0.3098	23	0.6660	7
Amsterdam	0.9776	4	0.5017	5	0.6942	4
Vienna	0.8617	12	0.3022	24	0.6631	8
Warsaw	0.6510	23	0.5417	4	0.4297	26
Lisbon	0.7045	19	0.3460	16	0.5071	16
Bucharest	0.3394	34	0.1393	34	0.3812	27
Krakow	0.7255	18	0.3201	21	0.5110	15
Bratislava	0.5851	28	0.1552	32	0.4379	24
Helsinki	0.8544	13	0.3330	19	0.5690	11
Stockholm	0.9807	3	0.4963	6	0.6774	5
London	1.0271	2	0.6389	2	0.7699	2
Zaragoza	0.8830	9	0.3731	13	0.5558	12
Oslo	0.9756	5	0.4457	9	0.6729	6
Zurich	0.8812	10	0.6867	1	0.7220	3
Moscow	0.5780	29	0.4782	7	0.3562	28
Kiev	0.4468	31	0.6047	3	0.0823	35
Rome	0.6416	24	0.2754	26	0.1976	33
Ankara	0.3659	33	0.1241	35	0.2466	32

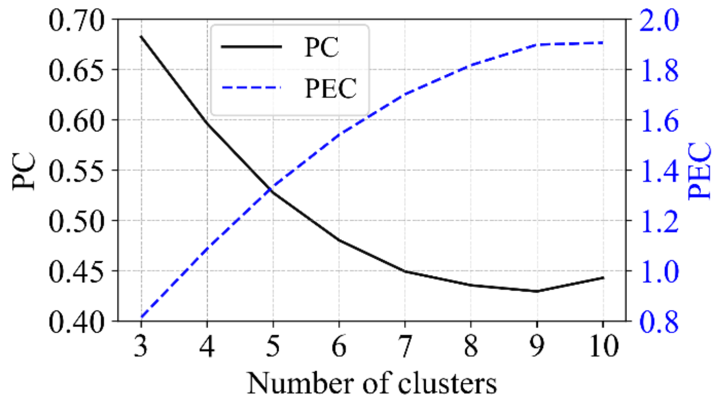
AC[1]: Accessibility; CWB[2] : Community well-being; EV[3] : Economic vibrancy

6.3.3. Clustered performance assessment

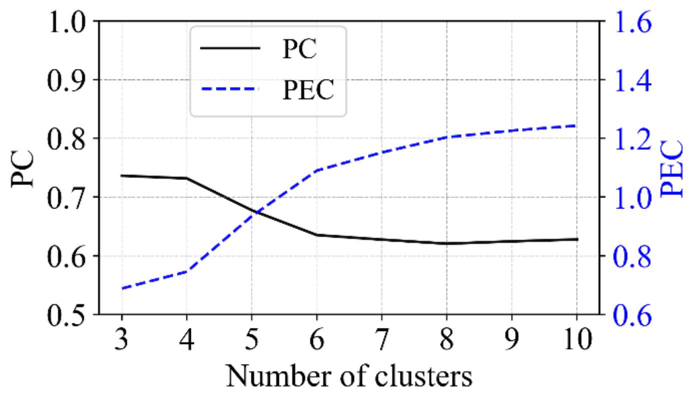
Fuzzy c-means algorithm is used to cluster the smart cities based on the scores obtained under each dimension of liveability and resilience. The number of clusters considered were within the range of [3, 10], and the optimum number of clusters were determined using two performance measures: namely, partition coefficient (PE) and partition entropy coefficient (PEC). The maximum value of PEC and the minimum value of PE corresponds to a good partition. The results of fuzzy c-means suggested that the optimum number of clusters corresponds to three, as can be observed in Figure 17(a)-3(c) showing the distribution of PEC and PE with the number of clusters for liveability, resilience, and aggregate performance, respectively.



a) Urban livability



b) Resilience

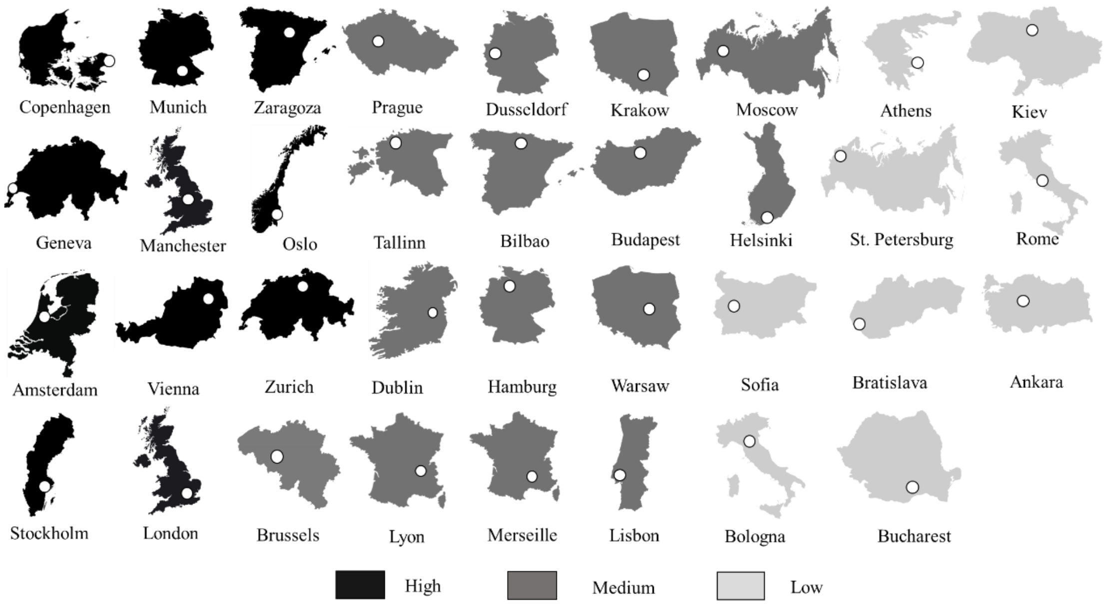


c) Aggregate performance

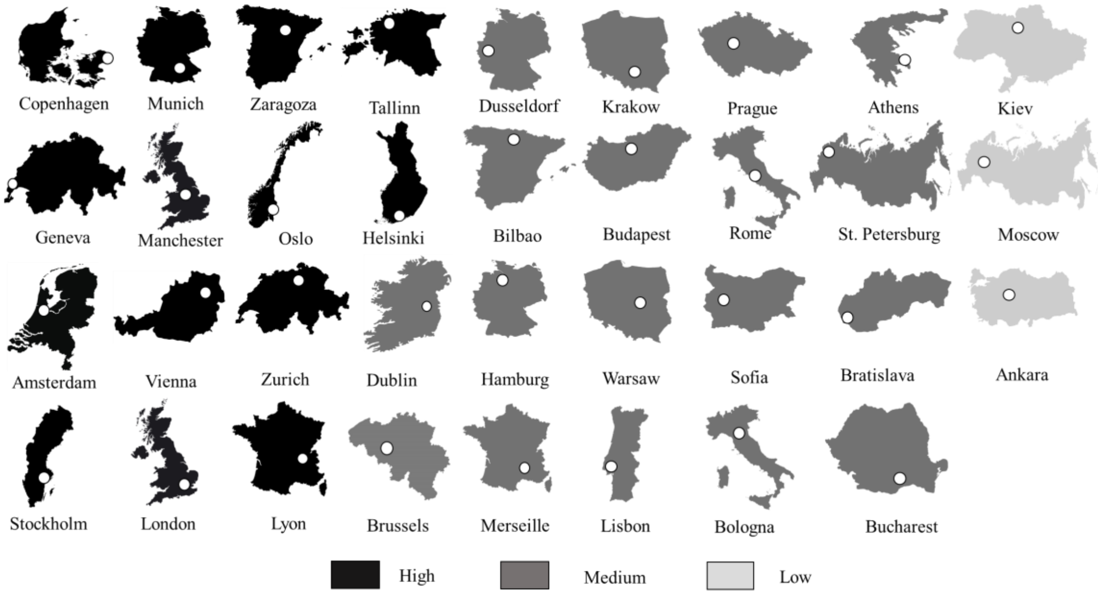
Figure 17. Variation of performance measures with the number of clusters

Figure 18(a)-(c) show the results of fuzzy c-means cluster analysis using the optimum number of clusters for urban liveability, city resilience, and aggregate performance, respectively as high, medium, or low. As can be observed in these figures, most of the smart cities fall under the medium level of liveability (43%), while 31% and 26% of the smart cities fall under high and low levels of liveability, respectively. With regard to the resilience level, the majority of the smart cities (51%) fall under the medium level of resilience, while 40% and 9% of the smart cities fall under the high and low levels of resilience, respectively. In Figure 18(a), Copenhagen, Geneva, Amsterdam, Stockholm, London, Vienna, Manchester, Munich, Zaragoza, Oslo, and Zurich were grouped under the high liveability performance class. However, all these smart cities remained unchanged with smart cities such as Lyon, Tallinn and Helsinki newly added to the high performing category while clustering cities based on resilience (Figure 18(b)). When attempting to understand the smart cities that co-create resilience and liveability together in their development model, it is seen that, all the smart cities that are under the high liveability performing class remains the same except for Manchester being replaced by the Finnish city of

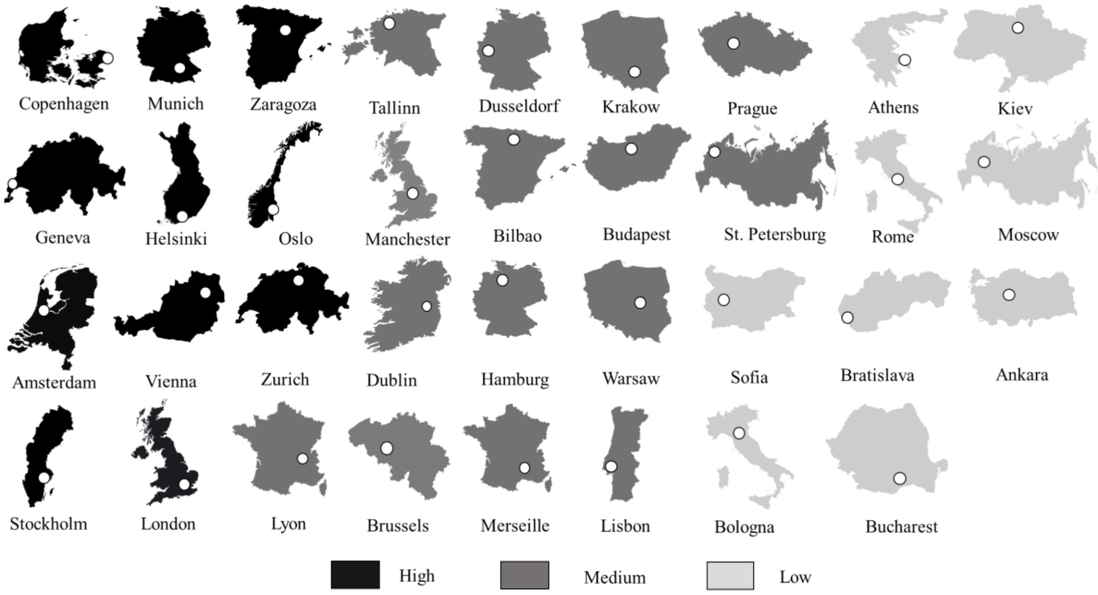
Helsinki. It is seen that Bologna, Sofia, Athens, St. Petersburg, Bratislava, Bucharest, Kiev, Rome, and Ankara fall under the low performance cluster for liveability. When taking a look into the smart cities classed under the aggregate category, we can see that St. Petersburg is pushed to the medium performance class while Moscow is added to the low performance cluster. All the other smart cities under the low liveability performance cluster remains same in the low aggregate performance cluster, Figure 18(c). While Kiev and Ankara remain in the low performance class in all the three assessments conducted with Moscow added to the list under resilience. The trend in performance of each of the European smart cities under liveability, resilience, and aggregate categorization over time from 2015 till 2020 are shown in Figure 19(a)-(c), respectively.



(a)

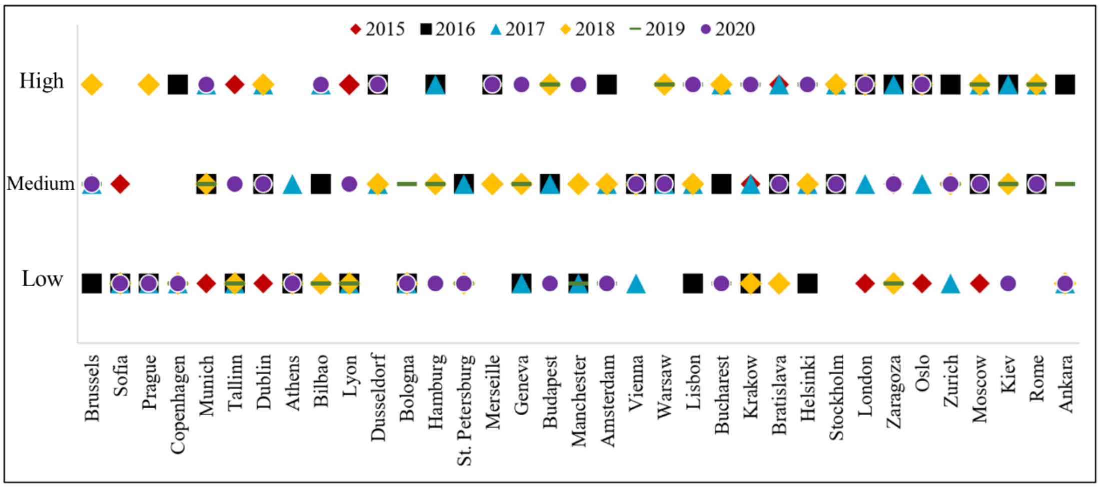


(b)

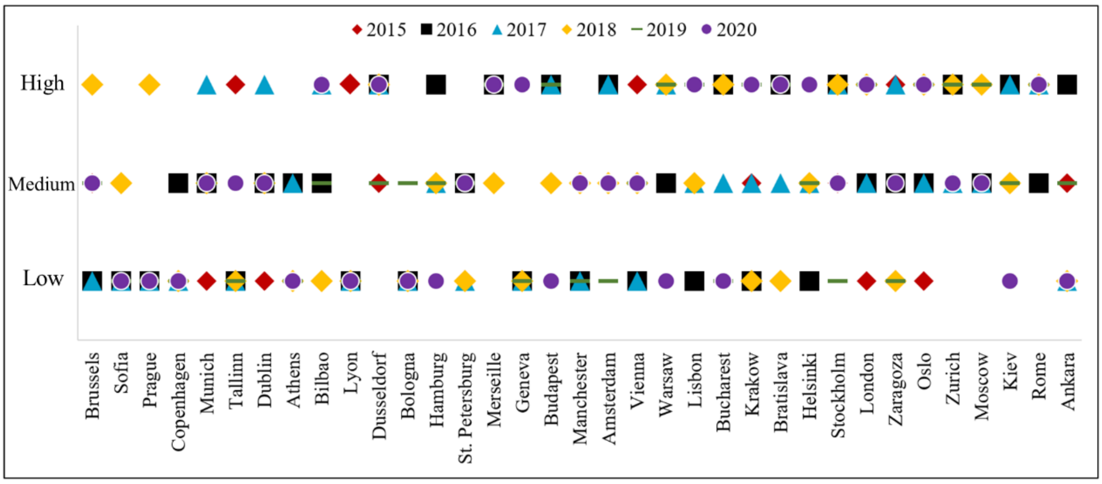


(c)

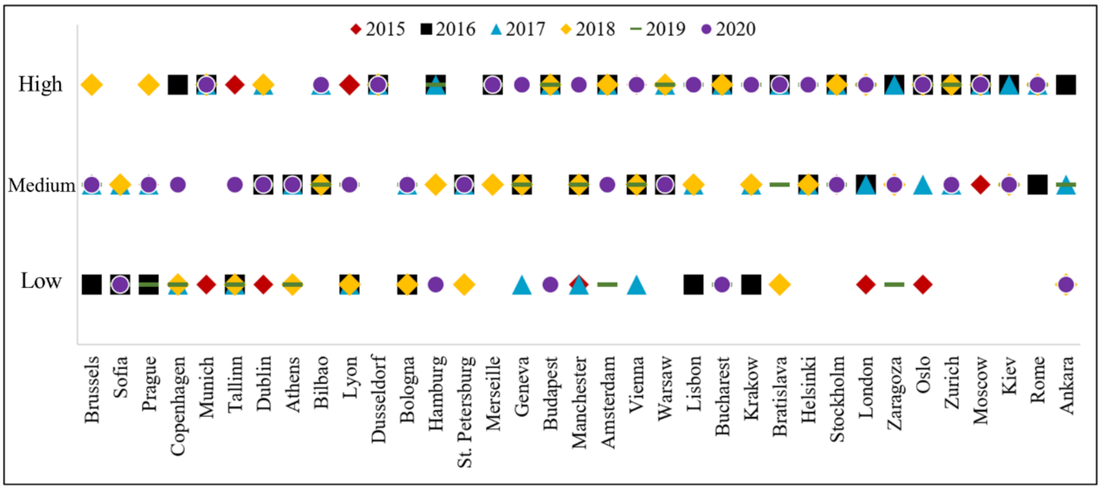
Figure 18. Distribution of the smart cities based on the level of (a) Livability (b) Resilience (c) Aggregate performance



(a) Liveability



(b) Resilience



(c) Aggregate performance

Figure 19. Progressive segmented performance of smart cities over time (2015-2020)

6.3.3. Classification models

Different ML algorithms were trained on the annual data for the smart cities (a total of 210 data points) to predict the level (high, medium, or low) of liveability and resilience of the smart cities based on the values for the indicators under each dimension Besides, ML-based models were proposed to predict the level of aggregate performance of smart cities based on the values for the indicators under the dimensions of the liveability and resilience criteria. To assess the degree of liveability of smart cities, the indicators under each dimension of the criteria liveability, namely; accessibility, community well-being, and economic vibrancy (a total of 10 indicators under each dimension) were considered as input features. Thus, the input vector for the assessment of liveability level comprised 30 predictors. Similarly, for resilience level, the indicators related to social resilience, economic resilience, infrastructure and built environment, and institutional resilience (a total of 38 indicators) were used as predictors that determined the response variable, namely, the level of resilience. The dataset was split into train and test sets that comprised of 80% and 20% of the complete dataset, respectively. The optimized hyperparameters for each model is presented in Table 15.

To compare the classification models, the coefficients namely; overall accuracy (ACC), Cohen's Kappa (κ), and the average area under the precision-recall curve (AUC-PR) were used. Table 16, Table 17 and Table 18 presents the accuracy, Cohen's Kappa, and average AUC-PR of each model on the training and test datasets. Among the single models, CART showed the highest performance in predicting the level of liveability in smart cities on the training dataset (95% accuracy), however, it showed low performance on the test dataset (78% accuracy). Similarly, despite a perfect agreement and an excellent level precision in the training group of the model created by CART (κ = 0.926; AUC-PR = 0.979), the resulting value showed only a moderate agreement (κ = 0.471) and marginal precision (AUC-PR = 0.642) in the testing group. These results show the low generalization ability of a single CART model. As listed in Table 16 and Table 17, the ensemble models showed higher accuracy compared to the single models. Among all models, the GBM model showed the most accurate prediction on the test dataset (95% accuracy), while the Naïve Bayes model showed the least predicted performance on the test dataset. Similarly, the GBM showed the best performance in predicting the level of resilience on the training dataset (ACC = 1.00, κ = 1.00, AUC-PR = 1.00). The accuracy of the GBM model in predicting the degree of resilience was 93% on the test dataset compared to 90%, 85%, 80%, 76%, and 73% for RF, CART, SVM, kNN, and Naïve Bayes, respectively, as listed in Table 17. Random forest is the second-best model in predicting the level of liveability and resilience of the smart cities, as listed in Table 16 and Table 17. The predictive accuracies of the ML algorithms for aggregate performance level are listed in Table 18. The Naïve Bayes classifier showed the least performance on the test set, as listed in Table 18. The GBM exhibited the highest performance with accuracies of 99% and 90% on the training and test sets, respectively. Similarly, in the training group, the GBM model exhibited a strong agreement (κ = 0.991) and a superior level of precision (AUC-PR = 1.00). Similarly, it showed the highest AUC-PR value of 0.913 and Cohen's Kappa κ value of 0.816 in the testing group. Precision-recall curve based on the test dataset for livability and resilience performance is shown in Figure C1(a)-(f) and Figure C2(a)-(f) respectively in Appendix C. For brevity, the precision-recall curve based on the train dataset is shown in Figure C3(a)-(f) for livability and Figure C4(a)-(f) for resilience.

Table 15. Optimal values for the hyper-parameters of the ML models

Model	Hyper-parameters	Optimal values		
		Liveability	Resilience	Aggregate
kNN	k	12	11	15
CART	Maximum depth	4	7	7
SVM	Kernel	poly	poly	poly
	C	0.01	0.01	0.1
RF	Number of estimators	13	50	14
	Maximum depth	4	9	4
	Minimum sample split	2	2	2
	Minimum sample leaf	1	1	1
	Maximum features	auto	auto	auto
GB	Number of estimators	10	5	3
	Maximum depth	3	10	3
	Learning rate	0.05	0.2	0.5
	Maximum features	sqrt	sqrt	sqrt

Table 16. Performance of different models in predicting liveability level

Model	Accuracy		Cohen's Kappa		Average AUCPR	
	Train set	Test set	Train set	Test set	Train set	Test set
Naïve Bayes	0.85	0.76	0.761	0.595	0.931	0.792
kNN	0.85	0.88	0.759	0.793	0.910	0.910
SVM	0.90	0.83	0.843	0.714	0.990	0.936
CART	0.95	0.78	0.926	0.471	0.979	0.642
RF	0.99	0.88	0.982	0.795	0.999	0.907
GBM	0.97	0.95	0.954	0.916	0.996	0.960

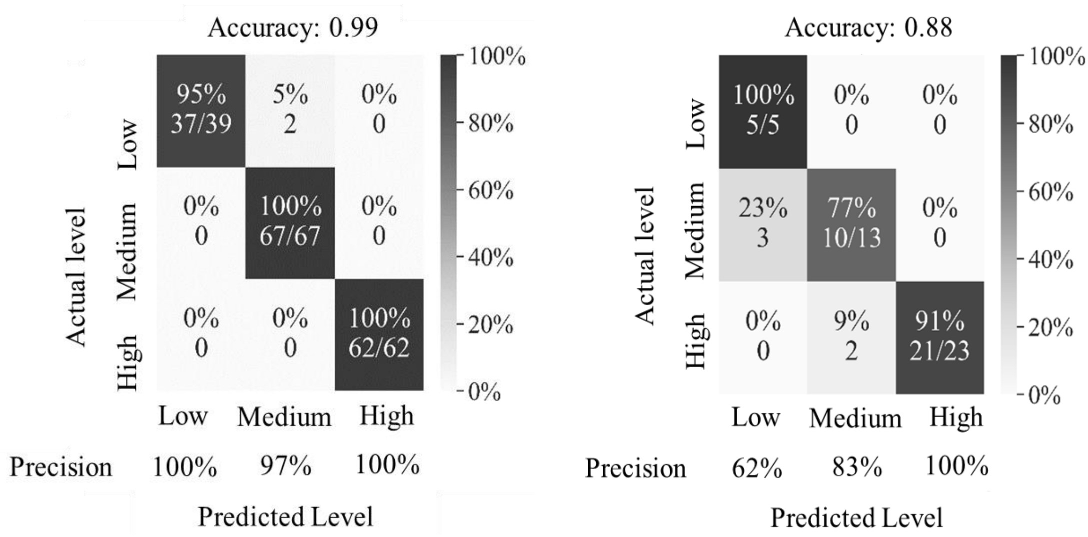
Table 17. Performance of different models in predicting resilience level

Model	Accuracy		Cohen's Kappa		Average AUCPR	
	Train set	Test set	Train set	Test set	Train set	Test set
Naïve Bayes	0.82	0.73	0.722	0.565	0.901	0.800
kNN	0.79	0.76	0.683	0.607	0.880	0.850
SVM	0.85	0.80	0.775	0.681	0.961	0.916
CART	0.98	0.85	0.973	0.792	0.991	0.812
RF	1.00	0.90	1.000	0.837	1.000	0.909
GBM	1.00	0.93	1.000	0.877	1.000	0.954

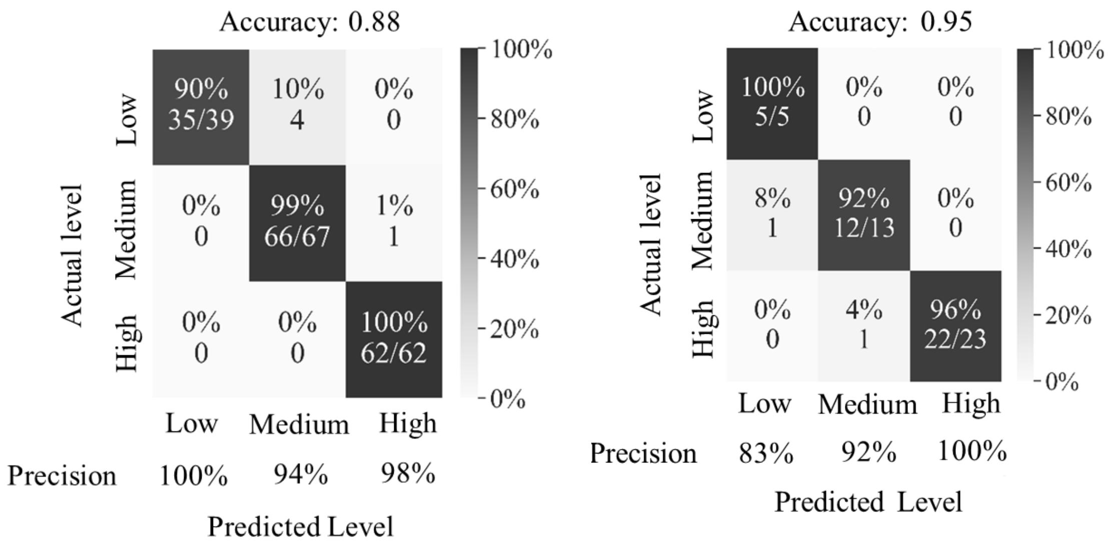
Table 18. Performance of different models in predicting aggregate performance level

Model	Accuracy		Cohen's Kappa		Average AUCPR	
	Train set	Test set	Train set	Test set	Train set	Test set
Naïve Bayes	0.89	0.73	0.835	0.543	0.961	0.751
kNN	0.80	0.78	0.681	0.623	0.882	0.877
SVM	0.99	0.76	0.991	0.578	0.999	0.932
CART	0.99	0.76	1.000	0.292	1.000	0.502
RF	0.98	0.85	0.972	0.733	0.999	0.896
GBM	0.99	0.90	0.991	0.816	1.000	0.913

The performance of the ensemble models, particularly, RF and GBM models, is further investigated with the aid of a confusion matrix, which is a table presenting the actual level versus the predicted level of liveability, resilience, and aggregate performance of smart cities. Other performance metrics include recall and precision. Precision refers to the percentage of the correctly predicted level of liveability or resilience of the smart cities by the ML model. In addition, the actual liveability/resilience/aggregate performance level that are correctly predicted by the algorithm is recall. Figure 20(a)-(d) show the confusion matrix for the level of liveability on both the train and test sets using the RF and GBM models, while Figure 21(a)-(d) show the confusion matrix using the RF and GBM for the resilience level of the smart cities. In these figures, the diagonal elements show the number of correctly predicted liveability/resilience levels along with recall in percentage. The proposed GBM showed high precision, recall, and accuracy in identifying the level of liveability and resilience of the smart cities, as shown in Figure 20(a)-(d) and Figure 21(a)-(d), respectively. Figure 22(a)-(d) show the confusion matrix for aggregate performance level based on the proposed RF and GBM models, where AP stands for aggregate performance. As can be observed in these figures, the proposed GBM model showed high accuracy, recall, and precision in predicting the aggregate performance level for the smart cities on both the training and test sets. Thus, it can be concluded that the proposed GBM can effectively be used to predict the level of liveability, resilience, and aggregate performance of future smart cities. Figure 23(a)-(c) show the Spider diagram denoting the balanced accuracy (ACC), precision (AUC-PR), and agreement (κ) on the classification outputs for all the different classifiers to establish resilience, liveability, and aggregate performance assessment.

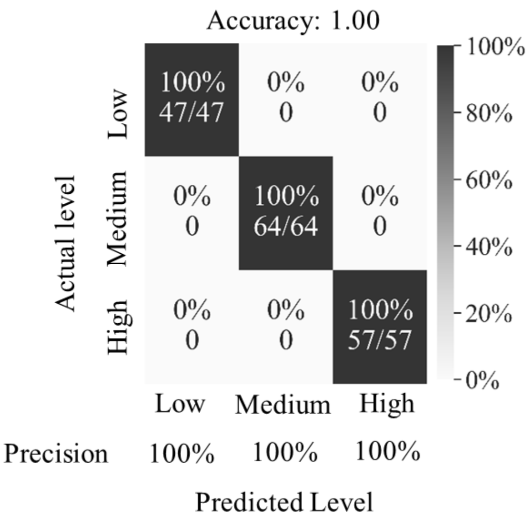


(a) RF on train set (b) RF on test set

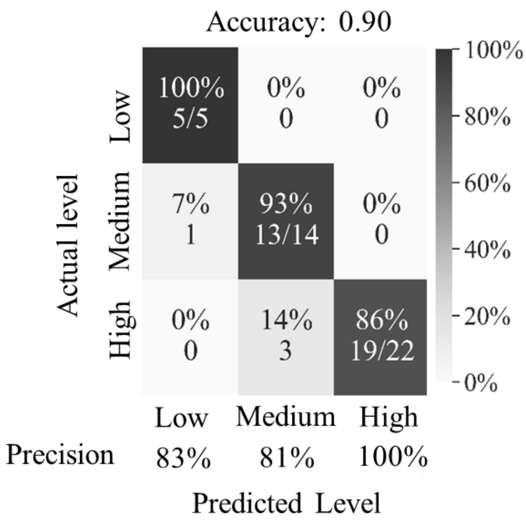


(c) GBM on train set (d) GBM on test set

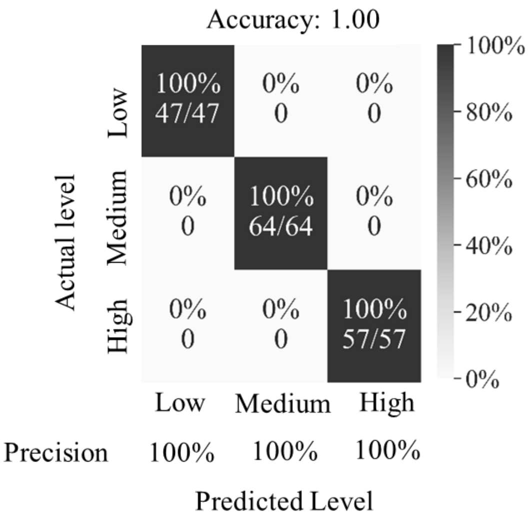
Figure 20. Confusion matrix of RF and GBM classifier for livability level



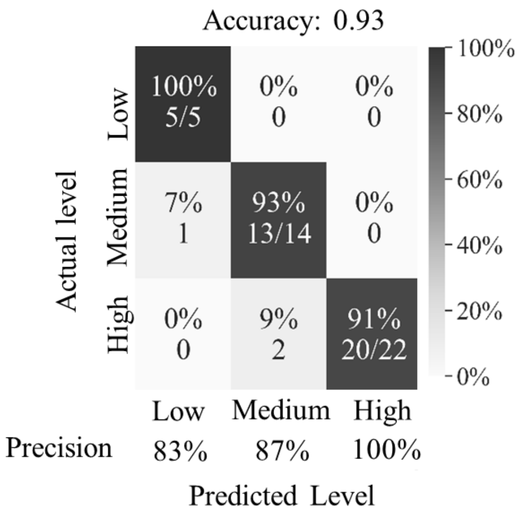
(a) RF on train set



(b) RF on test set

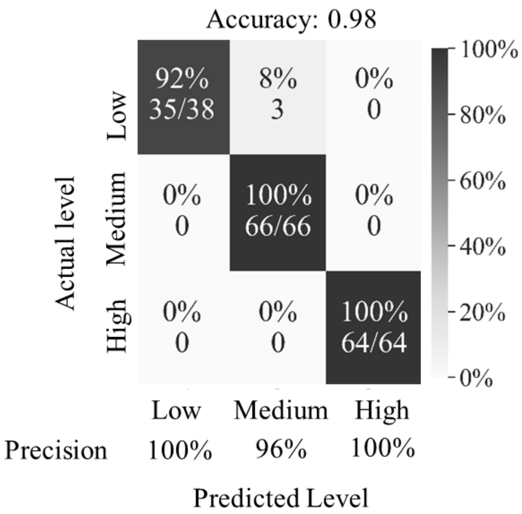


(c) GBM on train set

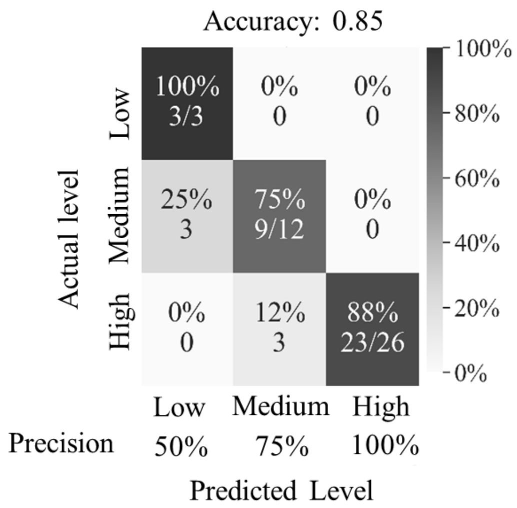


(d) GBM on test set

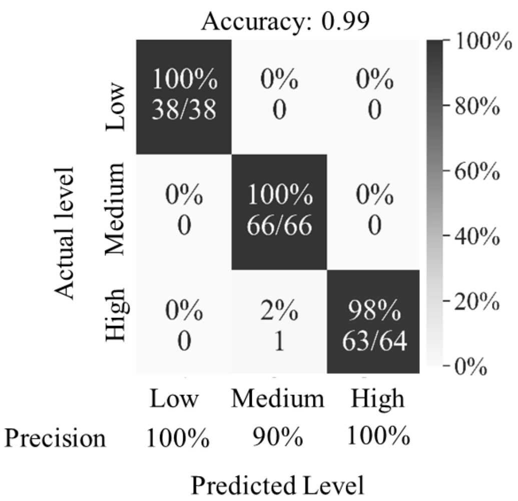
Figure 21. Confusion matrix of RF classifier on (a) train set and (b) test set, and GBM classifier on (c) train set and (d) test set for resilience level



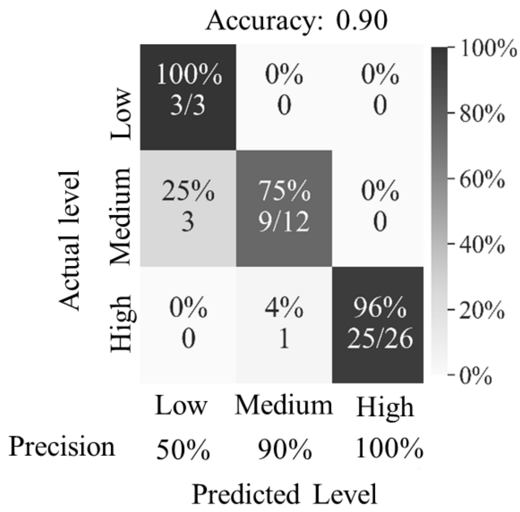
(a) RF on train set



(b) RF on test set

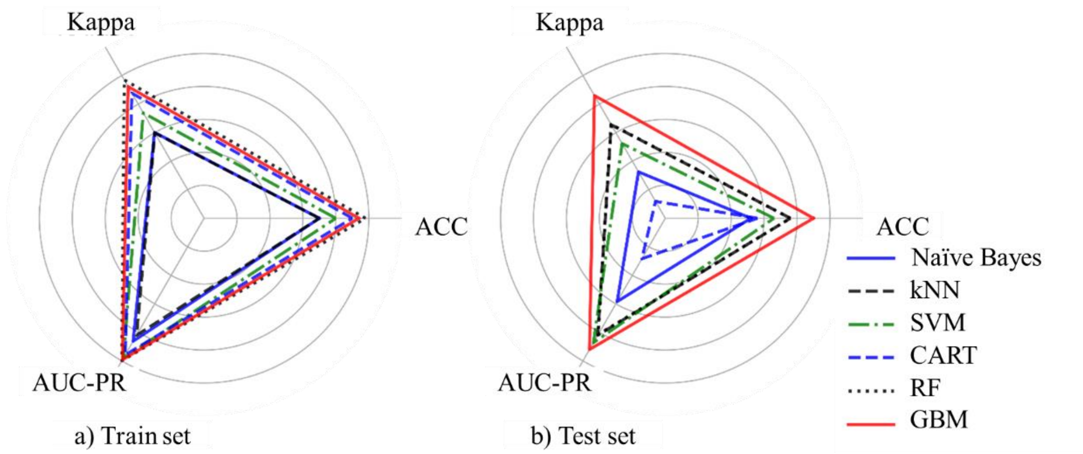


(c) GBM on train set

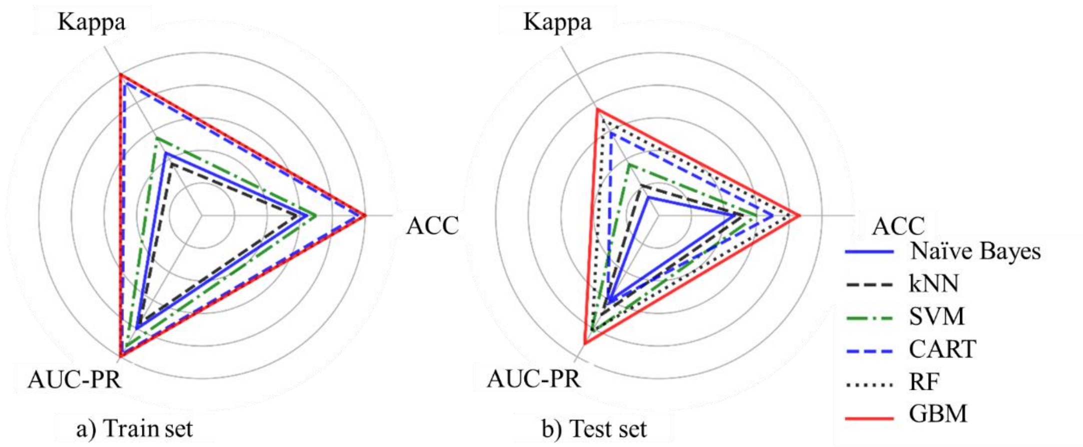


(d) GBM on test set

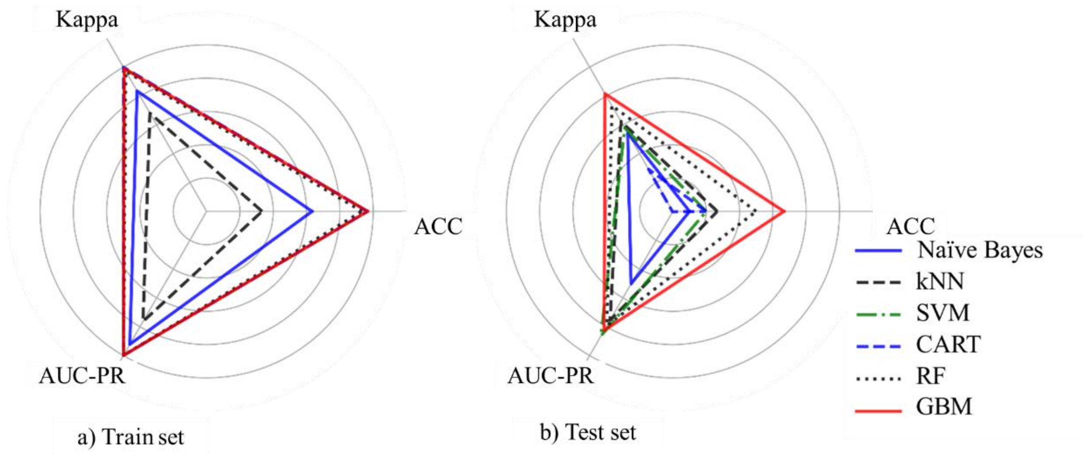
Figure 22. Confusion matrix of RF classifier on (a) train set and (b) test set, and GBM classifier on (c) train set and (d) test set for aggregate performance (AP) level



(a) Livability



(b) Resilience



(c) Aggregate

Figure 23. Spider diagram denoting the balanced accuracy (ACC), AUC-PR, and the agreement (κ) on the classification outputs for different classifiers

6.4. Chapter synopsis

Smart cities are the centers of economic opulence and a hope for standardized living. Understanding the shades of urban resilience and liveability in smart city models is of paramount importance. This chapter presented the implementation and validation of the proposed novel two-stage data driven model combining a multivariate metric-distance analysis with machine learning (ML) techniques for resilience and liveability assessment of smart cities, module 3 of the hybrid decision support model. A longitudinal dataset for 35 top-ranked European smart cities from 2015 till 2020 applied as the case study under the proposed framework. Initially, a metric distance-based weighting approach is used to weight the indicators and quantify the scores across each dimension under city resilience and urban liveability. The key dimensions under city resilience include social, economic, infrastructure and built environment and, institutional resilience, while under urban liveability, the dimensions include accessibility, community well-being, and economic vibrancy. Fuzzy c-means clustering as an unsupervised machine learning technique is used to sort smart cities based on the degree of performance. In addition, an intelligent approach is presented for prediction of the degree of liveability, resilience, and aggregate performance of smart cities based on various supervised ML techniques. Classification models such as Naïve Bayes, k-nearest neighbor (kNN), support vector machine (SVM), Classification and Regression Tree (CART) and, ensemble models including Random Forest (RF) and Gradient Boosting machine (GBM) were used. Three coefficients (accuracy, Cohen's Kappa (κ) and average area under the precision-recall curve (AUC-PR)) along with confusion matrix were used to appraise the performance of the classifier ML models. The results revealed GBM as the best classification and predictive model for the resilience, liveability, and aggregate performance assessment. The study in this chapter also revealed Copenhagen, Geneva, Stockholm, Munich, Helsinki, Vienna, London, Oslo, Zurich, and Amsterdam as the smart cities that co-create resilience and liveability in their development model with superior performance. The following chapter 7 would discuss in detail the aggregation of all the criteria’s, dimensions and indicators under the FSC index for the composite performance assessment.

CHAPTER 7: A NOVEL FUZZY MULTI-CRITERIA EXPERT MODEL BASED COMPOSITE PERFORMANCE ASSESSMENT

7.1. General outline

Future cities are insufficient and non-self-preservative without integrating the triple criteria of sustainability, resilience and livability with smartness. This chapter takes a step forward in implementing the necessitated triple criteria under a unified frame of assessment with inclusion of multiple sub-criteria (dimensions) to construct a composite index, the “FSC index” that aids in performance assessment. This chapter is thus the practical implementation and validation of the proposed novel fuzzy expert-based multi-criteria model (module 4) under the devised novel hybrid decision support model. An empirical analysis taking the same set of 35 high-tech smart cities in Europe as a case is used to implement the proposed model and, test the robustness and validity of the model. The 3-stage integrated model includes SF-AHP for weighting the dimensions and main-criteria followed by the distance function based-approach; the EDAS method to rank and score the smart cities. Fuzzy c-means algorithm is then used to segment the smart cities to allocate them into high, medium and low performance groups so as to ease the decision making process. Two different type of comparative analysis is used as a validation step to understand the robustness of the proposed model.

7.2. Significance and objective

While attempting to construct a composite index, Becker et al. (2016) stresses on the importance of making choices/decisions when weighting and combining different criteria at several decision-making (DM) steps. In this context of constructing a composite index within multidimensional frameworks, scholars insist on the profound efficacy of using the “Multicriteria Decision Making (MCDM)” techniques (Nardo et al., 2008). Several studies have developed and applied the MCDM tools to solve different problems in diverse fields such as manufacturing, energy production, urban and resilience planning, environment, and sustainability (Mardani et al., 2015). The MCDM has been widely used in the research field since the 1960s; numerous articles and books have been published to study it (Roy, 2005). MCDM methods have been developed to identify the idealistic alternative, categorize the provided alternatives into a smaller number of classes, and assist in ranking the alternatives in a preferable order. In other words, using MCDM is considered a way to solve complex problems by breaking the problem into smaller parts, weighing some extrarenal considerations, followed by finalizing judgments about smaller related components, reassembling the pieces at the end to present the overall situation comprehensively (Mardani et al., 2015). In the DM approach, the selection is made between the decision alternatives defined by their aspects. Over time, various MCDM tools and techniques have been developed with different theoretical backgrounds and types of questions asked. The expansion of MCDM research was enhanced between the 1980s and early 1990s to develop several techniques and approaches. For instance, Saaty, (1980) published a comprehensive study on the “Analytic Hierarchy Process (AHP)”, then in 1996, Saaty published a development study about the “Analytic Network Process (ANP)” method (Saaty, 1996). Later, Roy, (1996) summarized the material on “Elimination and Choice Expressing Reality” (ELECTRE) methods. Moreover, Brauers, (2003) presented a “multi-criteria model based on the multi-objective optimization by ratio analysis (MOORA)”. The development of hybrid methods is becoming recently important built on previously well-known methods. As an illustration, the “Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS)” (Hwang and Yoon, 1981), “Decision Making Trial and Evaluation

Laboratory (DEMATEL)" (Fontela and Gabus, 1976), and "Vise Kriterijumska Optimizacija I Kompromisno Resenje (VIKOR)" (Opricovic, 1998; Aboushaqrah et al., 2021) are some to start with. However, vagueness and uncertainties are bound to exist when weighting and aggregating criteria and sub-criteria to construct a composite index, despite the use of the recent hybrid methods. Weights assigned to criteria often increases uncertainty in the scores analyzed (Becker et al., 2017; Gan et al., 2017). Similarly, the use of equal weights for criteria ignores the relative importance and trade-offs between the criteria used in the assessment process. Fuzzy sets based on expert elicitation, proposed by Zadeh (1965) quantitatively characterizes these ambiguities and vagueness in decision making with multiple goals and criteria. These caveats have spurred research communities to develop robust fuzzy expert-based multi-criteria models when attempting to quantify multiple main and sub-criteria for the selection of alternatives by constructing composite indices, thus the spotlight of this research. To this end, to illuminate the uncharted hiatus in smart city decision making problems and expand the existing knowledge domain, we proposed the novel 3-stage model in module 4, which is practically implemented with the below mentioned custom tailored objectives for;

a) Constructing the first of its kind composite index used to evaluate the performance of smart cities under the sustainability, urban resilience, and liveability criteria using the proposed novel fuzzy expert-based multi-criteria decision support model.
b) Analyzing the performance of 35 European smart cities based on sustainability, resilience and livability as the case and rank them based on the scores obtained.
c) Segmenting the performance of smart cities based on the composite scores

using clustering techniques as high, medium, and low performing smart cities.

d) Conducting comparative analysis to assess the validity and robustness of the proposed model to rule out uncertainties in the decision-making process.

7.3. Numerical solution

7.3.1. Model implementation and composite indexing

In this study, a novel methodology integrating SF-AHP with the modified EDAS methodology and fuzzy c-means clustering is suggested to assess the composite performance of smart cities. We determine the weights of the main and sub-criteria via SF-AHP, followed by employing the extended EDAS method to obtain composite scores and ranks to gauge the smart city performance. Fuzzy c-means algorithm is used to then group smart cities into clusters of high, medium, and low performance, for improved decision making. To empirically test the proposed integrated approach, we choose 35 tech-driven smart cities of Europe, as per the ranks published in the 2021 IMD Smart City Index. Due to these cities covering nearly three-quarter of the list of top 50 leading global smart cities, the sample size is fairly large for the results to be economically extrapolated to a global level when understanding the combined performance of smart cities across the sustainability, resilience, and liveability dimensions in the current smart city development models. The sub-criteria were selected through literature review while the main-criteria form the prime dimensions of the "Futuristic smart city" paradigm, the cities we aspire. All the data across each sub-criteria for the years from 2015-2020 were obtained as scores from the results of module 2 and module 3 in the interval [0, 1], which is the input for the proposed assessment. Sustainability main-criteria considers namely; climate change (Koch and Ahmad, 2018), governance and institution (Estevez et al., 2021), economic dynamism (Bonnet et al., 2021), energy and environmental resources

(Battarra et al., 2018), safety and security (About-de Chastenet et al., 2016) and social cohesion and solidarity (Uzzell et al., 2002) as the sub-criteria. The resilience main-criteria considers four sub-criteria namely; social resilience (Säumel et al., 2019; Copeland et al., 2020), economic resilience (Williams and Vorley, 2014; Bastaminia et al., 2017), infrastructure and built environment (Masoomi, and van de Lindt, 2019), and institutional resilience (Guiraudon, 2014). While urban liveability is addressed under 3 sub-criteria namely; accessibility (Ziemke et al., 2018), community well-being (Phillips et al., 2014; Chao et al., 2017), and economic vibrancy. The main-criteria and sub-criteria (dimensions) selected for sustainability, urban liveability, and resilience along with their relevance for the composite index construction is presented in Table 19.

Table 19. Main-criteria and sub-criteria for the composite smart city index construction

Main-criteria	Sub-criteria	Symbol	Justification
Sustainability	Climate change	CC	Wendling et al., (2018)
	Governance and Institution	GI	Broccardo et al., (2019)
	Economic dynamism	E	Kulkki, (2017)
	Energy and environmental resource	EE	Pira, (2021)
	Safety and security	SS	Lacinák and Ristvej, (2017)
	Social cohesion and solidarity	SW	Cook and Swyngedouw, (2012)
Resilience	Social Resilience	S	Copeland et al., (2020)
	Economic Resilience	EC	Bastaminia et al., (2017)
	Infrastructure and Build Environment Resilience	IB	Tzioutziou and Xenidis, (2021)
	Institutional Resilience	IN	Wei, (2020)
Urban liveability	Accessibility	AC	Ziemke et al., (2018)
	Economic vibrancy	EV	Gonella, (2019)
	Community well-being	CWB	Chao et al., (2017)

Prior to stage 1, a questionnaire was designed to obtain the weights of each main-criteria and sub-criteria by smart city experts from both industry and academia under a spherical fuzzy environment. The designed questionnaire was sent as an email correspondence and the smart city expert opinions were collected based on the AHP questionnaires outlined by spherical fuzzy numbers as the linguistic labels to denote expert's unanimity during the weighting process (see Appendix D for the questionnaire). A nine-point summative scale was used as the linguistic weights for selecting 'k' number of criteria and '$\hat{k}$' number of sub-criteria as per expert ($\tilde{e}_j$) opinions. The linguistic weighting variables include; "Absolutely more importance (AMI), Very high importance (VHI), High importance (HI), Slightly more importance (SMI), Equally importance (EI), Slightly low importance (SLI), Low importance (LI), Very low importance (VLI), Absolutely low importance (ALI)".

Stage 1: SF- AHP to determine the weights of each main criteria and sub-criteria

Step 1. The hierarchical structure including the main and sub-criteria for the smart city selection problem is established as presented in Figure 24.

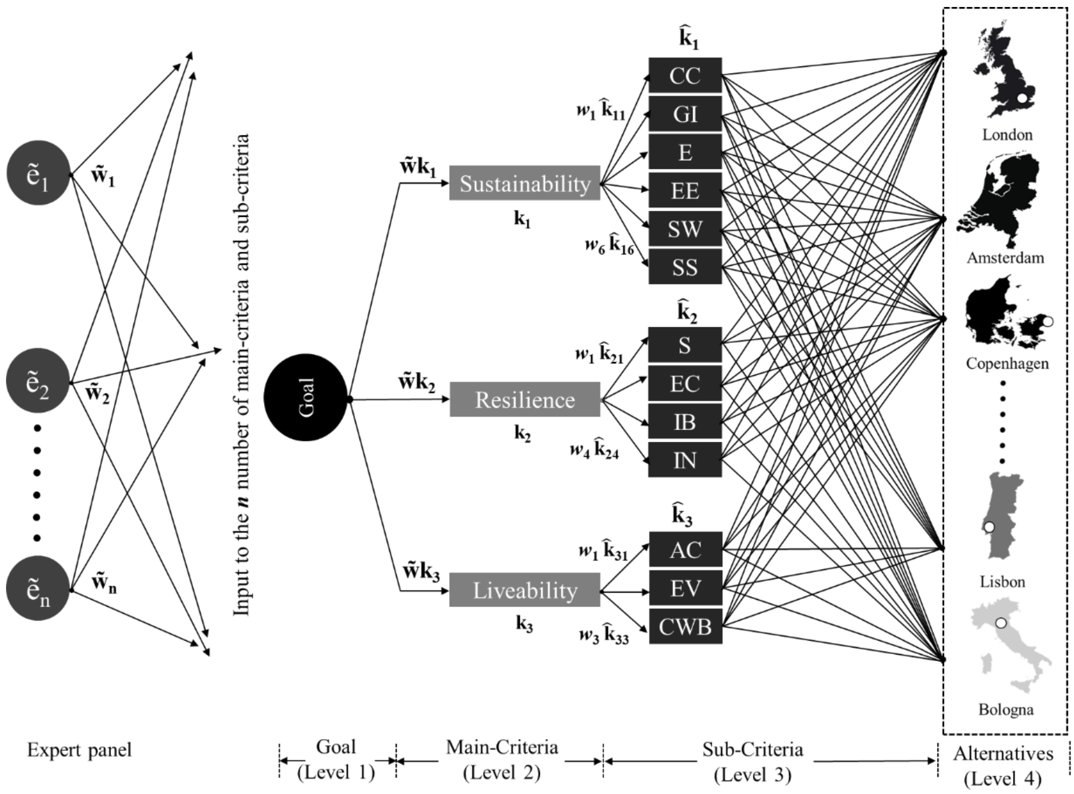


Figure 24. The hierarchical structure of the main and sub-criteria for the smart city composite index construction

Step 2. The pairwise comparison matrices for the main and sub-criteria are determined by a panel of experts, based on the survey outcomes using the importance scale presented in Table 19. The pairwise comparison matrices for main criteria is given in Table 20. The sub-criteria under the 3 main-criteria obtained as a result of expert judgments are given in Appendix B in Table B18(a)-Table B20(a).

Table 20. The pairwise comparison matrices for main criteria

		Sustainability	Resilience	Urban liveability
DM 1	Sustainability	EI	SMI	HI
	Resilience	SLI	EI	EI
	Urban liveability	LI	EI	EI
DM 2	Sustainability	EI	SMI	VHI
	Resilience	SLI	EI	SMI
	Urban liveability	VLI	SLI	EI
DM 3	Sustainability	EI	SMI	VHI
	Resilience	SLI	EI	SMI
	Urban liveability	VLI	SLI	EI

To continue, the aggregated fuzzy pairwise comparison matrix for main criteria is obtained as given in Table 21.

Table 21. Aggregated evaluations of experts based on with SF numbers for main criteria

	Sustainability	Resilience	Urban liveability
Sustainability	(0.50,0.40,0.40)	(0.60,0.40,0.30)	(0.77,0.23,0.13)
Resilience	(0.40,0.60,0.30)	(0.50,0.40,0.40)	(0.56,0.43,0.33)
Liveability	(0.23,0.77,0.13)	(0.43,0.56,0.33)	(0.50,0.40,0.40)

Also, the aggregated fuzzy pairwise comparison matrix for the main and sub-criteria is provided in Table B21-Table B23 in Appendix B.

Step 3. The spherical fuzzy global and local weights of main and sub-criteria are calculated, respectively, using the SWAM operator given in Definition 5, with respect to each criterion. The weighted arithmetic mean is used to compute the spherical fuzzy weights which is presented in Table 22.

Table 22. The spherical fuzzy global and local weights of main and sub criteria

Main-Criteria	Weight	Sub-criteria	Symbol	Local weights	Global weights
(k_n)	($\widetilde{w}$)	($\hat{k}_n$)	(S)	($\overline{w}$)	($\widehat{w}$)
Sustainability	0.435	Climate change	CC	0.226	0.098
		Governance and Institution	GI	0.117	0.051
		Economic dynamism	E	0.107	0.046
		Energy and Environmental Resource	EE	0.150	0.065
		Safety and security	SS	0.196	0.085
		Social cohesion and solidarity	SW	0.203	0.088
Resilience	0.313	Social Resilience	S	0.345	0.108
		Economic Resilience	EC	0.281	0.088
		Infrastructure and Build Environment Resilience	IB	0.210	0.066
		Institutional Resilience	IN	0.165	0.052
Urban liveability	0.252	Accessibility	AC	0.196	0.049
		Economic vibrancy	EV	0.360	0.091
		Community well-being	CWB	0.444	0.112

It is seen from Table 22, that the most important main-criteria for smart city performance assessment is Sustainability with a weight ($\widetilde{\boldsymbol{w}}$) of 0.435. The most important sub-criteria under the dimension's sustainability, resilience and urban livability are climate change ($\overline{\boldsymbol{w}}_1$ = 0.226), social resilience ($\overline{\boldsymbol{w}}_7$ = 0.345), and community well-being ($\overline{\boldsymbol{w}}_{13}$ = 0.444), respectively. The global weights reveal community well-being ($\widehat{\boldsymbol{w}}_{13}$ = 0.112) as the most important sub-criteria followed by social resilience ($\widehat{\boldsymbol{w}}_7$ = 0.108), climate change ($\widehat{\boldsymbol{w}}_1$ = 0.098), economic vibrancy ($\widehat{\boldsymbol{w}}_{12}$ = 0.091) and social cohesion and solidarity ($\widehat{\boldsymbol{w}}_6$ = 0.088) as the 5 most important sub-criteria.

Stage 2: Ranking of the alternatives using extended EDAS

Step 4-5: The decision-making matrix is constructed as shown in Table 23.

Table 23. Decision making matrix and average solution for all the dimension

Smart cities	Sustainability			Resilience			Livability		
	CC	···	SW	S	···	IN	AC	···	EV
Brussels	0.9508	···	0.9188	0.6225	···	0.4955	0.7472	···	0.6866
Sofia	0.9137	···	0.7695	0.4684	···	0.4889	0.6670	···	0.4480
Prague	0.8417	···	0.8016	0.5576	···	0.5234	0.6936	···	0.6826
Copenhagen	0.9583	···	0.8125	0.5650	···	0.4691	0.6684	···	0.6548
Munich	0.9526	···	0.9628	0.6615	···	0.6507	0.8888	···	0.7460
Tallinn	1.0000	···	0.8191	0.4393	···	0.4050	0.5835	···	0.5124
Dublin	1.0000	···	0.9763	0.6178	···	0.5097	0.7817	···	0.7003
Athens	1.0000	···	0.8668	0.5207	···	0.4938	0.6667	···	0.4891
Bilbao	0.7657	···	0.9602	0.6243	···	0.5780	0.7886	···	0.7354
Lyon	1.0000	···	0.9806	0.5309	···	0.4277	0.6730	···	0.6588
Dusseldorf	1.0000	···	0.7796	0.7638	···	0.7143	0.9340	···	0.8127
Bologna	0.9843	···	0.9256	0.3969	···	0.3580	0.6034	···	0.4810
Hamburg	1.0000	···	0.9977	0.6221	···	0.5890	0.7587	···	0.7136
Petersburg	0.8390	···	0.7662	0.5732	···	0.5061	0.7321	···	0.5856
Marseille	1.0000	···	0.8561	0.7220	···	0.6088	0.8759	···	0.7934
Geneva	1.0000	···	0.9995	0.5437	···	0.4502	0.7154	···	0.6845
Budapest	0.7516	···	0.7031	0.7402	···	0.6898	0.8680	···	0.7998
Manchester	1.0000	···	0.9807	0.4704	···	0.3899	0.7077	···	0.5343
Amsterdam	1.0000	···	0.9803	0.6537	···	0.6265	0.7928	···	0.6878
Vienna	0.9367	···	0.7889	0.6000	···	0.5236	0.7696	···	0.6731
Warsaw	0.7492	···	0.8168	0.7623	···	0.6219	0.8990	···	0.8024
Lisbon	0.7660	···	0.6678	0.6388	···	0.5280	0.7825	···	0.7623
Bucharest	0.8339	···	0.7716	0.6605	···	0.6250	0.8374	···	0.7346
Krakow	0.7903	···	0.6201	0.6143	···	0.5175	0.7983	···	0.6288
Bratislava	0.7824	···	0.6113	0.6580	···	0.6267	0.8140	···	0.7025
Helsinki	0.9643	···	0.7164	0.6738	···	0.5721	0.8164	···	0.7420
Stockholm	1.0000	···	0.9461	0.7539	···	0.5752	0.8701	···	0.7927
London	0.9827	···	1.0000	0.7288	···	0.5954	0.8550	···	0.8082
Zaragoza	0.7231	···	0.9049	0.6510	···	0.6212	0.8055	···	0.6941
Oslo	1.0000	···	1.0000	0.6779	···	0.5505	0.8360	···	0.7122
Zurich	1.0000	···	1.0000	0.6570	···	0.6561	0.8092	···	0.6879
Moscow	0.6845	···	0.9814	0.7143	···	0.6370	0.8362	···	0.7417
Kiev	0.4822	···	0.5613	0.7510	···	0.5889	0.8691	···	0.7773
Rome	0.7111	···	0.9601	0.7726	···	0.7090	0.8954	···	0.8330
Ankara	0.7599	···	0.6079	0.5995	···	0.5689	0.7756	···	0.6472
$\bar{x}_j$	0.8893	···	0.8518	0.6288	···	0.5569	0.7833	···	0.6899

Step 6: The P_{ij}^{+} and N_{ij}^{-} are estimated as given as Table 24 and Table 25.

Table 24. Positive distance (P_{ij}^{+}) from average solution of all alternatives

Smart cities	Sustainability			Resilience			Livability		
	CC	···	SW	S	···	IN	AC	···	EV
Brussels	0.0813	···	0.0780	0.0577	···	0.0646	0.0457	···	0.0594
Sofia	0.0548	···	0.0000	0.0000	···	0.0281	0.0108	···	0.0000
Prague	0.0165	···	0.0096	0.0585	···	0.0623	0.0659	···	0.0447
Copenhagen	0.0936	···	0.0117	0.1000	···	0.0481	0.0548	···	0.0721
Munich	0.0780	···	0.1303	0.1319	···	0.2255	0.1431	···	0.1116
Tallinn	0.1251	···	0.0179	0.0805	···	0.0428	0.0327	···	0.0453
Dublin	0.1251	···	0.1461	0.0651	···	0.0770	0.0764	···	0.0672
Athens	0.1251	···	0.0274	0.0179	···	0.0215	0.0127	···	0.0000
Bilbao	0.0000	···	0.1269	0.1331	···	0.1139	0.1101	···	0.0911
Lyon	0.1251	···	0.1514	0.0610	···	0.0070	0.0275	···	0.0626
Dusseldorf	0.1251	···	0.0309	0.2160	···	0.2828	0.1926	···	0.1867
Bologna	0.1066	···	0.0860	0.0147	···	0.0093	0.0092	···	0.0052
Hamburg	0.1251	···	0.1718	0.0918	···	0.1201	0.0940	···	0.1081
Petersburg	0.0647	···	0.0208	0.0327	···	0.0302	0.0213	···	0.0095
Marseille	0.1251	···	0.0319	0.1958	···	0.1297	0.1535	···	0.1612
Geneva	0.1251	···	0.1740	0.0305	···	0.0192	0.0277	···	0.0676
Budapest	0.0000	···	0.0000	0.2428	···	0.2906	0.1710	···	0.1800
Manchester	0.1251	···	0.1525	0.0371	···	0.0109	0.0280	···	0.0378
Amsterdam	0.1251	···	0.1511	0.1214	···	0.1270	0.0968	···	0.1013
Vienna	0.0827	···	0.0240	0.0413	···	0.0490	0.0349	···	0.0590
Warsaw	0.0000	···	0.0015	0.2352	···	0.1543	0.1568	···	0.1630
Lisbon	0.0408	···	0.0000	0.1156	···	0.0973	0.0735	···	0.1376
Bucharest	0.0384	···	0.0000	0.2026	···	0.2316	0.1466	···	0.1359
Krakow	0.0058	···	0.0000	0.0990	···	0.1256	0.0772	···	0.0670
Bratislava	0.0000	···	0.0000	0.1086	···	0.1282	0.1225	···	0.0976
Helsinki	0.1058	···	0.0000	0.1163	···	0.1195	0.0637	···	0.1393
Stockholm	0.1251	···	0.1114	0.2322	···	0.0897	0.1239	···	0.1499
London	0.1055	···	0.1746	0.2083	···	0.1677	0.1216	···	0.2020
Zaragoza	0.0000	···	0.0664	0.1547	···	0.2198	0.0980	···	0.1145
Oslo	0.1251	···	0.1746	0.1777	···	0.1285	0.1103	···	0.1277
Zurich	0.1251	···	0.1746	0.0920	···	0.2010	0.1059	···	0.0768
Moscow	0.0000	···	0.1525	0.1577	···	0.1908	0.0688	···	0.1335
Kiev	0.0000	···	0.0000	0.2167	···	0.1473	0.1422	···	0.1462
Rome	0.0000	···	0.1271	0.2376	···	0.2734	0.1428	···	0.2154
Ankara	0.0000	···	0.0000	0.1515	···	0.1629	0.0907	···	0.1236

Table 25. Negative distance (N^-_{ij}) from average solution of all alternatives

Smart cities	Sustainability			Resilience			Livability		
	CC	···	SW	S	···	IN	AC	···	EV
Brussels	0.0112	···	0.0000	0.0676	···	0.1749	0.0019	···	0.0642
Sofia	0.0270	···	0.0964	0.2550	···	0.1504	0.0000	···	0.3506
Prague	0.0706	···	0.0678	0.1719	···	0.1233	0.2528	···	0.0554
Copenhagen	0.0155	···	0.0568	0.2009	···	0.2054	0.0000	···	0.1230
Munich	0.0062	···	0.0000	0.0810	···	0.0584	0.0526	···	0.0304
Tallinn	0.0000	···	0.0569	0.3811	···	0.3157	0.0000	···	0.3028
Dublin	0.0000	···	0.0000	0.0833	···	0.1627	0.2674	···	0.0521
Athens	0.0000	···	0.0094	0.1906	···	0.1348	0.5288	···	0.2911
Bilbao	0.1387	···	0.0000	0.1407	···	0.0762	0.2952	···	0.0253
Lyon	0.0000	···	0.0000	0.2155	···	0.2378	0.0000	···	0.1077
Dusseldorf	0.0000	···	0.1159	0.0017	···	0.0000	0.0000	···	0.0086
Bologna	0.0000	···	0.0000	0.3828	···	0.3649	0.3671	···	0.3080
Hamburg	0.0000	···	0.0000	0.1022	···	0.0633	0.0000	···	0.0737
Petersburg	0.1202	···	0.1225	0.1205	···	0.1204	0.0000	···	0.1606
Marseille	0.0000	···	0.0257	0.0480	···	0.0361	0.1320	···	0.0111
Geneva	0.0000	···	0.0000	0.1662	···	0.2109	0.0891	···	0.0754
Budapest	0.1551	···	0.1755	0.0647	···	0.0521	0.0000	···	0.0206
Manchester	0.0000	···	0.0000	0.2901	···	0.3120	0.2427	···	0.2633
Amsterdam	0.0000	···	0.0000	0.0820	···	0.0014	0.0000	···	0.1044
Vienna	0.0290	···	0.0990	0.0872	···	0.1084	0.0000	···	0.0833
Warsaw	0.1590	···	0.0427	0.0228	···	0.0373	0.0000	···	0.0000
Lisbon	0.1839	···	0.2164	0.0999	···	0.1485	0.1792	···	0.0328
Bucharest	0.1007	···	0.0945	0.1518	···	0.1099	0.0000	···	0.0711
Krakow	0.1158	···	0.2714	0.1219	···	0.1951	0.0000	···	0.1556
Bratislava	0.1198	···	0.2818	0.0614	···	0.0027	0.0000	···	0.0795
Helsinki	0.0205	···	0.1601	0.0451	···	0.0924	0.0000	···	0.0639
Stockholm	0.0000	···	0.0000	0.0336	···	0.0575	0.0067	···	0.0009
London	0.0000	···	0.0000	0.0497	···	0.0991	0.1828	···	0.0303
Zaragoza	0.1890	···	0.0052	0.1199	···	0.1046	0.0000	···	0.1085
Oslo	0.0000	···	0.0000	0.1005	···	0.1404	0.2096	···	0.0953
Zurich	0.0000	···	0.0000	0.0468	···	0.0226	0.1612	···	0.0796
Moscow	0.2311	···	0.0000	0.0214	···	0.0474	0.0000	···	0.0584
Kiev	0.4592	···	0.3406	0.0221	···	0.0901	0.0000	···	0.0194
Rome	0.2001	···	0.0000	0.0087	···	0.0008	0.0000	···	0.0081
Ankara	0.1477	···	0.2865	0.1970	···	0.1398	0.0000	···	0.1855

Step 7: Weighted sum of P^+_{ij} (P^w_i) and N^-_{ij} (N^w_i) is calculated for all the alternatives

whose results are shown in Table 26 and Table 27 respectively.

Table 26. The weighted sum of P_{ij}^{+} (P_{i}^{w}) for all alternatives

Smart Cities	2015	2016	2017	2018	2019	2020
Brussels	0.057	0.013	0.041	0.170	0.115	0.088
Sofia	0.050	0.030	0.028	0.054	0.035	0.045
Prague	0.021	0.033	0.034	0.107	0.018	0.062
Copenhagen	0.163	0.153	0.042	0.030	0.036	0.048
Munich	0.093	0.119	0.219	0.153	0.119	0.213
Tallinn	0.149	0.027	0.028	0.035	0.031	0.041
Dublin	0.097	0.125	0.212	0.161	0.119	0.110
Athens	0.043	0.059	0.066	0.037	0.037	0.039
Bilbao	0.020	0.054	0.112	0.008	0.044	0.143
Lyon	0.152	0.040	0.032	0.029	0.059	0.024
Dusseldorf	0.107	0.206	0.148	0.103	0.201	0.189
Bologna	0.018	0.026	0.031	0.029	0.046	0.024
Hamburg	0.125	0.217	0.177	0.127	0.099	0.046
St. Petersburg	0.054	0.064	0.060	0.040	0.062	0.062
Merseille	0.105	0.158	0.021	0.081	0.172	0.158
Geneva	0.118	0.093	0.091	0.146	0.093	0.179
Budapest	0.183	0.123	0.078	0.160	0.149	0.006
Manchester	0.099	0.102	0.091	0.120	0.088	0.171
Amsterdam	0.249	0.206	0.175	0.100	0.052	0.087
Vienna	0.104	0.062	0.055	0.072	0.076	0.136
Warsaw	0.143	0.019	0.075	0.179	0.149	0.030
Lisbon	0.001	0.000	0.075	0.017	0.112	0.212
Bucharest	0.153	0.107	0.193	0.163	0.013	0.013
Krakow	0.030	0.005	0.044	0.007	0.106	0.193
Bratislava	0.154	0.119	0.081	0.029	0.080	0.075
Helsinki	0.042	0.044	0.104	0.075	0.132	0.176
Stockholm	0.084	0.126	0.237	0.197	0.062	0.044
London	0.089	0.169	0.108	0.210	0.267	0.198
Zaragoza	0.109	0.197	0.183	0.020	0.031	0.057
Oslo	0.099	0.155	0.102	0.178	0.312	0.249
Zurich	0.234	0.162	0.100	0.147	0.164	0.113
Moscow	0.061	0.132	0.111	0.168	0.224	0.091
Kiev	0.090	0.203	0.177	0.031	0.023	0.000
Rome	0.110	0.030	0.164	0.233	0.172	0.125
Ankara	0.186	0.189	0.006	0.000	0.066	0.000

Table 27. The weighted sum of N^{-}_{ij} (N^{w}_{i}) for all alternatives

Smart Cities	2015	2016	2017	2018	2019	2020
Brussels	0.0735	0.2096	0.0441	0.0125	0.0182	0.0377
Sofia	0.0673	0.2928	0.1292	0.0446	0.1692	0.2375
Prague	0.1232	0.1430	0.0863	0.0233	0.1499	0.1407
Copenhagen	0.0171	0.0094	0.1667	0.1850	0.2728	0.1067
Munich	0.1289	0.0012	0.0000	0.0166	0.0170	0.0297
Tallinn	0.0731	0.2692	0.4120	0.2125	0.4056	0.0776
Dublin	0.1550	0.0220	0.0000	0.0004	0.0242	0.0249
Athens	0.2566	0.1091	0.0555	0.1437	0.2244	0.0694
Bilbao	0.1421	0.1025	0.0706	0.1468	0.1301	0.0921
Lyon	0.0196	0.1559	0.1406	0.2533	0.1152	0.1468
Dusseldorf	0.0182	0.0188	0.0264	0.0168	0.0492	0.0049
Bologna	0.1913	0.3255	0.1481	0.3636	0.0586	0.1569
Hamburg	0.0317	0.0058	0.0128	0.0354	0.0383	0.2275
St. Petersburg	0.0880	0.0410	0.1363	0.1928	0.0607	0.0641
Merseille	0.0445	0.0319	0.0822	0.0528	0.0130	0.0206
Geneva	0.0847	0.0759	0.1874	0.0679	0.0650	0.0000
Budapest	0.0812	0.0697	0.0939	0.0861	0.0731	0.2350
Manchester	0.2674	0.0790	0.3141	0.0062	0.0854	0.0075
Amsterdam	0.0000	0.0040	0.0120	0.0158	0.1744	0.0645
Vienna	0.0500	0.0926	0.1597	0.0503	0.0525	0.0489
Warsaw	0.0809	0.0885	0.0723	0.0516	0.0926	0.1224
Lisbon	0.1919	0.2366	0.0934	0.1157	0.0604	0.0619
Bucharest	0.0573	0.0484	0.0627	0.0779	0.1884	0.3304
Krakow	0.1334	0.3453	0.0886	0.1537	0.1054	0.0910
Bratislava	0.0486	0.0701	0.0942	0.1674	0.0757	0.0840
Helsinki	0.0836	0.1502	0.0587	0.0834	0.0551	0.0567
Stockholm	0.0444	0.0522	0.0405	0.0335	0.0988	0.0674
London	0.1194	0.0144	0.0261	0.0209	0.0209	0.0209
Zaragoza	0.0667	0.0696	0.0309	0.1204	0.2467	0.0903
Oslo	0.2369	0.0000	0.0485	0.0026	0.0000	0.0000
Zurich	0.0080	0.0154	0.0923	0.0393	0.0096	0.0201
Moscow	0.1356	0.0230	0.0350	0.0354	0.0140	0.0229
Kiev	0.2075	0.1917	0.1609	0.1745	0.1690	0.2255
Rome	0.0745	0.0705	0.0782	0.0705	0.0267	0.0609
Ankara	0.1887	0.1317	0.2382	0.3400	0.2035	0.3985

Step 8: The values of P^{w}_{i} and N^{w}_{i} for all the alternatives are normalized as illustrated in Table 28 and Table 29.

Table 28. Normalized values of P_i^w (P_i^r) for all alternatives across years

Smart Cities	2015	2016	2017	2018	2019	2020
Brussels	0.230	0.062	0.175	0.727	0.370	0.352
Sofia	0.199	0.139	0.116	0.231	0.112	0.183
Prague	0.086	0.153	0.144	0.460	0.058	0.250
Copenhagen	0.658	0.706	0.176	0.130	0.114	0.191
Munich	0.375	0.548	0.924	0.655	0.381	0.855
Tallinn	0.599	0.124	0.118	0.149	0.100	0.164
Dublin	0.392	0.579	0.895	0.689	0.382	0.443
Athens	0.174	0.274	0.280	0.157	0.117	0.156
Bilbao	0.079	0.251	0.472	0.035	0.141	0.575
Lyon	0.613	0.183	0.134	0.123	0.190	0.094
Dusseldorf	0.431	0.951	0.623	0.440	0.645	0.758
Bologna	0.071	0.121	0.132	0.122	0.147	0.094
Hamburg	0.502	1.000	0.745	0.546	0.318	0.183
St. Petersburg	0.216	0.297	0.252	0.170	0.198	0.250
Merseille	0.421	0.727	0.089	0.347	0.550	0.637
Geneva	0.473	0.427	0.384	0.627	0.299	0.718
Budapest	0.738	0.568	0.327	0.688	0.479	0.025
Manchester	0.400	0.470	0.384	0.513	0.283	0.686
Amsterdam	1.000	0.951	0.739	0.427	0.165	0.349
Vienna	0.417	0.285	0.231	0.309	0.243	0.544
Warsaw	0.576	0.088	0.316	0.767	0.477	0.119
Lisbon	0.002	0.000	0.319	0.072	0.358	0.853
Bucharest	0.616	0.492	0.815	0.700	0.042	0.053
Krakow	0.119	0.022	0.186	0.028	0.339	0.775
Bratislava	0.618	0.551	0.344	0.126	0.257	0.299
Helsinki	0.169	0.204	0.438	0.319	0.423	0.708
Stockholm	0.336	0.583	1.000	0.846	0.198	0.178
London	0.358	0.781	0.455	0.900	0.856	0.795
Zaragoza	0.438	0.908	0.771	0.085	0.100	0.230
Oslo	0.400	0.715	0.430	0.764	1.000	1.000
Zurich	0.941	0.747	0.420	0.628	0.524	0.454
Moscow	0.245	0.611	0.468	0.719	0.718	0.365
Kiev	0.362	0.936	0.746	0.132	0.075	0.000
Rome	0.445	0.139	0.692	1.000	0.550	0.503
Ankara	0.749	0.873	0.027	0.000	0.211	0.000

Table 29. Normalized values of N_i^w (N_i^r) for all alternatives

Smart Cities	2015	2016	2017	2018	2019	2020
Brussels	0.725	0.393	0.893	0.965	0.955	0.905
Sofia	0.748	0.152	0.686	0.877	0.583	0.404
Prague	0.539	0.586	0.791	0.936	0.630	0.647
Copenhagen	0.936	0.973	0.595	0.491	0.328	0.732
Munich	0.518	0.996	1.000	0.954	0.958	0.925
Tallinn	0.727	0.220	0.000	0.416	0.000	0.805
Dublin	0.420	0.936	1.000	0.999	0.940	0.937
Athens	0.040	0.684	0.865	0.605	0.447	0.826
Bilbao	0.469	0.703	0.829	0.596	0.679	0.769
Lyon	0.927	0.548	0.659	0.303	0.716	0.632
Dusseldorf	0.932	0.945	0.936	0.954	0.879	0.988
Bologna	0.285	0.057	0.641	0.000	0.856	0.606
Hamburg	0.881	0.983	0.969	0.903	0.906	0.429
St. Petersburg	0.671	0.881	0.669	0.470	0.850	0.839
Merseille	0.834	0.908	0.800	0.855	0.968	0.948
Geneva	0.683	0.780	0.545	0.813	0.840	1.000
Budapest	0.696	0.798	0.772	0.763	0.820	0.410
Manchester	0.000	0.771	0.238	0.983	0.789	0.981
Amsterdam	1.000	0.988	0.971	0.956	0.570	0.838
Vienna	0.813	0.732	0.612	0.862	0.870	0.877
Warsaw	0.697	0.744	0.825	0.858	0.772	0.693
Lisbon	0.282	0.315	0.773	0.682	0.851	0.845
Bucharest	0.786	0.860	0.848	0.786	0.535	0.171
Krakow	0.501	0.000	0.785	0.577	0.740	0.772
Bratislava	0.818	0.797	0.771	0.540	0.813	0.789
Helsinki	0.688	0.565	0.857	0.771	0.864	0.858
Stockholm	0.834	0.849	0.902	0.908	0.756	0.831
London	0.554	0.958	0.937	0.942	0.948	0.947
Zaragoza	0.750	0.798	0.925	0.669	0.392	0.773
Oslo	0.114	1.000	0.882	0.993	1.000	1.000
Zurich	0.970	0.955	0.776	0.892	0.976	0.950
Moscow	0.493	0.933	0.915	0.903	0.965	0.943
Kiev	0.224	0.445	0.610	0.520	0.583	0.434
Rome	0.721	0.796	0.810	0.806	0.934	0.847
Ankara	0.294	0.619	0.422	0.065	0.498	0.000

Step 9-10: The Composite Score (CS) for all the smart cities (alternatives) are calculated and ranked as shown in Table 30 for all the smart cities across the years from 2015 till 2017. The alternative with the highest CS is the best choice among the

candidate alternatives (see Figure 25). The results show Amsterdam with a score of 1.000 is ranked 1st in 2015, followed by Zurich and Copenhagen as the 2nd and 3rd position.

Table 30. The composite scores (CS) for all alternatives for the years 2015-2017

Smart cities	2015		2016		2017	
	Score	Rank	Score	Rank	Score	Rank
Brussels	0.478	19	0.228	30	0.534	22
Sofia	0.474	20	0.146	33	0.401	29
Prague	0.313	27	0.369	28	0.467	24
Copenhagen	0.797	3	0.839	8	0.386	32
Munich	0.446	22	0.772	11	0.962	1
Tallinn	0.663	10	0.172	31	0.059	35
Dublin	0.406	25	0.757	12	0.947	3
Athens	0.107	35	0.479	23	0.573	17
Bilbao	0.274	30	0.477	24	0.650	14
Lyon	0.770	4	0.366	29	0.397	30
Dusseldorf	0.682	9	0.948	3	0.779	8
Bologna	0.178	33	0.089	34	0.386	31
Hamburg	0.692	8	0.992	1	0.857	4
St. Petersburg	0.443	23	0.589	21	0.460	26
Marseille	0.627	12	0.817	9	0.445	27
Geneva	0.578	17	0.604	20	0.464	25
Budapest	0.717	6	0.683	16	0.550	20
Manchester	0.200	32	0.621	19	0.311	33
Amsterdam	1.000	1	0.970	2	0.855	5
Vienna	0.615	13	0.508	22	0.422	28
Warsaw	0.637	11	0.416	26	0.570	18
Lisbon	0.142	34	0.157	32	0.546	21
Bucharest	0.701	7	0.676	17	0.832	7
Krakow	0.310	28	0.011	35	0.485	23
Bratislava	0.718	5	0.674	18	0.558	19
Helsinki	0.428	24	0.385	27	0.648	15
Stockholm	0.585	15	0.716	14	0.951	2
London	0.456	21	0.870	4	0.696	10
Zaragoza	0.594	14	0.853	6	0.848	6
Oslo	0.257	31	0.857	5	0.656	13
Zurich	0.956	2	0.851	7	0.598	16
Moscow	0.369	26	0.772	10	0.691	11
Kiev	0.293	29	0.690	15	0.678	12
Rome	0.583	16	0.467	25	0.751	9
Ankara	0.522	18	0.746	13	0.224	34

The German cities of Hamburg and Munich are ranked 1st in 2016 and 2017 respectively, highlighting their essence in co-creating the triple criteria of futuristic cities. Further, for the years 2018-2020, the composite performance scores for all the smart cities are calculated and ranked as shown in Table 31.

Table 31. The composite scores for all alternatives for the years 2018-2020

Smart cities	2018		2019		2020	
	Score	Rank	Score	Rank	Score	Rank
Brussels	0.846	5	0.663	9	0.629	17
Sofia	0.554	21	0.347	28	0.293	31
Prague	0.698	16	0.344	29	0.448	26
Copenhagen	0.310	30	0.221	34	0.462	25
Munich	0.805	9	0.670	8	0.890	2
Tallinn	0.282	32	0.050	35	0.484	24
Dublin	0.844	6	0.661	10	0.690	13
Athens	0.381	23	0.282	32	0.491	23
Bilbao	0.316	29	0.410	25	0.672	15
Lyon	0.213	33	0.453	24	0.363	28
Dusseldorf	0.697	17	0.762	4	0.873	3
Bologna	0.061	34	0.501	22	0.350	29
Hamburg	0.724	14	0.612	14	0.306	30
St. Petersburg	0.320	28	0.524	21	0.545	19
Marseille	0.601	19	0.759	5	0.792	8
Geneva	0.720	15	0.570	16	0.859	5
Budapest	0.725	13	0.649	11	0.217	32
Manchester	0.748	11	0.536	19	0.833	7
Amsterdam	0.692	18	0.368	26	0.594	18
Vienna	0.585	20	0.557	17	0.711	11
Warsaw	0.813	7	0.625	13	0.406	27
Lisbon	0.377	25	0.604	15	0.849	6
Bucharest	0.743	12	0.289	31	0.112	34
Krakow	0.303	31	0.540	18	0.774	10
Bratislava	0.333	26	0.535	20	0.544	20
Helsinki	0.545	22	0.644	12	0.783	9
Stockholm	0.877	4	0.477	23	0.504	21
London	0.921	1	0.902	2	0.871	4
Zaragoza	0.377	24	0.246	33	0.502	22
Oslo	0.879	3	1.000	1	1.000	1
Zurich	0.760	10	0.750	6	0.702	12
Moscow	0.811	8	0.842	3	0.654	16
Kiev	0.326	27	0.329	30	0.217	33
Rome	0.903	2	0.742	7	0.675	14
Ankara	0.032	35	0.354	27	0.000	35

It is seen from Table 31 that London is ranked 1st followed by Rome and

Oslo in the 2nd and 3rd position for the year 2018. While the least performing smart cities in 2018 are Ankara, Bologna and Lyon ranked 35, 34 and 33 among all the 35 smart cities. For the years 2019 and 2020, Oslo has retained its position as the top ranked smart city followed by London (Rank = 2) and the Russian capital city of Moscow (Rank = 3) for the year 2019 and, the German cities of Munich and Dusseldorf as the 2nd and 3rd best performing smart cities for the 2020 respectively.

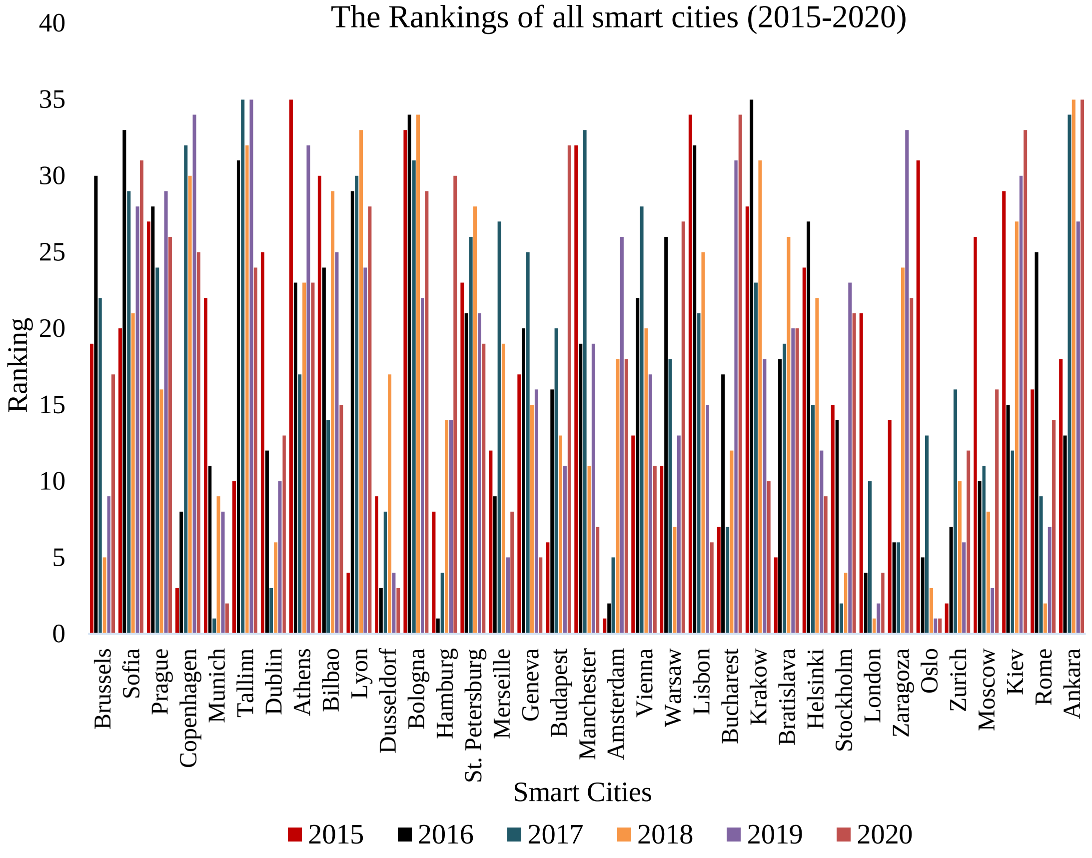


Figure 25. The rankings of all the alternatives estimated by proposed novel SF-AHP & extended EDAS model for 2015-2020

7.3.2. Performance segmentation

In Stage 3, Fuzzy c-means algorithm is used to cluster the smart cities based on the grouped score obtained for each smart city using the SF-AHP and EDAS method. The number of clusters considered were within the range of [3, 10], and the optimum number of clusters were determined using two performance measures: namely, partition coefficient (PE) and partition entropy coefficient (PEC). The maximum value of PEC and the minimum value of PE corresponds to a good partition. The results of fuzzy c-means suggested that the optimum number of clusters corresponds to 3, as can be observed in Figure 26, which shows the distribution of PEC and PE with the number of clusters for the composite score obtained.

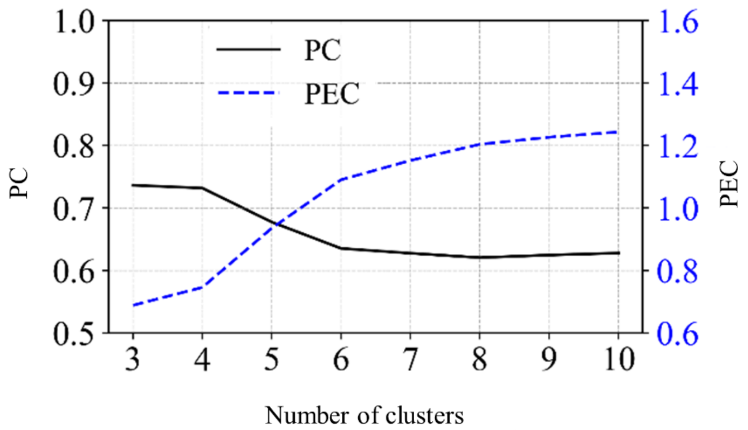
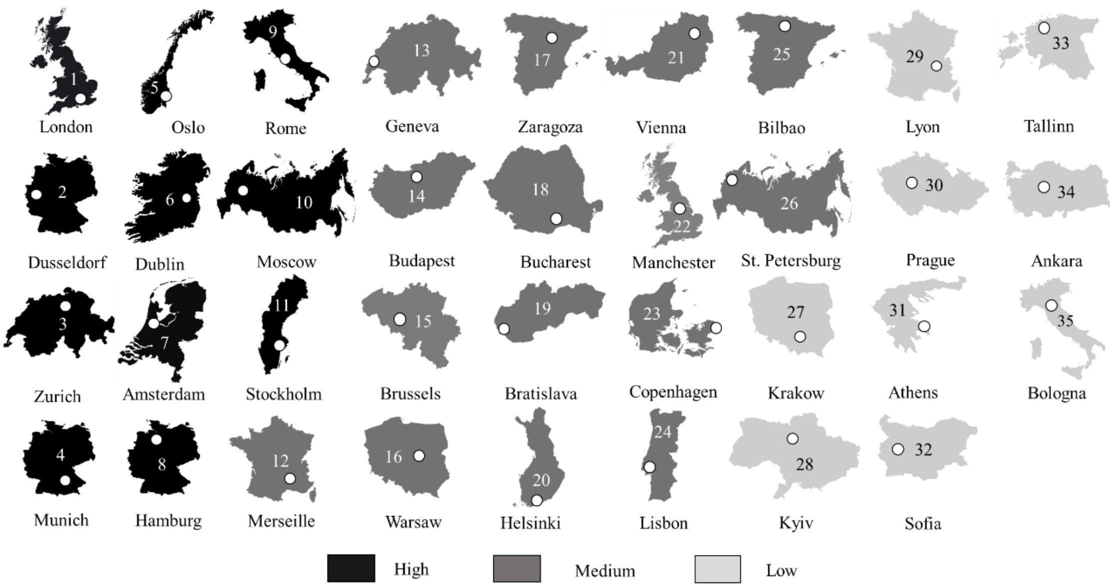
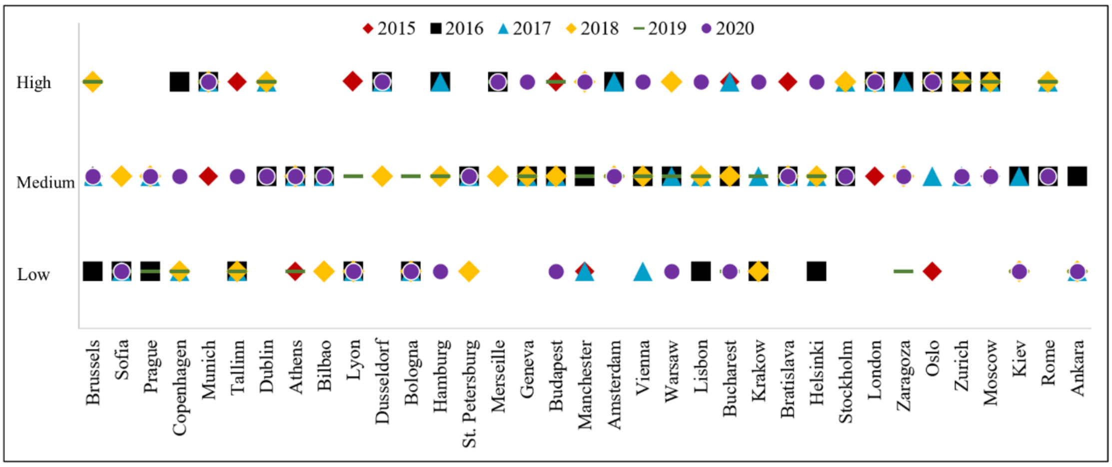


Figure 26. Variation of performance measures with the number of clusters

Figure 27(a) shows the results of the fuzzy c-means cluster analysis using the optimum number of clusters for the composite performance Score obtained from the results of the EDAS method, respectively as high, medium, or low. These show the grouped performance of the smart cities across the years. The results reveal most of the smart cities fall under the medium performance category (43%), while 31% and 26% of the smart cities fall under the high and low performance clusters, respectively. London is the top ranked smart city followed by Dusseldorf, Zurich and Munich as the 1st, 2nd, and 3rd runner up, respectively. The Norwegian capital city of Oslo, followed by Dublin, Amsterdam, Hamburg, Rome, Moscow, and Stockholm are also grouped under the high performance cluster. The results also reveal Bologna (Rank: 35) as the least performing smart city, accompanied by Ankara, Tallinn, Sofia, Athens, Prague, Lyon, Kiev, and Krakow in the low performance cluster. Figure 27(b) shows the clustered performance of all the 35 European smart cities under the high, medium, and low categories for each year from 2015-2020. When taking a closer look into the results, smart cities like Ankara, Kyiv, St. Petersburg, Bologna, Bilbao, Athens, Prague, and Sofia were placed either under the medium or low performance cluster over the years from 2015-2020. These smart cities were never categorized as high performing in terms of their combined performance under sustainability, resilience, and livability during the selected years. Similarly, Munich, Dublin, Dusseldorf, Marseille, Geneva, Amsterdam, Bratislava, Stockholm, London, Zurich, Moscow, and Rome were classed only under the high or medium performance cluster and were never categorized as low performing.



(a)



(b)

Figure 27. a) Distribution of smart cities based on segmented performance with respective ranks b) Progressive performance of smart cities over time (2015-2020) categorized as high, medium, and low

7.3.3. Comparative analysis

In this section, we conduct a comparative analysis to validate the effectiveness and robustness of the presented novel SF-AHP & EDAS model. First, we deployed different fuzzy sets in the presented model in order to reveal the effect of the different fuzzy sets on the total score and ranking of smart cities. Hence, we compared SF-AHP results for determining main and sub-criteria weights with Pythagorean Fuzzy-AHP (PF-AHP) (Yager, 2013), Intuitionistic Fuzzy-AHP (IF–AHP) (Atanassov,1986), and Interval-valued Neutrosophic Fuzzy-AHP (IVNF-AHP) (Radwan et al., 2016). Table 32 shows the criteria weights using NF -AHP, PF-AHP, and IF-AHP methods.

Figure 28 reveals that the most essential main-criteria for SF-AHP, NF-AHP, PF-AHP, and IF-AHP are Sustainability (0.435), Sustainability (0.444), Sustainability (0.691), and Sustainability (0.432), respectively. It is seen that the main criterion across the SF-AHP, NF-AHP, PF-AHP, and IF-AHP methods are same. It can be said that the presented methodology is robust and constant with respect to determining main criteria weights.

Table 32. Comparative analysis for the criteria weights using SF-AHP, NF-AHP, PF-AHP, and IF-AHP

Main-criteria	Main-criteria weights				Sub-criteria	Sub-criteria global weights			
	SF-AHP	NF-AHP	PF-AHP	IF-AHP		SF-AHP	NF-AHP	PF-AHP	IF-AHP
Sustainability	0.435	0.444	0.691	0.432	CC	0.098	0.124	0.330	0.097
					GI	0.051	0.024	0.014	0.053
					E	0.046	0.029	0.013	0.048
					EE	0.065	0.056	0.037	0.065
					SS	0.085	0.100	0.120	0.085
					SW	0.088	0.100	0.176	0.085
Resilience	0.313	0.338	0.194	0.328	S	0.108	0.128	0.126	0.110
					EC	0.088	0.098	0.048	0.093
					IB	0.066	0.073	0.013	0.071
					IN	0.052	0.032	0.007	0.053
Liveability	0.252	0.232	0.115	0.240	AC	0.049	0.037	0.005	0.050
					EV	0.091	0.089	0.035	0.088
					CWB	0.112	0.109	0.075	0.102

It is seen from the comparative analysis in the use of different fuzzy-based approaches with the AHP technique in assigning weights to main-criteria and sub-criteria that, the most important sub-criteria while using the SF-AHP, NF-AHP, PF-AHP, and IF-AHP were found to be community well-being (0.112), social resilience (0.128), climate change (0.330), and social resilience (0.110), respectively. The results of the comparative analysis using several fuzzy-based approach with AHP technique is depicted in Figure 29. It is seen that the most crucial sub-criterion for the NF-AHP and IF-AHP methods are the same. Climate change (0.330) is the most significant sub-criteria estimated by PF-AHP.

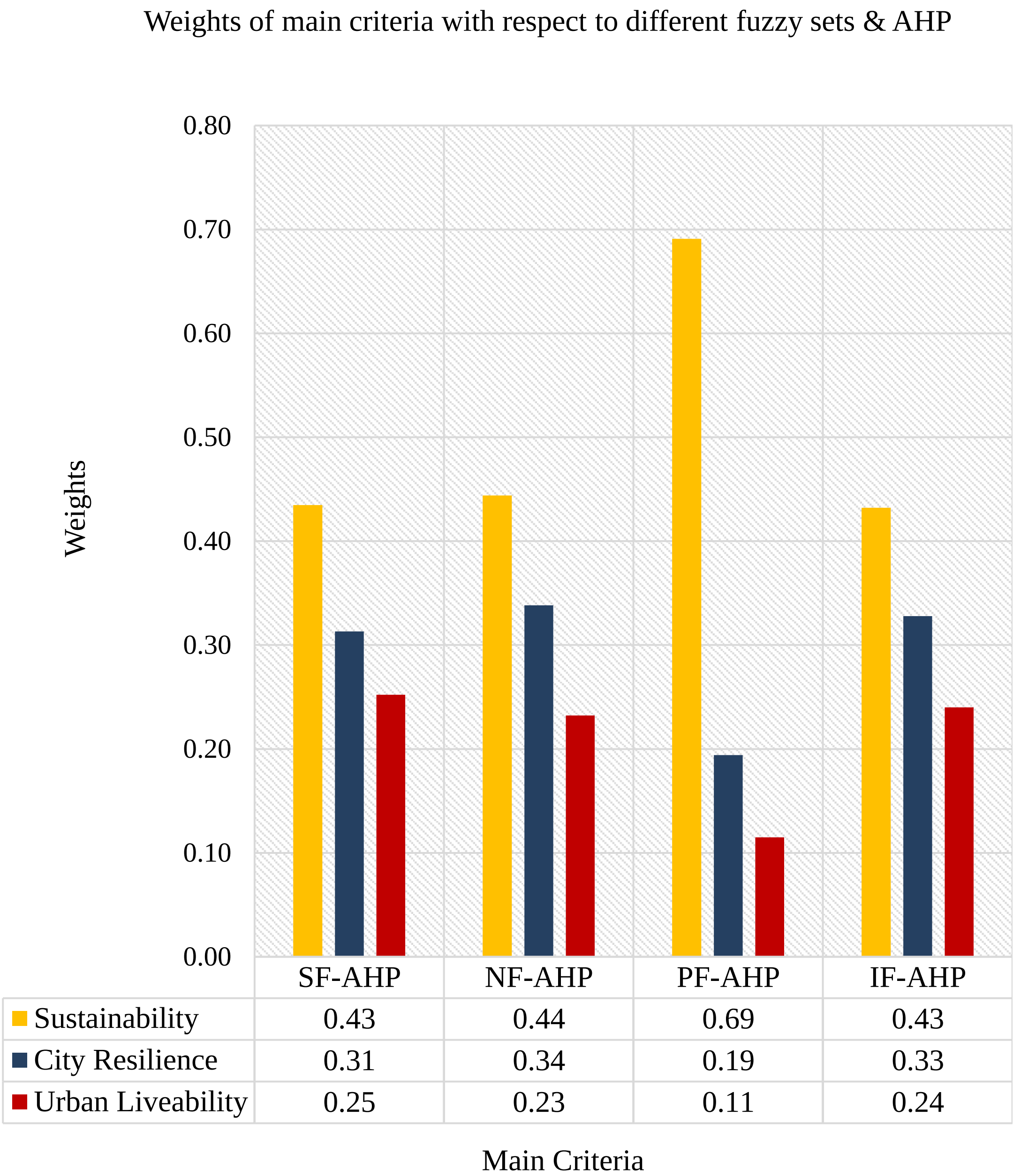
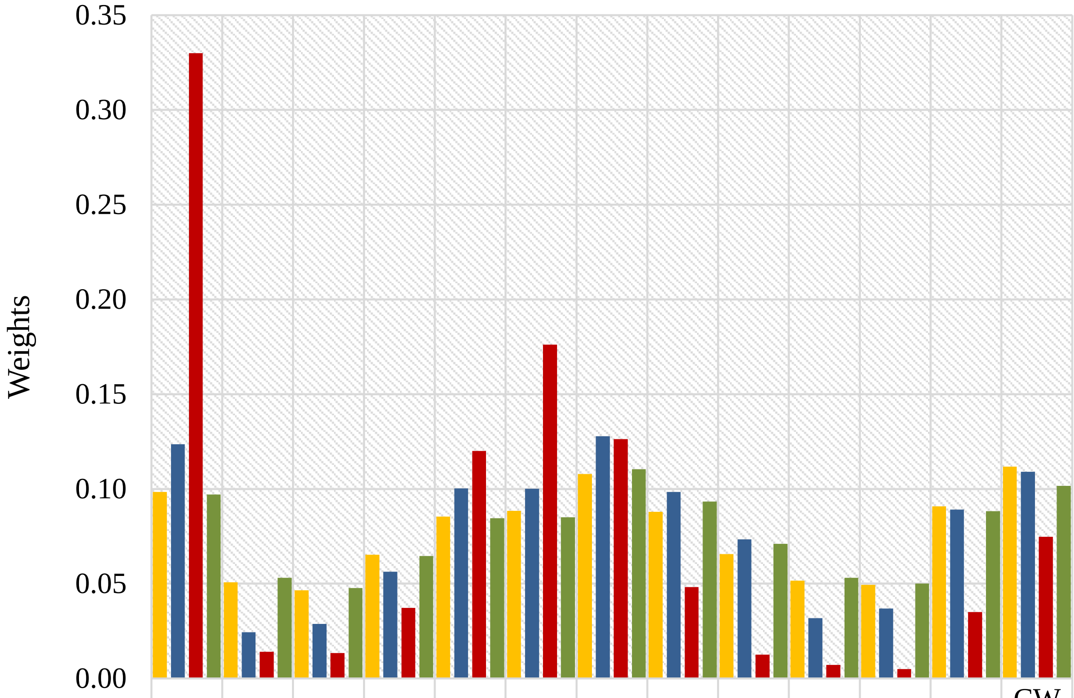


Figure 28. Weights of main criteria estimated via different fuzzy sets & AHP

PF sets generalize IF sets and consider uncertainties better than IF sets in uncertain environment. Therefore, in a high degree uncertain environment, the sub-criteria ‘climate change’ has more importance than the sub-criteria ‘social resilience’ according to PF set results. In addition, the most important criterion in the spherical fuzzy method is the ‘community well-being’ sub-criteria, due to the fact that SF methods considers high degree of uncertainty related to information better than other proposed methods.



	CC	GI	E	EE	SS	SW	S	EC	IB	IN	AC	EV	CW B
SF-AHP	0.09	0.05	0.04	0.06	0.08	0.08	0.10	0.08	0.06	0.05	0.04	0.09	0.11
NF-AHP	0.12	0.02	0.02	0.05	0.10	0.10	0.12	0.09	0.07	0.03	0.03	0.08	0.10
PF-AHP	0.33	0.01	0.01	0.03	0.12	0.17	0.12	0.04	0.01	0.00	0.00	0.03	0.07
IF-AHP	0.09	0.05	0.04	0.06	0.08	0.08	0.11	0.09	0.07	0.05	0.05	0.08	0.10

Sub-criteria

Figure 29. Weights of sub-criteria estimated via different fuzzy sets & AHP

We then solved the problem via NF-AHP & EDAS, PF-AHP & EDAS, and IF-AHP & EDAS, as well. The results of the comparative analysis for different weighting approach integrated with the EDAS method for the year 2020 is shown in Table 33. The results indicated that the solution obtained from different fuzzy sets integrated AHP-EDAS method is stable and robust.

Table 33. Comparable analysis for different weighting method integrated EDAS for 2020 year

Smart cities	SF-AHP&EDAS	NF-AHP&EDAS	PF-AHP&EDAS	IF-AHP&EDAS
Brussels	0.626	0.633	0.725	0.626
Sofia	0.297	0.269	0.371	0.297
Prague	0.449	0.451	0.469	0.449
Copenhagen	0.457	0.464	0.572	0.457
Munich	0.885	0.850	0.887	0.885
Tallinn	0.482	0.509	0.645	0.482
Dublin	0.691	0.670	0.741	0.691
Athens	0.490	0.488	0.602	0.490
Bilbao	0.669	0.689	0.600	0.669
Lyon	0.357	0.374	0.498	0.357
Dusseldorf	0.873	0.872	0.922	0.873
Bologna	0.346	0.374	0.504	0.346
Hamburg	0.302	0.301	0.463	0.302
St. Petersburg	0.542	0.535	0.588	0.542
Merseille	0.791	0.809	0.821	0.791
Geneva	0.861	0.846	0.862	0.861
Budapest	0.213	0.194	0.170	0.213
Manchester	0.832	0.828	0.874	0.832
Amsterdam	0.599	0.607	0.713	0.599
Vienna	0.706	0.719	0.705	0.706
Warsaw	0.402	0.410	0.385	0.402
Lisbon	0.849	0.873	0.733	0.849
Bucharest	0.105	0.084	0.080	0.105
Krakow	0.785	0.763	0.503	0.785
Bratislava	0.549	0.517	0.340	0.549
Helsinki	0.787	0.773	0.581	0.787
Stockholm	0.502	0.537	0.638	0.502
London	0.876	0.869	0.911	0.876
Zaragoza	0.504	0.492	0.382	0.504
Oslo	1.000	1.000	1.000	1.000
Zurich	0.700	0.685	0.789	0.700
Moscow	0.655	0.648	0.578	0.655
Kiev	0.215	0.210	0.154	0.215
Rome	0.682	0.672	0.525	0.682
Ankara	0.000	0.000	0.000	0.000

Comparative analysis for different weighting methods integrated with the EDAS approach is shown in Figure 30 for the year 2020 and in Figure C5 for all the years in Appendix C.

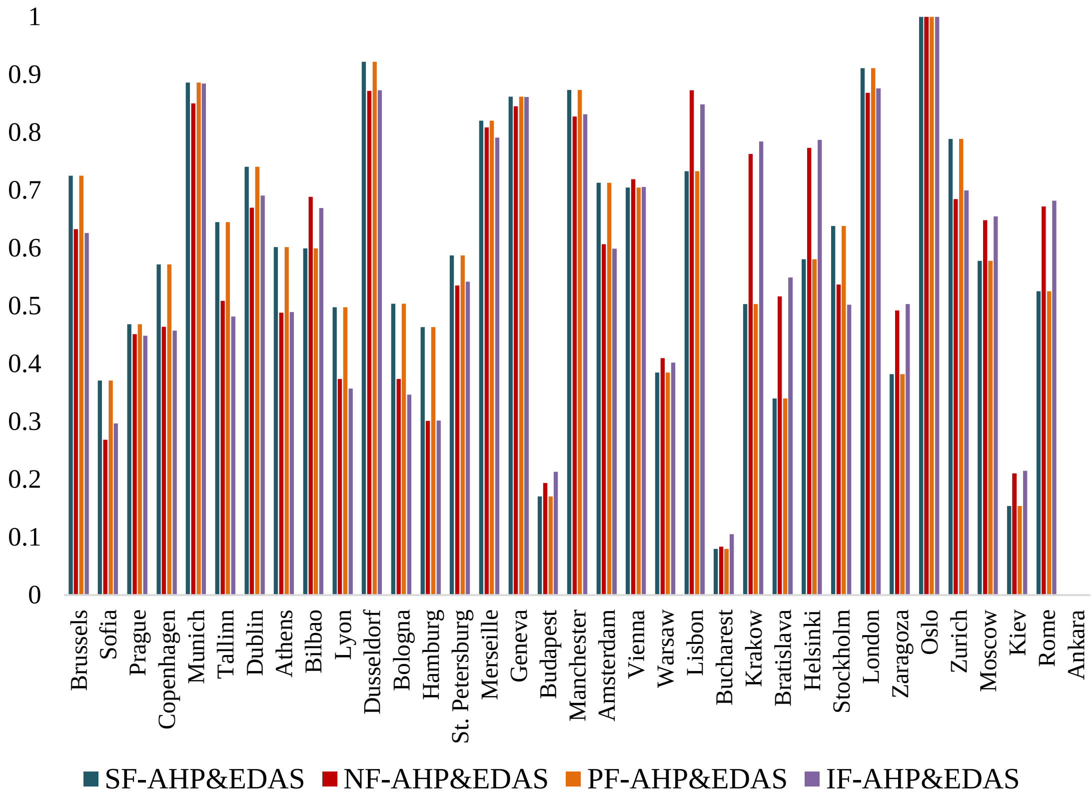


Figure 30. Comparative analysis for different weighting methods integrated with EDAS method for the year 2020

To continue, in this study, we employed the EDAS methodology to rank the alternatives (smart cities) with respect to the values of the composite scores (CS). We further compared the results of EDAS method with OCRA (Table 34 and Table 35), MAIRCA (Table 36 and Table 37), MARCOS (Table 38 and Table 39) and MABAC (Table 40 and Table 41) to reveal the validity and robustness of the results. Taking the example case of the Norwegian capital city, Oslo for the year 2020, it is seen that Oslo is ranked as the best smart city under the SF-AHP & EDAS method. The same is observed under the SF-AHP & OCRA and, SF-AHP & MAIRCA for Oslo (Rank =1). This shows that the proposed approach of SF-AHP & EDAS is robust in terms of ranking the alternatives, thus a valid approach for composite performance assessment with reduced uncertainties. The results for better visualization have also been represented graphically in Figure 31 for the year 2020 using the mentioned approach with the novel SF-AHP & EDAS method.

Table 34. The CS for all alternatives using SF-AHP & OCRA for the year 2015-17

Smart cities	2015		2016		2017	
	Score	Rank	Score	Rank	Score	Rank
Brussels	0.783	16	0.389	30	1.345	24
Sofia	0.728	21	0.233	32	1.362	23
Prague	0.432	30	0.545	29	1.321	25
Copenhagen	1.180	3	1.437	5	0.976	32
Munich	0.764	19	1.345	9	2.428	2
Tallinn	0.889	10	0.222	34	0.000	35
Dublin	0.694	22	1.273	12	2.530	1
Athens	0.265	33	0.931	22	1.638	20
Bilbao	0.302	32	0.708	27	1.932	11
Lyon	1.061	4	0.565	28	1.062	31
Dusseldorf	1.034	5	1.532	2	2.154	6
Bologna	0.367	31	0.239	31	1.253	28
Hamburg	0.968	8	1.624	1	2.195	5
St. Petersburg	0.771	17	1.125	17	1.288	27
Marseille	0.856	13	1.359	8	1.243	29
Geneva	0.883	11	1.042	20	1.065	30
Budapest	0.881	12	1.141	15	1.723	17
Manchester	0.522	27	1.133	16	0.525	34
Amsterdam	1.424	1	1.527	3	2.132	7
Vienna	1.003	7	0.930	23	1.293	26
Warsaw	0.841	14	0.769	26	1.732	16
Lisbon	0.000	35	0.229	33	1.375	22
Bucharest	1.008	6	1.191	13	2.085	8
Krakow	0.501	28	0.000	35	1.589	21
Bratislava	0.944	9	1.056	18	1.712	19
Helsinki	0.689	23	0.818	25	1.971	10
Stockholm	0.839	15	1.182	14	2.311	4
London	0.755	20	1.389	7	1.896	13
Zaragoza	0.765	18	1.282	11	2.382	3
Oslo	0.546	26	1.496	4	1.764	15
Zurich	1.350	2	1.393	6	1.717	18
Moscow	0.579	25	1.300	10	1.912	12
Kiev	0.238	34	0.960	21	1.867	14
Rome	0.640	24	0.822	24	2.004	9
Ankara	0.498	29	1.049	19	0.730	33

Table 35. The CS for all alternatives using SF-AHP & OCRA for the year 2018-20

Smart cities	2018		2019		2020	
	Score	Rank	Score	Rank	Score	Rank
Brussels	2.029	2	2.447	16	1.322	17
Sofia	1.468	21	1.438	31	0.775	30
Prague	1.871	10	1.647	28	1.095	22
Copenhagen	0.866	28	0.960	34	0.988	26
Munich	2.073	1	2.859	8	1.751	4
Tallinn	0.735	31	0.000	35	1.012	25
Dublin	1.887	9	2.470	15	1.529	10
Athens	0.822	30	1.188	33	1.069	23
Bilbao	0.873	27	1.688	26	1.219	20
Lyon	0.436	33	1.683	27	0.801	28
Dusseldorf	1.789	14	3.222	4	1.758	3
Bologna	0.000	35	2.216	19	0.793	29
Hamburg	1.637	16	2.622	10	0.765	31
St. Petersburg	0.863	29	2.305	18	1.213	21
Marseille	1.365	22	2.904	7	1.545	9
Geneva	1.556	19	2.147	20	1.792	2
Budapest	1.738	15	2.703	9	0.604	32
Manchester	1.863	11	1.910	22	1.710	5
Amsterdam	1.622	17	1.748	25	1.263	18
Vienna	1.588	18	2.308	17	1.471	12
Warsaw	1.936	8	2.542	12	0.915	27
Lisbon	0.922	25	2.482	14	1.506	11
Bucharest	1.814	13	1.472	30	0.484	34
Krakow	0.710	32	2.084	21	1.466	14
Bratislava	1.097	23	2.488	13	1.360	15
Helsinki	1.497	20	2.593	11	1.647	6
Stockholm	1.852	12	1.820	23	1.032	24
London	2.011	3	3.315	3	1.628	7
Zaragoza	1.092	24	1.307	32	1.239	19
Oslo	1.979	6	3.760	1	1.964	1
Zurich	1.979	5	3.139	5	1.551	8
Moscow	1.965	7	3.522	2	1.467	13
Kiev	0.880	26	1.582	29	0.551	33
Rome	1.993	4	2.996	6	1.331	16
Ankara	0.092	34	1.772	24	0.000	35

Table 36. The CS for all alternatives using SF-AHP & MAIRCA for 2015-2017

Smart cities	2015		2016		2017	
	Score	Rank	Score	Rank	Score	Rank
Brussels	0.011	21	0.016	30	0.010	15
Sofia	0.011	20	0.017	32	0.013	29
Prague	0.014	28	0.013	26	0.012	23
Copenhagen	0.007	4	0.006	7	0.013	30
Munich	0.011	19	0.007	9	0.003	1
Tallinn	0.009	12	0.017	31	0.020	35
Dublin	0.012	22	0.007	8	0.004	2
Athens	0.017	34	0.012	22	0.009	14
Bilbao	0.014	29	0.012	23	0.010	16
Lyon	0.006	3	0.013	28	0.013	26
Dusseldorf	0.009	8	0.006	6	0.007	7
Bologna	0.016	33	0.019	34	0.014	32
Hamburg	0.008	5	0.004	2	0.005	5
St. Petersburg	0.012	24	0.010	18	0.012	25
Marseille	0.009	9	0.007	11	0.011	21
Geneva	0.009	11	0.009	15	0.011	19
Budapest	0.009	7	0.010	17	0.012	22
Manchester	0.015	31	0.009	14	0.014	33
Amsterdam	0.003	1	0.004	1	0.005	3
Vienna	0.010	17	0.011	21	0.013	31
Warsaw	0.010	16	0.013	27	0.011	18
Lisbon	0.017	35	0.018	33	0.011	20
Bucharest	0.009	10	0.010	16	0.007	8
Krakow	0.015	30	0.021	35	0.013	28
Bratislava	0.008	6	0.010	19	0.012	24
Helsinki	0.013	25	0.014	29	0.010	17
Stockholm	0.010	14	0.008	13	0.005	4
London	0.011	18	0.005	3	0.007	6
Zaragoza	0.010	15	0.007	12	0.007	9
Oslo	0.014	27	0.005	4	0.007	10
Zurich	0.004	2	0.005	5	0.009	13
Moscow	0.013	26	0.007	10	0.008	11
Kiev	0.016	32	0.013	25	0.013	27
Rome	0.009	13	0.012	24	0.009	12
Ankara	0.012	23	0.011	20	0.018	34

Table 37. The CS for all alternatives using SF-AHP & MAIRCA for 2018-2020

Smart cities	2018		2019		2020	
	Score	Rank	Score	Rank	Score	Rank
Brussels	0.005	4	0.007	9	0.008	12
Sofia	0.009	19	0.013	27	0.016	31
Prague	0.008	16	0.014	28	0.014	27
Copenhagen	0.015	30	0.016	34	0.012	23
Munich	0.006	6	0.007	10	0.004	2
Tallinn	0.015	26	0.019	35	0.011	22
Dublin	0.004	3	0.007	8	0.007	9
Athens	0.012	23	0.015	29	0.011	21
Bilbao	0.015	29	0.013	26	0.010	18
Lyon	0.016	32	0.011	22	0.014	26
Dusseldorf	0.007	14	0.006	7	0.004	5
Bologna	0.020	34	0.010	20	0.014	29
Hamburg	0.007	13	0.008	12	0.015	30
St. Petersburg	0.015	27	0.010	18	0.010	19
Marseille	0.009	18	0.005	5	0.006	7
Geneva	0.007	11	0.008	11	0.004	3
Budapest	0.009	17	0.009	14	0.019	32
Manchester	0.006	7	0.009	15	0.005	6
Amsterdam	0.007	12	0.013	25	0.009	14
Vienna	0.010	21	0.009	16	0.008	11
Warsaw	0.008	15	0.010	19	0.014	28
Lisbon	0.013	24	0.010	17	0.007	10
Bucharest	0.009	20	0.016	31	0.021	34
Krakow	0.016	31	0.011	24	0.009	16
Bratislava	0.015	28	0.011	23	0.013	24
Helsinki	0.011	22	0.009	13	0.009	13
Stockholm	0.005	5	0.011	21	0.011	20
London	0.004	1	0.003	2	0.004	4
Zaragoza	0.014	25	0.016	33	0.013	25
Oslo	0.004	2	0.001	1	0.002	1
Zurich	0.006	9	0.005	4	0.007	8
Moscow	0.007	10	0.005	3	0.009	15
Kiev	0.017	33	0.016	32	0.019	33
Rome	0.006	8	0.006	6	0.009	17
Ankara	0.021	35	0.016	30	0.024	35

Table 38. The CS for all alternatives using SF-AHP & MARCOS for 2015-2017

Smart cities	2015		2016		2017	
	Score	Rank	Score	Rank	Score	Rank
Brussels	0.681	25	0.596	31	0.571	30
Sofia	0.705	20	0.580	32	0.526	33
Prague	0.642	27	0.644	29	0.626	28
Copenhagen	0.812	3	0.813	5	0.791	7
Munich	0.707	19	0.777	9	0.777	9
Tallinn	0.760	11	0.604	30	0.540	31
Dublin	0.694	22	0.772	11	0.774	10
Athens	0.576	34	0.661	27	0.669	22
Bilbao	0.629	30	0.666	26	0.659	25
Lyon	0.807	4	0.679	24	0.622	29
Dusseldorf	0.777	6	0.822	4	0.813	3
Bologna	0.601	33	0.541	34	0.508	34
Hamburg	0.785	5	0.841	2	0.835	1
St. Petersburg	0.695	21	0.725	18	0.714	19
Marseille	0.760	10	0.789	7	0.777	8
Geneva	0.749	13	0.740	17	0.717	17
Budapest	0.767	9	0.745	16	0.718	16
Manchester	0.620	31	0.712	20	0.720	15
Amsterdam	0.890	1	0.865	1	0.833	2
Vienna	0.754	12	0.711	21	0.679	21
Warsaw	0.746	15	0.682	23	0.644	26
Lisbon	0.569	35	0.552	33	0.532	32
Bucharest	0.771	8	0.756	14	0.730	14
Krakow	0.637	29	0.520	35	0.469	35
Bratislava	0.777	7	0.745	15	0.715	18
Helsinki	0.685	23	0.654	28	0.627	27
Stockholm	0.747	14	0.762	12	0.745	13
London	0.708	18	0.798	6	0.803	4
Zaragoza	0.736	16	0.772	10	0.762	12
Oslo	0.641	28	0.781	8	0.802	5
Zurich	0.873	2	0.833	3	0.797	6
Moscow	0.668	26	0.758	13	0.765	11
Kiev	0.609	32	0.669	25	0.669	23
Rome	0.732	17	0.695	22	0.664	24
Ankara	0.684	24	0.721	19	0.712	20

Table 39. The CS for all alternatives using SF-AHP & MARCOS for 2018-2020

Smart cities	2018		2019		2020	
	Score	Rank	Score	Rank	Score	Rank
Brussels	0.672	22	0.705	17	0.782	7
Sofia	0.611	31	0.637	29	0.695	21
Prague	0.655	26	0.664	23	0.731	16
Copenhagen	0.664	25	0.623	32	0.606	31
Munich	0.829	1	0.846	2	0.808	4
Tallinn	0.478	35	0.458	35	0.558	33
Dublin	0.829	2	0.846	1	0.824	1
Athens	0.704	14	0.715	16	0.657	24
Bilbao	0.704	15	0.718	14	0.635	26
Lyon	0.631	29	0.634	30	0.579	32
Dusseldorf	0.789	6	0.780	7	0.767	11
Bologna	0.596	33	0.624	31	0.525	34
Hamburg	0.819	3	0.813	5	0.775	10
St. Petersburg	0.666	24	0.650	27	0.616	28
Marseille	0.691	17	0.663	24	0.710	19
Geneva	0.667	23	0.651	26	0.733	15
Budapest	0.689	18	0.679	21	0.722	18
Manchester	0.609	32	0.573	33	0.730	17
Amsterdam	0.818	4	0.813	4	0.776	9
Vienna	0.649	27	0.639	28	0.693	22
Warsaw	0.684	20	0.697	18	0.755	13
Lisbon	0.646	28	0.682	20	0.648	25
Bucharest	0.765	9	0.776	8	0.752	14
Krakow	0.613	30	0.659	25	0.612	30
Bratislava	0.688	19	0.679	22	0.627	27
Helsinki	0.700	16	0.723	13	0.699	20
Stockholm	0.806	5	0.825	3	0.813	3
London	0.775	8	0.766	9	0.815	2
Zaragoza	0.784	7	0.791	6	0.675	23
Oslo	0.762	10	0.749	11	0.806	5
Zurich	0.737	12	0.717	15	0.766	12
Moscow	0.753	11	0.749	10	0.779	8
Kiev	0.681	21	0.685	19	0.615	29
Rome	0.726	13	0.746	12	0.785	6
Ankara	0.581	34	0.538	34	0.487	35

Table 40. The CS for all alternatives using SF-AHP & MABAC for 2015-2017

Smart cities	2015		2016		2017	
	Score	Rank	Score	Rank	Score	Rank
Brussels	0.005	20	-0.251	33	-0.067	28
Sofia	-0.016	24	-0.027	25	0.023	18
Prague	0.116	7	0.121	11	-0.107	30
Copenhagen	-0.014	23	0.139	9	0.218	5
Munich	0.209	6	-0.107	27	-0.214	33
Tallinn	-0.105	31	0.058	17	0.171	7
Dublin	-0.105	30	0.046	20	0.131	12
Athens	0.027	19	0.108	13	0.191	6
Bilbao	0.093	13	-0.110	28	-0.133	31
Lyon	0.090	14	0.114	12	0.095	14
Dusseldorf	-0.078	29	-0.188	31	0.000	22
Bologna	0.096	12	0.197	5	0.156	8
Hamburg	0.000	21	0.048	19	-0.017	23
St. Petersburg	0.114	9	0.193	6	0.040	17
Marseille	0.033	18	0.000	23	-0.106	29
Geneva	0.284	3	0.198	4	0.152	9
Budapest	-0.265	34	-0.052	26	-0.282	34
Manchester	0.332	1	0.285	2	0.253	2
Amsterdam	0.116	8	0.035	21	-0.030	26
Vienna	0.211	5	0.048	18	0.126	13
Warsaw	-0.134	32	-0.211	32	-0.030	25
Lisbon	-0.006	22	-0.013	24	0.132	11
Bucharest	-0.056	28	-0.257	34	0.005	20
Krakow	0.096	11	0.012	22	-0.024	24
Bratislava	-0.027	25	-0.135	29	-0.055	27
Helsinki	0.059	16	0.123	10	0.243	3
Stockholm	-0.052	27	0.108	14	0.070	16
London	0.227	4	0.290	1	0.264	1
Zaragoza	-0.232	33	0.065	16	0.010	19
Oslo	0.297	2	0.243	3	0.089	15
Zurich	0.057	17	0.189	8	0.218	4
Moscow	0.077	15	0.192	7	0.141	10
Kiev	-0.042	26	-0.148	30	0.001	21
Rome	0.110	10	0.089	15	-0.182	32
Ankara	-0.512	35	-0.472	35	-0.514	35

Table 41. The CS for all alternatives using SF-AHP & MABAC for 2018-2020

Smart cities	2018		2019		2020	
	Score	Rank	Score	Rank	Score	Rank
Brussels	0.075	19	-0.063	28	-0.150	30
Sofia	0.199	6	-0.034	25	-0.005	24
Prague	-0.140	29	-0.219	33	-0.053	28
Copenhagen	0.129	13	0.111	10	0.214	3
Munich	-0.069	26	-0.224	34	0.111	14
Tallinn	0.169	8	0.084	13	0.088	17
Dublin	0.026	22	-0.062	27	0.107	16
Athens	0.017	23	0.065	15	0.238	1
Bilbao	-0.275	33	-0.053	26	-0.164	31
Lyon	0.110	14	0.103	12	0.161	8
Dusseldorf	-0.244	32	0.113	9	0.017	22
Bologna	0.136	11	0.071	14	-0.168	32
Hamburg	-0.129	28	0.043	16	0.002	23
St. Petersburg	0.089	18	0.177	6	0.219	2
Marseille	0.091	17	0.041	18	0.209	6
Geneva	0.263	1	0.241	3	-0.027	26
Budapest	0.029	20	-0.086	30	0.043	20
Manchester	0.213	3	0.011	20	0.157	9
Amsterdam	0.098	15	0.104	11	0.144	10
Vienna	0.209	5	0.170	7	0.043	19
Warsaw	-0.113	27	-0.028	24	0.144	11
Lisbon	0.147	10	-0.132	32	-0.266	33
Bucharest	-0.160	30	0.002	23	0.049	18
Krakow	-0.217	31	-0.086	31	-0.045	27
Bratislava	0.028	21	0.123	8	0.110	15
Helsinki	0.192	7	0.017	19	-0.026	25
Stockholm	0.213	4	0.249	2	0.213	5
London	0.012	24	-0.080	29	0.119	13
Zaragoza	0.135	12	0.199	5	0.129	12
Oslo	0.167	9	0.204	4	0.189	7
Zurich	0.257	2	0.304	1	0.213	4
Moscow	0.008	25	0.006	21	-0.133	29
Kiev	0.096	16	0.042	17	0.025	21
Rome	-0.282	34	0.003	22	-0.321	34
Ankara	-0.508	35	-0.527	35	-0.530	35

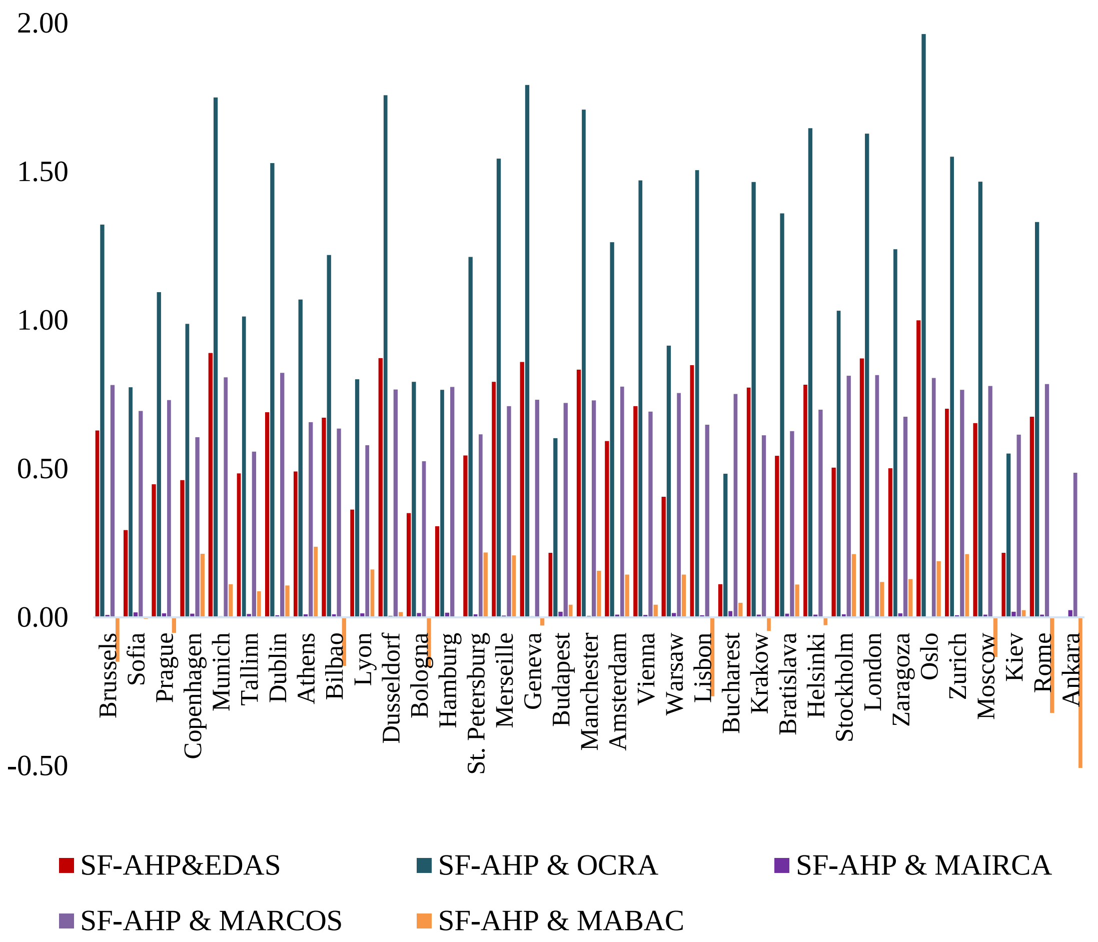


Figure 31. Comparative analysis results for all the smart cities in the year 2020 using several distance-based methods combined with SF-AHP

7.4. Chapter synopsis

Cities of the 21st century are buffeted with challenges, leaving potentially serious consequences on the future of urban living. Smartening development in cities have reinvented hopes in melting down predicaments in early 2000s'. However, perplexed by the intensifying complexities in smart cities, urban living in smart cities need to be evaluated with multiple conflicting criteria. Multi-criteria based evaluations have been an answer to this case when attempting to gauge the composite performance of multiple decision making entities. Several multi-criteria assessment techniques exist when dealing with selection problems. Nonetheless, the vagueness associated with the methodologies accompanied by uncertainties and complexities are inevitable in multi-attribute assessments. Fuzzy based multi-criteria models are often an answer to such uncertainties when modelling real-world problems. This chapter used the proposed novel fuzzy expert-based multi-criteria decision support model (module 4 of the hybrid decision support model), where the Analytical Hierarchy Process (AHP) is combined with the extended Evaluation based on Distance from Average Solution (EDAS) approach under a spherical fuzzy environment to create the "Futuristic Smart City" FSC index for comprehensive performance monitoring. The case of 35 high-tech European cities were used to empirically validate the proposed novel approach and thus constructing a composite index. The composite index considers the intricate facet of integrating the concept of smart cities with sustainability, urban resilience, and livability under a unified framework. Fuzzy c-means algorithm was then used to segment smart cities into high, medium, and low performing class. We performed a comparative analysis to validate the effectiveness and robustness of the proposed novel SF-AHP & EDAS model. For this, firstly, we presented the "pythagorean fuzzy", "intuitionistic fuzzy", and "interval valued neutrosophic fuzzy integrated AHP & EDAS" in order to reveal the effect of the different fuzzy sets on the total score and ranking of smart cities. Secondly, we compared the results of SF-AHP& EDAS method with SF-AHP& OCRA, SF-AHP& MAIRCA, SF-AHP& MARCOS and SF-AHP& MABAC to reveal the validity and robustness of the results. The results revealed London as the top ranked smart city that co-create sustainability, resilience, and livability into their development model. Dusseldorf, Zurich, Munich, Oslo, Dublin, Amsterdam, Hamburg, Rome, Moscow, and Stockholm were no exemption to addressing the tritactic criteria well into their urban development plan and were placed in the high performance cluster. The proposed model is efficient to express decision makers preferences in a larger space and model functional parameters including hesitancy independently in 3D domain. The model supports decision makers and relocation analysts to assess the performance of smart cities and set targets to improve performance to remodel urban development for the cities to be smart, sustainable, resilient and livable dwelling units.

CHAPTER 8: CONCLUSION, RECOMMENDATIONS, AND FUTURE PERSPECTIVES

This dissertation proposed a hybrid decision support model for composite smart city performance assessment with novel analytical techniques at various "levels of performance measurement". The proposed model was implemented, tested, and validated with longitudinal data from 35 European smart cities. The concluding remarks, future perspectives and limitations of each model that form the integral building blocks of the hybrid decision support model in terms of the chapters outlined in this dissertation are detailed in the succeeding paragraphs. The proposed hybrid model revealed robustness and is a sought assessment technique to reduce several degrees of uncertainties due to the combination of advanced and novel methods. As a future perspective, a computer-based decision support system can be created based on the developed decision support model, that is user friendly for decision makers with significantly less rigour. In addition, the 118 indicators spread across the 3 dimensions of sustainability, resilience, and livability can be integrated with the 91 indicators proposed under the U4SSC initiative to measure the progress of cities towards urban smartness and meeting the UN SDGs. This can help any city across the world in not only monitoring their level of livability, resilience and sustainability, but also urban smartness.

In **Chapter 4**, "Systems thinking" as a qualitative tool is used in understanding the complex interactions. This is the primary module of the proposed integrated decision support model (module 1: systems-thinking module). Systems thinking through causal loop diagrams help in unwinding complexities in systems (Onat et al., 2017). The author highlight that the cities we want are not just cities with digital innovation and smart solutions, but an ecosystem with high grade of complexity that is capable to effectively rebound post stress, bring harmony and cohesion in living with elevated standards and, sustainable in the production, consumption and utilization patterns all made up of multiple partners including city residents, government bodies, corporate firms and industries, and social groups working towards achieving a desired outcome. These desired outcomes can vary from technology, productivity, governance, intelligence, sustainable urban development, climate mitigation, accessibility, policy, and many more to a much broader concept based on the targets set by the city to be accomplished in light of city development. The author further comment that smart cities of future must hold several key features addressed under the SRL concept across numerous segments of economy, policies and administration, society and urban environment namely: (a) Integration of Information and communication technologies (ICTs) with the public services and enhancing the accessibility of these services swiftly through several digital platforms and strong internet connectivity; (b) Adequate social infrastructures (which includes proper health care facilities like hospitals, clinics, dispensaries etc.; educational institutions like schools, universities, nurseries and research centers ; recreational areas like parks, playgrounds and ball fields) which are well equipped and efficient; (c) Proper safety and security of the inhabitants; (d) Sufficient finance and funding for social inclusive technology based sustainable development; (e) Effective public services (which includes timely waste collection, utilization and management of non-renewable resources etc.) that are more accountable, accessible, reasonable and transparent for the public; (f) Efficient transportation network made accessible to citizens by promoting increased usage of public transport and discouraging private owned modes of transportation, encouraging alternative mode to commute within the city and its outskirts (which includes embracing practices of urban sharing like ride sharing, carpooling and other peer to peer car sharing services) and effective traffic planning to avoid traffic congestion using digital intelligent solutions; (g) Aligning the socioeconomic and environmental sustainability aspects with the city development goals to promote sustainable development.

When analyzing the strand of sustainable development under the UNDP 2030 agenda vis-à-vis smart cities, one must take into consideration all the sustainability, resilience and liveability aspects leading to urban development and growth. All these aspects required for urban development and advancement including resource utilization, establishment retrofitting, technological advancement, etc. needs to be consistent to meet the needs of the present and future generation. The development should be structured with an equilibrium between the dimensions of environment, social, institutional, and economic under the resilience aspect; accessibility, economic vibrancy, and community well-being under the liveability aspect; and, safety and security, societal well-being, natural and energy resources, climate change, and, governance and institution under the sustainability aspect. All the aspects should be in line with the smart city agenda aimed at enhancing the quality of life and livelihood of the inhabitants, implementing unique architectural language to enhance and diversify the economy and attaining city specific goals to meet the alarming demand of sustainability adopted through digital intelligent solutions.

In **Chapter 5**, the sustainability performance of 35 leading European smart cities were studied from the optimistic, pessimistic, and double-frontier perspective through a novel DF-SBM DEA model under the extended strong disposability assumptions. This formed the module 2, the sustainability assessment module of the proposed hybrid decision support model. The change in productive performance over time for the smart cities from 2015 till 2020 was analysed using a modified DF-MPI model that accounted for the inclusion of undesirable factors while carrying out the assessment. After running the models to understand the optimistic and pessimistic DEA-MPI values for all the smart cities in the study, the findings clearly show that the productivity values vary significantly under both the perspectives. Thus, the traditional approach to only computing the optimistic MPI values when trying to understand the productivity change can lead to partial results and not a comprehensive overview of the productivity change. Thus, the DF-MPI approach used in the study to compute the sustainable productivity change of smart cities result in a panoramic view of how smart cities respond to the call of sustainable development over the years through technological change. They are geometrically averaged to produce a full ranking or an overall assessment of the DMUs. The results after running the models for the sustainable development capacity assessment also reveal the true essence of measuring the aggregate sustainability performance using the double-frontier approach. It is noticed that, under the social cohesion and solidarity dimension, about 57% of the efficiencies are overestimated by the SBM optimistic model to a score of $\eta_{optimistic}$ = 1.000. Similarly, under the economic dynamism dimension, Stockholm ranks 30th under both the optimistic and pessimistic scenario, with $\eta_{optimistic}$ and $\eta_{pessimistic}$ values equal to 0.5793 and 0.9886, respectively. These variations in results can lead to different policies when decision making. Thus, a simultaneous evaluation of sustainability performance under both the viewpoints using the aggregated model as carried out in this study is best recommended. The preliminary application of the proposed DF-SBM DEA model in the case of European smart cities, confirmed its potential applicability for assessing and comparing cities that aspire a sustainable transformation. The author plans to implement proposed methods in several case studies across various scopes of urban sustainability in the future, namely the sustainable city, the eco-city, the low-carbon city, the green city etc., to fine-tune the proposed steps and validate its applicability. The proposed approach focuses on a solid and unified evaluation process for a city-oriented progress assessment towards sustainability, capable of generating clear, sufficient, understandable, and ready-for-benchmarking results and conclusions for all cities globally with similar or different sets of sustainability indicators.

The math to perform better is sceptical and an intricate puzzle even for several best performing smart cities. It is best recommended that the sustainable growth patterns in cities need to be decoupled from carbon-intensive activities in attempts to encourage foreign investments for smarter transition of cities. Nevertheless, the increasing use of energy and environmental resources to exemplify the economy (examples of Athens, Tallinn and Sofia); declining employment rate in attempts to shut down carbon-intensive industries (Munich, Moscow and Vienna); lack of capacity to contrive with the judicial system to eliminate crime and theft (Kiev, Rome and Bratislava); political instability due to lack of will and opposition from public; and an imbalance in the share of renewables among the cities due to new energy dependant pathways in action (Kiev, Bucharest and Sofia); can all subpar the performance of smart cities, which can also be read from the empirical findings of this paper. The least performing European smart cities should set a specific timetable and objective for climate change mitigation and distribute carbon reduction duties through top-down effects, which will help to monitor and facilitate achieving the objective. In recent years, it has been demonstrated that the technological advancements of energy, architecture, transportation, agriculture, fisheries, and manufacturing, which are driven by climate policies, are closely related to and promote the transformation of the current fossil fuels and black economy (high-pollution) into a green economy. If fiscal tax is taken as an incentive or punishment, it will involve an overall economic transformation (Al-Buenain et al., 2021). Thus, a combination of high-level decision-making and coordination among the different parts will facilitate change. Taking a top-down approach regarding the allocation of carbon reduction responsibilities, timeframes and targets in European smart cities is essential to the supervision and achievement of goals. The high awareness of environmental protection and the robustness of the regulatory framework can facilitate the effective implementation of policies in the least performing smart cities, as industries must comply with relevant laws and meet market demands by constantly improving production technology and efficiency. A delicate balance between the pillars of sustainable development, protectionist measure against unfair competition, building capacity to invite funds and investments without tampering the sustainable urban development initiatives and positioning as an ambitious de facto leader considering the success of the benchmarks can all pave ways for smart cities to target the ever-ambitious goal of transition into a smart sustainable city.

From a methodological point of view, the proposed OSBM and PSBM models are non-translation invariant and non-negative undesirable models, i.e., the proposed models are capable to only handle positive input and output data. The general case where there are negative data for inputs or outputs is non-trivial and deserves further discussions. Although technically it should be always possible to transfer such cases and then apply the proposed non-negative undesirable models, there are many reasons that people still prefer to use negative data in some applications. The author suggests Range Directional (RD) models to derive merit functions that can be used to treat the presence of negative data for performance assessment. The author further suggests using Evidential Reasoning algorithms with mass functions to aggregate the sustainability performance under the double frontier approach as a future work. Furthermore, if we wish to use a single ratio to measure the radial extension or contraction for both desirable and undesirable part of inputs or outputs, then we may have to deal with DEA models with objective functions like $\theta + 1/\theta$. Thus, it is difficult to directly combine the proposed Extended Strong Disposability model with standard radial measure while keeping the original input-output orientation. Alternatively, Super-SBM models can be used for the optimistic performance evaluation along with inverted-SBM models for pessimistic evaluations in future. Enhanced Russell Measurement (ERM) models can then be combined to understand the change in the input and output orientations, which can help support decision making by controlling outcomes for studies that are highly dependent on the input-output relationships. In addition, the proposed DF-DEA based MPI can be easily extended to the global MPI that measures the optimistic efficiencies with a unified efficiency frontier and the pessimistic efficiencies with a unified inefficiency frontier for time periods t and $t + 1$. Interested readers may refer to Pastor and Lovell, (2005) for the discussions on the global MPI.

In **Chapter 6**, the proposed novel two-stage assessment model combining multivariate analysis and numerous machine learning models for the first time to thoroughly investigate the resilience and liveability of smart cities for a selected set of indicators over time was conducted. This chapter formed the implementation of module 3 of the proposed hybrid decision support model, the machine learning model. 35 top-ranked European smart cities were taken as the case to study the co-creation of resilience and liveability in the current existing development models of smart cities using the proposed model in module 3. The results of the multivariate analysis revealed only 31% of the smart cities as high performing in terms of both resilience and liveability. While 43% of smart cities marginally co-create resilience and liveability in their smart development models, nearly 26% of smart cities need to make considerable improvements in moving from the low performing to the high performing class while structuring smart city policies. Different machine learning classifiers were used in the study to predict the level of resilience, liveability, and aggregate performance. Parameters such as ACC, Kappa (κ), and AUC-PR were used to identify the quality and predictive capacity of each model. The models which showed the highest value across each parameter was selected as the best quality model. The comparison of different classifiers revealed the proposed Gradient boosting machine classifier as the most accurate classifier model that can be used to predict the level of liveability, resilience, and aggregate performance of future smart cities. It is seen that ensemble modelling delivers accurate and superior predictive models over any single learning model. This is attributed to the reduced error variance and limited dispersion of model forecasts using ensemble models.

The author exemplifies the importance in creating liveable smart cities with a citizen centric approach. Least liveable and resilient cities can learn from the success stories and custom-made initiatives of the best performing smart cities. The author recommends taking a closer look into every aspect of the growth puzzle to transform smart cities to smarter, resilient, liveable, and sustainable dwelling units. The success of Copenhagen, Geneva, Stockholm, Munich, Helsinki, Vienna, London, Oslo, Zurich, and Amsterdam, as revealed in the current assessment in co-creating liveability and resilience into their development model, can be attributed to their people centric initiatives to apprehend the standard of living. The well-integrated bicycle lanes in the unified metropolitan regions of Amsterdam and Copenhagen have brought cycling as a social activity than a means to commute around the streets (aspects: community well-being, infrastructure and built environment). The Tour de Force initiative by the Danes and the Dutch Cycling Embassy (DCE) initiative have created a liveable culture among people to adopt a healthy style of living through cycling practice, resulting in improved quality of public spaces, social benefits in terms of the total urban kilometres travelled within the cities, increased activity rate of youth population, improved accessibility, and reduced impact on the overall carbon emissions. Similarly, the Cultural and Creative Cities (CCC) initiative ensures socio-economic vitality and cultural engagement through job creation and innovation in cities, an important parameter for resilient and liveable cities (aspects: social resilience, economic resilience and, economic vibrancy). High performing cities like Geneva, Stockholm, London, and Zurich are a part of this initiative since 2015 thus, pointing out the success mantra in their performance. The 'Cultural Heritage in Action' (CHA) programs adopted by cities of Eindhoven, Helsinki, Amsterdam, and Munich have resulted in establishing a balance in smart targeted growth and resilience by bringing cultural investments into the lives of citizens (aspects: community well-being, social resilience). With highest density of electric car users on road, Oslo's success in strategizing the ambitious 'Climate and Energy Initiative' across the years from 2015 till 2020 as reported by the GREENGOV research project has resulted in socio-economic and environmental resilience. Such are many among the few examples that least performing smart cities can take a look into to slide in improvements to their existing smart growth agenda.

Improving inclusive growth with a structured institutional framework is what is recommended by the author. The European smart cities loose the shared growth agenda while competing for stronger growth. This is well evident in the case of German smart cities like Munich, Dusseldorf, and Hamburg. Munich has pushed its boundaries over the years to reach top rank in addressing resilience and liveability paradigms while, Dusseldorf and Hamburg remain under marginal performance with less growth seen over the years. The reason attributed for the same can be the fragmented jurisdictional structure prevalent in the German state, which is evident from the ranking of these cities under the institutional resilience and economic vibrancy aspects in this study. The author highlights that shared growth must also focus across the regions within countries, while most often it is seen only among the population. The growth has to be strong, shared, and resilient, as to which the future research direction should focus. From a methodological point, the author recommends using model-agnostics such as LIME, Surrogate models, and Shapley values to explain what different classifiers are doing so as to improve the model interpretability. Similarly, an iterative procedure can be adopted to the proposed metric-distance based weighting scheme which revises the indicators under each aspect based on the highest average spelled coefficient, so as to achieve a model with best quality.

In **Chapter 7**, the proposed novel fuzzy expert-based multi-criteria decision support model integrating AHP under a spherical fuzzy environment with extended EDAS method was implemented. This formed the module 4, the multi-criteria assessment module of the proposed hybrid decision support model. The integrated approach is combined with fuzzy c-means algorithm to categorize the alternatives into respective clusters for improved decision making. The unique characteristic of our model is the use of AHP and extended EDAS methodology in an extended form under a spherical fuzzy environment. The proposed methodology is used to construct a composite index, the FSC index for smart cities with sustainability, resilience, and livability as the main-criteria (dimensions) and other 13 sub-criteria (indicators) distributed under each main criteria. A comparative analysis was conducted, which revealed the robustness of the proposed SF-AHP and EDAS method in comparison to several recent MCATs under the fuzzy environment. The weights assigned to each main-criteria and sub-criteria using the SF-AHP approach reveal climate change as the most important sub-criteria. The author exemplifies the fact that climate change adaption can significantly reduce the exposure of cities to hazards and decrease vulnerability. However, The lower rank of smart cities may correspond to an unmitigated climate change due to the maladaptation of sustainable and resilient practices aimed at strengthening the infrastructure and built environment to resist unexpected predicaments. The sync between the impact of climate change on social resilience and community well-being, an interaction well discussed among the urban planning community is also well acknowledged by the expert panel and thus reflected in assigning importance to social resilience and community well-being, which were considered a prioritized sub-criteria based on the weight outcome. These paradigms have been applied in practice well when taking the success stories of London, Dusseldorf, Zurich, Munich, Oslo, Dublin, Amsterdam, Hamburg, Rome, Moscow, and Stockholm. These smart cities have clearly showcased high ability in co-creating sustainability, livability, and resilience into their development model, which can be attributed to both their techno-centric and people-centric initiatives to apprehend the standard of living. The constant high performance of London over the years as seen in our analysis translates to its policies and well-tailored priorities set to strengthen resilience, livability, and sustainability through initiatives such as, ‘Smart London Plan’. The smart telecare solutions have helped Zurich deliver effective behavioral health to the citizens. The “fix-your-street” initiative of Dublin has helped to increase the safety and security of urban inhabitants by reporting potholes and vandalism through a real time application. Such are some real-time success initiatives for many developing cities that aspire for better performance to learn from.

Identifying synergies between the sub-criteria across each main-criteria is vital. The global weights obtained using the SF-AHP also reveal the significant priority of the sub-criteria “community-wellbeing”. Research has it that, building parks, sidewalks, and bicycle tracks can help improve community well-being and increase the access of people to connect within every point in city, thus accessibility. The ‘Bicycle for Everyone’ initiative by the Dutch city of Amsterdam and the innovative strategy ‘Dublin Bikes’ by Dublin are some examples from the many targeted initiatives by the local government at improving community well-being and accessibility in these cities. One of the fundamental requirements of the modern cities is the provision of shaded places aligned with pedestrian walkways for improving comfort, which is crucial to improve liveability. The provision of shaded corridors in cities can be achieved with artificial structures, while mature trees can provide shaded spaces without the use of aluminium, metals, plastic, or any kind of chemically treated fabrics. As a part of the existing design guidance, shading with artificial structures is recommended in addition to shading provided by building structures. Shading structures in Balkan regions of Europe are typically provided with aluminium, wood, steel, and hard plastic structures. Hard plastic has the most embodied energy emissions as it cannot be recycled. Recycled steel is available in the region, but the material with the most recycled content (>80%) is aluminium. However, both materials, even including large amounts of recycled content, still have embodied energy and, hence, emit carbon during the production of the final product. Combating these emissions can bring sustainable outcomes on the society and on the energy resource criterions. Concepts of circular and lean construction principles suggest that salvaged material could be used for non-structural-components. Similarly, ensuring the fit of European building stocks to compact the changing climatic conditions and geographic disruptions is a question of sustainable materials for resilient construction, a focus on the infrastructure and built environment pillars of urban resilience. Using wood certified by the Forest Stewardship Council (FSC) is a sustainable structure material, where sustainable forests to produce such materials do exist in the East European provinces and Balkan regions (e.g., Athens, Ankara, Kiev, Moscow, and Bucharest), as such, the emissions associated with transportation from foreign sites is reduced. Finally, there is no available information related to energy consumed to produce solar irradiation reflecting fabrics, but these fabrics are expected to have high associated emissions during production. In contrast, shaded paths using locally grown trees provide a responsible solution for eliminating unnecessary consumption and production of any materials. Therefore, the provision of shaded spaces using trees align with responsible consumption and production practices of the United Nations Sustainable Development Goals (SDG 12) and enhance community living, thus liveability. In addition, introducing trees appropriately within the urban environment can significantly reduce the heat stress for park users and reduce air particulate matter in the surrounding space in cities, thus attempting to score better in community well-being and built environment resilience.

Although the consistency analysis revealed stable results, certain deal of inconsistency may occur in the ranking of decision making entities (DMU) due to the variations in the threshold parameter (λ). As a future work, revising the EDAS methodology under a fuzzy environment with a provision to flexibly adjust the λ value can resolve the trade-offs associated with the gain or loss of important DMU and help decision makers arrive at a better choice DMU. Further, a dynamic-fuzzy based approach can be integrated with the EDAS methodology, that can handle further alterations in the number of alternatives, criteria, and preference of experts across time. The proposed approach in this research fails when the expert preferences on the weighting of each criteria and sub-criteria changes with respect to time. Despite the influence of time in this research, we have ignored the “change in weight” phenomenon for computational simplicity. Further investigation is required to address these caveats. Author recommends also in adding a translational vector ‘δ’ to the elements that hold a negative value in the average solution to transform into a positive value in future. In addition, the rank reversal phenomenon when adding additional DMUs is a possible case of discussion in future, which remained out of scope for the proposed analysis. Alternative techniques to AHP can be used in future to deal with the consistency problems as the matrix size increases, when broadening the set of criteria and sub-criteria. Further, the composite scores obtained from the EDAS method can be regressed against covariates. The composite scores obtained can be taken as the response variable of a fractional regression model and modelled using Quasi-maximum likelihood estimations to check if the predicted scores lie within the defined interval of the original scores obtained from the EDAS approach.

The outcomes of this dissertation is disseminated through high quality peer-reviewed journal publications and a conference paper whose list is presented in Appendix E. Furthermore, based on the outcomes of the study conducted in this dissertation, the author has provided a blueprint of recommendations for cities embarking on tailoring their landscape to attempt transformation to the meta goal of futuristic smart cities. In order to attain the meta goal of aligning United Nations Sustainable Development agenda in smart cities and to reach the penultimate goal of futuristic cities, urban planners and smart city decision makers around the globe can adopt the following guidelines, namely:

1 Despite the fact that smart cities are multi-perspective concepts, human-centric approaches are often assumed to be the keystone of city development and comprehensive smart strategies as they support economic development in cities. Human-centric approaches often act as an antidote for liveable growth in intelligent cities. For this, smart cities should act as active learning centres that support quality education and lifelong learning opportunities that would, in turn, support the growth of smart people. Smart people would contribute to more economic growth and flexibility and would act as an inviting factor for innovative industries to establish a place in the market. This in turn would open a new job market. Such approaches can undoubtfully connect city development with SDGs such as SDG 8, SDG 9, and SDG 4.

2 A multi-level policy and governance framework that includes; civil society, multiple stakeholders, public and private sectors, investors, and digitally and sustainably enabled landscape is felt necessary. Governance strategies should be transparent and should include all the actors and common people so as to facilitate an unambiguous bureaucracy, thus structuring better responsible governance for citizens. Such governance strategies should offer incentives for actors who engage in compacting several sustainability challenges (social, economic, and environmental) and promoting sustainable growth in smart cities. Such initiatives can link smart city development with sustainable development goals such as SDG 1, SDG 2, SDG 6, SDG 7, SDG 9, SDG 11, SDG 13, SDG 14, and SDG 15.

3 Cities must tap into creating a smart plan that includes engagement with universities, research centres, non-profit organizations, non-government foreign actors, and international advisory boards. These partnerships facilitate several benefits to smart cities. One such benefit is the maximization of limited government budget allotted for smart city development. This is acquired through PPP. Another benefit is the continuity of ongoing smart city projects that may face certain challenges and oppressions due to changes in the ruling party during the project execution phase. This is acquired by partnering with non-profit organizations, non-government foreign actors, and international advisory agents. Partnerships can also offer better expertise in the field of smart cities, which cannot be acquired otherwise. This is made possible through educational institutions and research centres. Such initiatives can link smart city development with sustainable development goals such as SDG 9, SDG 11, SDG 16, and SDG 17.

4 Smart cities are often perceived as a web 2.0 and industry 4.0 marketplace that act as competing rings for self-made goals of corporates and multinational firms. This may raise several development challenges in specific areas of community-based development, as selfish competitions by corporates to reap high profits from multibillion projects often fail to address the social challenges of the weaker sections of the community, like the availability of clean and safe drinking water (SDG 6), sustainable consumption patterns (SDG 12) and food security issues (SDG 2). These corporates often tend to focus on the needs of the elite class like home automation, smart banking, smart cars, sophisticated apps, and platforms for commercial purposes, etc. As a result, a socially inclusive and adaptive framework is necessary to curb social inequalities and

other social challenges prevailing in cities, thus aligning these futuristic change strategies of smart cities with SDG 1, SDG 3, SDG 5, SDG 6, SDG 10, and SDG 12.

5 Futuristic smart city transformation is not complete if the smart projects are not backed by committed leaders that support the smart city development prospect. These strong leaderships need not necessarily be within the local governing bodies like Mayors, District Attorneys, or Governors but can also be the project managers, planning directors, members of the execution community, NGO activists, etc. These initiatives can connect SDGs 11, 16, and 17 with smart city development strategies.

REFERENCES

Abbas, H., Shaheen, S. I., Elhoseny, M., & Singh, A. K. (2018). Systems thinking for developing sustainable complex smart cities based on self-regulated agent systems and fog computing. *Sustainable Computing: Informatics and Systems, 19*, 204-213. doi:10.1016/j.suscom.2018.05.005

Abdel-Razek, S. A. (2021). Governance and SDGs in smart cities context. In *Smart Cities and the un SDGs* (pp. 61-70). Elsevier.

Abdella, G. M., Al-Khalifa, K. N., Kim, S., Jeong, M. K., Elsayed, E. A., & Hamouda, A. M. (2017). Variable selection-based multivariate cumulative sum control chart. *Quality and Reliability Engineering International*, *33*(3), 565-578.

Abdella, G. M., Kim, J., Al-Khalifa, K. N., & Hamouda, A. M. (2019). Penalized Conway-Maxwell-Poisson regression for modelling dispersed discrete data: The case study of motor vehicle crash frequency. *Safety Science*, *120*, 157-163.

Abdella, G. M., Kucukvar, M., Kutty, A. A., Abdelsalam, A. G., Sen, B., Bulak, M. E., & Onat, N. C. (2021). A novel approach for developing composite eco-efficiency indicators: The case for US food consumption. *Journal of Cleaner Production*, *299*, 126931.

Abdella, G. M., Kucukvar, M., Onat, N. C., Al-Yafay, H. M., & Bulak, M. E. (2020). Sustainability assessment and modeling based on supervised machine learning techniques: The case for food consumption. *Journal of Cleaner Production*, *251*, 119661.

Abdella, G. M., Maleki, M. R., Kim, S., Al-Khalifa, K. N., & Hamouda, A. M. S. (2020a). Phase-I monitoring of high-dimensional covariance matrix using an adaptive thresholding LASSO rule. *Computers & Industrial Engineering*, *144*, 106465.

Abdella, G. M., & Shaaban, K. (2021). Modeling the impact of weather conditions on pedestrian injury counts using LASSO-based poisson model. *Arabian Journal for Science and Engineering*, *46*(5), 4719-4730.

Aboushaqrah, N. N., Onat, N. C., Kucukvar, M., Hamouda, A. M. S., Kusakci, A. O., & Ayvaz, B. (2021). Selection of alternative fuel taxis: a hybridized approach of life cycle sustainability assessment and multi-criteria decision making with neutrosophic sets. *International Journal of Sustainable Transportation*, 1-14.

About-de Chastenet, C., Belziti, D., Bessis, B., Faucheux, F., Le Sceller, T., Monaco, F. X., & Pech, P. (2016). The French eco-neighbourhood evaluation model: Contributions to sustainable city making and to the evolution of urban practices. *Journal of Environmental Management*, *176*, 69-78.

Abreu, L. M., da Hora, H. R. M., Rangel, J. J. A., Erthal, M., Razmjooy, N., Estrela, V. V., ... & Iano, Y. (2020). A Multi-criteria Modelling for Ranking CO 2 Emitting G20 Countries from the Kaya Identity and Their Impacts on Elderly Health. In *Brazilian Technology Symposium* (pp. 477-487). Springer, Cham.

Abu-Rayash, A., & Dincer, I. (2021). Development of integrated sustainability performance indicators for better management of smart cities. *Sustainable Cities and Society*, *67*, 102704.

Abusaada, H., & Elshater, A. (2021). Nightlife in Smart Public Spaces. In *Transforming Urban Nightlife and the Development of Smart Public Spaces* (pp. 1-12). IGI Global.

Aceleanu, M. I., Şerban, A. C., Suciu, M. C., & Biţoiu, T. I. (2019). The management of municipal waste through circular economy in the context of smart cities development. *IEEE Access*, *7*, 133602-133614.

Aguilera, R. C., Ortiz, M. P., Ortiz, J. P., & Banda, A. A. (2021). Internet of things expert system for smart cities using the blockchain technology. *Fractals*, *29*(01), 2150036.

Akande, A., Cabral, P., Gomes, P., & Casteleyn, S. (2019). The Lisbon ranking for smart sustainable cities in Europe. *Sustainable Cities and Society*, *44*, 475-487.

Al-Buenain, A., Al-Muhannadi, S., Falamarzi, M., Kutty, A. A., Kucukvar, M., & Onat, N. C. (2021). The Adoption of Electric Vehicles in Qatar Can Contribute to Net Carbon Emission Reduction but Requires Strong Government Incentives. Vehicles 2021, 3, 618–63.

Alagirisamy, B., & Ramesh, P. (2022). Smart Sustainable Cities: Principles and Future Trends. In *Sustainable Cities and Resilience* (pp. 301-316). Springer, Singapore.

Ali-Toudert, F., & Ji, L. (2017). Modeling and measuring urban sustainability in multi-criteria based systems-A challenging issue. *Ecological Indicators*, *73*, 597-611.

Ali, A., & Seiford, L. M. (1990). Translation invariance in data envelopment analysis. *Operations Research Letters*, 10, 403–405.

Allen, T. F. H., & Hoekstra, T. W. (1993). Toward a definition of sustainability. *Sustainable ecological systems: implementing an ecological approach to land management. Rocky Mountain Forest and Range Experiment Station, Fort Collins, Colorado*, 98-107.

Alpaydin, E. (2020). *Introduction to machine learning*. MIT press.

Alrashdi, I., Alqazzaz, A., Aloufi, E., Alharthi, R., Zohdy, M., & Ming, H. (2019, January). Ad-iot: Anomaly detection of iot cyberattacks in smart city using machine learning. In *2019 IEEE 9th Annual Computing and Communication Workshop and Conference (CCWC)* (pp. 0305-0310). IEEE.

Alsarayreh, M. M. M., AlSuwaidi, M. F., Al Sharif, R. A., & Kutty, A. A. (2020). The factors affecting CO_2 emission in the European union countries: A statistical approach to sustainability across the food industry. In *2020 IEEE 7th international conference on industrial engineering and applications (ICIEA)* (pp. 599-604). IEEE.

Amaba, B. A. (2014). Industrial and business systems for Smart Cities. *EMASC 2014 - Proceedings of the 1st International Workshop on Emerging Multimedia Applications and Services for Smart Cities* (pp. 21-22). Orlando, United States: Association for Computing Machinery, Inc. doi:10.1145/2661704.2661713

Amado, C. A., São José, J. M., & Santos, S. P. (2016). Measuring active ageing: a data envelopment analysis approach. *European Journal of Operational Research*, *255*(1), 207-223.

Andrade, R. O., Yoo, S. G., Tello-Oquendo, L., & Ortiz-Garcés, I. (2021). Cybersecurity, sustainability, and resilience capabilities of a smart city. In *Smart Cities and the un SDGs* (pp. 181-193). Elsevier.

Antanasijević, D., Pocajt, V., Ristić, M., & Perić-Grujić, A. (2017). A differential multi-criteria analysis for the assessment of sustainability performance of European countries: Beyond country ranking. *Journal of cleaner production*, *165*, 213-220.

Antonov, I. (1995). On a new geometrical interpretation of the intuitionistic fuzzy sets. *Notes on Intuitionistic Fuzzy Sets*, *1*(1), 29-31.

Appleyard, D., Gerson, M. S., & Lintell, M. (1981). *Livable streets, protected neighborhoods*. University of California Press.

Arup and Rockefeller Foundation. (2014). City Resilience Framework. Ove Arup & Partners International Limited, London. Available online at https://www.urban-response.org/system/files/cont ent/resource/files/main/city-resilience-framework-arup-april-2014.pdf

Atanassov, K. T. (1986). Intuitionistic fuzzy sets. *Fuzzy Sets and Systems*, *20*(1), 87-96, https://doi.org/10.1016/S0165-0114(86)80034-3

Atanassov, K.T. (1999). Intuitionistic Fuzzy Sets. In: *Intuitionistic Fuzzy Sets*. Studies in Fuzziness and Soft Computing, *35*. Physica, Heidelberg. https://doi.org/10.1007/978-3-7908-1870-3_1

Ayu, W. P. (2020). Application To Measuring Food Business Opportunities For The Development Of Smart Cities. In *IOP Conference Series: Materials Science and Engineering* (Vol. 858, No. 1, p. 012056). IOP Publishing.

Azizi, H. (2011). The interval efficiency based on the optimistic and pessimistic points of view. *Applied Mathematical Modelling*, *35*(5), 2384-2393.

Azizi, H. (2014). DEA efficiency analysis: A DEA approach with double frontiers. *International Journal of Systems Science*, *45*(11), 2289-2300.

Azizi, H., & Ajirlu, S. F. (2010). Measurement of overall performances of decision-making units using ideal and anti-ideal decision-making units. *Computers & Industrial Engineering*, *59*(3), 411-418.

Babanli, M. B. (2019). Fuzzy Logic and Fuzzy Expert System-Based Material Synthesis Methods. In (Ed.), *Fuzzy Logic*. IntechOpen. https://doi.org/10.5772/intechopen.84493

Balestra, C., Boarini, R., & Tosetto, E. (2018). What matters most to people?

Evidence from the OECD better life index users' responses. *Social Indicators Research*, *136*(3), 907-930.

Balsas, C. J. (2004). Measuring the livability of an urban centre: an exploratory study of key performance indicators. *Planning, Practice & Research*, *19*(1), 101-110.

Banker, R. D., Charnes, A., & Cooper, W. W. (1984). Some Models for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis. *Management Science*, *30*(9). doi:https://doi.org/10. 1287/mnsc.30.9.1078

Bao, Q., Ruan, D., Shen, Y., Hermans, E., & Janssens, D. (2012). Improved hierarchical fuzzy TOPSIS for road safety performance evaluation. *Knowledge-based systems*, *32*, 84-90.

Bastaminia, A., Rezaei, M. R., & Dastoorpoor, M. (2017). Identification and evaluation of the components and factors affecting social and economic resilience in city of Rudbar, Iran. *International journal of disaster risk reduction*, *22*, 269-280.

Battarra, R., Pinto, F., & Tremiterra, M. R. (2018). Indicators and Actions for the Smart and Sustainable City: A Study on Italian Metropolitan Cities. In *Smart Planning: Sustainability and Mobility in the Age of Change* (pp. 83-107). Springer, Cham.

Batty, M., Axhausen, K. W., Giannotti, F., Pozdnoukhov, A., Bazzani, A., Wachowicz, M., ... & Portugali, Y. (2012). Smart cities of the future. *The European Physical Journal Special Topics*, *214*(1), 481-518.

Beatley, T., & Newman, P. (2013). Biophilic cities are sustainable, resilient cities. *Sustainability*, *5*(8), 3328-3345.

Beck, G. A. (2016). Surviving involuntary unemployment together: The role of resilience-promoting communication in familial and committed relationships. *Journal of Family Communication*, *16*(4), 369-385.

Becker, W., Saisana, M., Paruolo, P., & Vandecasteele, I. (2017). Weights and importance in composite indicators: Closing the gap. *Ecological indicators*, *80*, 12-22.

Bellini, E., Nesi, P., & Bellini, P. (2017). *Information Model and Interoperability*. RESOLUTE Project, D4.4, University of Florence: Florence, Italy.

Bellini, E., Nesi, P., Pantaleo, G., & Venturi, A. (2016). Functional resonance analysis method based-decision support tool for urban transport system resilience management. *IEEE 2nd International Smart Cities Conference: Improving the Citizens Quality of Life, ISC2 2016 - Proceedings.* Trento, Italy: IEEE. doi:10.1109/ISC2.2016.7580833

Bellocchi, G., Acutis, M., Fila, G., & Donatelli, M. (2002). An Indicator of Solar Radiation Model Performance based on a Fuzzy Expert System. *Agronomy Journal*, *94*(6), 1222-1233. doi: https://doi.org/10.2134/agronj2002.1222

Benita, F., Kalashnikov, V., & Tunçer, B. (2021). A Spatial Livability Index for dense urban centers. *Environment and Planning B: Urban Analytics and City Science*, *48*(7), 2006-2022.

Beretta, I. (2018). The social effects of eco-innovations in Italian smart cities. *Cities*, *72*, 115-121.

Berkowitz, A. R., Nilon, C. H., & Hollweg, K. S. (Eds.). (2003). *Understanding urban ecosystems: a new frontier for science and education*. Springer Science & Business Media.

Bertalanffy, L. V. (1976). *Perspectives on General System Theory: Scientific-Philosophical Studies* (1 ed.). George Braziller: The International library of systems theory and philosophy.

Betz, M. R., Partridge, M. D., & Fallah, B. (2016). Smart cities and attracting knowledge workers: Which cities attract highly-educated workers in the 21st century?. *Papers in Regional Science*, *95*(4), 819-841

Bianchi, M., Valle, I. d., & Tapia, C. (2020). Measuring eco-efficiency in European regions: Evidence from a territorial perspective. *Journal of Cleaner Production*, *276*, 123-246. doi:https://doi.org/10.1016/j. jclepro.2020.123246

Bibri, S. E. (2020). A methodological framework for futures studies: integrating normative backcasting approaches and descriptive case study design for strategic data-driven smart sustainable city planning. *Energy Informatics*, *3*(1), 1-42.

Bibri, S. E. (2021a). A novel model for data-driven smart sustainable cities of the future: the institutional transformations required for balancing and advancing the three goals of sustainability. *Energy Informatics*, *4*(1), 1-37.

Bibri, S. E. (2021b). Data-driven smart sustainable cities of the future: urban computing and intelligence for strategic, short-term, and joined-up planning. *Computational Urban Science*, *1*(1), 1-29.

Bibri, S. E. (2021c). The core academic and scientific disciplines underlying data-driven smart sustainable urbanism: an interdisciplinary and transdisciplinary framework. *Computational Urban Science*, *1*(1), 1-32.

Bibri, S. E. (2021d). A Novel Model for Data-Driven Smart Sustainable Cities of the Future: A Strategic Planning Process of Transformative Change towards Sustainability.

Bibri, S. E., & Krogstie, J. (2017). Smart sustainable cities of the future: An extensive interdisciplinary literature review. *Sustainable Cities and Society, 31*, 183-212.

doi:https://doi.org/10.1016/j.scs.2017.02.016

Bibri, S. E., & Krogstie, J. (2020). The emerging data–driven Smart City and its innovative applied solutions for sustainability: The cases of London and Barcelona. *Energy Informatics*, *3*(1), 1-42.

Bingöl, E. S. (2022). Citizen participation in smart sustainable cities. In *Research Anthology on Citizen Engagement and Activism for Social Change* (pp. 967-987). IGI Global.

Bishop, C. M. (2006). *Pattern recognition and machine learning.* Springer-Verlag New York.

Bland, L. C., Sowa, C. J., & Callahan, C. M. (1994). An overview of resilience in gifted children. *Roeper Review*, *17*(2), 77-80

Bonnet, J., Coll-Martínez, E., & Renou-Maissant, P. (2021). Evaluating sustainable development by composite index: Evidence from french departments. *Sustainability*, *13*(2), 761.

Boost, M., Promberger, M., Meier, L., & Sowa, F. (2020). "Developing the concept of poverty and resilience". In *Poverty, Crisis and Resilience*. Cheltenham, UK: Edward Elgar Publishing. doi: https://doi.org/10.4337/9781788973205.00013

Bosisio, A., Moncecchi, M., Morotti, A., & Merlo, M. (2021). Machine Learning and GIS Approach for Electrical Load Assessment to Increase Distribution Networks Resilience. *Energies*, *14*(14), 4133.

Bowyer J., Bratkovich S., Lindberg A., & Fernholz K. (2008). Wood products and carbon protocols: carbon storage and low energy intensity should be considered. Minneapolis, *Dovetail Partners*, Inc

Boykova, M., Ilina, I., Salazkin, M. (2016). The Smart City Approach as a Response to Emerging Challenges for Urban Development. *Foresight and STI*

Governance, *10*(3), 65–75. doi: 10.17323 /1995-459X.2016.3.65.75

Brauers, W. K. (2003). *Optimization methods for a stakeholder society: a revolution in economic thinking by multi-objective optimization* (Vol. 73). Springer Science & Business Media. https://doi.org/10.1007/978-1-4419-9178-2

Breiman, L. (1996). Bagging predictors. *Machine learning*, *24*(2), 123-140, doi: 10.3390/risks8030083.

Breiman, L., Friedman, J. H., Olshen, R. A., & Stone, C. J. (1984). *Classification and regression trees*. Routledge.

Brenner, N., Marcuse, P., & Mayer, M. (2009). Cities for people, not for profit. *City*, *13*(2-3), 176-184.

Broccardo, L., Culasso, F., & Mauro, S.G. (2019), Smart city governance: exploring the institutional work of multiple actors towards collaboration, *International Journal of Public Sector Management*, *32*(4), 367-387, doi: https://doi.org/10.1108/IJPSM-05-2018-0126

Brown, C., & Lall, U. (2006, November). Water and economic development: The role of variability and a framework for resilience. In *Natural resources forum* (Vol. 30, No. 4, pp. 306-317). Oxford, UK: Blackwell Publishing Ltd.

Bruzzone, M., Dameri, R. P., & Demartini, P. (2021). Resilience Reporting for Sustainable Development in Cities. *Sustainability*, *13*(14), 7824.

BSI (2014). *Smart Cities Framework–Guide to Establishing Strategies for Smart Cities and Communities*. PAS 181:2014. London, UK: BSI Standards Limited.

Buch, T., Hamann, S., Niebuhr, A., & Rossen, A. (2014). What makes cities attractive? The determinants of urban labour migration in Germany. *Urban Studies*, *51*(9), 1960-1978.

Buldeo Rai, H., Van Lier, T., Meers, D., & Macharis, C. (2018). An indicator approach to sustainable urban freight transport. *Journal of Urbanism: International Research on Placemaking and Urban Sustainability*, *11*(1), 81-102.

Burange, A. W., & Misalkar, H. D. (2015, March). Review of Internet of Things in development of smart cities with data management & privacy. In *2015 International Conference on Advances in Computer Engineering and Applications* (pp. 189-195). IEEE.

Calzada, I. (2017). Metropolitan and city-regional politics in the urban age: why does "(smart) devolution" matter?. *Palgrave Communications*, *3*(1), 1-17.

Camero, A., & Alba, E. (2019). Smart City and information technology: A review. *Cities, 93*, 84-94. doi:https://doi.org/10.1016/j.cities.2019.04.014

Caputo, F., Walletzky, L., & Štepánek, P. (2019). Towards a systems thinking based view for the governance of a smart city's ecosystem: A bridge to link Smart Technologies and Big Data. *Kybernetes, 48*(1), 108-123. doi:https://doi.org/10.1108/K-07-2017-0274

Castellano, R., Ferretti, M., Musella, G., & Risitano, M. (2020). Evaluating the economic and environmental efficiency of ports: Evidence from Italy. *Journal of Cleaner Production, 271*. doi:https://doi.org/10.1016/j.jclepro.2020.122560.

Cavallaro, F. (2020). Development of an Index for Sustainable Energy Technologies Based on an Intelligent Fuzzy Expert System. *Studies in Systems, Decision and Control*, 288, 137-143.

Chao, T. Y. S., Liu, S. K., Kalman, B., Lu, H. C. C., & Cai, M. (2017). Delivering community well-being from the happy city concept: A practical approach to urban planning and design. In *Handbook of Community Well-Being Research* (pp. 435-452). Springer, Dordrecht.

Chakraborty, S., & Dabla-Norris, E. (2011). The quality of public investment. *The BE Journal of Macroeconomics*, *11*(1).

Charnes, A., & Cooper, W. W. (1962). Programming with linear fractional functionals. *Naval Research logistics quarterly*, *9*(3-4), 181-186.

Charnes, A., Cooper, W. W., & Li, S. (1989). Using data envelopment analysis to evaluate efficiency in the economic performance of Chinese cities. *Socio-Economic Planning Sciences*, *23*(6), 325-344.

Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European journal of operational research, 2*(6), 429-444.

Chatterjee, A., Vaidya, G., Paulose, N. K., & Gupta, P. D. (2020). Exploring Livability in the Era of Smart City: A Case of Bhopal. In *Smart Living for Smart Cities* (pp. 103-144). Springer, Singapore.

Chen, L. J., Ho, Y. H., Lee, H. C., Wu, H. C., Liu, H. M., Hsieh, H. H., ... & Lung, S. C. C. (2017). An open framework for participatory PM2. 5 monitoring in smart cities. *IEEE Access*, *5*, 14441-14454.

Chen, Y., & Zhang, D. (2020). Evaluation of city sustainability using multi-criteria decision-making considering interaction among criteria in Liaoning province China. *Sustainable Cities and Society, 59*, 102211.

Chen, L., & Zhang, Z. (2021). Community Participation and Subjective Wellbeing: Mediating Roles of Basic Psychological Needs Among Chinese Retirees. *Frontiers in psychology, 12*.

Choi, J. H., Lee, H. B., Choi, J. W., & Kim, S. C. (2016). Mutual interference suppression using clipping and weighted-envelope normalization for automotive FMCW radar systems. *IEICE Transactions on*

Communications, *99*(1), 280-287.

Chourabi, H., Nam, T., Walker, S., Gil-Garcia, J. R., Mellouli, S., Nahon, K., . . . Scholl, H. J. (2012). Understanding Smart Cities: An Integrative Framework. *45th Hawaii International Conference on System Sciences*, (pp. 2289-2297).

Chu, Z., Cheng, M., & Song, M. (2021). What determines urban resilience against COVID-19: City size or governance capacity?. *Sustainable Cities and Society*, *75*, 103304.

Chudiniva, O., & Afonina, M. (2018). Formation of "Urban planning" indicators for "Smart City" concept (on the example of SKOLKOVO, Moscow). In MATEC Web of Conferences (Vol. 170, p. 02021). EDP Sciences.

Cinelli, M., Coles, S. R., & Kirwan, K. (2014). Analysis of the potentials of multi criteria decision analysis methods to conduct sustainability assessment. *Ecological indicators*, *46*, 138-148.

Clemente, A. A. (2020). Bicycle paths as a contribution to urban resilience in high-density areas. *UPLanD-Journal of Urban Planning, Landscape & environmental Design*, *5*(1), 93-110.

Cohen, B. (2012). The Boyd-Cohen Smart City Index. Available online: https://www.fastcompany.com /3038818/the-smartest-cities-inthe-world-2015-methodology (accessed on 05 February, 2021).

Collins, A. J., Jordan, C. A., Robinson, R. M., Cornelius, C., & Gore, R. (2020). Exploring good cycling cities using multivariate statistics. *Environment systems and decisions*, *40*(4), 526-543.

Cook, I. R., & Swyngedouw, E. (2012). Cities, social cohesion, and the environment: towards a future research agenda. *Urban studies*, *49*(9), 1959-1979.

Copeland, S., Comes, T., Bach, S., Nagenborg, M., Schulte, Y., & Doorn, N. (2020).

Measuring social resilience: Trade-offs, challenges, and opportunities for indicator models in transforming societies. *International Journal of Disaster Risk Reduction*, *51*, 101799.

Correia, J. S., Ferreira, F. A., Meidutė-Kavaliauskienė, I., Pereira, L. F., Zopounidis, C., & Correira, R. J. (2020). Factors influencing urban investment attractiveness: an FCM-SD approach. *International journal of strategic property management*, *24*(4), 237-250.

Cox, R. S., & Hamlen, M. (2015). Community disaster resilience and the rural resilience index. *American Behavioral Scientist*, *59*(2), 220-237.

Curşeu, P. L., Semeijn, J. H., & Nikolova, I. (2021). Career challenges in smart cities: A sociotechnical systems view on sustainable careers. *human relations*, *74*(5), 656-677.

Cuttaree, V., & Mandri-Perrott, X. C. (2011). *Public-private partnerships in Europe and Central Asia: designing crisis-resilient strategies and bankable projects*. World Bank Publications.

Czudec, A., & Zając, D. (2021). Economic Effects of Public Investment Activity in Rural Municipalities of Eastern Poland. *Economy of Region/Ekonomika Regiona*, *17*(4).

D'Aniello, G., Gaeta, M., Orciuoli, F., Sansonetti, G., & Sorgente, F. (2020). Knowledge-Based Smart City Service System. *Electronics*, *9*(6), 965.

Danilina, N., & Slepnev, M. (2018). Managing smart-city transportation planning of "Park-and-ride" system: case of Moscow metropolitan. In *IOP Conference Series: Materials Science and Engineering* (Vol. 365, No. 2, p. 022002). IOP Publishing.

Darmawan, A. K., Siahaan, D. O., Susanto, T. D., Umam, B. A., Yulianto, T., Walid, M., ... & Hidayanto, A. N. (2020, November). A hybrid Approach with Balanced Score Card and Fuzzy Topsis Method for Identifying Critical Factors Affecting Smart Regency Development. In *2020 Fifth International Conference on Informatics and Computing (ICIC)* (pp. 1-8). IEEE.

De Mare, G., Granata, M. F., & Nesticò, A. (2015). Weak and strong compensation for the prioritization of public investments: multidimensional analysis for pools. *Sustainability*, *7*(12), 16022-16038.

Deprins, D., Simar, L. H., & Tulkens. (1984). Measuring labor inefficiency in post offices. *The Performance of Public Enterprises: Concepts and measurements. M. Marchand, P. Pestieau and H. Tulkens (eds.), Amsterdam, North-Holland,* 243-267.

DeRolph, C. R., McManamay, R. A., Morton, A. M., & Nair, S. S. (2019). City energy sheds and renewable energy in the United States. *Nature Sustainability*, *2*(5), 412-420.

Di, X., Wang, L., Yang, L., & Dai, X. (2021). Impact of Economic Accessibility on Realized Utilization of Home-Based Healthcare Services for the Older Adults in China. In *Healthcare*, *9*(2), 218. Multidisciplinary Digital Publishing Institute.

Diaz-Balteiro, L., González-Pachón, J., & Romero, C. (2017). Measuring systems sustainability with multi-criteria methods: A critical review. *European Journal of Operational Research*, *258*(2), 607-616.

Dirks, S., & Keeling, M. (2009). A vision of smarter cities: How cities can lead the way into a prosperous and sustainable future. *IBM Institute for business Value*, *8*.

Do, M. (2008). Antenatal Care Service Availability and Utilization in Rural Viet

Nam. *Asia-Pacific Population Journal*, *23*(1).

Dodgson, M., & Gann, D. (2011). Technological innovation and complex systems in cities. *Journal of Urban Technology*, *18*(3), 101-113.

Dong, X., Shi, T., Zhang, W., & Zhou, Q. (2020). Temporal and spatial differences in the resilience of smart cities and their influencing factors: Evidence from non-provincial cities in China. *Sustainability*, *12*(4), 1321.

Dunn, J. C. (1973). A fuzzy relative of the ISODATA process and its use in detecting compact well-separated clusters. *Journal of Cybernetics*, 3(3), 32-57, doi: 10.1080/01969727308546046

Eesa, A. S., & Arabo, W. K. (2017). A normalization method for backpropagation: a comparative study. *Science Journal of University of Zakho*, *5*(4), 319-323.

Egilmez, G., Gumus, S., & Kucukvar, M. (2015). Environmental sustainability benchmarking of the U.S. and Canada metropoles: An expert judgment-based multi- criteria decision-making approach. *Cities, 42*(A), 31-41. doi:https://doi.org/10.1016/j.cities.2014.08.006

Elhmoud, E. R., & Kutty, A. A. (2021). Sustainability assessment in aviation industry: a mini-review on the tools, models and methods of assessment. In *Proceedings of the 2nd African International Conference on Industrial Engineering and Operations Management, Harare, Zimbabwe* (pp. 7-10).

Emrouznejad, A., Anouze, A. L., & Thanassoulis, E. (2010). A semi-oriented radial measure for measuring the efficiency of decision making units with negative data, using DEA. *European Journal of Operational Research*, *200*(1), 297-304.

Entani, T., Maeda, Y., & Tanaka, H. (2002). Dual models of interval DEA and its extension to interval data. *European Journal of Operational Research*, *136*(1), 32-45.

Ericsson, A. B. (2016). Networked Society City Index. *Networked Society Lab*, Available online: http://mb.cision.com/Public/15448/2245037/93894148bfbf1118.pdf

Escrig-Olmedo, E., Rivera-Lirio, J. M., Muñoz-Torres, M. J., & Fernández-Izquierdo, M. Á. (2017). Integrating multiple ESG investors' preferences into sustainable investment: A fuzzy multicriteria methodological approach. *Journal of cleaner production*, *162*, 1334-1345.

Esliger, D. W., Sherar, L. B., & Muhajarine, N. (2012). Smart cities, healthy kids: The association between neighbourhood design and children's physical activity and time spent sedentary. *Canadian Journal of Public Health*, *103*(3), S22-S28.

Esmaeilpoorarabi, N., Yigitcanlar, T., Kamruzzaman, M., & Guaralda, M. (2020). How does the public engage with innovation districts? Societal impact assessment of Australian innovation districts. *Sustainable Cities and Society*, *52*, 101813.

Estevez, E., Pardo, T. A., & Scholl, H. J. (Eds.). (2021). *Smart Cities and Smart Governance: Towards the 22nd Century Sustainable City* (Vol. 37). Springer Nature.

European Green Capital. (2021). Green City Tool, *European Commission*, Available online: https://webgate.ec.europa.eu/greencitytool/ topic/

Faber, M. H., Giuliani, L., Revez, A., Jayasena, S., Sparf, J., & Mendez, J. M. (2014). Interdisciplinary approach to disaster resilience education and research. *Procedia Economics and Finance*, *18*, 601-609.

Fallahpour, A., Wong, K.Y., Rajoo, S., Olugu, E.U., Nilashi, M., & Turskis, Z.

(2020). A fuzzy decision support system for sustainable construction project selection: An integrated fpp-fis model. *Journal of Civil Engineering and Management*, 26(3), 247-258.

Färe, R., & Grosskopf, S. (2004). Modeling undesirable factors in efficiency evaluation: comment. *European Journal of Operational Research*, *157*(1), 242-245.

Färe, R., Grosskopf, S., Lindgren, B., & Roos, P. (1992). Productivity changes in Swedish pharamacies 1980–1989: A non-parametric Malmquist approach. *Journal of productivity Analysis*, *3*(1), 85-101.

Farmanbar, M., & Toygar, Ö. (2016). Feature selection for the fusion of face and palmprint biometrics. *Signal, Image and Video Processing*, *10*(5), 951-958.

Feng, M., Ren, J., He, J., Chan, F. K. S., & Wu, C. (2022). Potency of the pandemic on air quality: An urban resilience perspective. *Science of the Total Environment*, *805*, 150248.

Feygin, S. A., Lazarus, J. R., Forscher, E. H., Golfier-Vetterli, V., Lee, J. W., Gupta, A., ... & Bayen, A. M. (2020). BISTRO: Berkeley Integrated System for Transportation Optimization. *ACM Transactions on Intelligent Systems and Technology (TIST)*, *11*(4), 1-27.

Figueiredo, L., T. Honiden & A. Schumann (2018). Indicators for Resilient Cities, *OECD Regional Development Working Papers*, No. 2018/02, OECD Publishing, Paris, https://doi.org/10.1787/6f1f60 65-en.

Fontela, E., & Gabus, A. (1976). The DEMATEL Observer. DEMATEL 1976 report, Battelle Geneva Research Center, Switzerland, Geneva.

Frankenberger, T. R., Constas, M. A., Neson, S., & Starr, L. (2014). *Current approaches to resilience programming among nongovernmental* *organizations* (Vol. 7). Intl Food Policy Res Inst.

Frare, M. B., Clauberg, A. P., Sehnem, S., Campos, L. M., & Spuldaro, J. (2020). Toward a sustainable development indicators system for small municipalities. *Sustainable Development*.

Freund, Y., & Schapire, R. E. (1997). A decision-theoretic generalization of on-line learning and an application to boosting. *Journal of computer and system sciences*, *55*(1), 119-139, doi:10.1006/jcss. 1997.1504

Fu, Y., He, C., & Luo, L. (2021). Does the low-carbon city policy make a difference? Empirical evidence of the pilot scheme in China with DEA and PSM-DID. *Ecological Indicators, 122*, 107238.

Galderisi, A., Limongi, G., & Salata, K. D. (2020). Strengths and weaknesses of the 100 Resilient Cities Initiative in Southern Europe: Rome and Athens' experiences. *City, Territory and Architecture*, *7*(1), 1-22.

Gan, X., Fernandez, I. C., Guo, J., Wilson, M., Zhao, Y., Zhou, B., & Wu, J. (2017). When to use what: Methods for weighting and aggregating sustainability indicators. *Ecological Indicators*, *81*, 491-502.

Ganji, S. S., & Rassafi, A. A. (2019). DEA Malmquist productivity index based on a double-frontier slacks-based model: Iranian road safety assessment. *European Transport Research Review*, *11*(1), 1-32.

Galderisi, A., Limongi, G., & Salata, K. D. (2020). Strengths and weaknesses of the 100 Resilient Cities Initiative in Southern Europe: Rome and Athens' experiences. *City, Territory and Architecture*, *7*(1), 1-22.

Ge, X., Xu, J., Xie, Y., Guo, X., & Yang, D. (2021). Evaluation and Dynamic Evolution of Eco-Efficiency of Resource-Based Cities-A Case Study of Typical Resource-Based Cities in China. *Sustainability*, *13*(12), 6802.

Ghosh, A., Kumari, K., Kumar, S., Saha, M., Nandi, S., & Saha, S. (2019, January). Noiseprobe: Assessing the dynamics of urban noise pollution through participatory sensing. In *2019 11th International Conference on Communication Systems & Networks (COMSNETS)* (pp. 451-453). IEEE.

Giffinger, R., Haindlmaier, G., & Kramar, H. (2010). The role of rankings in growing city competition. *Urban research & practice*, *3*(3), 299-312.

Glaeser, E. L. (2021). What Can Developing Cities Today Learn From the Urban Past?. *Regional Science and Urban Economics*, 103698.

Golany, B., & Roll, Y. (1989). An application procedure for DEA. *Omega: The International Journal of Management Science*, 17, 237–250.

Golubchikov, O., & Thornbush, M. (2020). Artificial intelligence and robotics in smart city strategies and planned smart development. *Smart Cities*, *3*(4), 1133-1144.

Gómez, N.I.M., Rojas, K.R., Rivera, D.C., Arévalo, J.L.D., & Jiménez, P.A.L. (2020). Using Machine Learning Tools to Classify Sustainability Levels in the Development of Urban Ecosystems. *Sustainability*, 12, 3326, doi:10.3390/su12083326.

Gonella, F. (2019). The smart narrative of a smart city. *Frontiers in Sustainable Cities*, *1*, 9.

Greco, S., Ishizaka, A., Tasiou, M., & Torrisi, G. (2019). On the methodological framework of composite indices: A review of the issues of weighting, aggregation, and robustness. *Social indicators research*, *141*(1), 61-94.

Green, L. V. (2002). How many hospital beds?. *INQUIRY: The Journal of Health Care Organization, Provision, and Financing*, *39*(4), 400-412.

Guedoudj, W., Ghenouchi, A., & Toussaint, J. Y. (2020). Urban attractiveness in public squares: the mutual influence of the urban environment and the social activities in Batna. *urbe. Revista Brasileira de Gestão Urbana*, *12*.

Guiraudon, V. (2014). Economic crisis and institutional resilience: The political economy of migrant incorporation. *West European Politics*, *37*(6), 1297-1313.

Guo, L., Yang, J. J., Peng, L., Li, J., & Liang, Q. (2015). A computer-aided healthcare system for cataract classification and grading based on fundus image analysis. *Computers in Industry*, *69*, 72-80.

Habernal, I., Ptacek, T., & Steinberger, J. (2013). Sentiment Analysis in Czech Social Media Using Supervised Machine Learning. *Proceedings of the 4th Workshop on Computational Approaches to Subjectivity, Sentiment and Social Media Analysis*, (pp. 65-74). Atlanta, Georgia.

Haider, H., Hewage, K., Umer, A., Ruparathna, R., Chhipi-Shrestha, G., Culver, K., ... & Sadiq, R. (2018). Sustainability assessment framework for small-sized urban neighbourhoods: An application of fuzzy synthetic evaluation. *Sustainable cities and society*, *36*, 21-32.

Hajduk, S., & Jelonek, D. (2021). A Decision-Making Approach Based on TOPSIS Method for Ranking Smart Cities in the Context of Urban Energy. *Energies*, *14*(9), 2691.

Hamman, P., Anquetin, V., & Monicolle, C. (2017). Contemporary Meanings of the 'Sustainable City': A Comparative Review of the French- and English-Language Literature. *Sustainable Development*, *25*(4), 336-355. doi: https://doi.org/10.1002 /sd.1660

Hammond G., Jones G. (2011). Embodied Carbon - The inventory of Carbon Energy (ICE). BSRIA Guide. BSRIA BG, UK

Han, B. A., Schmidt, J. P., Bowden, S. E., & Drake, J. M. (2015). Rodent reservoirs of future zoonotic diseases. *Proceedings of the National Academy of Sciences*, *112*(22), 7039-7044.

Hartatik, Aziz, A., Hartono, R., & Abdilah, R. (2020, June). Decision Support System for Detection of Skin Diseases in Smart Health development planning. In *IOP Conference Series: Materials Science and Engineering* (Vol. 858, No. 1, p. 012051). IOP Publishing.

Hastie, T., Tibshirani, R., & Friedman, J. (2001). The elements of statistical learning. Springer series in statistics. In *:*. Springer.

Hatefi, S. M., & Torabi, S. A. (2010). A common weight MCDA–DEA approach to construct composite indicators. *Ecological Economics*, *70*(1), 114-120.

Hatuka, T., & Zur, H. (2020). From smart cities to smart social urbanism: A framework for shaping the socio-technological ecosystems in cities. *Telematics and Informatics, 55,* 101430.

Higgs, C., Badland, H., Simons, K., Knibbs, L. D., & Giles-Corti, B. (2019). The Urban Liveability Index: developing a policy-relevant urban liveability composite measure and evaluating associations with transport mode choice. *International journal of health geographics*, *18*(1), 1-25.

Hills, A. (2000). Revisiting institutional resilience as a tool in crisis management. *Journal of Contingencies and Crisis Management*, *8*(2), 109-118.

Ho, W. (2008). Integrated analytic hierarchy process and its applications–A literature review. *European Journal of operational research*, *186*(1), 211-228.

Honma, S., & Hu, J. L. (2008). Total-factor energy efficiency of regions in Japan. *Energy Policy*, *36*(2), 821-833.

Howard-Grabman, L., Miltenburg, A. S., Marston, C., & Portela, A. (2017). Factors affecting effective community participation in maternal and newborn health programme planning, implementation, and quality of care interventions. *BMC pregnancy and childbirth*, *17*(1), 1-18.

Hudec, O., Reggiani, A., & Šiserová, M. (2018). Resilience capacity and vulnerability: A joint analysis with reference to Slovak urban districts. *Cities*, *73*, 24-35, doi: 10.1016/j.cities.2017.10.004.

Huynh-The, T., Hua, C. H., Tu, N. A., & Kim, D. S. (2020). Physical activity recognition with statistical-deep fusion model using multiple sensory data for smart health. *IEEE Internet of Things Journal*, *8*(3), 1533-1543.

Hwang, C. L., & Yoon, K. (1981). Methods for multiple attribute decision making. In *Multiple attribute decision making* (pp. 58-191). Springer, Berlin, Heidelberg.

IAI (2009). Global aluminium recycling - A cornerstone of sustainable development. Global Aluminium Recycling Committee (GARC). *International Aluminium Institute*, UK.

Ibrahim, M. D., & Alola, A. A. (2020). Integrated analysis of energy-economic development-environmental sustainability nexus: Case study of MENA countries. *Science of the Total Environment*, *737*.

Innovation Cities Index. (2019). Innovation Cities™ Index 2019 : Global, *Bizkaia Innovation Observatory*, Available Online: https://www.innovation-cities.com/index-2019-global-cityrankings/18842/ (accessed on 05 February, 2021).

ITU. (2019). U4SSC Key Performance Indicators for Smart Sustainable Cities, *International Trade Union*, Available Online: https://www.itu.int/en/ITU-D/RegionalPresence/CIS/Documents/Events/2019/02_Minsk/Presentations/Tr aining-S1-and-S2-Pres2-SmiciklasJohn-U4SSC_KPIs-John-Smiciklas.pdf (accessed on 24 April, 2021).

Ivanova, M., Ilieva, R., & Lu, Z. (2020). Construction of Fuzzy-Classification Expert System in Cerebral Palsy for Learning Performance Facilitation. *International Conference in Methodologies and intelligent Systems for Techhnology Enhanced Learning*, (pp. 5-14).

Jahanshahloo, G. R., Lotfi, F. H., Rezaie, V., & Khanmohammadi, M. (2011). Ranking DMUs by ideal points with interval data in DEA. *Applied Mathematical Modelling*, *35*(1), 218-229.

Jain, A., Nandakumar, K., & Ross, A. (2005). Score normalization in multimodal biometric systems. *Pattern recognition*, *38*(12), 2270-2285.

Järv, O., Tenkanen, H., Salonen, M., Ahas, R., & Toivonen, T. (2018). Dynamic cities: Location-based accessibility modelling as a function of time. *Applied geography*, *95*, 101-110.

Jonek-Kowalska, I., & Wolniak, R. (2021). Economic opportunities for creating smart cities in Poland. Does wealth matter?. *Cities*, *114*, 103222.

Jovanovic, A., Jeli´c, M., Rosen, T., Klimek, P., Macika, S., Øien, K. (2019). *The ResilienceTool" of the SmartResilience Project*, SmartResilience project, D3.7, EU-VRi: Stuttgart, Germany.

Kaal, H. (2011). A conceptual history of livability: Dutch scientists, politicians, policy makers and citizens and the quest for a livable city. *City*, *15*(5), 532-547.

Kamruzzaman, M., & Giles-Corti, B. (2019). Accessibility to Community Infrastructure and the Quality of Life. *Journal of Transport & Health*, *14*, 100745.

Kamruzzaman, M., Shatu, F., & Habib, K. N. (2020). Travel behaviour in Brisbane:

Trends, saturation, patterns and changes. *Transportation Research Part A: Policy and Practice, 140,* 231-250.

Kang, I. S., Jin, K., Wang, B., Lau, K. M., Shukla, J., Krishnamurthy, V., ... & Liu, Y. (2002). Intercomparison of the climatological variations of Asian summer monsoon precipitation simulated by 10 GCMs. *Climate Dynamics*, *19*(5), 383-395.

Kasparian, J., & Rolland, A. (2012). OECD's 'Better Life Index': can any country be well ranked?. *Journal of Applied Statistics*, *39*(10), 2223-2230.

Kerényi, Á. (2011). The better life index of the organization for economic co-operation and development. *Public Finance Quarterly, 56*(4), 518.

Keshavarz-Ghorabaee, M. (2021). A simple modification to the EDAS method for two exceptional cases. *Preprints,* 2021040111, doi: 10.20944/preprints202104.0111.v1.

Khansari, N., Darabi, H. R., Mansouri, M., & Mostashari, A. (2015). Case study of energy behavior: Systems thinking approach. *9th Annual IEEE International Systems Conference, SysCon 2015 - Proceedings*, (pp. 373-376). Vancouver, Canada.

Khansari, N., Mostashari, A., & Mansouri, M. (2014). Conceptual modeling of the impact of smart cities on household energy consumption. *Procedia Computer Science, 28,* 81-86. doi:https://doi.org/10.1016/j.procs.2014.03.011

Kılkış, Ş. (2016). Sustainable development of energy, water and environment systems index for Southeast European cities. *Journal of cleaner production*, *130*, 222-234.

Kim, M.-S., Lee, E.-B., Jung, I.H., Alleman, D. (2018). Risk assessment and mitigation model for overseas steel-plant project investment with analytic hierarchy process-fuzzy inference system. *Sustainability*, 10(12), 4780.

Koch, F., & Ahmad, S. (2018). How to measure progress towards an inclusive, safe, resilient, and sustainable city? Reflections on applying the indicators of sustainable development goal 11 in Germany and India. In *Urban transformations* (pp. 77-90). Springer, Cham.

Koopmans, T. C. (1951). Analysis of production as an efficient combination of activities. In T. C. Koopmans (Ed.), *Activity analysis of production and allocation, Cowles Commission*, 33–97. New York: Wiley.

Kourtit, K., Nijkamp, P., & Suzuki, S. (2021). Comparative urban performance assessment of safe cities through data envelopment analysis. *Regional Science Policy & Practice*, *13*(3), 591-602.

Kourtit, K. (2021). Cities and Spatial Data in the New Urban World: A Data-Analytic Exploration. In *A Broad View of Regional Science* (pp. 91-110). Springer, Singapore.

Kramers, A., Höjer, M., Lövehagen, N., & Wangel, J. (2014). Smart sustainable cities–Exploring ICT solutions for reduced energy use in cities. *Environmental modelling & software*, *56*, 52-62.

Kreffter, K., Götz, S., Lisak-Wahl, S., Nguyen, T. H., Dragano, N., & Weyers, S. (2021). Doctors as disseminators? Practicing physicians as multipliers for community-based prevention networks in a large city in western Germany. *Journal of Public Health*, 1-9.

Kreishan, F. M. (2011). Economic growth and unemployment: An empirical analysis. *Journal of Social Sciences*, *7*(2), 228-231.

Kucukvar, M., Ismaen, R., Onat, N. C., Al-Hajri, A., Al-Yafay, H., & Al-Darwish, A. (2019). Exploring the social, economic and environmental footprint of food consumption: a supply chain-linked sustainability assessment. In *2019 IEEE 6th International Conference on Industrial Engineering and Applications (ICIEA)* (pp. 733-742). IEEE.

Kucukvar, M., Cansev, B., Egilmez, G., Onat, N. C., & Samadi, H. (2016). Energy-climate-manufacturing nexus: New insights from the regional and global supply chains of manufacturing industries. *Applied energy*, *184,* 889-904.

Kucukvar, M., Onat, N. C., & Haider, M. A. (2018). Material dependence of national energy development plans: The case for Turkey and United Kingdom. *Journal of Cleaner Production*, *200*, 490-500.

Kucukvar, M., Kutty, A. A., Al-Hamrani, A., Kim, D., Nofal, N., Onat, N. C., ... & Al-Nahhal, W. (2021). How circular design can contribute to social sustainability and legacy of the FIFA World Cup Qatar 2022™? The case of innovative shipping container stadium. *Environmental Impact Assessment Review*, *91*, 106665.

Kularatne, T., Wilson, C., Månsson, J., Hoang, V., & Lee, B. (2019). Do environmentally sustainable practices make hotels more efficient? A study of major hotels in Sri Lanka. *Tourism Management*, *71*, 213-225.

Kulkki, S. (2017). Cities for New Growth and Socio-Economic Dynamism?: The Case of Smart Cities and RDI-Driven Participative Democracy and Governance. *International Journal of Public Administration in the Digital Age (IJPADA)*, *4*(4), 1-19.

Kutlu Gündoğdu, F., & Kahraman, C. (2019). Spherical fuzzy analytic hierarchy process (AHP) and its application to industrial robot selection. In *International Conference on Intelligent and Fuzzy Systems*, 988-996, Springer, Cham.

Kutlu Gündoğdu, F., & Kahraman, C. (2020). A novel spherical fuzzy analytic hierarchy process and its renewable energy application. *Soft Computing*, *24*(6), 4607-4621. https://doi.org/10.1007/ s005 00-019-04222-w

Kutty, A. A., & Abdella, G. M. (2020). Tools and techniques for food security and sustainability related assessments: a focus on the data and food waste management system. In *Proceedings of the 5th NA Conference on Industrial Engineering and Operations Management* (pp. 10-14).

Kutty, A. A., Abdella, G. M., & Kucukvar, M. (2020a). Ridge Penalization-based weighting approach for Eco-Efficiency assessment: The case in the food industry in the United States. In *IOP conference series: Materials science and engineering* (Vol. 947, No. 1, p. 012003). IOP Publishing.

Kutty, A. A., Abdella, G. M., Kucukvar, M., Onat, N. C., & Bulu, M. (2020). A system thinking approach for harmonizing smart and sustainable city initiatives with United Nations sustainable development goals. *Sustainable Development*, *28*(5), 1347-1365.

Kutty, A. A., Kucukvar, M., Abdella, G. M., Bulak, M. E., & Onat, N. C. (2022). Sustainability Performance of European Smart Cities: A Novel DEA Approach with Double Frontiers. *Sustainable Cities and Society*, 103777.

Kutty, A. A., Yetiskin, Z., Abraham, M. M., Nooh, M. A., Kucukvar, M., & Abdella, G. M. (2020b). An empirical assessment on the transportation sustainability indicators and their impact on economic productivity. In *Proceedings of the 5th North American International Conference on Industrial Engineering and Operations Management, Detroit, Michigan, United States*. Michigan, USA: IEOM.

Labaka, L., Maraña, P., Giménez, R., & Hernantes, J. (2019). Defining the roadmap towards city resilience. *Technological Forecasting and Social Change*, *146*, 281-296.

Lacinák, M., & Ristvej, J. (2017). Smart city, safety, and security. *Procedia Engineering*, *192*, 522-527.

Lagravinese, R. (2015). Economic crisis and rising gaps North–South: evidence from the Italian regions. *Cambridge Journal of Regions, Economy and Society*, *8*(2), 331-342.

Lai, E., Lundie, S., Ashbolt, N.J. (2008). Review of multi-criteria decision aid for integrated sustainability assessment of urban water systems. *Urban Water J*, *5*(4):315–327.

Latacz-Lohmann, U., & Foster, C. (1997). From “niche” to “mainstream”-strategies for marketing organic food in Germany and the UK. *British food journal*.

Lee, L. H., Braud, T., Hosio, S., & Hui, P. (2021). Towards Augmented Reality Driven Human-City Interaction: Current Research on Mobile Headsets and Future Challenges. *ACM Computing Surveys (CSUR)*, *54*(8), 1-38.

Ley, D. (1980). Liberal ideology and the post-industrial city. *Annals of the Association of American geographers*, *70*(2), 238-258.

Li, Y. (1996). Impact of population size on market demand under a market economy. *Chinese journal of population science*, *8*(2), 163-168.

Li, Q., Wu, Z.Y., & Rahman, A. (2019). Evolutionary deep learning with extended Kalman filter for effective prediction modelling and efficient data assimilation. *Journal of Computing in Civil Engineering*, 33(3): 04019014.

Li, X., Xu, X., & Chen, H. (2005). Temporal and spatial changes of urban efficiency in the 1990s. *ACTA GEOGRAPHICA SINICA-CHINESE EDITION-*, *60*(4), 615.

Liang, L., Li, Y., & Li, S. (2009). Increasing the discriminatory power of DEA in the presence of the undesirable outputs and large dimensionality of data sets with PCA. *Expert Systems with Applications*, *36*(3), 5895-5899.

Liao, Y., & Lee, J.-B. (2004). A fuzzy-expert system for classifying power quality disturbances. *International Journal of Electrical Power & Energy Systems, 26*(3), 199-205. doi:https://doi.org/10.1016/j.ijepes.2003.10.012

Lin, C .J., Belis, T.T., Caesaron, D., Jiang, B.C., Kuo, T.C. (2020). Development of sustainability indicators for employee-activity based production process using fuzzy Delphi method. *Sustainability (Switzerland)*, 12(16), 6378, https://doi.org/10.3390/su12166378.

Lind, D. (2012). Information and communications technologies creating livable, equitable, sustainable cities. In *State of the World 2012* (pp. 66-76). Island Press/Center for Resource Economics.

Liu, W. B., Meng, W., Li, X. X., & Zhang, D. Q. (2010). DEA models with undesirable inputs and outputs. *Annals of Operations Research*, *173*(1), 177-194.

Liu, Q., Ullah, H., Wan, W., Peng, Z., Hou, L., Qu, T., & Ali Haidery, S. (2020). Analysis of green spaces by utilizing big data to support smart cities and environment: A case study about the city center of shanghai. *ISPRS International Journal of Geo-Information*, *9*(6), 360.

Lo Storto, C. (2016). Ecological efficiency based ranking of cities: A combined DEA cross-efficiency and Shannon's entropy method. *Sustainability*, *8*(2), 124.

Lourenço, V., Mann, P., Guimaraes, A., Paes, A., & de Oliveira, D. (2018, July). Towards safer (smart) cities: Discovering urban crime patterns using logic-based relational machine learning. In *2018 International Joint Conference on Neural Networks (IJCNN)* (pp. 1-8). IEEE.

Lovell, C. K., Grosskopf, S., Ley, E., Pastor, J. T., Prior, D., & Eeckaut, P. V. (1994). Linear programming approaches to the measurement and analysis of productive efficiency. *Top*, *2*(2), 175-248.

Lozano, S., Gutiérrez, E., & Moreno, P. (2013). Network DEA approach to airports performance assessment considering undesirable outputs. *Applied Mathematical Modelling*, *37*(4), 1665-1676.

Maclaren, V. W. (1996). Urban sustainability reporting. *Journal of the American planning association*, *62*(2), 184-202.

Maglaras, L. A., Al-Bayatti, A. H., He, Y., Wagner, I., & Janicke, H. (2016). Social internet of vehicles for smart cities. *Journal of Sensor and Actuator Networks*, *5*(1), 3.

Majumdar, S., Subhani, M. M., Roullier, B., Anjum, A., & Zhu, R. (2021). Congestion prediction for smart sustainable cities using IoT and machine learning approaches. *Sustainable Cities and Societies, 64*. doi:10.1016/j.scs.2020.102500

Mamlook, R., Al-Jayyousi, O., Alabyooki, S., & Attallah, S. A. A. (2019, April). Smart City and Technology Transfer: Towards Sustainable Infrastructure in Bahrain. In *The International Research & Innovation Forum* (pp. 255-268). Springer, Cham.

Manyena, B., O'Brien, G., O'Keefe, P., & Rose, J. (2011). Disaster resilience: a bounce back or bounce forward ability?. *Local Environment: The International Journal of Justice and Sustainability*, *16*(5), 417-424.

Mardani, A., Jusoh, A., Nor, K., Khalifah, Z., Zakwan, N., & Valipour, A. (2015). Multiple criteria decision-making techniques and their applications–a review of the literature from 2000 to 2014. *Economic research-Ekonomska* *istraživanja*, *28*(1), 516-571.

Margarita, A., Isabel, F., Eleni, K., & Meia, W. (2020). Co-creation Techniques and Tools for Sustainable and Inclusive Planning at Neighbourhood Level. Experience from Four European Research and Innovation Projects. In *Conference on Sustainable Urban Mobility* (pp. 562-572). Springer, Cham.

Marinakis, V., Doukas, H., Tsapelas, J., Mouzakitis, S., Sicilia, Á., Madrazo, L., & Sgouridis, S. (2018). From big data to smart energy services: An application for intelligent energy management. *Future Generation Computer Systems*.

Marsal-Llacuna, M.-L., Colomer-Llinàs, J., & Meléndez-Frigola, J. (2015). Lessons in urban monitoring taken from sustainable and livable cities to better address the Smart Cities initiative. *Technological Forecasting and Social Change, Vol.90*, 611-622.

Martin, R. (2012). Regional economic resilience, hysteresis, and recessionary shocks. *Journal of economic geography*, *12*(1), 1-32.

Marzouk, M., & Othman, A. (2020). Planning utility infrastructure requirements for smart cities using the integration between BIM and GIS. *Sustainable Cities and Society*, 102120.

Masoomi, H., & van de Lindt, J. W. (2019). Community-resilience-based design of the built environment. *ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part A: Civil Engineering*, *5*(1), 04018044.

Mata, A. M. (2018). Is smart city an utopia? Lessons learned and final reflections. *Smart and Sustainable Cities for Innovative Urban Planning in Mexico; Editorial Academica Espanola: Beau Bassin, Mauritius*, 198-207.

Mayaud, J. R., Tran, M., & Nuttall, R. (2019). An urban data framework for assessing equity in cities: Comparing accessibility to healthcare facilities in

Cascadia. *Computers, Environment and Urban Systems*, *78*, 101401

Mazziotta, M., & Pareto, A. (2013). Methods for constructing composite indices: One for all or all for one. *Rivista Italiana di Economia Demografia e Statistica*, *67*(2), 67-80.

McKinsey (2018). *Smart cities: Digital solutions for a more livable future*. McKinsey Global Institute. Available online at: https://www.mckinsey.com/business-functions/operations/our-insights/smart-cities-digital-solutions-for-a-more-livable-future (accessed on: February 4, 2022)

Mdari, Y. E., Daoud, M. A., Namir, A., & Hakdaoui, M. (2022). Casablanca Smart City Project: Urbanization, Urban Growth, and Sprawl Challenges Using Remote Sensing and Spatial Analysis. In *Proceedings of Sixth International Congress on Information and Communication Technology* (pp. 209-217). Springer, Singapore

Mega, V. (1996). Our city, our future: towards sustainable development in European cities. *Environment and Urbanization*, *8*(1), 133-154.

Mekonnen, K., Amede, T., Duncan, A. J., & Gebrekirstos, A. (2013). Sustainable agricultural intensification and its role on the climate resilient green economy initiative in Ethiopia: Report of the 3rd national platform meeting on land and water management in Ethiopia, Addis Ababa, 23− 24 July 2012.

Mele, C. (2021). Smart Cities and Sustainability: A Complex and Strategic Issue–The Case of Torino Smart City. In *Handbook of Research on Developing Smart Cities Based on Digital Twins* (pp. 1-15). IGI Global.

Menconi, M. E., Sipone, A., & Grohmann, D. (2021). Complex Systems Thinking Approach to Urban Greenery to Provide Community-Tailored Solutions and Enhance the Provision of Cultural Ecosystem Services. *Sustainability*, *13*(21), 11787.

Meyer, G., Adomavicius, G., Johnson, P. E., Elidrisi, M., Rush, W. A., Sperl-Hillen, J. M., & O'Connor, P. J. (2014). A Machine Learning Approach to Improving Dynamic Decision Making. *Information Systems Research, 25*(2). doi:10.1287/isre.2014.0513

Milošević, M., Milošević, D., & Stanojević, A. (2020, July). Managing Cultural Built Heritage in Smart Cities Using Fuzzy and Interval Multi-criteria Decision Making. In *International Conference on Intelligent and Fuzzy Systems* (pp. 599-607). Springer, Cham.

Minsky, M. (2019). A Framework For Representing Knowledge. In D. Metzing (Ed.), *Frame Conceptions and Text Understanding* (pp. 1-25). Berlin, Boston: De Gruyter. https://doi.org/10.1515/9783110858778-003

Mizobuchi, H. (2014). Measuring world better life frontier: a composite indicator for OECD better life index. *Social Indicators Research*, *118*(3), 987-1007.

Mizuki, F., Mikawa, K., & Kurisu, H. (2012). Intelligent water system for smart cities. *Hitachi Review*, *61*(3), 147.

Molden, D., Murray-Rust, H., Sakthivadivel, R., & Makin, I. (2003). A water-productivity framework for understanding and action. *Water productivity in agriculture: Limits and opportunities for improvement*, (1).

Molinaro, R., K Najjar, M., WA Hammad, A., Haddad, A., & Vazquez, E. (2020). Urban Development Index (UDI): A Comparison between the City of Rio de Janeiro and Four Other Global Cities. *Sustainability*, *12*(3), 823.

Moore, Q. L., Kulesza, C., Kimbro, R., Flores, D., & Jackson, F. (2020). The role of prosocial behavior in promoting physical activity, as an indicator of resilience, in a low-income neighborhood. *Behavioral Medicine*, *46*(3-4), 353-365.

Moorhouse, A., & Caltabiano, M. L. (2007). Resilience and unemployment: Exploring risk and protective influences for the outcome variables of depression and assertive job searching. *Journal of Employment Counseling*, *44*(3), 115-125.

Mora, L., Bolici, R., & Deakin, M. (2017). The First Two Decades of Smart-City Research: A Bibliometric Analysis. *Journal of Urban Technology*, *24*(1), 3-27. doi:10.1080/10630732.2017.1285123

Mora, L., Deakin, M., Reid, A., & Angelidou, M. (2019). How to overcome the dichotomous nature of smart city research: Proposed methodology and results of a pilot study. *Journal of Urban Technology*, *26*(2), 89-128.

Morais, P., & Camanho, A. S. (2011). Evaluation of performance of European cities with the aim to promote quality of life improvements. *Omega*, *39*(4), 398-409.

Motta, M., de Castro Neto, M., & Sarmento, P. (2021). A mixed approach for urban flood prediction using Machine Learning and GIS. *International Journal of Disaster Risk Reduction*, *56*, 102154.

Mouratidis, K. (2021). Urban planning and quality of life: A review of pathways linking the built environment to subjective well-being. *Cities*, *115*, 103229.

Mourre, G. (2009). *What explains the differences in income and labour utilization and drives labour and economic growth in Europe? A GDP accounting perspective* (No. 354). Directorate General Economic and Financial Affairs (DG ECFIN), European Commission.

Mozaffari, M. R., Ostovan, S., & Wanke, P. F. (2020). A Hybrid Genetic Algorithm-Ratio DEA Approach for Assessing Sustainable Efficiency in Two-Echelon Supply Chains. *Sustainability*, *12*(19), 1-17.

MSA (2015). Aluminium recyclability and recycling - Towards sustainable cities.

Architecture and Tectonics Research Group & International Aluminium Institute.

Mubangizi, B. C. (2021). Rural-Urban Migration and Smart Cities: Implications for Service Delivery in South Africa. *African Renaissance (1744-2532), 18*(1).

Mukhlis, I., Suwanan, A. F., Hidayati, B., Roudhotus, S., & Rizaludin, M. S. (2021). Can the Implementation of Smart City Promote Inclusive Development of a Local Economy?. In *XV International Conference" Russian Regions in the Focus of Changes"(ICRRFC 2020)* (pp. 73-81). Atlantis Press

Murray, P. (2018). *40 Brilliant Examples of Smart City Projects Which Uses Open Data.* Retrieved from https://lavaprotocols.com/2018/06/28/40-smart-city-projects-open- data/

Nagpal, A. (2018). Sustainable Waste Water Management for Smart Cities. *International Journal of Environmental Planning and Development*, *3*(1), 1-11.

Nardo, M., Saisana, M., Saltelli, A., & Tarantola, S., Giovannini, E., & Hoffman, A. (2008). *Handbook on constructing composite indicators. Methodology and user guide*, Technical report, OECD publishing , Paris.

Nasution, N., Bhawika, G. W., Wanto, A., Ginantra, N. L. W. S. R., & Afriliansyah, T. (2020). Smart City Recommendations Using the TOPSIS Method. In *IOP Conference Series: Materials Science and Engineering* (Vol. 846, No. 1, p. 012028). IOP Publishing.

Newman, P. W. (1999). Sustainability and cities: extending the metabolism model. *Landscape and urban planning*, *44*(4), 219-226.

NIBIO (2018). The environmental impacts of wood compared to other building materials. *Norsk Insitutt for Biookonomi*. By order of the Norwegian Ministry for Agriculture and Food. NIBIO Rapport. 4(56)

Nikolaev, B. (2014). Economic freedom and quality of life: Evidence from the OECD's Your Better Life Index. *Journal of Private Enterprise*, *29*(3), 61-96.

Nitschke, J. P., Forbes, P. A., Ali, N., Cutler, J., Apps, M. A., Lockwood, P. L., & Lamm, C. (2021). Resilience during uncertainty? Greater social connectedness during COVID-19 lockdown is associated with reduced distress and fatigue. *British Journal of Health Psychology*, *26*(2), 553-569.

Nota, L., Soresi, S., & Zimmerman, B. J. (2004). Self-regulation and academic achievement and resilience: A longitudinal study. *International journal of educational research*, *41*(3), 198-215.

Nutkiewicz, A., Yang, Z., Jain, R.K. (2017). Data-driven Urban Energy Simulation (DUE-S): Integrating machine learning into an urban building energy simulation workflow. *Energy Procedia*, 142, 2114-2119.

Oberascher, M., Dastgir, A., Li, J., Hesarkazzazi, S., Hajibabaei, M., Rauch, W., & Sitzenfrei, R. (2021). Revealing the Challenges of Smart Rainwater Harvesting for Integrated and Digital Resilience of Urban Water Infrastructure. *Water*, *13*(14), 1902.

Odendaal, N. (2003). Information and communication technology and local governance: understanding the difference between cities in developed and emerging economies. *Computers, Environment and Urban Systems, 27*(6), 585-607. doi:https://doi.org/10.1016/S0198-9715(03)00016-4

Ogasawara, E., Martinez, L. C., De Oliveira, D., Zimbrão, G., Pappa, G. L., & Mattoso, M. (2010, July). Adaptive normalization: A novel data normalization approach for non-stationary time series. In *The 2010 International Joint Conference on Neural Networks (IJCNN)* (pp. 1-8). IEEE.

Oh, J., Yang, J., & Lee, S. (2012). Managing uncertainty to improve decision-making in NPD portfolio management with a fuzzy expert system. *Expert Systems with Applications, 39*(10), 9868-9885. doi:https://doi.org/10.1016/j.eswa.2012.02.164

Onag, G. (2018). *PPPs essential to a successful smart city.* Online Source. Retrieved from https://www.cw.com.hk/smart-city/ppps-essential-to-a-successful-smart-city

Onat, N. C., Kucukvar, M., Halog, A., & Cloutier, S. (2017). Systems thinking for life cycle sustainability assessment: A review of recent developments, applications, and future perspectives. *Sustainability*, *9*(5), 706.

Opricovic, S. (1998). Multicriteria Optimization of Civil Engineering Systems. PhD Thesis, Faculty of Civil Engineering, Belgrade, 302 p.

Osobajo, O. A., Oke, A., Omotayo, T., & Obi, L. I. (2020). A systematic review of circular economy research in the construction industry. *Smart and Sustainable Built Environment*.

O'Sullivan, F. (2020). *Is Vienna Really All That Livable? Depends on Where You Look*, Bloomberg CityLab, Available online [Report]: https://www.bloomberg.com/news/articles/2020-03-05/the-problem-with-vienna-s-lofty-livability-ranking

Ozkaya, G., & Erdin, C. (2020). Evaluation of smart and sustainable cities through a hybrid MCDM approach based on ANP and TOPSIS technique. *Heliyon*, *6*(10), e05052.

Pan, L., Zhang, L., Qin, S., Yan, H., Peng, R., & Li, F. (2021). Study on an Artificial Society of Urban Safety Livability Change. *ISPRS International Journal of Geo-Information*, *10*(2), 70.

Pan, W.-T., Zhuang, M.-E., Zhou, Y.-Y., & Yang, J.-J. (2021). Research on sustainable development and efficiency of China's E-Agriculture based on a data envelopment analysis-Malmquist model. *Technological Forecasting and Social Change, 162*. doi:https://doi.org/10.1016/j.techfore.2020. 120298

Pandey, R. U., Mitra, T., Wadwekar, M., Nigam, J., & Trivedi, K. (2021). Green Infrastructure as a Tool for Improving Livability of Area Based Development Projects Under Smart City Mission. In *Geospatial Technology and Smart Cities* (pp. 447-468). Springer, Cham.

Papadopoulou, C. A., & Hatzichristos, T. (2020). Allocation of Residential Areas in Smart Insular Communities: The Case of Mykonos, Greece. *International Journal of E-Planning Research (IJEPR)*, *9*(4), 40-60.

Papapostolou, A., Karakosta, C., & Doukas, H. (2017). Analysis of policy scenarios for achieving renewable energy sources targets: A fuzzy TOPSIS approach. *Energy & Environment*, *28*(1-2), 88-109.

Paracchini, M. L., Pacini, C., Calvo, S., & Vogt, J. (2008). Weighting and aggregation of indicators for sustainability impact assessment in the SENSOR context. In *Sustainability impact assessment of land use changes* (pp. 349-372). Springer, Berlin, Heidelberg.

Paramita, S. A., Yamazaki, C., Hilfi, L., Sunjaya, D. K., & Koyama, H. (2021). Social cohesion and quality of life in Bandung: A cross sectional study. *Plos one*, *16*(10), e0258472

Parker, H., & Ameen, K. (2018). The role of resilience capabilities in shaping how firms respond to disruptions. *Journal of Business Research, 88,* 535-541.

Paskaleva, K. A. (2009). Enabling the smart city: The progress of city e-governance in Europe. *International Journal of Innovation and regional* *development*, *1*(4), 405-422.

Pastor, J. T. (1996). Translation invariance in data envelopment analysis: A generalization. *Annals of Operations Research*, *66*(2), 91-102.

Patel, R., & Nosal, L. (2016). Defining the resilient city. *New York: United Nations University Centre for Policy Research.* Available online [Report]: https://cpr.unu.edu/research/projects/defining-the-resilient-city.html

Paul, A., & Sen, J. (2020). A critical review of liveability approaches and their dimensions. *Geoforum*, 117, 90-92.

Petrović, M., Bojković, N., Anić, I., Stamenković, M., & Tarle, S. P. (2014). An ELECTRE-based decision aid tool for stepwise benchmarking: An application over EU Digital Agenda targets. *Decision Support Systems*, *59*, 230-241.

Phillips, G., Bottomley, C., Schmidt, E., Tobi, P., Lais, S., Yu, G., ... & Renton, A. (2014). Well London Phase-1: results among adults of a cluster-randomised trial of a community engagement approach to improving health behaviours and mental well-being in deprived inner-city neighbourhoods. *J Epidemiol Community Health*, *68*(7), 606-614.

Pichler, M. (2017). *Smart City Vienna: System Dynamics Modelling as a Tool for Understanding Feedbacks and Supporting Smart City Strategies.* Dissertation Thesis, Universidade Nove de Lisboa, Faculdade De Ciencias E Technologia.

Pira, M. (2021). A novel taxonomy of smart sustainable city indicators. *Humanities and Social Sciences Communications*, *8*(1), 1-10.

Portugali, J. (2016). What Makes Cities Complex? In *Complexity, Cognition, Urban Planning and Design* (pp. 3-19). Springer Proceedings in Complexity book series (SPCOM).

Pretorius, L., Pretorius, J.-H. C., & Benade, S. (2014). A system dynamics approach to technology interaction: From asymptotic to cyclic behavior. *Technological Forecasting and Social Change*. doi:10.1016/j.techfore.2014.11.001

Psycharis, Y., Tsiapa, M., & Tselios, V. (2020). Exports and regional resilience: Evidence from Greece. In *Handbook on regional economic resilience*. Edward Elgar Publishing.

Punt, E. P., Geertman, S. C., Afrooz, A. E., Witte, P. A., & Pettit, C. J. (2020). Life is a scene and we are the actors: Assessing the usefulness of planning support theatres for smart city planning. *Computers, Environment and Urban Systems*, *82*, 101485.

Quackenbush, J. (2002). Microarray data normalization and transformation. *Nature genetics*, *32*(4), 496-501.

Radwan, N. M., Senousy, M. B., & Alaa El Din, M. R. (2016). *Neutrosophic AHP multi criteria decision making method applied on the selection of learning management system*. Infinite Study.

Rakhshan K., Morel J-C., Alaka H. & Rabia Charef R. (2020). Components reuse in the building sector – A systematic review. Waste Management & Research. *International Solid Waste Association*. 38(4), 347-370

Ramboll. (2020). *Creative liveable cities with people: How technology can improve urban life*, (Report). Nordic edge white paper. https://ramboll.com/-/media/3737fe033bf9402fbb06fe7b37cc3682.pdf

Ramirez Lopez, L. J., & Grijalba Castro, A. I. (2021). Sustainability and resilience in smart city planning: A Review. *Sustainability*, *13*(1), 181.

Redmond, A. M., & Alshawi, M. (2018). Applying System Science and System Thinking Techniques to BIM Management. *10th International Conference on Developments in eSystems Engineering, DeSE*, (pp. 3-8). Paris, France.

Reggiani, A., Nijkamp, P., & Lanzi, D. (2015). Transport resilience and vulnerability: The role of connectivity. *Transportation research part A: policy and practice*, *81*, 4-15.

Renschler, C. S., Frazier, A. E., Arendt, L. A., Cimellaro, G. P., Reinhorn, A. M., & Bruneau, M. (2010). *A framework for defining and measuring resilience at the community scale: The PEOPLES resilience framework* (pp. 10-0006). Buffalo: MCEER.

Repette, P., Sabatini-Marques, J., Yigitcanlar, T., Sell, D., & Costa, E. (2021). The Evolution of City-as-a-Platform: Smart Urban Development Governance with Collective Knowledge-Based Platform Urbanism. *Land*, *10*(1), 33.

Ringel, M. (2021). Smart City Design Differences: Insights from Decision-Makers in Germany and the Middle East/North-Africa Region. *Sustainability*, *13*(4), 2143.

Rodin, J. (2014). *The resilience dividend: Being strong in a world where things go wrong*. New York, NY: Public Affairs.

Rodrigues, M., & Franco, M. (2019). Measuring the urban sustainable development in cities through a Composite Index: The case of Portugal. *Sustainable Development*. doi:https://doi.org/10.1002/sd.2005

Rosati, U., & Conti, S. (2016). What is a smart city project? An urban model or a corporate business plan?. *Procedia-Social and Behavioral Sciences*, *223*, 968-973.

Rouf, K. A., Abdella, G. M., Al-Khalifa, K. N., & Alhajyaseen, W. (2018). Ridge penalization-based generalized linear model (GzLM) for predicting risky-driving index. In *The Proceedings of the International Conference on Industrial Engineering and Operations Management, Washington DC, USA,* *September 27–29, 2018* (pp. 1462-1473).

Roy, B. (1996). *Multicriteria methodology for decision aiding* (Vol. 12). Springer Science & Business Media. https://doi.org/10.1007/978-1-4757-2500-1

Roy, B. (2005). Paradigms and challenges. In *Multiple criteria decision analysis: state of the art surveys* (pp. 3-24). Springer, New York, NY.

Ruiz, F., Cabello, J. M., & Pérez-Gladish, B. (2018). Building Ease-of-Doing-Business synthetic indicators using a double reference point approach. *Technological Forecasting and Social Change*, *131*, 130-140.

Ryff, C. D. (1989). Happiness is everything, or is it? Explorations on the meaning of psychological well-being. *Journal of personality and social psychology*, *57*(6), 1069.

Saaty, T. L. (1980). *The Analytic Hierarchy Process: Planning, Priority Setting, Resource Allocation*. McGraw-Hill International Book Company.

Saaty, T. L. (1996). *Decision Making with Dependence and Feedback: The Analytic Network Process : the Organization and Prioritization of Complexity*. RWS Publications.

Saisana, M., Tarantola, S. (2002). *State-of-the-art report on current methodologies and practices for composite indicator development*. Technical report, Joint Research Centre, European Commission, Ispra, Italy.

Sanchez, A. X., Van der Heijden, J., & Osmond, P. (2018). The city politics of an urban age: urban resilience conceptualisations and policies. *Palgrave Communications*, *4*(1), 1-12.

Santos,J., Machi, C. T., Morillas, S., & Cerezo, V. (2020): A fuzzy logic expert system for selecting optimal and sustainable life cycle maintenance and rehabilitation strategies for road pavements. *International Journal of*

Pavement Engineering, doi:10.1080/10298436.2020. 1751161

Saranya, C., & Manikandan, G. (2013). A study on normalization techniques for privacy preserving data mining. *International Journal of Engineering and Technology (IJET), 5*(3), 2701-2704.

Sarkis, J. (2007). Preparing your data for DEA. In *Modeling data irregularities and structural complexities in data envelopment analysis* (pp. 305-320). Springer, Boston, MA.

Säumel, I., Reddy, S. E., & Wachtel, T. (2019). Edible City solutions—One step further to foster social resilience through enhanced socio-cultural ecosystem services in cities. *Sustainability*, *11*(4), 972.

SCEWC. (2018). *World Smart City Awards: 2018.* Fira Barcelona. Retrieved from http://www.smartcityexpo.com/en/awards

Schaffers, H., Komninos, N., Tsarchopoulos, P., Pallot, M., Trousse, B., Posio, E., et al. (2012). *Landscape and Roadmap of Future Internet and Smart Cities*. Technical Report, https://hal.inria.fr/hal-00769715

Scheel, H. (2001). Undesirable outputs in efficiency valuations. *European journal of operational research*, *132*(2), 400-410.

Sehovac, L., Nesen, C., Grolinger, K. (2019). Forecasting building energy consumption with deep learning: A sequence to sequence approach. *Proceedings - 2019 IEEE International Congress on Internet of Things, ICIOT 2019, 8815666, (pp. 108-116).* Milan, Italy:151496.

Seiford, L. M., & Zhu, J. (2002). Modeling undesirable factors in efficiency evaluation. *European journal of operational research*, *142*(1), 16-20.

Shamsuzzoha, A., Niemi, J., Piya, S., & Rutledge, K. (2021). Smart city for sustainable environment: A comparison of participatory strategies from

Helsinki, Singapore, and London. *Cities, 114*, 103194.

Sharif, R. A., & Pokharel, S. (2021). Smart City Perspectives in the Context of Qatar. In *Sustainable Smart Cities and Territories International Conference* (pp. 103-113). Springer, Cham.

Sharifi, A., & Yamagata, Y. (2015). A conceptual framework for assessment of urban energy resilience. *Energy Procedia, 75*, 2904-2909

Sharp, J. A., Meng, W., & Liu, W. (2007). A modified slacks-based measure model for data envelopment analysis with 'natural' negative outputs and inputs. *Journal of the Operational Research Society, 58*(12), 1672-1677.

Shehab, M. J., Kassem, I., Kutty, A. A., Kucukvar, M., Onat, N., & Khattab, T. (2021). 5G Networks Towards Smart and Sustainable Cities: A Review of Recent Developments, Applications and Future Perspectives. *IEEE Access*.

Shields, K., Langer, H., Watson, J., & Stelzner, K. (2009). *European Green City Index. Assessing the environmental impact of Europe's major cities*, Siemens AG: München, Germany.

Shier, D. E. (2004). Well log normalization: methods and guidelines. *Petrophysics-The SPWLA Journal of Formation Evaluation and Reservoir Description*, *45*(03).

Shmelev, S. E., & Shmeleva, I. A. (2018). Global urban sustainability assessment: A multidimensional approach. *Sustainable Development*, *26*(6), 904-920.

Shmelev, S. E., & Shmeleva, I. A. (2019). Multidimensional sustainability benchmarking for smart megacities. *Cities, 92*, 134-163.

Sibille, A. D. C. T., Cloquell-Ballester, V. A., Cloquell-Ballester, V. A., & Darton, R. (2009). Development and validation of a multicriteria indicator for the assessment of objective aesthetic impact of wind farms. *Renewable and*

Sustainable Energy Reviews, *13*(1), 40-66.

Singh, P. K., & Ohri, A. (2021). Sensitivity Analysis of the Smart City Environmental Sustainability Index (SCESI). *Nature Environment & Pollution Technology*, *20*(2).

Soeiro, D. (2021). Smart cities and innovative governance systems: a reflection on urban living labs and action research. *Fennia–International Journal of the Geographical Society of Finland*.

Solaimani, S., & Sedighi, M. (2020). Toward a holistic view on lean sustainable construction: a literature review. *Journal of Cleaner Production*, *248*, 119213.

Spanos, I., Kucukvar, M., Bell, T. C., Elnimah, A., Hamdan, H., Al Meer, B., ... & AlKhereibi, A. H. (2021). How FIFA World Cup 2022™ can meet the carbon neutral commitments and the United Nations 2030 Agenda for Sustainable Development?: Reflections from the tree nursery project in Qatar. *Sustainable Development*.

Srinivasan. (2017). *Nine examples of low investment smart city innovations with maximum output.* Smart City Hub (Online Source). Retrieved from https://smartcityhub.com /technology-innnovation/nine-examples-smart-city-innovations minimal-costs/

Stead, D. (2003). Is urban living becoming more attractive?. *Local Environment*, *8*(5), 559-565.

Sueyoshi, T. (1998). Privatization of Nippon Telegraph and Telephone: Was it a good policy decision?. *European Journal of Operational Research*, *107*(1), 45-61.

Sun, L., Chen, J., Li, Q., & Huang, D. (2020). Dramatic uneven urbanization of large cities throughout the world in recent decades. *Nature communications*, *11*(1), 1-9.

Sun, Y., Garrido-Baserba, M., Molinos-Senante, M., Donikian, N. A., Poch, M., & Rosso, D. (2020). A composite indicator approach to assess the sustainability and resilience of wastewater management alternatives. *Science of The Total Environment*, *725*, 138286.

Sutton, C. D. (2005). Classification and regression trees, bagging, and boosting. *Handbook of statistics*, *24*, 303-329, doi: 10.1016/S0169-7161(04)24011-1.

Sutriadi, R., & Noviansyah, A. (2021). City thematic approach to achieve liveable city: case study of Bandung City. In *IOP Conference Series: Earth and Environmental Science* (Vol. 778, No. 1, p. 012020). IOP Publishing.

Svetnik, V., Liaw, A., Tong, C., Culberson, J. C., Sheridan, R. P., & Feuston, B. P. (2003). Random forest: a classification and regression tool for compound classification and QSAR modelling. *Journal of chemical information and computer sciences*, *43*(6), 1947-1958, doi:10.1021/ ci034160g

Szép, T. S., Szendi, D., Nagy, Z., & Tóth, G. (2020). A gazdasági reziliencia és a városhálózaton belüli centralitás közötti összefüggések vizsgálata. *Területi Statisztika*, *60*(3), 352-369.

Tang, M., Hong, J., Wang, X., & He, R. (2020). Sustainability accounting of neighborhood metabolism and its applications for urban renewal based on emergy analysis and SBM-DEA. *Journal of Environmental Management*, *275*. doi:https://doi.org/10.1016/j.jenvman. 2020.111177

Tang, J., Tang, L., Li, Y., & Hu, Z. (2020a). Measuring eco-efficiency and its convergence: empirical analysis from China. *Energy Efficiency*, *13*(6), 1075-1087.

Tapsuwan, S., Mathot, C., Walker, I., & Barnett, G. (2018). Preferences for sustainable, liveable, and resilient neighbourhoods and homes: A case of Canberra, Australia. *Sustainable Cities and Society*, *37*, 133-145.

Tavassoli, M., Ketabi, S., & Ghandehari, M. (2020). Developing a network DEA model for sustainability analysis of Iran's electricity distribution network. *International Journal of Electrical Power & Energy Systems, 122*, 106-187. doi:https://doi.org/10.1016/j.ijepes. 2020.106187

Tayala, A., Solanki, A., & Singh, S. P. (2020). Integrated frame work for identifying sustainable manufacturing layouts based on big data, machine learning, meta-heuristic and data envelopment analysis. *Sustainable Cities and Society, 62*. doi:https://doi.org/10.1016/ j.scs.2020.102383

The China Urban Sustainability Index 2016. (2016). Available online: http://www.urbanchinainitiative.org /en/resources/report. html (accessed on 5 February, 2021).

Toch, E., & Feder, E. (2016). International Case Studies of Smart Cities: Tel Aviv, Israel. *Inter-American Development Bank,* doi: 10.18235/0000416.

Tone, K. (2001). A slacks-based measure of efficiency in data envelopment analysis. *European journal of operational research*, *130*(3), 498-509.

Toppeta, D. (2010). The smart city vision: how innovation and ICT can build smart,"livable", sustainable cities. *The innovation knowledge foundation*, *5*, 1-9. Available online at: http://www.think innovation.org/file/research /23/en/Toppeta_Report_005_ 2010.pdf

Torra, V. (2010). Hesitant fuzzy sets. *International journal of intelligent systems*, *25*(6), 529-539. doi: https://doi.org/10.1002/int.20418

Tsoukatou, V. (2019). Examination of the Correlation between Working Time Reduction and Employment. *arXiv preprint arXiv:1912.01605*.

Turban, E. (1993). *Decision Support and Expert Systems: Management Support Systems.* Prentice Hall PTR, United States.

Tzioutziou, A., & Xenidis, Y. (2021). A study on the integration of resilience and smart city concepts in urban systems. *Infrastructures, 6*(2), 24.

Uitermark, J. (2009). An in memoriam for the just city of Amsterdam. *City*, *13*(2-3), 347-361.

Ullah, F., Qayyum, S., Thaheem, M. J., Al-Turjman, F., & Sepasgozar, S. M. (2021). Risk management in sustainable smart cities governance: A TOE framework. *Technological Forecasting and Social Change*, *167*, 120743.

United Nations. (2019). *World Urbanization Prospects: The 2019 Revision (Key facts).* Department of Economic and Social Affairs. United Nations. Retrieved from https://esa.un.org/unpd/wup/Publications/Files/WUP2019-KeyFacts.pdf

Uzzell, D., Pol, E., & Badenas, D. (2002). Place identification, social cohesion, and enviornmental sustainability. *Environment and behavior*, *34*(1), 26-53.

Vedachalam, S., & Riha, S. J. (2015). Who's the cleanest of them all? Sanitation scores in Indian cities. *Environment and Urbanization*, *27*(1), 117-136.

Wang, D. D. (2019). Performance assessment of major global cities by DEA and Malmquist index analysis. *Computers, Environment and Urban Systems*, *77*, 101365.

Wang, Q., Dai, H. N., & Wang, H. (2017). A smart MCDM framework to evaluate the impact of air pollution on city sustainability: A case study from China. *Sustainability*, *9*(6), 911.

Wang, L., & El-Gohary, N. M. (2017). Data-driven residential building energy consumption prediction for supporting multiscale sustainability assessment. In *Computing in Civil Engineering 2017* (pp. 324-332).

Wang, J., Kong, Y., & Fu, T. (2019). Expressway crash risk prediction using back propagation neural network: A brief investigation on safety resilience. *Accident Analysis & Prevention*, *124*, 180-192.

Wang, D., & Li, T. (2018). Carbon emission performance of independent oil and natural gas producers in the United States. *Sustainability*, *10*(1), 110.

Wang, Q. J., Shrestha, D. L., Robertson, D. E., & Pokhrel, P. (2012). A log-sinh transformation for data normalization and variance stabilization. *Water Resources Research*, *48*(5).

Wang, Z., & Song, W.-K. (2020). Sustainable airport development with performance evaluation forecasts: A case study of 12 Asian airports. *Journal of Air Transport Management, 89*. doi:https://doi.org/10.1016/j.jairtraman.2020.101925

Wang, J., Wang, Z., Yang, C., Wang, N., & Yu, X. (2012). Optimization of the number of components in the mixed model using multi-criteria decision-making. *Applied Mathematical Modelling*, *36*(9), 4227-4240.

Wang, Y. M., & Yang, J. B. (2007). Measuring the performances of decision-making units using interval efficiencies. *Journal of Computational and Applied Mathematics*, *198*(1), 253-267.

Wei, R. (2020). Research on Urban Resilience Evaluation Model and Its Application in China. *Open Journal of Social Sciences*, *8*(3), 407-416.

Wei, L., Du, H., Mahesar, Q. A., Al Ammari, K., Magee, D. R., Clarke, B., ... & Cohn, A. G. (2020). A decision support system for urban infrastructure inter-asset management employing domain ontologies and qualitative uncertainty-based reasoning. *Expert Systems with Applications*, 113461

Weichselgartner, J., & Kelman, I. (2014). Geographies of resilience: Challenges and opportunities of a descriptive concept. *Progress in Human Geography*, *39*(3), 249-267, doi:10.1177/03091325135188 34.

Wendling, L. A., Huovila, A., zu Castell-Rüdenhausen, M., Hukkalainen, M., & Airaksinen, M. (2018). Benchmarking nature-based solution and smart city assessment schemes against the sustainable development goal indicator framework. *Frontiers in Environmental Science*, *6*, 69.

Wey, W. M., & Peng, T. C. (2021). Study on Building a Smart Sustainable City Assessment Framework Using Big Data and Analytic Network Process. *Journal of Urban Planning and Development*, *147*(3), 04021031.

Wiens, J., Campbell, W. N., Franklin, E. S., Guttag, J. V., & Horvitz, E. (2014, September). Learning data-driven patient risk str. jpegication models for Clostridium difficile. In *Open forum infectious diseases* (Vol. 1, No. 2). Oxford University Press.

Williams, N., & Vorley, T. (2014). Economic resilience and entrepreneurship: lessons from the Sheffield City Region. *Entrepreneurship & Regional Development*, *26*(3-4), 257-281.

World Urban Forum. (2018). CITIES 2030, Cities For All: Implementing The New Urban Agenda. *UN Habitat Report*, Available online : https://mirror.unhabitat.org/downloads/docs/13435_1_596292 .pdf

Yager, R. R. (2013). Pythagorean fuzzy subsets. In *2013 joint IFSA world congress and NAFIPS annual meeting (IFSA/NAFIPS)*, 57-61. IEEE.

Yang, Y., & Chiclana, F. (2009). Intuitionistic fuzzy sets: spherical representation and distances. *International Journal of Intelligent Systems*, *24*(4), 399-420.

Yang, W. C., Lee, Y. M., & Hu, J. L. (2016). Urban sustainability assessment of Taiwan based on data envelopment analysis. *Renewable and Sustainable*

Energy Reviews, *61*, 341-353.

Yasmeen, H., Tan, Q., Zameer, H., Tan, J., & Nawaz, K. (2020). Exploring the impact of technological innovation, environmental regulations and urbanization on ecological efficiency of China in the context of COP21. *Journal of Environmental Management*, *274*.

Yigitcanlar, T. (2021). Smart City Beyond Efficiency: Technology–Policy–Community at Play for Sustainable Urban Futures.

Yigitcanlar, T., Desouza, K. C., Butler, L., & Roozkhosh, F. (2020). Contributions and risks of artificial intelligence (AI) in building smarter cities: Insights from a systematic review of the literature. *Energies*, *13*(6), 1473.

Yigitcanlar, T., Foth, M., & Kamruzzaman, M. (2019a). Towards post-anthropocentric cities: Reconceptualizing smart cities to evade urban ecocide. *Journal of Urban Technology*, *26*(2), 147-152.

Yigitcanlar, T., Han, H., & Kamruzzaman, M. (2019b). Approaches, advances, and applications in the sustainable development of smart cities: A commentary from the guest editors:4554.

Yigitcanlar, T., Kamruzzaman, M., Foth, M., Sabatini-Marques, J., da Costa, E., & Ioppolo, G. (2019c). Can cities become smart without being sustainable? A systematic review of the literature. *Sustainable cities and society*, *45*, 348-365.

Yigitcanlar, T., & Kamruzzaman, M. (2019). Smart cities and mobility: does the smartness of Australian cities lead to sustainable commuting patterns?. *Journal of Urban Technology*, *26*(2), 21-46.

Yigitcanlar, T., & Lee, S. H. (2014). Korean ubiquitous-eco-city: A smart-sustainable urban form or a branding hoax?. *Technological Forecasting and Social Change*, *89*, 100-114.

Yin, G. K. (2009). Temporary-effect legislation, political accountability, and fiscal restraint. *NYUL Rev.*, *84*, 174.

Yoon, D. K., Kang, J. E., & Brody, S. D. (2016). A measurement of community disaster resilience in Korea. *Journal of Environmental Planning and Management*, *59*(3), 436-460.

Yu, J. (2001). Aristotle on" Eudaimonia": after Plato's" Republic". *History of Philosophy Quarterly*, *18*(2), 115-138.

Yu, M. M. (2004). Measuring physical efficiency of domestic airports in Taiwan with undesirable outputs and environmental factors. *Journal of Air Transport Management*, *10*(5), 295-303.

Yu, H., & Kim, S. (2012). SVM Tutorial-Classification, Regression and Ranking. *Handbook of Natural computing*, *1*, 479-506, doi: 10.1007/978-3-540-92910-9_15.

Yuan, X. C., Wang, Q., Wang, K., Wang, B., Jin, J. L., & Wei, Y. M. (2015). China's regional vulnerability to drought and its mitigation strategies under climate change: data envelopment analysis and analytic hierarchy process integrated approach. *Mitigation and Adaptation Strategies for Global Change*, *20*(3), 341-359.

Zadeh, L. A. (1965). Fuzzy sets. *Information and control*, *8*(3), 338-353, https://doi.org/10.1016/ S0019-9958(65)90241-X

Zadeh, L. A. (1975). The concept of a linguistic variable and its application to approximate reasoning—I. *Information sciences*, *8*(3), 199-249.

Zander, J., & Mosterman, P. J. (Eds.). (2013). *Computation for humanity: Information technology to advance society*. CRC Press.

Zhang, H., Qian, Y., Yu, L., & Wang, Z. (2020). Integrated Development of

Information Technology and the Real Economy in China Based on Provincial Panel Data. *Sustainability*, *12*(17), 6773.

Zhou, Q., Zhu, M., Qiao, Y., Zhang, X., & Chen, J. (2021). Achieving resilience through smart cities? Evidence from China. *Habitat International*, *111*, 102348.

Zhu, J. (1996). Data envelopment analysis with preference structure. *Journal of the Operational Research Society*, *47*(1), 136-150.

Zhu, W., Zhu, Y., & Yu, Y. (2019). China's regional environmental efficiency evaluation: a dynamic analysis with biennial Malmquist productivity index based on common weights. *Environmental Toxicology and Risks Associated with Human Health*, *27*, 39726–39741.

Ziemke, D., Joubert, J. W., & Nagel, K. (2018). Accessibility in a post-apartheid city: Comparison of two approaches for accessibility computations. *Networks and Spatial Economics*, *18*(2), 241-271.

Ziguras, C., & Pham, A. T. N. (2014). Assessing participation in cross-border higher education in cities: Foreign education provision in Ho Chi Minh City. *Asia Pacific Viewpoint*, *55*(2), 169-181

Zoph, B., Vasudevan, V., Shlens, J., & Le, Q. V. (2018). Learning Transferable Architectures for Scalable Image Recognition. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)* (pp. 8697-8710). IEEE Xplore.

APPENDIX A: SUPPLEMENTARY EQUATIONS

S1. Optimistic and Pessimistic SBM in time

Let us consider an evaluation problem to measure the relative sustainable development capacity of ***n*** European smart cities over time *t*, *t+1*,…*t+n*. The optimistic SBM model (see Eq. 8) can be readily modified into the following linear programming model to obtain the OSBM in time *t*, α_0^t (w^t_{io}, x^t_{ko}, y^t_{ro}, z^t_{vo}) as (see Eq. 97-104):

α_0^t (w^t_{io}, x^t_{ko}, y^t_{ro}, z^t_{vo}) =

$$\text{Minimize } \boldsymbol{\eta}_{\textit{optimistic}} = f - \left[\left(\frac{1}{|m|+|t|}\right)\left(\sum_{i=1}^{m} \mathbf{S}_{\mathbf{I}}^{\mathbf{XD-}} / w^{t}_{io} + \sum_{v=1}^{t} \mathbf{S}_{\mathbf{v}}^{\mathbf{YU-}} / z^{t}_{vo}\right)\right] \quad (97)$$

Subject to

$$1 = f + \left[\left(\frac{1}{|s|+|p|}\right)\left(\sum_{r=1}^{s} \mathbf{S}_{\mathbf{r}}^{\mathbf{YD+}} / y_{ro} + \sum_{k=1}^{p} \mathbf{S}_{\mathbf{k}}^{\mathbf{XU+}} / x_{ko}\right)\right] \quad (98)$$

$$\sum_{j=1}^{n} x^{t}_{kj}\Lambda_j - \mathbf{S}_{\mathbf{k}}^{\mathbf{XU+}} = f\, x^{t}_{ko} \quad (99)$$

$$\sum_{j=1}^{n} w^{t}_{ij}\Lambda_j + \mathbf{S}_{\mathbf{I}}^{\mathbf{XD-}} = f\, w^{t}_{io} \quad (100)$$

$$\sum_{j=1}^{n} y^{t}_{rj}\Lambda_j - \mathbf{S}_{\mathbf{r}}^{\mathbf{YD+}} = f y^{t}_{ro} \quad (101)$$

$$\sum_{j=1}^{n} z^{t}_{vj}\Lambda_j + \mathbf{S}_{\mathbf{v}}^{\mathbf{YU-}} = f z^{t}_{vo} \quad (102)$$

$$\sum_{j=1}^{n} \Lambda_j = 1 \text{ for Variable Returns to Scale (VRS)} \quad (103)$$

$$\Lambda_j,\ \mathbf{S}_{\mathbf{k}}^{\mathbf{XU+}},\ \mathbf{S}_{\mathbf{I}}^{\mathbf{XD-}},\ \mathbf{S}_{\mathbf{r}}^{\mathbf{YD+}},\ \mathbf{S}_{\mathbf{v}}^{\mathbf{YU-}} \geq 0;\ \forall j, k, i, r, v \text{ and } f > 0 \quad (104)$$

where $\Lambda_j = f\lambda_j$, $\mathbf{S}_{\mathbf{I}}^{\mathbf{XD-}} = f s_I^{XD-}$, $\mathbf{S}_{\mathbf{v}}^{\mathbf{YU-}} = f s_v^{YU-}$, $\mathbf{S}_{\mathbf{r}}^{\mathbf{YD+}} = f s_r^{YD+}$, $\mathbf{S}_{\mathbf{k}}^{\mathbf{XU+}} = f s_k^{XU+}$; and $w_{io} = X_{io}^{DI}$, $x_{ko} = X_{ko}^{UI}$, $y_{ro} = Y_{ro}^{DO}$, $z_{vo} = Y_{vo}^{UO}$.

Likewise, OSBM in time *t* +1, α_0^{t+1} (w^{t+1}_{io}, x^{t+1}_{ko}, y^{t+1}_{ro}, z^{t+1}_{vo}) can be computed by replacing (x^t_{ko}, x^t_{kj}, w^t_{io}, w^t_{ij}, y^t_{ro}, y^t_{rj}, z^t_{vo}, z^t_{vj}) with (x^{t+1}_{ko}, x^{t+1}_{kj}, w^{t+1}_{io}, w^{t+1}_{ij}, y^{t+1}_{ro}, y^{t+1}_{rj}, z^{t+1}_{vo}, z^{t+1}_{vj}). The modified OSBM model in time *t* +1 can be mathematically represented through the Eqs. 105-112:

$$\text{Minimize } \boldsymbol{\eta}_{\textit{optimistic}} = f - \left[\left(\frac{1}{|m| + |t|}\right)\left(\sum_{i=1}^{m} \mathbf{S_I^{XD\,-}} / w^{t+1}{}_{io} + \sum_{v=1}^{t} \mathbf{S_v^{YU\,-}} / z^{\,t+1}{}_{vo}\right)\right] \tag{105}$$

Subject to

$$1 = f + \left[\left(\frac{1}{|s| + |p|}\right)\left(\sum_{r=1}^{s} \mathbf{S_r^{YD+}} / y_{ro} + \sum_{k=1}^{p} \mathbf{S_k^{XU+}} / x_{ko}\right)\right] \tag{106}$$

$$\sum_{j=1}^{n} x_{kj}^{t+1}\,\Lambda_j - \mathbf{S_k^{XU+}} = f\, x^{t+1}{}_{ko} \tag{107}$$

$$\sum_{j=1}^{n} w_{ij}^{t+1}\,\Lambda_j + \mathbf{S_I^{XD-}} = f\, w^{t+1}{}_{io} \tag{108}$$

$$\sum_{j=1}^{n} y_{rj}^{t+1}\,\Lambda_j - \mathbf{S_r^{YD+}} = f\; y^{t+1}{}_{ro} \tag{109}$$

$$\sum_{j=1}^{n} z_{vj}^{t+1}\,\Lambda_j + \mathbf{S_v^{YU-}} = f\; z^{\,t+1}{}_{vo} \tag{110}$$

$$\sum_{j=1}^{n} \Lambda_j = 1 \text{ for Variable Returns to Scale (VRS)} \tag{111}$$

$$\Lambda_j,\ \mathbf{S_k^{XU+}},\ \mathbf{S_I^{XD-}},\ \mathbf{S_r^{YD+}},\ \mathbf{S_v^{YU-}} \geq 0;\ \forall\ \text{j, k, i, r, v and } \theta > 0 \tag{112}$$

Similarly, the PSBM model (see Eq. 24) can be transformed into the following linear programming model to obtain the PSBM in time *t*, α_0^t ($w^{\,t}{}_{io}$, $x^{\,t}{}_{ko}$, $y^{\,t}{}_{ro}$, $z^{\,t}{}_{vo}$) as represented through Eqs. 113-120;

α_0^t ($w^{\,t}{}_{io}$, $x^{\,t}{}_{ko}$, $y^{\,t}{}_{ro}$, $z^{\,t}{}_{vo}$) =

$$\text{Maximize } \boldsymbol{\eta}_{\textit{pessimistic}} = f + \left[\left(\frac{1}{|m| + |t|}\right)\left(\sum_{i=1}^{m} \mathbf{S_I^{XD\,+}} / w^{\,t}{}_{io} + \sum_{v=1}^{t} \mathbf{S_v^{YU\,+}} / z^{\,t}{}_{vo}\right)\right] \tag{113}$$

Subject to

$$1 = f - \left[\left(\frac{1}{|s| + |p|}\right)\left(\sum_{r=1}^{s} \mathbf{S_r^{YD\,-}} / y_{ro} + \sum_{k=1}^{p} \mathbf{S_k^{XU\,-}} / x_{ko}\right)\right] \tag{114}$$

$$\sum_{j=1}^{n} x_{kj}^{t}\Lambda_j + \mathbf{S_k^{XU-}} = f\, x^{t}{}_{ko} \tag{115}$$

$$\sum_{j=1}^{n} w_{ij}^{t}\Lambda_j - \mathbf{S_I^{XD+}} = f\, w^{t}{}_{io} \tag{116}$$

$$\sum_{j=1}^{n} y_{rj}^{t}\Lambda_j + \mathbf{S_r^{YD-}} = f\, y^{\,t}{}_{ro} \tag{117}$$

$\sum_{j=1}^{n} z_{vj}^{t}\Lambda_j - \mathbf{S_v^{YU+}} = f z^t_{vo}$ (118)

$\sum_{j=1}^{n} \Lambda_j = 1$ for Variable Returns to Scale (VRS) (119)

Λ_j, $\mathbf{S_k^{XU-}}$, $\mathbf{S_I^{XD+}}$, $\mathbf{S_r^{YD-}}$, $\mathbf{S_v^{YU+}} \geq 0$; $\forall$ j, k, i, r, v and $f > 0$ (120)

where $\Lambda_j = f\lambda_j$, $\mathbf{S_I^{XD+}} = f s_I^{XD+}$, $\mathbf{S_v^{YU+}} = f s_v^{YU+}$, $\mathbf{S_r^{YD-}} = f s_r^{YD-}$, $\mathbf{S_k^{XU-}} = f s_k^{XU-}$; and $w_{io} = X_{io}^{DI}$, $x_{ko} = X_{ko}^{UI}$, $y_{ro} = Y_{ro}^{DO}$, $z_{vo} = Y_{vo}^{UO}$.

Alternatively, by applying the substitution for (x^t_{ko} , x^t_{kj} , w^t_{io} , w^t_{ij} , y^t_{ro} , y^t_{rj} , z^t_{vo} , z^t_{vj}) with (x^{t+1}_{ko} , x^{t+1}_{kj} , w^{t+1}_{io} , w^{t+1}_{ij} , y^{t+1}_{ro} , y^{t+1}_{rj} , z^{t+1}_{vo} , z^{t+1}_{vj}), the PSBM in time $t+1$, α_0^{t+1} (w^{t+1}_{io}, x^{t+1}_{ko}, y^{t+1}_{ro}, z^{t+1}_{vo}) can be calculated and mathematically represented as in Eqs. 121-127:

Minimize $\boldsymbol{\eta}_{\boldsymbol{optimistic}} = f + \left[\left(\frac{1}{|m| + |t|}\right)\left(\sum_{i=1}^{m} \mathbf{S_I^{XD+}} / w^{t+1}_{io} + \sum_{v=1}^{t} \mathbf{S_v^{YU+}} / z^{t+1}_{vo}\right)\right]$ (121)

Subject to

$1 = f - \left[\left(\frac{1}{|s| + |p|}\right)\left(\sum_{r=1}^{s} \mathbf{S_r^{YD-}} / y_{ro} + \sum_{k=1}^{p} \mathbf{S_k^{XU-}} / x_{ko}\right)\right]$ (122)

$\sum_{j=1}^{n} x_{kj}^{t+1}\Lambda_j + \mathbf{S_k^{XU-}} = f x^{t+1}_{ko}$ (123)

$\sum_{j=1}^{n} w_{ij}^{t+1}\Lambda_j - \mathbf{S_I^{XD+}} = f w^{t+1}_{io}$ (124)

$\sum_{j=1}^{n} y_{rj}^{t+1}\Lambda_j + \mathbf{S_r^{YD-}} = f y^{t+1}_{ro}$ (125)

$\sum_{j=1}^{n} z_{vj}^{t+1}\Lambda_j - \mathbf{S_v^{YU+}} = f z^{t+1}_{vo}$ (126)

$\sum_{j=1}^{n} \Lambda_j = 1$ for Variable Returns to Scale (VRS) (127)

Λ_j, $\mathbf{S_k^{XU-}}$, $\mathbf{S_I^{XD+}}$, $\mathbf{S_r^{YD-}}$, $\mathbf{S_v^{YU+}} \geq 0$; $\forall$ j, k, i, r, v and $\theta > 0$

All the other variables and parameters for OSBM in time $t+1$, is same as the PSBM model (Eqs. 113-127).

APPENDIX B: SUPPLEMENTARY TABLES

Table B1. Indicators for urban livability assessment under respective dimensions with desirability values

Dimensions	Indicators	Symbol	Units	Desirability	Justification
Accessibility 	1. Share of population with access to portable drinking water system.	AC1	%	+	Nagpal, (2018)
	2. Share of households connected to the sewerage treatment systems.	AC2	%	+	Mizuki et al., (2012)
	3. Percentage of population with access to high-speed internet connectivity living in the city.	AC3	% of household	+	Burange & Misalkar, (2015)
	4. Estimated share of households with access to at least one vehicle to commute for work and other needs.	AC4	% of household	+	Maglaras et al., (2016)
	5. Net housing cost overburden rate.	AC5	%	+	Balsas, (2004)
	6. Percentage of population with no access to health insurance coverage (private /public) and/or “free” healthcare services	AC6	%	–	Mayaud et al., (2019)
	7. Information access to requests submitted within 90 days	AC7	%	+	Lind, (2012)
	8. Share of population with access to proper sanitation coverage	AC8	%	+	Vedachalam & Riha, (2015)

Table B1. Indicators for urban livability assessment under respective dimensions with desirability values (cont.)

Dimensions	Indicators	Symbol	Units	Desirability	Justification
	9. Number of convenience stores, supermarkets, grocery stores and hypermarkets within 2.0 Km buffer zone	AC9	In numbers	+	Järv et al., (2018)
	10. Percentage of population with access to equitable education, participation, and progression	AC10	%	+	Ziguras & Pham, (2014)
Economic vibrancy 	11. Annual number of patent applications filed with the European Patent Office per million inhabitants.	EV1	In numbers	+	Mamlook et al., (2019)
	12. Employment rates of recent graduates in technological enterprises relocated to and/or established within the city.	EV2	%	+	Betz et al., (2016)
	13. Eco-innovation within city	EV3	Index, EU=100	+	Beretta, (2018)
	14. Expected work-life duration	EV4	Years	+	Mizobuchi, (2014)
	15. Share of knowledge-driven employment	EV5	% employed	+	Betz et al., (2016)
	16. Single-sector economic-dependence	EV6	%	–	Nikolaev, (2014)
	17. Residents living in household with low work intensity	EV7	% age < 60[1]	–	Balestra et al., (2018)
	18. Share of woman members in leadership positions	EV8	%	+	Kerényi, (2011)

Table B1. Indicators for urban livability assessment under respective dimensions with desirability values (cont.)

Dimensions	Indicators	Symbol	Units	Desirability	Justification
	19. Share of households receiving local housing allowance in city	EV9	%	+	Kasparian & Rolland, (2012)
	20. City municipal-waste recycling and composting rates	EV10	%	+	Aceleanu et al., (2019)
Community Well-being 	21. Share of green urban areas, sports, and recreational facilities per capita.	CW1	%	+	Liu et al., (2020)
	22. Total capacity of cinema theatres and leisure venues per inhabitant in the city within 50 sq.km.	CW2	In numbers	+	Punt et al., (2020)
	23. Share of population with no engagement in physical activities as a percentage of total population living in city.	CW3	%	−	Batty et al., (2012)
	24. Disability-free “Healthy Life Years” in absolute value at the age of 65.	CW4	Years	+	Balestra et al., (2018)
	25. Share of population claiming to suffer from noise pollution living in houses within the city.	CW5	%	−	Ghosh et al., (2019)
	26. Number of visits to pubs, bars, night clubs and outdoor dines as free time activity by adult population (per year).	CW6	Visits in number	+	Abusaada & Elshater, (2021)

Table B1. Indicators for urban livability assessment under respective dimensions with desirability values (cont.)

Dimensions	Indicators	Symbol	Units	Desirability	Justification
	27. Share of people who are overweight living in the city based on the BMI value.	CW7	%	−	Esliger et al., (2012)
	28. Water productivity	CW8	€/cubic m[2]	+	Molden et al., (2003)
	29. Urban population exposed to PM_{10} concentrations exceeding the daily limit value (50 μg/m3 on more than 35 days in a year)	CW9	%	−	Chen et al., (2017)
	30. Shelf space in supermarkets allotted to vegan and/or organic products and food items	CW10	%	+	Latacz-Lohmann, & Foster, (1997)

[1] Percentage of total population aged less than 60; [2] Euro per cubic meter equivalent

Table B2. Indicators for resilience assessment under respective dimensions with desirability values in the proposed framework

Dimensions	Indicators	Symbol	Units	Desirability	Justification
Social	1. Number of practicing physicians (medical doctors) per 100,000 inhabitants.	S1	In numbers	+	Kreffter et al., (2021)
	2. Number of hospital beds available per 100, 000 inhabitants.	S2	In numbers	+	Green, (2002)
	3. Number of people living in households (0-59yrs.) with relatively low work intensity.	S3	Thousand persons	−	Boost et al., (2020)
	4. Percentage of hospitals in the city that have performed disaster drills to test response capabilities to emergencies over the past year.	S4	%	+	Figueiredo et al., (2018)
	5. Share of population at risk of relative poverty after social benefits.	S5	%	−	Boost et al., (2020)
	6. Percentage of materially deprived population in the city	S6	%	−	Boost et al., (2020)
	7. Number of civic-social advocacy organizations and/or NGOs per 10, 000 population	S7	In numbers	+	Frankenberger et al., (2014)
	8. Proportion of population > 16 years of age who perceive their health status to be "very good"	S8	%	+	Smith & Plunkett, (2019)
	9. Average police response time to highest priority emergency calls	S9	Minutes	−	Figueiredo et al., (2018)

Table B2. Indicators for resilience assessment under respective dimensions with desirability values (Cont.)

Dimensions	Indicators	Symbol	Units	Desirability	Justification
	10. Proportion of population with perceived interpersonal community level network support	S10		+	Renschler et al., (2010)
Economic 	11. Percentage of active population unemployed for a period more than 6 months with access to employment schemes.	EC1	%	−	Figueiredo et al., (2018)
	12. Number of new business entities registered in the city over the past year per 100, 000 inhabitants.	EC2	In numbers	+	Arup and Rockefeller Foundation, (2014)
	13. City unemployment rate	EC3	Rate	−	Moorhouse & Caltabiano, (2007)
	14. Tertiary educational attainment (level 5-8) across labour force	EC4	%	+	Beck, (2016)
	15. Individual firm dependence	EC5	%	−	Parker, & Ameen, (2018)
	16. Activity rate - % of total population aged 15-64 years	EC6	%	+	Moore et al., (2020)
	17. Liabilities related to private-public partnerships (PPPs) recorded off-government balance sheet	EC7	% GDP[1]	−	Cuttaree & Mandri-Perrott, (2011)

Table B2. Indicators for resilience assessment under respective dimensions with desirability values (Cont.)

Dimensions	Indicators	Symbol	Units	Desirability	Justification
	18. Percentage share of high-technology exports to the total manufactured exports	EC8	%	+	Psycharis et al., (2020)
	19. Share of population unemployed due to caring responsibilities	EC9	% of inactive population	–	Moorhouse & Caltabiano, (2007)
	20. Underachievement in the field of science, mathematics, and technology	EC10	%	–	Bland et al., (1994)
Infrastructure & Built Environment	21. Length of dedicated bicycle paths and lanes (span of bicycle network per km^2)	IB1	km	+	Clemente, (2020)
	22. Share of population living in a dwelling with a leaking roof, damp walls, floors or foundation, or rot-in window frames or floors.	IB2	%	–	Arup and Rockefeller Foundation, (2014)
	23. Share of housing units resilient to hazards, shocks, and stresses subject to hazard resistant building design and retrofits.	IB3	%	+	Figueiredo et al., (2018)
	24. Share of households connected to urban wastewater collection and treatment systems.	IB4	Treatment level in %	+	Sun et al., (2020)
	25. Percentage of total arable land utilized for organic crop cultivation.	IB5	%	+	Mekonnen et al., (2013)

Table B2. Indicators for resilience assessment under respective dimensions with desirability values (Cont.)

Dimensions	Indicators	Symbol	Units	Desirability	Justification
	26. People killed as a result of road traffic injuries per 10, 000 population.	IB6	% share	−	Wang et al., (2019)
	27. GHG emissions released per unit of energy consumed	IB7	Index (2000 = 100)	−	Sharifi & Yamagata, (2015)
	28. Water Exploitation Index +	IB8	%	−	Brown & Lall, (2006)
	29. Percentage of wetland loss	IB9	%	−	Mekonnen et al., (2013)
	30. Number of days the city fuel supplies could maintain essential household functions during disruptions	IB10	Days	+	Figueiredo et al., (2018)
Institutional	31. Percentage of children over the age of 6yrs who have received basic education and training on disaster mitigation and risk reduction.	IN1	%	+	Faber et al., (2014)
	32. Percentage of communities in the city with local emergency groups.	IN2	%	+	Cox & Hamlen, (2015)
	33. Housing units with insurance coverage against damage from high-risk hazards and natural calamities.	IN3	%	+	Arup and Rockefeller Foundation, (2014)

Table B2. Indicators for resilience assessment under respective dimensions with desirability values (Cont.)

Dimensions	Indicators	Symbol	Units	Desirability	Justification
	34. Share of government budget spend on emergency services and social protection.	IN4	€/inhabitant[2]	+	Yoon et al., (2016)
	35. Average rate of trust in the local area governance system	IN5	%	+	Hills, (2000)
	36. Percentage of civilian population that have received basic training on first-aid, cardiopulmonary resuscitation (CPR) and professional ambulance care in past 2 years.	IN6	%	+	Arup and Rockefeller Foundation, (2014)
	37. Number of city development programs (CDP) and workshops conducted over the past 2 years with focus on resilience planning	IN7	%	+	Labaka et al., (2019)
	38. Percentage of members of cooperatives	IN8	%	+	Aligica & Tarko, (2014)

[1] Percentage of Gross Domestic Product; [2] Euro per inhabitant

Table B3. Dimensions and indicators for sustainable development capacity assessment

Dimensions	Indicators	Symbol	Units	Technology set		Desirability		SDG Alignment
				Input	Output	Desirable	Undesirable	
Energy & Environmental Resources	1. Total energy available for end users	ER1	Mtoe [1]	√			√	7 AFFORDABLE AND CLEAN ENERGY
	2. Fresh water use as a percentage of total available renewable water resources	ER2	%	√		√		
	3. Total energy consumed by end-users	ER3	Mtoe		√		√	6 CLEAN WATER AND SANITATION
	4. Per capita total household energy consumption	ER4	kgoe [2]		√		√	
	5. City wide energy productivity	ER5	€/kg energy.eqv[3]		√	√		
	6. Total renewable energy sources in the gross final energy consumption	ER6	%		√	√		
Governance & Institution	7. R&D Expenditure as a percentage of GDP	GI1	% of GDP	√			√	5 GENDER EQUALITY
	8. Percentage of active population assigned for R&D related activities	GI2	%	√			√	8 DECENT WORK AND ECONOMIC GROWTH
	9. Active population hired in science and technology sector	GI3	%	√			√	9 INDUSTRY, INNOVATION AND INFRASTRUCTURE
	10. City employment rate	GI4	%	√			√	
	11. Working poverty rate	GI5	%	√		√		10 REDUCED INEQUALITIES
	12. Gender pay gap	GI6	%	√		√		
	13. Income distribution	GI7	Rate		√		√	

Table B3. Dimensions and indicators for sustainable development capacity assessment (cont.)

Dimensions	Indicators	Symbol	Units	Technology set		Desirability		SDG Alignment
				Input	Output	Desirable	Undesirable	
	14. Total revenue generated from service provided	GI8	%		√	√		
Economic Dynamism	15. Contribution of environmental goods and services to the city GDP	E1	€M [4]	√			√	
	16. Gross disposable household income per capital	E2	PPS per inhabitant [5]	√			√	
	17. Gross investment as a share of percentage GDP	E3	%	√		√		
	18. Territorial consumer price index	E4	Index		√		√	
	19. Real GDP per capita	E5	Euro per capita		√	√		
Social cohesion & Solidarity	20. Share of population with access to city waste water treatment facilities	SC1	%	√			√	
	21. Share of public transit modes in the city among the total inland transport	SC2	%	√			√	
	22. Accessibility to secondary waste water treatment facilities	SC3	% of population	√			√	
	23. Share of population in the city with excellent perceived health	SC4	%	√			√	
	24. Share of population unable to keep their house warm	SC5	%	√		√		

[1] Mtoe: Million tons of oil equivalent; [2] kgoe: kg of oil equivalent; [3] Euro per kg of energy usage equivalent;

Table B3. Dimensions and indicators for sustainable development capacity assessment (Cont.)

Dimensions	Indicators	Symbol	Units	Technology set		Desirability		SDG Alignment
				Input	Output	Desirable	Undesirable	
	25. Percentage of population leaving in overcrowded households within the city	SC6	%	√		√		
	26. Share of population with no household sanitation facilities	SC7	%	√		√		
	27. Household outflow (tax returns to city residents)	SC8	Population aged < 60 (in %)		√		√	
	28. Total resource consumption in relation to territorial service provided	SC9	PPS per Kg[6]		√	√		
	29. Life expectancy at birth	SC10	Age in numbers		√			
Climate Change	30. Recycling rate of municipal waste in city	CC1	%	√			√	
	31. City residents covered by EU climate action program: convent of mayors	CC2	% of population	√			√	
	32. Amount of non-mineral hazardous waste generated	CC3	Kg per capita	√		√		
	33. Share of population claiming to suffer from noise pollution living in the houses	CC4	%	√		√		
	34. Particulate pollutants causing atmospheric pollution	CC5	Particulates < 2.5μm	√		√		

€M [4] : Million Euros; PPS per inhabitant [5]: Purchasing power standard per inhabitant; PPS per Kg[6] : Purchasing power standard per Kilogram

Table B3. Dimensions and indicators for sustainable development capacity assessment (cont.)

Dimensions	Indicators	Symbol	Units	Technology set		Desirability		SDG Alignment
				Input	Output	Desirable	Undesirable	
	35. Soil Sealing Index	CC6	%	√		√		13 CLIMATE ACTION 15 LIFE ON LAND
	36. CO_2 emission from new passenger vehicles registered in the city	CC7	Kg's of CO_2 emission per km		√		√	
	37. GHG emissions released per unit of energy consumed	CC8	Index 2000 = 100		√		√	
	38. Total greenhouse gas emission (GHG)	CC9	tonnes per capita		√		√	
	39. Air quality by mean concentration of particulate matter (PM.10)	CC10	Particulates < 10µm		√	√		
	40. Circular material consumption rate	CC11	%		√	√		
Safety and security	41. Share of population reporting criminal activities within the city	SS1	%		√	√		3 GOOD HEALTH AND WELL-BEING 8 DECENT WORK AND ECONOMIC GROWTH
	42. Share of government expenditure spend on judicial system and setting up of law courts	SS2	€/resident [7]	√			√	
	43. Corruption perception index	SS3	Number	√		√		
	44. Risk of poverty rate	SS4	Relative poverty gap	√		√		
	45. Share of population at risk of poverty and social exclusion	SS5	%	√		√		

€/resident [7] : Euro per city residents;

Table B3. Dimensions and indicators for sustainable development capacity assessment (cont.)

Dimensions	Indicators	Symbol	Units	Technology set		Desirability		SDG Alignment
				Input	Output	Desirable	Undesirable	
	46. Subjective claims on unattended medical care in the city	SS6	%	√		√		16 PEACE, JUSTICE AND STRONG INSTITUTIONS 10 REDUCED INEQUALITIES 11 SUSTAINABLE CITIES AND COMMUNITIES
	47. Road fatalities per 100,000 city inhabitants	SS7	Rate		√		√	
	48. Number of fatalities per 100,000 employees at work	SS8	Incident rate		√		√	
	49. Deaths by homicide per 100,000 resident population in the city	SS10	Rate		√		√	
	50. Mortality rates from HIV, TB, and Hepatitis related causes	SS11	Percentage		√		√	

Table B4. Interval midpoint and width for ranking interval numbers across the climate change, economic dynamism and, governance and institution dimensions for the bounded DEA-model

	Climate change			Economy			Governance and Institution		
	m(A_i)	*w*(A_i)	R^*	m(A_i)	*w*(A_i)	R^*	m(A_i)	*w*(A_i)	R
Brussels	0.5791	0.4209	7	0.3773	0.1927	27	0.5296	0.4704	6
Sofia	0.4411	0.3512	32	0.5140	0.4860	12	0.2935	0.1485	31
Prague	0.4625	0.3366	28	0.3124	0.2316	34	0.1770	0.0320	35
Copenhagen	0.5340	0.4660	18	0.3792	0.2718	24	0.4054	0.3076	18
Munich	0.5289	0.4281	20	0.3593	0.2917	31	0.3020	0.1570	30
Tallinn	0.5871	0.4129	5	0.3778	0.1932	26	0.3470	0.2020	25
Dublin	0.5595	0.4405	11	0.5607	0.4003	3	0.4765	0.4075	15
Athens	0.5380	0.4620	16	0.5560	0.4440	4	0.4783	0.4227	14
Bilbao	0.5011	0.2649	25	0.3482	0.2578	32	0.2638	0.2342	34
Lyon	0.6076	0.3924	2	0.4521	0.3229	16	0.3203	0.2577	28
Dusseldorf	0.5789	0.4211	8	0.4873	0.4157	13	0.5221	0.4779	8
Bologna	0.5927	0.3566	4	0.3878	0.2032	22	0.4122	0.3148	17
Hamburg	0.5800	0.4200	6	0.4724	0.3776	14	0.5013	0.4537	13
Petersburg	0.5037	0.3353	24	0.5293	0.4027	9	0.5299	0.4701	5
Merseille	0.5497	0.4503	12	0.4644	0.3736	15	0.3339	0.2621	27
Geneva	0.6105	0.3895	1	0.5190	0.4810	10	0.3529	0.2701	22
Budapest	0.4569	0.3213	29	0.5147	0.3943	11	0.3419	0.2581	26
Manchester	0.5450	0.4550	13	0.5493	0.4507	6	0.5115	0.4885	12
Amsterdam	0.5703	0.4297	9	0.3883	0.2077	21	0.4323	0.3937	16
Vienna	0.5997	0.4003	3	0.3269	0.2031	33	0.2922	0.2188	32
Warsaw	0.5427	0.3065	14	0.3740	0.2650	28	0.3925	0.3495	19
Lisbon	0.5310	0.4690	19	0.4105	0.2925	17	0.3490	0.2040	23
Bucharest	0.5684	0.3961	10	0.3608	0.2642	30	0.5159	0.4841	9
Krakow	0.4907	0.2993	26	0.5426	0.3864	8	0.5130	0.4870	11
Bratislava	0.4759	0.2397	27	0.4007	0.2713	20	0.5261	0.4469	7
Helsinki	0.5359	0.4641	17	0.3688	0.2292	29	0.5430	0.4570	4
Stockholm	0.5416	0.4584	15	0.3807	0.1983	23	0.5460	0.4540	3
London	0.4564	0.3936	30	0.3789	0.2261	25	0.5510	0.4490	2
Zaragoza	0.4228	0.1866	33	0.4033	0.2477	19	0.3639	0.2981	21
Oslo	0.5229	0.4771	21	0.5701	0.4209	1	0.5513	0.4487	1
Zurich	0.5123	0.4877	22	0.5688	0.4312	2	0.5153	0.4847	10
Moscow	0.3829	0.3007	34	0.5485	0.4355	7	0.3110	0.2430	29
Kiev	0.3692	0.1330	35	0.2113	0.0267	35	0.2680	0.1230	33
Rome	0.5114	0.3799	23	0.5541	0.4259	5	0.3721	0.3039	20
Ankara	0.4489	0.2128	31	0.4048	0.2202	18	0.3478	0.2462	24

R^* = Rank

Table B5. Interval midpoint and width for ranking interval numbers across the energy and environmental resource, safety, and security, and, social cohesion and solidarity dimensions for the bounded DEA-model

	Energy resource			Safety and security			Social cohesion and solidarity		
	m(A$_i$)	*w*(A$_i$)	R*	m(A$_i$)	*w*(A$_i$)	R*	m(A$_i$)	*w*(A$_i$)	R
Brussels	0.3115	0.2392	26	0.4400	0.2877	30	0.5084	0.4916	13
Sofia	0.2408	0.1746	34	0.5304	0.4696	19	0.3228	0.2467	33
Prague	0.2967	0.1028	29	0.5362	0.4638	14	0.5118	0.4882	9
Copenhagen	0.5834	0.4166	7	0.4040	0.3331	32	0.4217	0.3741	26
Munich	0.5883	0.4117	4	0.3303	0.2924	35	0.5312	0.4688	3
Tallinn	0.2892	0.0952	32	0.5348	0.4652	17	0.4315	0.3804	23
Dublin	0.5879	0.4121	5	0.4757	0.3222	28	0.5077	0.4923	14
Athens	0.2303	0.1875	35	0.5533	0.3321	8	0.4650	0.4092	21
Bilbao	0.2784	0.2045	33	0.4971	0.1837	25	0.5091	0.4909	12
Lyon	0.4217	0.2973	17	0.5469	0.4530	12	0.4267	0.3787	25
Dusseldorf	0.4526	0.3253	14	0.5290	0.4710	20	0.5042	0.4958	18
Bologna	0.5193	0.4807	10	0.5485	0.2352	10	0.5076	0.4924	15
Hamburg	0.4406	0.3181	16	0.5167	0.4833	23	0.5072	0.4928	17
Petersburg	0.5193	0.4807	11	0.5393	0.4607	13	0.5114	0.4886	10
Merseille	0.3718	0.2652	21	0.5361	0.4639	15	0.5113	0.4887	11
Geneva	0.5949	0.4051	1	0.5589	0.3348	7	0.5236	0.4764	6
Budapest	0.3493	0.2625	24	0.6037	0.3756	2	0.3777	0.3254	29
Manchester	0.5125	0.4875	12	0.5469	0.4531	11	0.5198	0.4802	7
Amsterdam	0.3967	0.2527	18	0.3591	0.3283	34	0.5373	0.4627	1
Vienna	0.5935	0.4065	2	0.4134	0.3346	31	0.4280	0.3774	24
Warsaw	0.2925	0.2163	31	0.5175	0.4825	22	0.4211	0.3690	27
Lisbon	0.3313	0.1373	25	0.4818	0.3161	26	0.5131	0.4869	8
Bucharest	0.3071	0.2149	28	0.5502	0.4498	9	0.3322	0.2561	32
Krakow	0.3090	0.2215	27	0.5051	0.3643	24	0.3182	0.2420	34
Bratislava	0.3737	0.2937	20	0.5617	0.4383	6	0.3633	0.3313	31
Helsinki	0.5893	0.4107	3	0.5214	0.4786	21	0.5274	0.4726	4
Stockholm	0.3912	0.2677	19	0.3800	0.2928	33	0.4397	0.3930	22
London	0.5776	0.4224	8	0.4505	0.1371	29	0.5019	0.4981	19
Zaragoza	0.5676	0.4324	9	0.5361	0.4639	16	0.5072	0.4928	16
Oslo	0.5876	0.4124	6	0.5636	0.3561	5	0.5358	0.4642	2
Zurich	0.4458	0.3049	15	0.4801	0.1668	27	0.5271	0.4729	5
Moscow	0.5107	0.4893	13	0.5316	0.4684	18	0.3682	0.2920	30
Kiev	0.3583	0.2743	22	0.6058	0.3727	1	0.1398	0.0636	35
Rome	0.3537	0.2496	23	0.5990	0.3601	3	0.5004	0.4996	20
Ankara	0.2966	0.2461	30	0.5690	0.4310	4	0.3786	0.3025	28

R* = Rank

Table B6(a). Productivity change for the 35 European smart cities over the years from 2015 till 2020 under the Climate change dimension

Smart cities	Optimistic MPI				
	2015/16	2016/17	2017/18	2018/19	2019/20
Brussels	0.9681	1.0398	1.0225	1.0085	1.0085
Sofia	1.0000	1.0000	1.0000	0.9213	1.0234
Prague	0.3849	0.6849	0.6286	1.1948	1.4227
Copenhagen	0.9453	1.0273	0.9435	1.0624	0.9064
Munich	0.9082	0.9207	0.9861	0.9675	1.0062
Tallinn	1.0946	1.1063	1.1903	0.9667	1.0183
Dublin	0.6895	1.0838	1.0215	0.9254	0.9674
Athens	0.4909	0.9033	1.2776	0.6164	1.0416
Bilbao	1.0477	0.9799	0.9458	1.0498	0.8830
Lyon	0.9209	0.9182	0.9094	0.9111	0.9203
Dusseldorf	0.8062	1.2265	1.1999	1.1054	1.0379
Bologna	0.8757	1.0001	1.0214	0.9467	1.0481
Hamburg	1.0666	1.2649	1.0815	0.9220	1.0919
St. Petersbrg	0.9405	0.5837	0.9142	1.1489	1.1290
Merseille	1.2312	0.7389	1.1884	0.7408	1.1280
Geneva	1.1748	1.0726	1.2069	1.0000	1.0000
Budapest	0.9411	0.6205	0.6763	1.1805	1.3880
Manchester	1.0689	0.9353	0.7292	1.2933	0.5916
Amsterdam	1.0000	1.0000	1.0000	1.0000	1.0000
Vienna	1.0363	0.9694	0.9803	0.9862	1.0609
Warsaw	1.0000	1.0373	0.9853	0.9088	1.0000
Lisbon	0.7759	0.9475	0.9431	0.9778	0.9336
Bucharest	0.6973	1.2770	0.4995	1.0646	0.7918
Krakow	0.8695	0.9785	1.0017	0.9596	0.9692
Bratislava	0.9391	0.7944	0.9265	0.9624	1.0290
Helsinki	0.8497	1.0766	1.0824	1.0177	0.8359
Stockholm	0.8878	0.7619	0.6949	0.9413	2.1602
London	1.0124	1.0754	0.9854	1.0000	0.9983
Zaragoza	1.0000	1.0000	1.0000	1.0000	1.0000
Oslo	1.0829	1.0491	0.7959	0.9246	1.1764
Zurich	1.0077	1.0000	1.2424	1.0000	1.0000
Moscow	1.0603	1.1347	1.5525	0.2059	0.2001
Kiev	0.8558	1.0218	1.2087	1.0000	1.0670
Rome	4.6243	1.2183	3.1108	1.0000	1.0392
Ankara	0.9234	1.2435	1.0132	1.0857	1.0343

Table B6(b). Productivity change for the 35 European smart cities over the years from 2015 till 2020 under the Climate change dimension

Smart cities	Pessimistic MPI				
	2015/16	2016/17	2017/18	2018/19	2019/20
Brussels	0.9768	1.0150	1.0224	1.0017	1.0254
Sofia	0.9558	0.9965	1.0399	0.9906	0.9576
Prague	1.0164	1.0000	1.0000	1.0000	1.0306
Copenhagen	0.9598	0.9878	0.9465	1.0112	1.0014
Munich	0.9631	0.9770	0.9935	0.9914	1.0019
Tallinn	1.0241	0.9261	1.0000	1.0000	1.0239
Dublin	1.0000	0.8969	1.0000	0.9151	1.0085
Athens	1.0000	1.0083	1.0000	1.1732	1.0000
Bilbao	1.0502	0.9924	0.9481	1.0278	0.9678
Lyon	0.9345	1.0460	1.0000	1.0000	1.0012
Dusseldorf	0.9703	1.0000	1.0000	0.8753	0.8135
Bologna	0.9727	1.0969	0.9409	1.1443	1.0115
Hamburg	0.9417	1.1900	1.0107	0.9884	0.7810
St. Petersbrg	1.1296	0.9250	0.9500	1.0211	1.0578
Merseille	0.9966	0.9883	1.1434	0.9861	0.9027
Geneva	1.0000	1.0000	1.0000	1.0000	1.0000
Budapest	0.9678	0.9510	0.9702	1.0025	1.0063
Manchester	0.9642	1.0000	1.0000	1.0000	1.0000
Amsterdam	0.9588	1.0585	0.9895	1.0991	1.0682
Vienna	0.9751	0.9634	0.9714	1.0125	1.0291
Warsaw	0.9373	1.0009	0.9060	0.9866	0.9159
Lisbon	1.0000	0.9780	0.9742	0.9928	0.9631
Bucharest	1.0000	1.0000	1.0000	1.0416	1.0000
Krakow	0.9047	0.9889	0.9997	0.9936	0.9985
Bratislava	1.0000	0.9725	1.0121	1.0075	0.9855
Helsinki	0.9629	1.0000	1.0080	1.0000	0.9212
Stockholm	1.0000	1.0000	1.0000	1.0000	1.0000
London	1.0038	1.0575	0.9845	0.9986	1.0138
Zaragoza	1.0000	1.0000	1.0000	1.0000	1.0000
Oslo	0.9762	1.0000	1.0000	1.0000	0.9973
Zurich	0.9458	0.9445	1.0551	1.0159	0.9483
Moscow	1.0000	1.0000	1.0000	1.0000	1.0000
Kiev	1.0000	1.0000	1.0000	1.0000	1.0000
Rome	1.0000	1.0000	1.0000	1.0000	1.0000
Ankara	0.9924	1.0039	1.0088	0.9616	1.0000

Table B7(a). Productivity change for the 35 European smart cities over the years from 2015 till 2020 under the economic dynamism dimension

Smart cities	Optimistic MPI				
	2015/16	2016/17	2017/18	2018/19	2019/20
Brussels	1.1478	0.8785	1.0631	0.9504	0.9522
Sofia	1.0503	0.9602	1.0157	0.9743	0.9727
Prague	1.1041	0.9158	1.0276	0.9656	0.9569
Copenhagen	1.1261	0.8542	1.0446	0.9602	0.9121
Munich	1.2940	0.9208	0.9584	0.9425	0.8682
Tallinn	1.0685	0.9598	1.0091	0.9489	0.9839
Dublin	1.2124	0.7714	1.0102	1.0165	0.9794
Athens	1.0166	0.9249	0.9903	0.9546	1.0480
Bilbao	1.1701	0.8111	0.9633	0.9628	0.9287
Lyon	0.8989	0.9396	1.0790	0.9177	0.8523
Dusseldorf	1.0388	0.9496	0.9759	0.9940	0.9912
Bologna	1.0973	0.8687	1.0298	0.9396	0.8938
Hamburg	1.0125	0.9054	0.8273	0.8927	1.0259
St. Petersbrg	0.9660	0.9639	1.0038	0.9560	0.9181
Merseille	0.9723	0.9560	0.9639	0.9809	0.9601
Geneva	0.9829	1.0000	1.0000	1.0000	1.0000
Budapest	0.9729	0.9505	1.0653	0.9308	0.9448
Manchester	1.2412	0.8579	1.0214	0.9631	0.8325
Amsterdam	1.1441	0.7582	1.1315	0.9594	0.9159
Vienna	1.1120	0.8808	0.9950	0.9863	0.9071
Warsaw	1.0492	0.9167	1.0820	0.9848	0.9099
Lisbon	1.0302	0.8768	0.9708	0.9452	0.9629
Bucharest	1.0261	0.9432	0.9678	0.9478	0.9835
Krakow	1.1175	0.9477	1.0272	0.9354	0.9806
Bratislava	0.9094	0.8935	1.0455	0.9606	1.0964
Helsinki	1.2995	0.8453	0.9885	0.9216	0.8763
Stockholm	1.1700	0.7791	1.0354	0.9734	0.9493
London	0.9850	0.9151	1.0641	0.9996	0.9077
Zaragoza	0.9800	0.8713	1.1100	0.9038	0.8735
Oslo	1.0030	0.9212	1.0485	0.9984	0.9491
Zurich	1.1102	0.8921	1.0451	0.9997	0.9541
Moscow	1.0794	0.9386	0.9862	0.9524	0.9160
Kiev	0.9293	0.8740	0.9442	0.9949	0.9969
Rome	0.9610	0.9763	0.9803	0.9581	0.8940
Ankara	1.0444	0.9287	0.9892	0.9994	0.9344

Table B7(b). Productivity change for the 35 European smart cities over the years from 2015 till 2020 under the economic dynamism dimension

Smart cities	Pessimistic MPI				
	2015/16	2016/17	2017/18	2018/19	2019/20
Brussels	1.3093	0.8212	1.0922	0.9222	0.9654
Sofia	1.1314	0.9063	1.0000	0.9963	1.0000
Prague	1.2423	0.8203	1.0052	0.9367	0.8942
Copenhagen	1.1314	0.8180	1.0637	0.9575	0.8814
Munich	1.5152	0.7895	0.9459	0.9246	0.8458
Tallinn	1.4276	0.8482	1.0890	1.0092	0.9300
Dublin	1.1927	0.8623	0.9891	1.0306	1.0252
Athens	1.0000	0.9964	1.0000	0.9830	1.0000
Bilbao	1.3975	0.7116	0.9421	0.9386	0.8516
Lyon	0.8795	0.9308	1.2164	0.8370	0.8655
Dusseldorf	1.2814	0.8529	0.9025	0.9848	0.8609
Bologna	1.3357	0.7824	1.0492	0.9009	0.8240
Hamburg	1.0989	1.0000	0.6555	0.8911	0.9999
St. Petersbrg	1.0753	0.9054	1.1938	0.6469	0.9483
Merseille	1.2931	0.8054	1.0028	1.0342	1.0267
Geneva	1.1242	0.9778	1.0777	0.5544	0.9340
Budapest	1.2229	0.7194	1.7145	0.5990	0.8937
Manchester	1.0000	0.9847	1.1223	1.2224	1.0000
Amsterdam	1.2321	0.6688	1.1685	0.9385	0.8606
Vienna	1.1593	0.8259	0.9982	0.9880	0.8468
Warsaw	1.1710	0.8334	1.1443	0.9711	0.8006
Lisbon	1.2086	0.7556	0.9526	0.7995	0.8482
Bucharest	1.4003	0.7957	1.0150	0.9206	0.8884
Krakow	1.2471	0.8773	0.9740	0.9333	0.7613
Bratislava	1.1213	0.8215	1.2381	0.9437	1.3417
Helsinki	1.3472	0.8425	1.0068	0.9138	0.8737
Stockholm	1.1741	0.7904	1.0588	0.9691	0.9152
London	1.0723	0.8271	1.1059	0.9995	0.8450
Zaragoza	0.9775	0.8007	1.1795	0.8481	0.7940
Oslo	1.0032	0.9371	1.0586	0.9971	0.9550
Zurich	1.2985	0.7451	1.0638	0.9858	0.9096
Moscow	1.1511	0.9268	1.0078	0.9768	0.8889
Kiev	0.8954	0.7712	1.2443	1.0258	1.0208
Rome	0.9459	0.8390	0.9679	0.7902	0.4331
Ankara	1.2020	0.7399	0.9094	0.8747	0.8846

Table B8(a). Productivity change for the 35 European smart cities over the years from 2015 till 2020 under the governance and institution dimension

Smart cities	Optimistic MPI				
	2015/16	2016/17	2017/18	2018/19	2019/20
Brussels	1.0049	1.0215	1.0092	0.9828	0.9878
Sofia	0.9076	1.0159	0.9116	0.9875	1.0139
Prague	1.0583	0.9410	1.0682	1.0000	0.9789
Copenhagen	1.0126	0.9515	1.0218	0.9187	0.9793
Munich	0.9550	0.9996	1.0149	0.9871	1.0015
Tallinn	0.8627	1.0569	0.9912	0.9708	0.9517
Dublin	0.9171	1.0312	0.9728	0.9941	1.0570
Athens	1.0224	1.0120	0.9084	1.0292	0.9034
Bilbao	0.9382	0.9738	0.9793	0.9914	0.9713
Lyon	1.0012	1.0263	0.9734	1.0025	0.9986
Dusseldorf	1.0242	1.0197	0.9903	0.9549	1.0389
Bologna	1.0324	0.9958	0.9990	0.9746	0.9881
Hamburg	1.1302	0.9317	0.9716	0.9390	0.9867
St. Petersbrg	0.9759	0.9773	1.1818	1.0309	2.3088
Merseille	1.0209	1.0166	1.0897	1.0878	0.9947
Geneva	1.0685	0.9687	0.9813	0.9716	1.0226
Budapest	1.0134	0.9188	0.9739	1.0355	0.9811
Manchester	1.0363	1.0258	1.0137	0.9245	0.9911
Amsterdam	0.8892	1.0528	0.8394	0.9702	0.9874
Vienna	1.0381	0.9650	0.9962	0.9699	1.0099
Warsaw	0.9616	0.9918	1.0670	0.9769	0.9380
Lisbon	0.9558	0.9658	1.0128	1.0045	0.9559
Bucharest	1.2804	1.0760	1.0347	0.8839	1.0957
Krakow	0.8919	0.9249	1.0135	0.9142	0.9480
Bratislava	0.9840	0.9632	0.9810	0.9735	0.9956
Helsinki	1.0000	1.0448	1.1742	0.8997	1.0489
Stockholm	1.0065	0.9737	1.0438	1.0034	0.9391
London	0.9775	1.0614	0.9568	0.9946	0.9370
Zaragoza	1.2044	0.7843	1.0111	1.0068	0.9827
Oslo	1.0800	0.9168	0.9858	0.9924	0.9825
Zurich	1.0906	0.8778	1.0383	0.9469	1.0304
Moscow	0.6660	0.9885	0.9979	0.9347	0.9968
Kiev	0.4909	0.8977	0.8821	1.0354	0.9274
Rome	0.9047	1.0080	0.9705	1.0219	1.0922
Ankara	0.8641	1.2680	1.3121	0.8583	1.3633

Table B8(b). Productivity change for the 35 European smart cities over the years from 2015 till 2020 under the governance and institution dimension

Smart cities	Pessimistic MPI				
	2015/16	2016/17	2017/18	2018/19	2019/20
Brussels	1.0000	1.0000	1.0000	1.0000	1.0000
Sofia	0.9100	1.0966	0.9265	0.9930	0.9960
Prague	1.0450	0.9589	1.0000	1.0000	1.0000
Copenhagen	0.9900	0.9557	1.0181	0.8999	0.9902
Munich	1.0290	0.9496	0.9998	0.9710	1.1473
Tallinn	1.0137	0.9931	1.0149	0.9864	0.9448
Dublin	0.9186	1.0103	0.9362	1.0177	1.0366
Athens	1.0030	0.9997	0.9295	1.0262	0.9233
Bilbao	1.0376	0.9886	0.9667	0.9927	0.9153
Lyon	0.9571	1.0610	0.9823	1.0411	1.0020
Dusseldorf	1.0000	1.0000	1.0000	1.0000	1.0000
Bologna	1.0634	0.9667	1.0470	0.9615	0.9847
Hamburg	1.0445	0.9203	0.9857	0.9777	0.9785
St. Petersbrg	1.0138	1.0313	1.1409	0.8989	0.8769
Merseille	1.0291	1.1070	1.0641	1.0625	0.9951
Geneva	0.9582	0.9351	0.9898	0.9853	1.1493
Budapest	1.0219	0.8553	0.9959	1.0243	0.9485
Manchester	1.0320	1.0000	1.0000	0.9505	1.0000
Amsterdam	0.8828	1.0511	0.8930	0.9687	1.0201
Vienna	1.0355	0.9211	1.0270	1.0147	0.9735
Warsaw	1.0337	1.0082	1.0353	0.9591	0.9282
Lisbon	1.0095	0.9893	1.0486	0.9839	0.9678
Bucharest	1.0000	1.0474	1.0000	1.0000	1.0000
Krakow	0.9359	0.8488	1.0399	1.0401	0.9626
Bratislava	0.9873	0.9603	1.0000	0.9226	0.9334
Helsinki	0.9922	1.0153	1.0000	0.9700	1.0000
Stockholm	1.0000	0.9569	1.1409	0.9856	0.8926
London	1.0466	1.0403	0.9519	1.0010	0.9961
Zaragoza	1.2399	0.7791	0.9708	1.0919	1.0483
Oslo	1.0980	0.9495	1.0118	1.0107	0.9275
Zurich	1.1274	0.8296	1.0701	0.9610	1.0559
Moscow	0.9500	1.0000	1.0000	1.0000	1.0000
Kiev	1.0000	1.0000	1.0000	1.0000	1.0000
Rome	0.9965	1.1651	1.0611	0.8587	0.9515
Ankara	1.0000	1.0000	1.0000	1.0000	1.0000

Table B9(a). Productivity change for the 35 European smart cities over the years from 2015 till 2020 under the social cohesion and solidarity dimension

Smart cities	Optimistic MPI				
	2015/16	2016/17	2017/18	2018/19	2019/20
Brussels	1.3605	0.7262	1.1512	0.5627	0.5974
Sofia	1.0053	0.9953	0.9675	0.9917	1.0105
Prague	0.9967	1.0140	1.0247	0.9861	1.0051
Copenhagen	0.9670	1.0287	0.9645	0.9887	0.9933
Munich	0.9948	1.0000	1.0000	1.0000	1.0000
Tallinn	0.9788	0.9583	0.9746	1.0410	0.9982
Dublin	1.0000	1.1339	1.3989	1.0000	1.0000
Athens	0.9794	1.0130	0.9672	0.9670	0.8934
Bilbao	0.9915	1.0170	1.0000	1.0987	0.8988
Lyon	1.0608	0.9586	1.0417	0.9916	0.9934
Dusseldorf	0.9091	0.9978	1.0362	0.9830	1.0302
Bologna	0.9948	1.0000	0.8588	1.0097	1.0000
Hamburg	1.2436	0.6118	1.1931	0.9580	1.2999
St. Petersbrg	0.9893	1.0281	0.9885	1.0746	0.9655
Merseille	0.9679	1.0261	0.9993	1.0293	0.9667
Geneva	1.0000	1.0174	1.0735	0.9677	1.0000
Budapest	1.0013	0.9968	0.9693	1.0138	0.9818
Manchester	0.9955	1.0000	1.0000	0.9900	1.1043
Amsterdam	1.0000	1.0000	0.9932	1.0000	1.0000
Vienna	1.0105	0.9840	1.0201	1.0284	0.9784
Warsaw	1.0337	1.0166	0.9982	1.0131	1.0211
Lisbon	1.0680	0.9357	0.9212	1.0038	0.9822
Bucharest	0.9869	0.9826	1.0023	0.9781	0.9925
Krakow	1.0358	1.0238	1.0054	1.0251	1.0094
Bratislava	1.0130	0.9937	1.0183	0.9697	0.9628
Helsinki	1.0484	1.1326	0.9141	1.1054	0.9440
Stockholm	1.1759	0.9714	1.0000	1.0000	1.0000
London	0.9908	1.0000	0.9751	0.5525	0.9836
Zaragoza	1.4495	0.7032	0.9838	1.0067	0.9933
Oslo	1.1243	1.1449	0.9969	0.9452	1.0000
Zurich	1.0200	1.0000	1.0000	1.0000	1.0000
Moscow	1.0629	1.1475	0.8559	0.9576	1.0000
Kiev	0.3446	0.6827	0.6942	3.4868	1.0893
Rome	0.8887	1.0052	1.0025	1.0388	0.9615
Ankara	0.9919	1.0348	0.9413	1.0305	1.0286

Table B9(b). Productivity change for the 35 European smart cities over the years from 2015 till 2020 under the Social cohesion and solidarity dimension

Smart cities	Pessimistic MPI				
	2015/16	2016/17	2017/18	2018/19	2019/20
Brussels	1.0000	1.0000	1.0231	0.9075	1.0115
Sofia	0.9913	1.0023	0.9947	0.9905	1.0048
Prague	1.0000	1.0000	0.9731	1.0000	1.0000
Copenhagen	0.9964	1.0084	0.9911	1.0006	0.9977
Munich	1.0000	1.0000	1.0000	1.0000	1.0000
Tallinn	1.0000	1.0000	1.0000	0.9986	1.0000
Dublin	1.1412	1.0000	0.9727	1.0000	1.0134
Athens	0.9953	0.9949	0.9612	0.9607	0.9726
Bilbao	1.0162	0.9128	0.9994	0.9472	0.9693
Lyon	0.9826	1.0684	0.9956	0.9750	0.9961
Dusseldorf	1.0000	1.0000	1.0000	1.0000	0.9204
Bologna	1.0000	1.0000	1.0336	0.8859	0.9808
Hamburg	1.0000	0.9973	1.0000	0.9977	1.0000
St. Petersbrg	0.9917	0.9336	1.0000	1.0123	0.9936
Merseille	1.0000	1.0000	1.0000	1.0000	1.0000
Geneva	1.0000	1.0511	1.0017	1.0000	1.0028
Budapest	1.0031	0.9809	0.9908	0.9991	0.9997
Manchester	0.9983	1.0000	1.0000	0.9989	1.0000
Amsterdam	1.0000	1.1336	1.0000	1.0000	1.0188
Vienna	1.0058	0.9949	1.0068	1.0018	0.7819
Warsaw	1.0130	0.9983	1.0067	0.9984	1.0004
Lisbon	1.0000	1.0000	1.0000	1.0000	1.0000
Bucharest	0.9964	0.9927	1.0044	1.0015	0.9959
Krakow	1.0000	0.9453	1.0000	1.0000	1.0000
Bratislava	1.0077	0.9943	1.0087	0.9940	0.9956
Helsinki	1.0465	1.0322	1.0000	1.0000	1.0000
Stockholm	0.9835	0.9996	0.9954	1.0165	1.0005
London	1.0568	1.0414	0.9542	1.0176	0.9640
Zaragoza	1.0000	1.0000	1.0000	1.0000	1.0000
Oslo	1.0000	1.0000	1.0000	1.0000	1.0000
Zurich	1.0024	1.0000	1.0000	1.0000	1.0164
Moscow	1.0000	1.0000	1.0000	1.0000	1.0000
Kiev	1.0000	1.0000	0.9020	1.0000	1.0000
Rome	0.9964	1.0000	1.0000	1.0000	1.0000
Ankara	0.9965	1.0033	0.9750	1.0054	1.0066

Table B10(a). Productivity change for the 35 European smart cities over the years from 2015 till 2020 under the energy and environmental resource dimension

Smart cities	Optimistic MPI				
	2015/16	2016/17	2017/18	2018/19	2019/20
Brussels	0.9800	1.0483	0.9516	0.9927	1.0553
Sofia	0.9791	1.0167	1.0367	0.9860	0.9919
Prague	1.0171	1.0130	1.0175	1.0185	0.9920
Copenhagen	1.0000	1.0100	0.9915	1.0000	1.0011
Munich	1.0000	0.8691	1.0072	1.0000	1.0000
Tallinn	1.0019	1.0769	0.9283	1.0750	0.9511
Dublin	1.0075	1.0178	0.9900	1.0189	1.0222
Athens	1.0290	1.0614	1.0256	0.9913	0.9806
Bilbao	0.9969	0.9781	1.0175	0.9775	1.0371
Lyon	0.9832	1.0005	1.0280	1.0004	0.9851
Dusseldorf	1.0046	1.0011	0.9851	1.0976	0.9935
Bologna	1.0179	0.9904	1.0006	0.9878	1.0213
Hamburg	0.9627	0.9789	0.9397	0.9826	0.9827
St. Petersbrg	0.9708	1.0750	0.8023	0.8052	1.2470
Merseille	1.0244	1.0045	1.0072	1.0271	1.0575
Geneva	0.5659	0.9128	0.9877	1.2296	0.7386
Budapest	0.9946	1.0142	0.9921	1.0402	0.9820
Manchester	1.0518	1.1392	1.1277	0.8098	1.0583
Amsterdam	0.9646	1.0083	0.9974	1.0131	1.0012
Vienna	0.9640	1.0071	1.0037	1.0022	0.9957
Warsaw	1.0208	1.0053	1.0203	1.0229	0.9995
Lisbon	1.0101	0.9712	1.0035	0.9798	1.0271
Bucharest	1.0052	0.9897	1.0170	0.9878	1.0101
Krakow	1.0096	1.1478	0.9785	1.0083	0.9962
Bratislava	1.0495	0.9652	1.0093	1.0587	1.0165
Helsinki	0.6779	1.0406	1.2906	1.6301	0.9755
Stockholm	0.9715	1.0674	0.9974	0.9793	0.9927
London	0.7999	1.8477	1.5314	2.2704	1.3017
Zaragoza	0.9913	1.0000	1.0000	1.0000	0.9742
Oslo	1.0000	1.0000	1.0000	1.0000	1.0337
Zurich	0.9021	0.9853	1.1869	1.0536	1.0005
Moscow	1.1065	0.9086	0.9255	0.8804	0.8832
Kiev	1.1250	1.0702	0.9476	0.9545	1.0772
Rome	1.1065	0.9293	1.0153	1.0587	1.0092
Ankara	0.9616	1.0093	0.9881	1.0085	0.9885

Table B10(b). Productivity change for the 35 European smart cities from 2015 till 2020 under the energy and environmental resource dimension

Smart cities	Pessimistic MPI				
	2015/16	2016/17	2017/18	2018/19	2019/20
Brussels	0.9665	1.0505	0.9656	0.9907	1.0398
Sofia	0.9756	1.0157	1.0365	0.9871	0.9968
Prague	0.9817	1.0179	1.0247	1.0178	0.9888
Copenhagen	1.0300	1.0316	1.0436	1.0009	1.0092
Munich	0.9737	0.9548	1.0189	1.0933	0.9793
Tallinn	0.9981	1.0502	0.9447	1.0527	0.9652
Dublin	1.0452	1.1250	0.9549	1.0697	1.0549
Athens	1.0278	1.0596	1.0250	0.9915	0.9814
Bilbao	0.9971	0.9788	1.0166	0.9783	1.0354
Lyon	1.0291	0.9775	0.9676	1.0345	0.9702
Dusseldorf	1.0135	0.9907	0.9852	1.0966	0.9947
Bologna	1.0144	0.9925	0.9987	0.9894	1.0186
Hamburg	0.9746	0.9850	0.9575	0.9867	0.9866
St. Petersbrg	1.0169	0.9637	1.0111	1.0105	1.0000
Merseille	1.0215	1.0041	1.0065	1.0219	1.0572
Geneva	1.1861	0.9684	1.0051	1.1433	0.8694
Budapest	0.9916	1.0134	0.9924	1.0416	0.9803
Manchester	1.1227	1.0396	1.0212	0.9461	0.9949
Amsterdam	0.9649	1.0075	0.9975	1.0119	1.0011
Vienna	0.9889	0.9957	0.9933	1.0023	0.9975
Warsaw	1.0182	1.0049	1.0187	1.0212	0.9999
Lisbon	1.0159	0.9752	1.0046	0.9807	1.0241
Bucharest	1.0052	0.9898	1.0170	0.9889	1.0100
Krakow	1.0149	1.1414	0.9525	1.0163	0.9894
Bratislava	1.0549	0.9655	1.0087	1.0580	1.0169
Helsinki	0.9510	1.0210	1.0413	1.0698	0.9963
Stockholm	0.9729	1.0516	0.9962	0.9878	0.9888
London	1.0304	1.1742	0.9713	1.2932	0.9356
Zaragoza	0.9357	1.0449	1.0654	1.0225	1.0616
Oslo	1.0778	0.9952	1.5492	1.0105	1.0067
Zurich	0.9580	1.0113	1.0695	1.0139	1.0126
Moscow	0.9754	0.9883	1.0268	0.9775	0.9999
Kiev	1.0258	1.0952	0.9641	0.9727	1.0718
Rome	1.1052	0.9300	1.0145	1.0442	1.0210
Ankara	0.9629	1.0087	0.9884	1.0079	0.9890

Table B11 (a). Productivity change for the 35 European smart cities over the years from 2015 till 2020 under the safety and security dimension

Smart cities	Optimistic MPI				
	2015/16	2016/17	2017/18	2018/19	2019/20
Brussels	1.0156	1.0630	0.8376	1.0366	0.9094
Sofia	1.0160	1.0956	1.0000	0.9587	0.9528
Prague	0.9708	0.9951	0.9667	1.0404	1.0783
Copenhagen	1.1579	0.9425	0.9980	1.0116	1.0893
Munich	0.9196	1.0197	1.0391	0.9971	0.9568
Tallinn	1.0000	0.9873	1.0592	1.0000	1.0000
Dublin	0.9292	1.0490	1.0244	0.9904	1.0635
Athens	1.0461	1.0180	0.9090	1.0460	0.9445
Bilbao	1.0223	0.9968	1.0164	0.9944	0.9815
Lyon	0.9755	1.0666	0.9445	1.0247	0.9367
Dusseldorf	0.7945	1.0964	0.6743	1.3310	1.0288
Bologna	0.9736	0.9225	0.8812	0.9734	0.9643
Hamburg	1.0199	0.9753	1.0000	1.0386	0.8200
St. Petersbrg	1.0000	1.0000	1.0000	1.0000	1.0000
Merseille	1.0000	0.7186	1.2941	0.6918	1.2970
Geneva	0.9558	0.9957	0.7646	1.0491	0.8326
Budapest	1.0078	1.0438	1.0671	1.0584	0.9721
Manchester	0.8780	1.0348	1.0704	1.1166	0.8154
Amsterdam	0.9796	1.0011	0.9908	0.9825	0.9794
Vienna	1.0281	0.9529	1.0447	0.8217	0.9661
Warsaw	0.9093	0.8697	0.8098	1.0414	1.0635
Lisbon	0.8973	1.0270	1.0488	0.9486	1.0750
Bucharest	1.0811	1.0000	1.0000	1.0000	1.0394
Krakow	0.9349	1.0641	1.0149	0.9791	1.0451
Bratislava	1.0253	0.9737	1.1546	1.0539	1.0355
Helsinki	1.0512	1.0676	0.9574	1.0192	0.9014
Stockholm	0.9216	1.0419	1.0193	1.0099	1.0079
London	1.0098	0.9560	0.9534	1.0730	0.9217
Zaragoza	1.0116	0.8758	1.0778	0.8348	0.8319
Oslo	1.0544	0.8506	0.9710	1.0622	0.9650
Zurich	0.9523	0.9322	0.9333	1.0036	1.0703
Moscow	1.0095	0.9228	1.0581	0.8770	0.7667
Kiev	1.0509	1.0647	1.0827	0.9520	1.2120
Rome	1.0226	0.9345	0.9884	1.1268	0.9404
Ankara	0.9835	1.0727	0.9028	1.0696	0.9258

Table B11 (b). Productivity change for the 35 European smart cities over the years from 2015 till 2020 under the safety and security dimension

Smart cities	Pessimistic MPI				
	2015/16	2016/17	2017/18	2018/19	2019/20
Brussels	1.0204	1.1079	0.7932	0.9990	0.8728
Sofia	1.0000	1.0000	1.0018	1.0863	1.0000
Prague	1.0000	1.0000	1.0690	0.9487	1.0000
Copenhagen	1.2902	0.7658	1.1453	0.8538	1.1039
Munich	0.9351	1.0477	0.9848	0.9583	1.0106
Tallinn	0.7442	1.2205	0.9944	1.2946	0.6759
Dublin	0.7537	1.2085	1.0398	0.8968	1.1328
Athens	0.8792	1.6788	0.4734	0.9633	0.9489
Bilbao	0.9088	1.0213	1.1087	0.9398	1.0413
Lyon	0.8734	1.0596	0.8363	1.0687	0.8800
Dusseldorf	1.0000	1.0000	1.0782	1.0000	1.0000
Bologna	0.8623	0.7186	0.6839	0.9409	0.9457
Hamburg	1.0000	1.0000	1.0000	1.0000	0.9018
St. Petersbrg	1.0612	0.8541	0.8976	0.9580	0.8009
Merseille	1.0000	1.0547	0.8022	1.0676	1.0000
Geneva	1.0801	0.9254	0.6142	1.5278	0.5663
Budapest	0.9795	1.0561	1.0133	1.0000	1.0000
Manchester	0.6389	1.0624	1.1202	1.0281	0.8141
Amsterdam	0.9462	1.1107	0.9702	0.9701	1.1335
Vienna	1.0680	0.8698	1.0707	0.8151	0.9369
Warsaw	0.8983	1.1788	0.7989	1.0981	1.1973
Lisbon	0.7974	0.9860	1.0397	0.8876	1.1260
Bucharest	1.0000	1.0000	1.0307	1.2563	0.9667
Krakow	0.7790	1.4367	1.0788	0.8529	1.1387
Bratislava	1.0001	1.0000	1.0810	1.0000	1.0000
Helsinki	0.7756	0.9716	1.0000	1.0000	0.9834
Stockholm	0.9057	1.0003	1.0116	0.9913	1.1187
London	1.1302	0.8472	0.9285	1.0804	0.8733
Zaragoza	1.0000	1.0000	1.0000	1.0000	1.3480
Oslo	0.9590	0.6823	0.7317	1.3291	0.9195
Zurich	1.0137	0.7569	0.6970	1.2426	0.7122
Moscow	1.0000	1.0000	1.0000	1.0000	1.0000
Kiev	1.0604	0.9929	1.0077	1.0565	1.0000
Rome	0.9563	0.7117	0.9638	1.4214	0.8689
Ankara	0.8668	1.0000	1.0000	1.0000	0.8813

Table B12(a). Results for the comparative analysis on the overall change in productivity over time under the climate change dimension

Smart Cities	2015/2020 Optimistic MPI	2015/2020 Pessimistic MPI	DF-Malmquist index	Rank
Brussels	1.00948	1.00826	1.00887	11
Sofia	0.98892	0.98808	0.98850	19
Prague	0.86320	1.00940	0.93344	34
Copenhagen	0.97696	0.98135	0.97916	21
Munich	0.95775	0.98538	0.97147	23
Tallinn	1.07524	0.99480	1.03424	4
Dublin	0.93754	0.96411	0.95073	30
Athens	0.86595	1.03631	0.94731	32
Bilbao	0.98123	0.99725	0.98921	18
Lyon	0.91599	0.99633	0.95532	29
Dusseldorf	1.07517	0.93182	1.00093	14
Bologna	0.97839	1.03326	1.00545	12
Hamburg	1.08537	0.98237	1.03259	5
Petersburg	0.94327	1.01671	0.97930	20
Merseille	1.00544	1.00342	1.00443	13
Geneva	1.09085	1.00000	1.04444	2
Budapest	0.96127	0.97956	0.97037	24
Manchester	0.92367	0.99284	0.95763	28
Amsterdam	1.00000	1.03480	1.01725	7
Vienna	1.00661	0.99033	0.99844	17
Warsaw	0.98627	0.94933	0.96762	25
Lisbon	0.91559	0.98162	0.94803	31
Bucharest	0.86603	1.00832	0.93447	33
Krakow	0.95568	0.97710	0.96633	26
Bratislava	0.93029	0.99552	0.96235	27
Helsinki	0.97244	0.97843	0.97543	22
Stockholm	1.08923	1.00000	1.04366	3
London	1.01431	1.01165	1.01298	10
Zaragoza	1.00000	1.00000	1.00000	16
Oslo	1.00577	0.99471	1.00023	15
Zurich	1.05002	0.98191	1.01540	8
Moscow	0.83070	1.00000	0.91143	35
Kiev	1.03064	1.00000	1.01521	9
Rome	2.19852	1.00000	1.48274	1
Ankara	1.06002	0.99334	1.02614	6

Table B13 (a). Results for the comparative study on the overall change in productivity over time under the Economic dynamism dimension

Smart Cities	2015/2020 Optimistic MPI	2015/2020 Pessimistic MPI	DF-Malmquist Index	Rank
Brussels	0.99839	1.02206	1.01016	4
Sofia	0.99463	1.00681	1.00070	7
Prague	0.99401	0.97976	0.98686	15
Copenhagen	0.97944	0.97041	0.97491	22
Munich	0.99679	1.00418	1.00048	8
Tallinn	0.99403	1.06078	1.02686	2
Dublin	0.99799	1.01997	1.00892	5
Athens	0.98689	0.99588	0.99138	12
Bilbao	0.96722	0.96828	0.96775	27
Lyon	0.93750	0.94584	0.94166	31
Dusseldorf	0.98991	0.97651	0.98318	17
Bologna	0.96583	0.97845	0.97212	24
Hamburg	0.93276	0.92908	0.93092	34
Petersburg	0.96153	0.95393	0.95772	29
Merseille	0.96665	1.03243	0.99900	10
Geneva	0.99658	0.93360	0.96458	28
Budapest	0.97285	1.02988	1.00096	6
Manchester	0.98322	1.06588	1.02372	3
Amsterdam	0.98184	0.97369	0.97776	21
Vienna	0.97626	0.96363	0.96993	25
Warsaw	0.98853	0.98410	0.98631	16
Lisbon	0.95719	0.91291	0.93478	32
Bucharest	0.97367	1.00401	0.98872	13
Krakow	1.00167	0.95861	0.97990	20
Bratislava	0.98108	1.09325	1.03565	1
Helsinki	0.98623	0.99679	0.99150	11
Stockholm	0.98145	0.98153	0.98149	19
London	0.97431	0.96998	0.97214	23
Zaragoza	0.94771	0.91995	0.93373	33
Oslo	0.98407	0.99019	0.98713	14
Zurich	1.00024	1.00057	1.00040	9
Moscow	0.97451	0.99027	0.98236	18
Kiev	0.94787	0.99149	0.96943	26
Rome	0.95395	0.79524	0.87099	35
Ankara	0.97922	0.92211	0.95023	30

Table B14 (a). Results for the comparative study on the overall change in productivity over time under the Governance and Institution dimension

Smart Cities	2015/2020 Optimistic MPI	2015/2020 Pessimistic MPI	DF-Malmquist Index (DF-MPI)	Rank
Brussels	1.00124	1.00000	1.00062	15
Sofia	0.96731	0.98443	0.97584	27
Prague	1.00930	1.00079	1.00504	8
Copenhagen	0.97679	0.97079	0.97379	30
Munich	0.99161	1.01935	1.00538	7
Tallinn	0.96667	0.99057	0.97855	25
Dublin	0.99443	0.98390	0.98915	23
Athens	0.97509	0.97634	0.97571	28
Bilbao	0.97079	0.98021	0.97549	29
Lyon	1.00040	1.00870	1.00454	9
Dusseldorf	1.00561	1.00000	1.00280	12
Bologna	0.99797	1.00465	1.00131	14
Hamburg	0.99184	0.98133	0.98657	24
Petersburg	1.29493	0.99236	1.13360	1
Merseille	1.04193	1.05156	1.04673	3
Geneva	1.00252	1.00357	1.00304	10
Budapest	0.98455	0.96918	0.97683	26
Manchester	0.99829	0.99649	0.99739	16
Amsterdam	0.94780	0.96312	0.95543	32
Vienna	0.99583	0.99438	0.99510	19
Warsaw	0.98707	0.99289	0.98997	21
Lisbon	0.97896	0.99984	0.98934	22
Bucharest	1.07416	1.00949	1.04132	4
Krakow	0.93849	0.96545	0.95187	34
Bratislava	0.97945	0.96071	0.97003	31
Helsinki	1.03354	0.99550	1.01434	5
Stockholm	0.99333	0.99519	0.99426	20
London	0.98548	1.00717	0.99627	17
Zaragoza	0.99787	1.02600	1.01183	6
Oslo	0.99150	0.99951	0.99550	18
Zurich	0.99681	1.00879	1.00278	13
Moscow	0.91676	0.98999	0.95267	33
Kiev	0.84671	1.00000	0.92017	35
Rome	0.99946	1.00659	1.00302	11
Ankara	1.13315	1.00000	1.06450	2

Table B15(a). Results for the comparative study on the overall change in productivity over time under the social cohesion and solidarity dimension

Smart Cities	2015/2020 Optimistic MPI	2015/2020 Pessimistic MPI	DF-Malmquist Index	Rank
Brussels	0.87959	0.98841	0.93242	35
Sofia	0.99405	0.99674	0.99539	22
Prague	1.00532	0.99461	0.99995	17
Copenhagen	0.98844	0.99885	0.99363	25
Munich	0.99896	1.00000	0.99948	18
Tallinn	0.99020	0.99971	0.99495	23
Dublin	1.10656	1.02547	1.06524	2
Athens	0.96401	0.97695	0.97046	33
Bilbao	1.00120	0.96900	0.98497	30
Lyon	1.00923	1.00354	1.00638	12
Dusseldorf	0.99124	0.98407	0.98765	29
Bologna	0.97266	0.98005	0.97635	32
Hamburg	1.06127	0.99900	1.02967	3
St. Petersburg	1.00920	0.98624	0.99766	20
Merseille	0.99784	1.00000	0.99892	19
Geneva	1.01172	1.01111	1.01142	9
Budapest	0.99262	0.99473	0.99367	24
Manchester	1.01795	0.99945	1.00866	11
Amsterdam	0.99864	1.03047	1.01443	6
Vienna	1.00428	0.95822	0.98098	31
Warsaw	1.01657	1.00338	1.00995	10
Lisbon	0.98218	1.00000	0.99105	27
Bucharest	0.98850	0.99818	0.99333	26
Krakow	1.01987	0.98906	1.00435	13
Bratislava	0.99151	1.00006	0.99578	21
Helsinki	1.02889	1.01575	1.02230	4
Stockholm	1.02946	0.99910	1.01417	7
London	0.90040	1.00682	0.95213	34
Zaragoza	1.02730	1.00000	1.01356	8
Oslo	1.04225	1.00000	1.02091	5
Zurich	1.00400	1.00374	1.00387	14
Moscow	1.00476	1.00000	1.00238	15
Kiev	1.25952	0.98040	1.11123	1
Rome	0.97934	0.99929	0.98926	28
Ankara	1.00543	0.99735	1.00138	16

Table B16(a). Results for the comparative study on the overall change in productivity over time under the Energy and Environmental resource dimension

Smart Cities	2015/2020 Optimistic MPI	2015/2020 Pessimistic MPI	DF-Malmquist Index	Rank
Brussels	1.00559	1.00263	1.00411	20
Sofia	1.00207	1.00234	1.00220	22
Prague	1.01163	1.00620	1.00891	17
Copenhagen	1.00051	1.02306	1.01172	15
Munich	0.97525	1.00401	0.98953	32
Tallinn	1.00663	1.00217	1.00439	18
Dublin	1.01127	1.04995	1.03043	5
Athens	1.01758	1.01707	1.01733	12
Bilbao	1.00143	1.00126	1.00134	24
Lyon	0.99942	0.99579	0.99761	27
Dusseldorf	1.01638	1.01616	1.01627	13
Bologna	1.00362	1.00274	1.00318	21
Hamburg	0.96931	0.97806	0.97368	33
St. Petersburg	0.98008	1.00044	0.99020	31
Merseille	1.02414	1.02224	1.02319	9
Geneva	0.88691	1.03443	0.95783	35
Budapest	1.00463	1.00385	1.00424	19
Manchester	1.03735	1.02488	1.03110	4
Amsterdam	0.99690	0.99658	0.99674	28
Vienna	0.99455	0.99556	0.99506	29
Warsaw	1.01375	1.01260	1.01317	14
Lisbon	0.99834	1.00009	0.99921	26
Bucharest	1.00197	1.00217	1.00207	23
Krakow	1.02808	1.02290	1.02549	7
Bratislava	1.01983	1.02080	1.02032	10
Helsinki	1.12295	1.01589	1.06808	2
Stockholm	1.00167	0.99945	1.00056	25
London	1.55020	1.08096	1.29449	1
Zaragoza	0.99310	1.02604	1.00943	16
Oslo	1.00674	1.12788	1.06559	3
Zurich	1.02568	1.01308	1.01936	11
Moscow	0.94084	0.99359	0.96686	34
Kiev	1.03490	1.02592	1.03040	6
Rome	1.02380	1.02298	1.02339	8
Ankara	0.99118	0.99141	0.99129	30

Table B17(a). Results for the comparative study on the overall change in productivity over time under the Safety and security dimension

Smart Cities	2015/2020 Optimistic MPI	2015/2020 Pessimistic MPI	DF-Malmquist Index	Rank
Brussels	0.97246	0.95867	0.96554	27
Sofia	1.00464	1.01763	1.01112	7
Prague	1.01027	1.00355	1.00690	9
Copenhagen	1.03986	1.03179	1.03582	3
Munich	0.98646	0.98731	0.98689	19
Tallinn	1.00930	0.98591	0.99754	14
Dublin	1.01130	1.00632	1.00881	8
Athens	0.99271	0.98872	0.99071	18
Bilbao	1.00227	1.00396	1.00311	11
Lyon	0.98960	0.94363	0.96634	26
Dusseldorf	0.98498	1.01563	1.00019	13
Bologna	0.94302	0.83028	0.88486	35
Hamburg	0.97075	0.98035	0.97554	23
Petersburg	1.00000	0.91436	0.95622	31
Merseille	1.00031	0.98489	0.99257	17
Geneva	0.91957	0.94277	0.93110	33
Budapest	1.02984	1.00978	1.01976	6
Manchester	0.98304	0.93274	0.95756	29
Amsterdam	0.98669	1.02617	1.00623	10
Vienna	0.96271	0.95211	0.95740	30
Warsaw	0.93874	1.03431	0.98537	20
Lisbon	0.99932	0.96734	0.98320	21
Bucharest	1.02410	1.05075	1.03734	2
Krakow	1.00761	1.05722	1.03212	5
Bratislava	1.04861	1.01620	1.03228	4
Helsinki	0.99933	0.94612	0.97236	24
Stockholm	1.00013	1.00552	1.00282	12
London	0.98278	0.97190	0.97732	22
Zaragoza	0.92636	1.06961	0.99541	15
Oslo	0.98067	0.92432	0.95208	32
Zurich	0.97834	0.88449	0.93023	34
Moscow	0.92681	1.00000	0.96271	28
Kiev	1.07247	1.02351	1.04770	1
Rome	1.00254	0.98443	0.99344	16
Ankara	0.99086	0.94963	0.97003	25

Table B18(a). Pairwise comparison matrix for sub-criteria of Sustainability main-criteria with SF numbers

		CC	GI	E	EE	SS	SW
DM1	CC	EI	AMI	AMI	VHI	HI	SMI
	GI	ALI	EI	EI	SLI	LI	VLI
	E	ALI	EI	EI	SLI	SLI	VLI
	EE	VLI	SMI	SMI	EI	LI	SLI
	SS	LI	HI	SMI	HI	EI	SMI
	SW	SLI	VHI	VHI	SMI	SLI	EI
DM2	CC	EI	AMI	VHI	AMI	SMI	HI
	GI	ALI	EI	EI	EI	VLI	ALI
	E	VLI	EI	EI	LI	VLI	VLI
	EE	ALI	EI	HI	EI	VLI	SLI
	SS	SLI	VHI	VHI	VHI	EI	SLI
	SW	LI	AMI	VHI	SMI	SMI	EI
DM3	CC	EI	AMI	AMI	VHI	HI	SMI
	GI	ALI	EI	EI	LI	LI	ALI
	E	ALI	EI	EI	LI	VLI	VLI
	EE	VLI	HI	HI	EI	VLI	SLI
	SS	LI	HI	VHI	VHI	EI	SMI
	SW	SLI	AMI	VHI	SMI	SLI	EI

Table B19 (a). Pairwise comparison matrix for sub-criteria of Resilience main-criteria with SF numbers

		S	EC	IB	IN
DM 1	S	EI	SMI	HI	AMI
	EC	SLI	EI	SMI	HI
	IB	LI	SLI	EI	EI
	IN	ALI	LI	EI	EI
DM 2	S	EI	HI	HI	AMI
	EC	LI	EI	SMI	VHI
	IB	LI	SLI	EI	SMI
	IN	ALI	VLI	SLI	EI
DM 3	S	EI	HI	HI	AMI
	EC	LI	EI	HI	VHI
	IB	LI	LI	EI	SMI
	IN	ALI	VLI	SLI	EI

Table B20(a). Pairwise comparison matrix for sub-criteria of urban liveability main-criteria with SF numbers

		AC	EV	CWB
DM 1	AC	EI	SLI	VLI
	EV	SMI	EI	LI
	CWB	VHI	HI	EI
DM 2	AC	EI	LI	ALI
	EV	HI	EI	LI
	CWB	AMI	HI	EI
DM 3	AC	EI	ALI	VLI
	EV	AMI	EI	SMI
	CWB	VHI	SLI	EI

Table B21 (a).Aggregated pairwise matrix for Sustainability sub-criteria

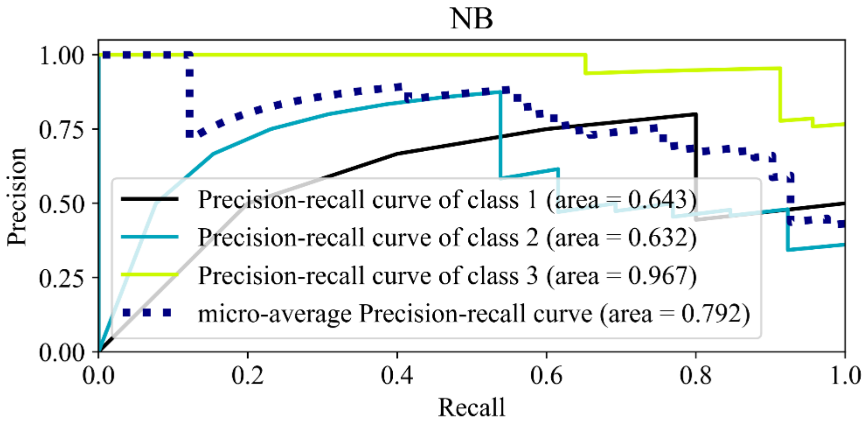
	CC	GI	E
CC	(0.50,0.40,0.40)	(0.90,0.10,0.00)	(0.87,0.13,0.00)
GI	(0.10,0.90,0.00)	(0.50,0. 40,0.40)	(0.50,0.40,0.40)
E	(0.13,0.87,0.00)	(0.50,0. 40,0.40)	(0.50,0.40,0.40)
EE	(0.16,0.83,0.00)	(0.59,0.39,0.29)	(0.66,0.33,0.23)
SS	(0.33,0.66,0.23)	(0.73,0.26,0.16)	(0.73,0.25,0.14)
SW	(0.36,0.63,0.26)	(0.87,0.13,0.00)	(0.80,0.20,0.10)
	EE	SS	SW
CC	(0.83,0.16,0.00)	(0.66,0.33,0.23)	(0.63,0.36,0.26)
GI	(0.39,0.55,0.29)	(0.26,0.73,0.16)	(0.13,0.87,0.00)
E	(0.33,0.66,0.23)	(0.25,0.73,0.14)	(0.20,0.80,0.10)
EE	(0.50,0.40,0.40)	(0.23,0.77, 0.13)	(0.40,0.60,0.30)
SS	(0.77,0.23,0.13)	(0.50,0.40,0.40)	(0.52,0.46,0.30)
SW	(0.60,0.40,0.30)	(0.46,0.52,0.30)	(0.50,0.40,0.40)

Table B22 (a).Aggregated pairwise matrix for Resilience sub-criteria

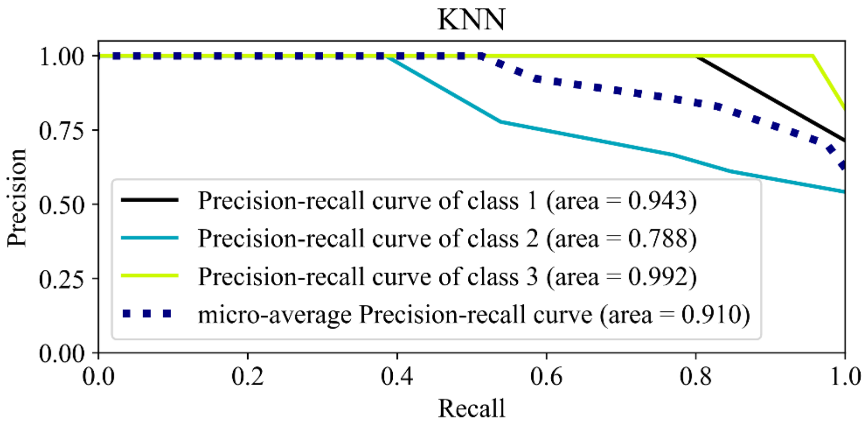
	S	EC	IB	IN
S	(0.50,0.40,0.40)	(0.66,0.33,0.23)	(0.70,0.30,0.20)	(0.90,0.10,0.00)
EC	(0.33,0.66,0.23)	(0.50,0.40,0.40)	(0.63,0.36,0.26)	(0.77,0.23,0.13)
IB	(0.30,0.70,0.20)	(0.36,0.63,0.26)	(0.50,0.40,0.40)	(0.56,0.40,0.33)
IN	(0.10,0.90,0.00)	(0.23,0.77,0.13)	(0.40,0.56,0.33)	(0.50,0.40,0.40)

Table B23 (a).Aggregated pairwise matrix for Urban liveability sub-criteria

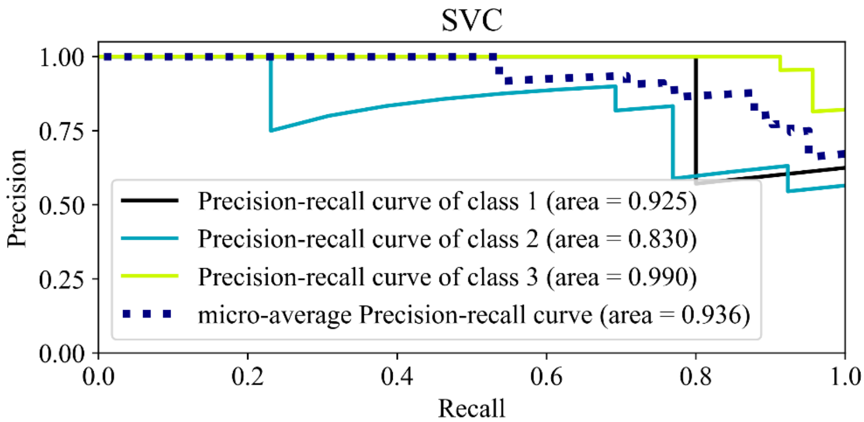
	AC	EV	CWB
AC	(0.50,0.40,0.40)	(0.23,0.72,0.00)	(0.16,0.83,0.00)
EV	(0.72,0.23,0.00)	(0.50,0.40,0.40)	(0.38,0.58,0.23)
CWB	(0.83,0.16,0.00)	(0.58,0.38,0.23)	(0.50,0.40,0.40)


NB
Precision
Recall
0.00
0.25
0.50
0.75
1.00
0.0
0.2
0.4
0.6
0.8
1.0
Precision-recall curve of class 1 (area = 0.643)
Precision-recall curve of class 2 (area = 0.632)
Precision-recall curve of class 3 (area = 0.967)
micro-average Precision-recall curve (area = 0.792)

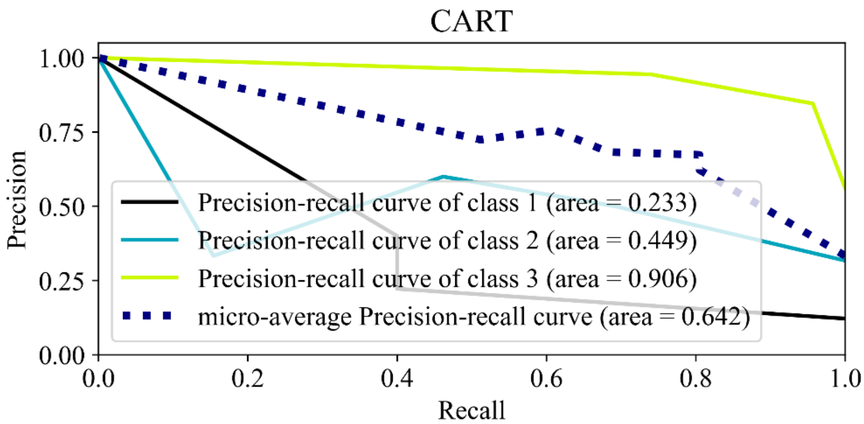
(a)


KNN
Precision
Recall
0.00
0.25
0.50
0.75
1.00
0.0
0.2
0.4
0.6
0.8
1.0
Precision-recall curve of class 1 (area = 0.943)
Precision-recall curve of class 2 (area = 0.788)
Precision-recall curve of class 3 (area = 0.992)
micro-average Precision-recall curve (area = 0.910)

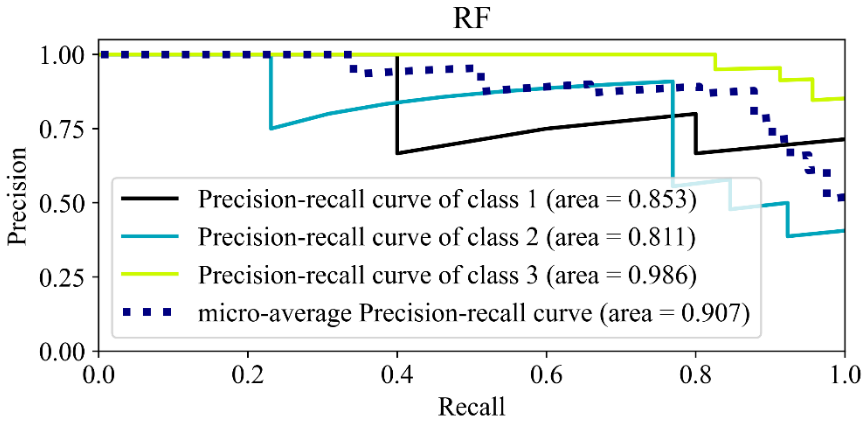
(b)


SVC
Precision
Recall
0.00
0.25
0.50
0.75
1.00
0.0
0.2
0.4
0.6
0.8
1.0
Precision-recall curve of class 1 (area = 0.925)
Precision-recall curve of class 2 (area = 0.830)
Precision-recall curve of class 3 (area = 0.990)
micro-average Precision-recall curve (area = 0.936)

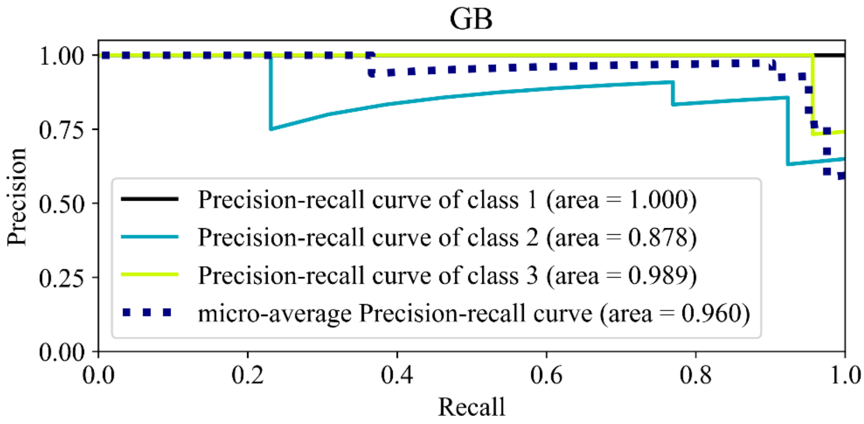
(c)


CART
Precision
Recall
0.00
0.25
0.50
0.75
1.00
0.0
0.2
0.4
0.6
0.8
1.0
Precision-recall curve of class 1 (area = 0.233)
Precision-recall curve of class 2 (area = 0.449)
Precision-recall curve of class 3 (area = 0.906)
micro-average Precision-recall curve (area = 0.642)

(d)

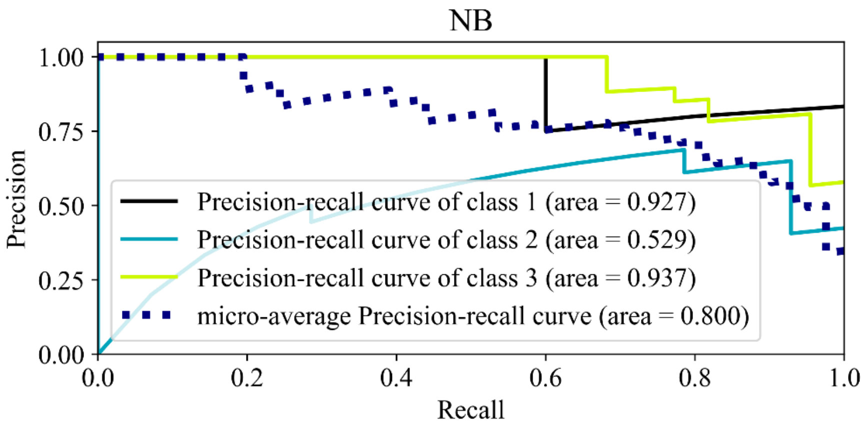


(e)

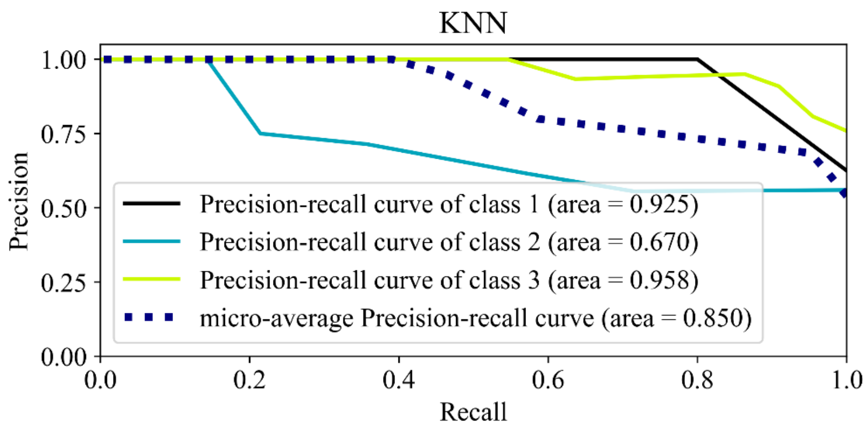


(f)

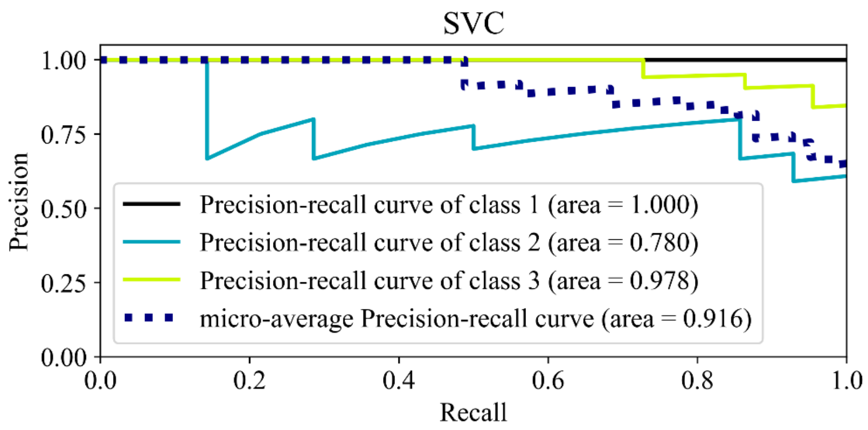
Figure C1.Precision-recall for curve based on the test dataset for livability



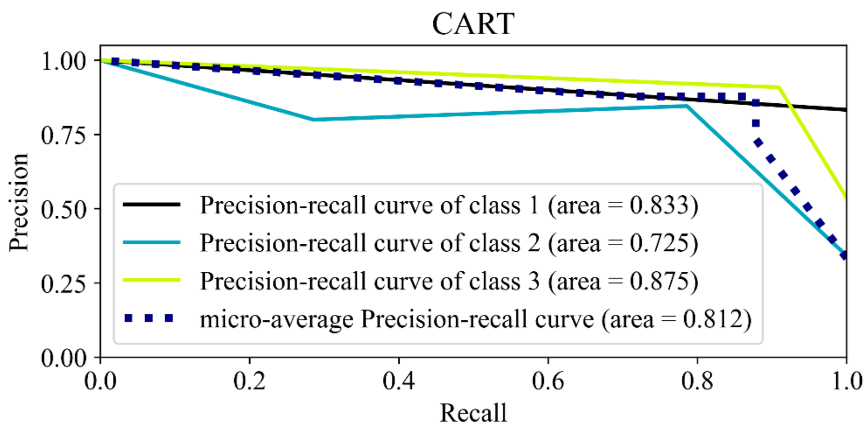
(a)


KNN
1.00
0.75
0.50
0.25
0.00
Precision
0.0
0.2
0.4
0.6
0.8
1.0
Recall
Precision-recall curve of class 1 (area = 0.925)
Precision-recall curve of class 2 (area = 0.670)
Precision-recall curve of class 3 (area = 0.958)
micro-average Precision-recall curve (area = 0.850)

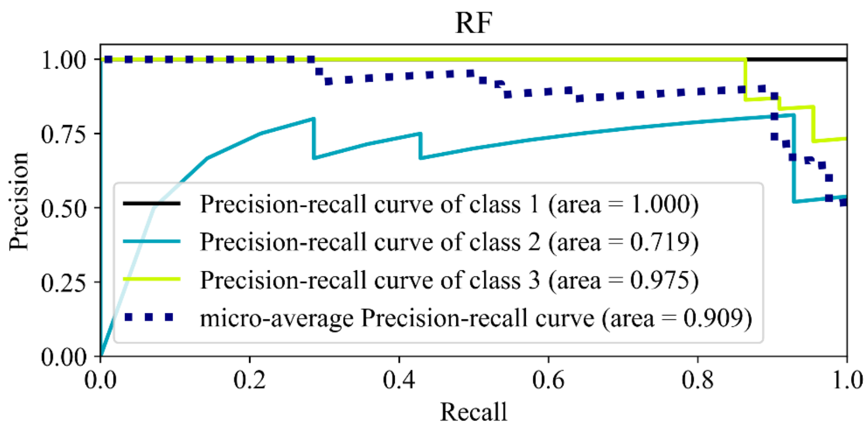
(b)


SVC
1.00
0.75
0.50
0.25
0.00
Precision
0.0
0.2
0.4
0.6
0.8
1.0
Recall
Precision-recall curve of class 1 (area = 1.000)
Precision-recall curve of class 2 (area = 0.780)
Precision-recall curve of class 3 (area = 0.978)
micro-average Precision-recall curve (area = 0.916)

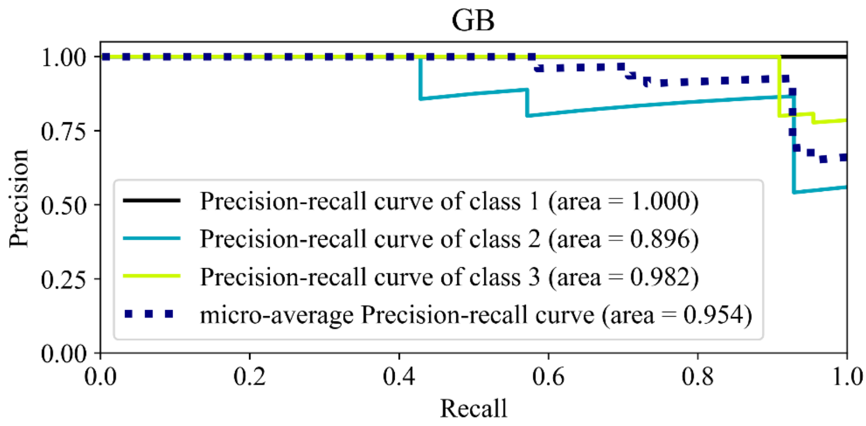
(c)


CART
1.00
0.75
0.50
0.25
0.00
Precision
0.0
0.2
0.4
0.6
0.8
1.0
Recall
Precision-recall curve of class 1 (area = 0.833)
Precision-recall curve of class 2 (area = 0.725)
Precision-recall curve of class 3 (area = 0.875)
micro-average Precision-recall curve (area = 0.812)

(d)

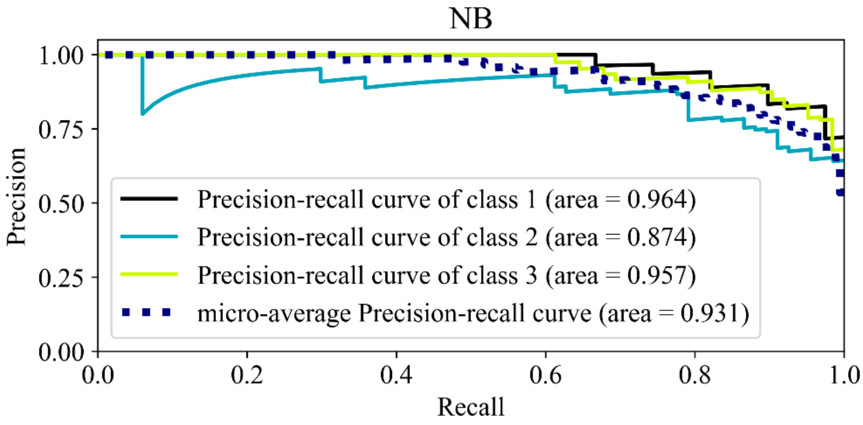


(e)

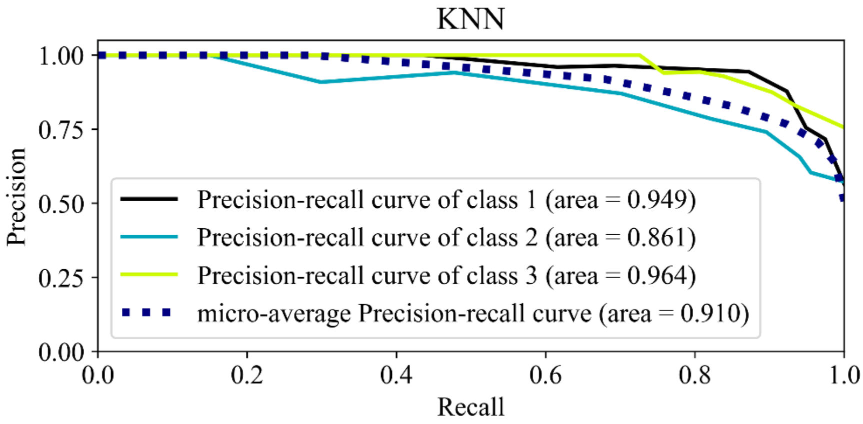


(f)

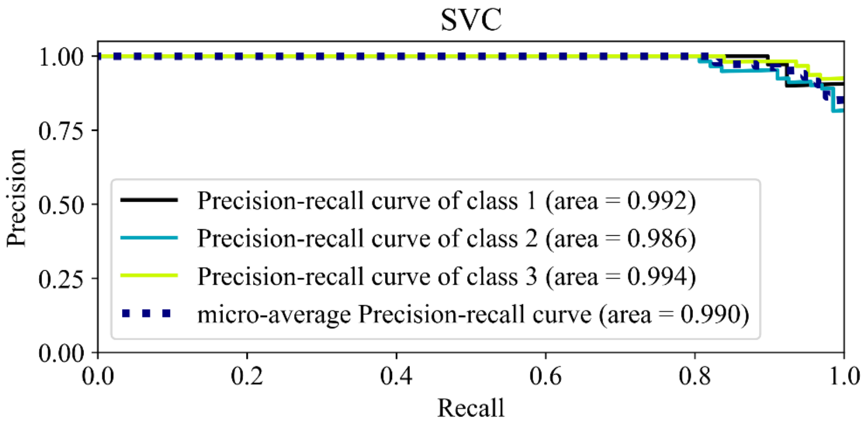
Figure C2.Precision-recall for curve based on the test dataset for resilience


NB
Precision
Recall
Precision-recall curve of class 1 (area = 0.964)
Precision-recall curve of class 2 (area = 0.874)
Precision-recall curve of class 3 (area = 0.957)
micro-average Precision-recall curve (area = 0.931)

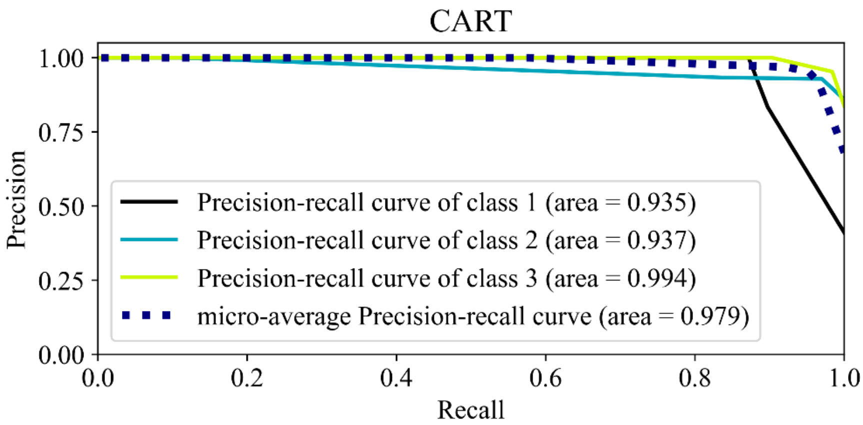
(a)


KNN
Precision
Recall
Precision-recall curve of class 1 (area = 0.949)
Precision-recall curve of class 2 (area = 0.861)
Precision-recall curve of class 3 (area = 0.964)
micro-average Precision-recall curve (area = 0.910)

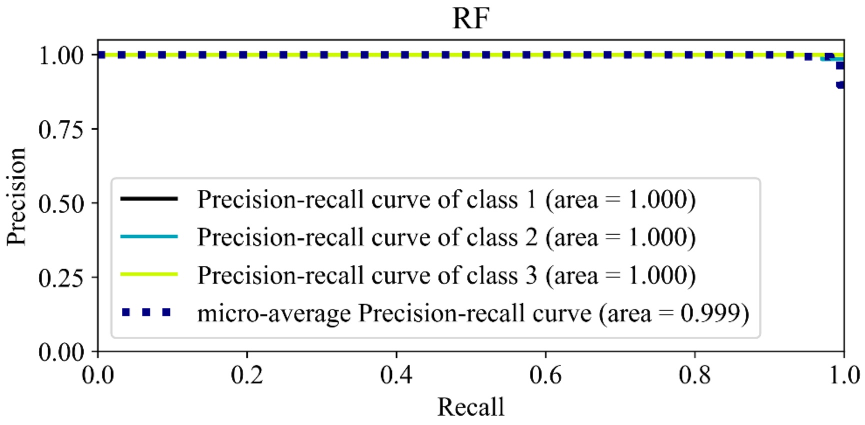
(b)


SVC
Precision
Recall
Precision-recall curve of class 1 (area = 0.992)
Precision-recall curve of class 2 (area = 0.986)
Precision-recall curve of class 3 (area = 0.994)
micro-average Precision-recall curve (area = 0.990)

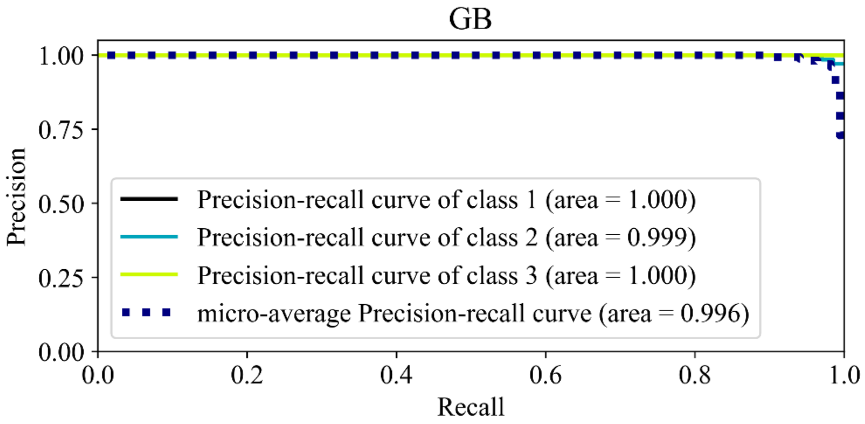
(c)


CART
Precision
Recall
Precision-recall curve of class 1 (area = 0.935)
Precision-recall curve of class 2 (area = 0.937)
Precision-recall curve of class 3 (area = 0.994)
micro-average Precision-recall curve (area = 0.979)

(d)

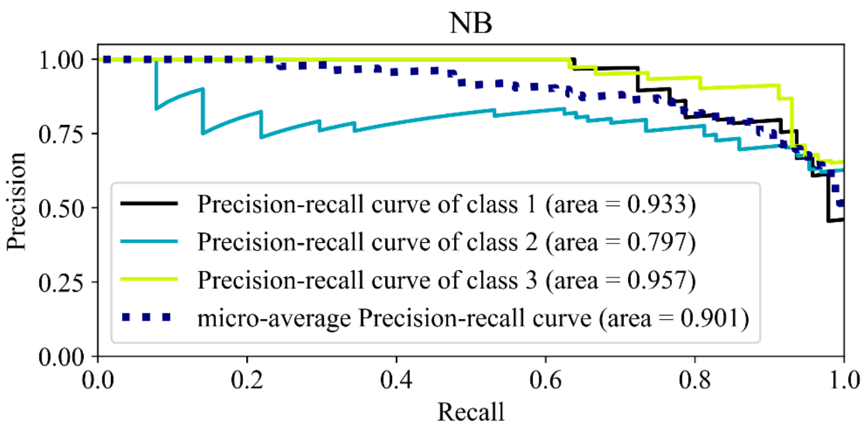


(e)

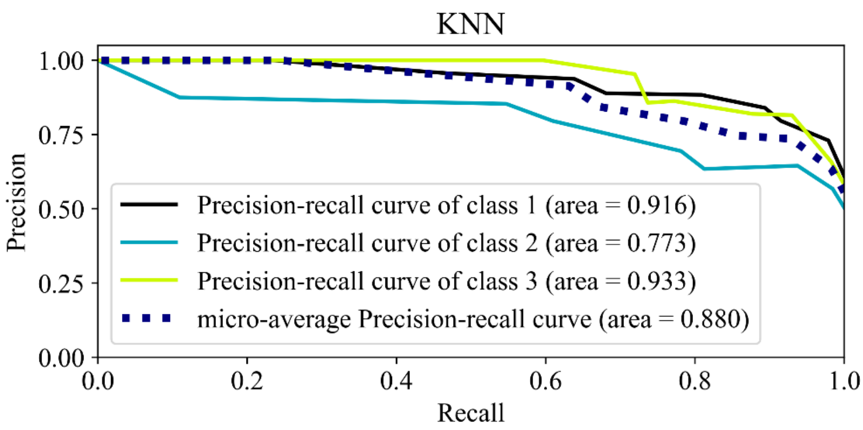


(f)

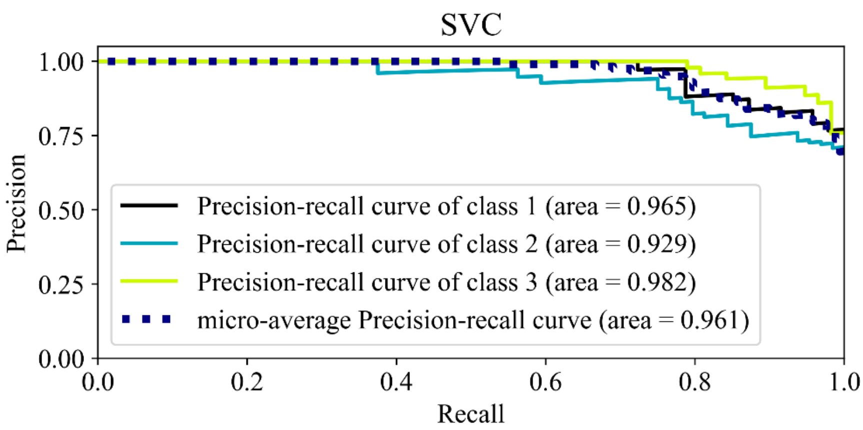
Figure C3.Precision-recall for curve based on the train dataset for livability


NB
Precision
Recall
1.00
0.75
0.50
0.25
0.00
0.0
0.2
0.4
0.6
0.8
1.0
Precision-recall curve of class 1 (area = 0.933)
Precision-recall curve of class 2 (area = 0.797)
Precision-recall curve of class 3 (area = 0.957)
micro-average Precision-recall curve (area = 0.901)

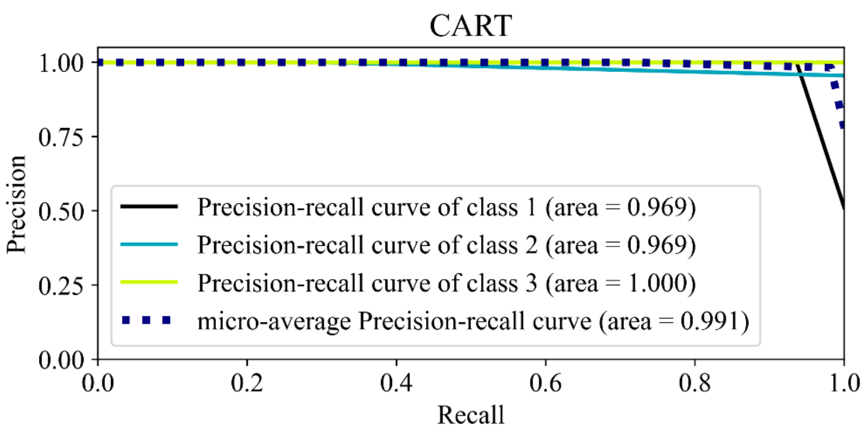
(a)


KNN
Precision
Recall
1.00
0.75
0.50
0.25
0.00
0.0
0.2
0.4
0.6
0.8
1.0
Precision-recall curve of class 1 (area = 0.916)
Precision-recall curve of class 2 (area = 0.773)
Precision-recall curve of class 3 (area = 0.933)
micro-average Precision-recall curve (area = 0.880)

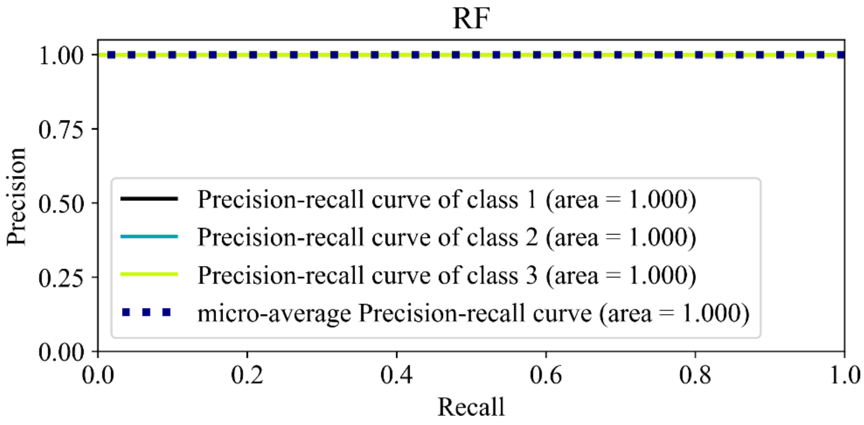
(b)


SVC
Precision
Recall
1.00
0.75
0.50
0.25
0.00
0.0
0.2
0.4
0.6
0.8
1.0
Precision-recall curve of class 1 (area = 0.965)
Precision-recall curve of class 2 (area = 0.929)
Precision-recall curve of class 3 (area = 0.982)
micro-average Precision-recall curve (area = 0.961)

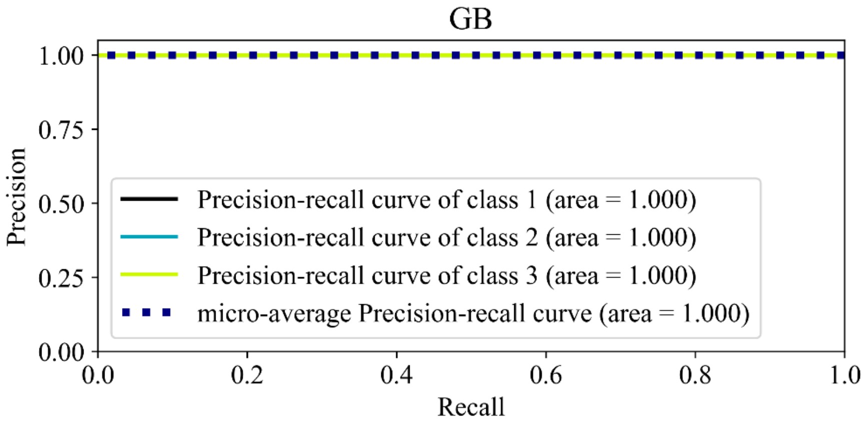
(c)


CART
Precision
Recall
1.00
0.75
0.50
0.25
0.00
0.0
0.2
0.4
0.6
0.8
1.0
Precision-recall curve of class 1 (area = 0.969)
Precision-recall curve of class 2 (area = 0.969)
Precision-recall curve of class 3 (area = 1.000)
micro-average Precision-recall curve (area = 0.991)

(d)



(e)



(f)

Figure C4.Precision-recall for curve based on the train dataset for resilience

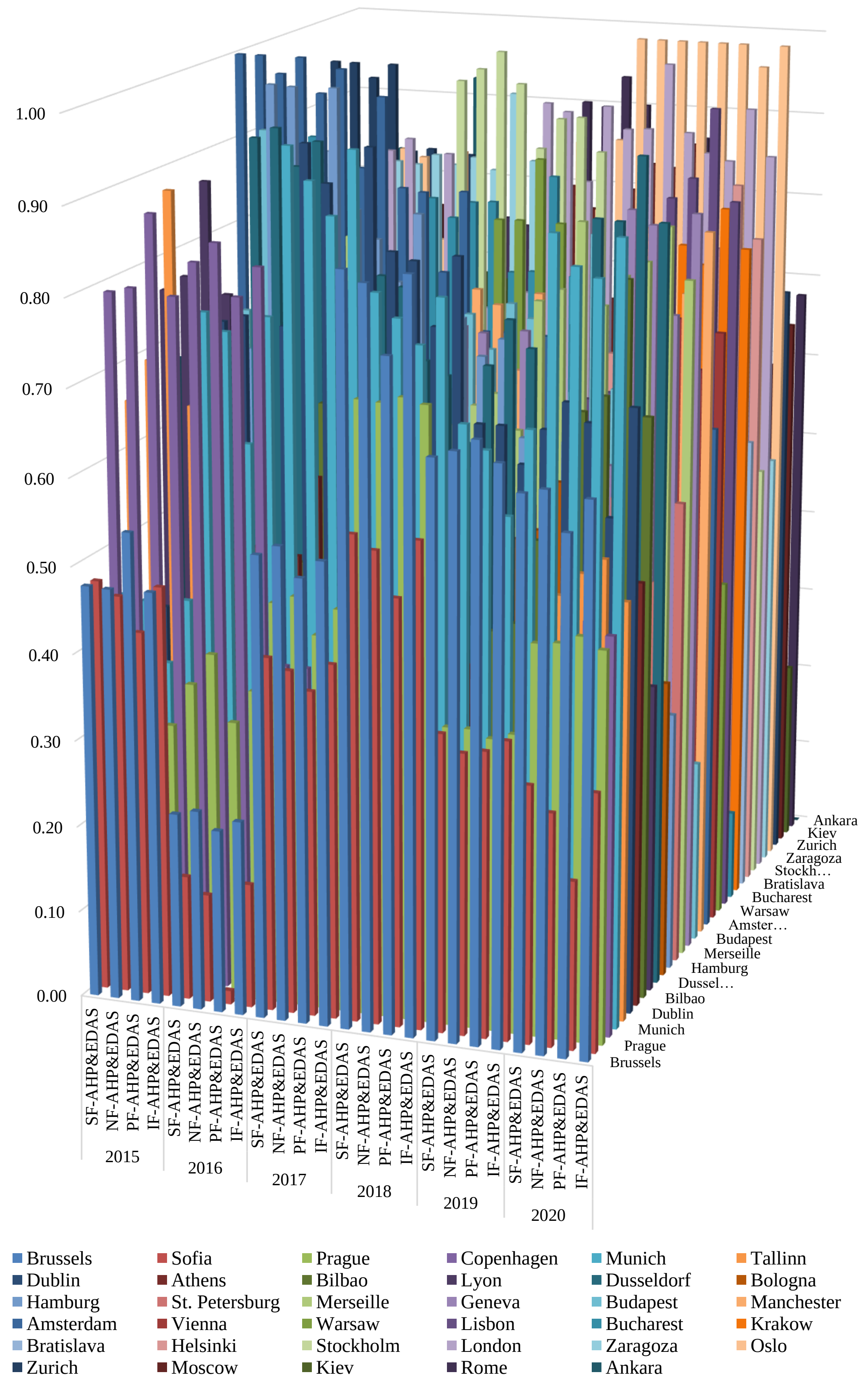


Figure C5.Comparative analysis for different weighting methods integrated with the EDAS method for the years 2015-2019

APPENDIX D: QUESTIONNAIRE DESIGN FOR EXPERT SURVEY

To: Academic and industrial practitioners

Subject: Invite to participate in a questionnaire-based survey on smart city performance monitoring

It is an immense pleasure to invite you to participate in a survey for an ongoing research titled "A Novel Fuzzy Expert-Based Multi-Criteria Decision Support Model For Composite Smart City Performance Assessment". Your response and valuable feedbacks on the attached questionnaire is appreciated to further proceed with the entitled research. All answers will be highly confidential and will solely be used for the purpose of research. The responses of the survey will be used by the researcher to quantify the weights of each main-criteria and sub-criteria to construct a composite smart city performance index using the spherical fuzzy-based AHP technique.

The survey requires to rate and score each criteria and sub-criteria based on their importance. Table 1a. shows the dimensions (main-criteria) and indicators (sub-criteria) used to create the aggregate index and Table 1.b shows the linguistic scales and their corresponding Score respectively. The task to accomplish is briefed through a simple example below:

Example: "Safety and security" of urban inhabitants holds a significant impact on transforming a smart city to a sustainable dwelling unit. Therefore, "Safety and security" is **absolutely more importance** (score: 9) on the sustainability criteria to support smart city transition to a sustainable, resilient, and livable city under the tritactic pillar of futuristic city development.

Table 1a. Criteria and Sub-criteria for the smart city composite performance assessment

Criteria	Sub-criteria	Symbol
Sustainability	Climate change	CC
	Governance and Institution	GI
	Economic dynamism	E
	Energy and environmental resource	EE
	Safety and security	SS
	Social cohesion and solidarity	SW
Urban Resilience	Social Resilience	S
	Economic Resilience	EC
	Infrastructure and Build Environment Resilience	IB
	Institutional Resilience	IN
Urban liveability	Accessibility	AC
	Economic vibrancy	EV
	Community well-being	CWB

Table 1b. Linguistic scale and corresponding Score

Linguistic scale	Abbreviation	Score
Absolutely more importance	AMI	9
Very high importance	VHI	7
High importance	HI	5
Slightly more importance	SMI	3
Equally importance	EI	1
Slightly low importance	SLI	1/3
Low importance	LI	1/5
Very low importance	VLI	1/7
Absolutely low importance	ALI	1/9

As an expert with immense experience in the field of smart city, urban regeneration, and transformative spatial planning, we wish to translate your expertise, ideas, and opinions in evaluating critical main-criteria and sub-criteria that affect smart city transformation to a more resilient, sustainable, and livable dwelling units, while quantifying the overall performance. 3 main dimensions categorized as the main-criteria and 13 indicators considered as the sub-criteria as listed in Table 1a for the basis of the assessment. For the same, kindly please support the survey by:

1. Rating each main-criteria (see Table 2a.) and sub-criteria (see Table 2b-d.) based on the linguistic scales and the corresponding Score that portray the importance of each linguistic terms.
2. Commenting on the relevance of the choice of each main-criteria (dimensions) and sub-criteria (indicators) if any, as appropriate.
3. Returning the completed survey within at least 2 weeks on receiving the questionnaire.

Sincere cooperation in completing the survey is highly solicited.

Table 2a. SF-AHP Questionnaire for the main-criteria

Evaluation of main-criteria																		
Criteria A	Linguistic Scale																	Criteria B
	9	7	5	3	1	1/3	1/5	1/7	1/9	1/7	1/5	1/3	1	3	5	7	9	
Sustainability																		Resilience
Sustainability																		Livability
Resilience																		Livability

Table 2b. SF-AHP Questionnaire for the sub-criteria under urban resilience

Evaluation of sub-criteria																		
Criteria A	Linguistic Scale																	Criteria B
	9	7	5	3	1	1/3	1/5	1/7	1/9	1/7	1/5	1/3	1	3	5	7	9	
S																		EC
S																		IB
S																		IN
EC																		IB
EC																		IN
IB																		IN

S: Social; EC: Economic; IB: Infrastructure and Built-Environment; IN: Institutional

Table 2c. SF-AHP Questionnaire for the sub-criteria under urban livability

Evaluation of main-criteria																		
Criteria A	Linguistic Scale																	Criteria B
	9	7	5	3	1	1/3	1/5	1/7	1/9	1/7	1/5	1/3	1	3	5	7	9	
AC																		EV
AC																		CWB
CWB																		EV

AC: Accessibility; EV: Economic vibrancy; CWB: Community well-being

Table 2d. SF-AHP Questionnaire for the sub-criteria under sustainability

Evaluation of sub-criteria																		
Criteria A	Linguistic Scale																	Criteria B
	9	7	5	3	1	1/3	1/5	1/7	1/9	1/7	1/5	1/3	1	3	5	7	9	
CC																		GI
CC																		E
CC																		EE
CC																		SS
CC																		SW
GI																		E
GI																		EE
GI																		SS
GI																		SW
E																		EE
E																		SS
E																		SW
EE																		SS
EE																		SW
SS																		SW

APPENDIX E: LIST OF PUBLICATIONS

1. **Kutty, A. A.,** Abdella, G. M., Kucukvar, M., Onat, N. C., & Bulu, M. (2020). A system thinking approach for harmonizing smart and sustainable city initiatives with United Nations sustainable development goals. *Sustainable Development*, *28*(5), 1347-1365.

2. **Kutty, A. A.,** Kucukvar, M., Abdella, G. M., Bulak, M. E., & Onat, N. C. (2022). Sustainability Performance of European Smart Cities: A Novel DEA Approach with Double Frontiers. *Sustainable Cities and Society*, 103777.

3. **Kutty, A. A.**, Kucukvar, M., Abdella, G. M., Kutty, N., Onat, N. C., (2022). Linking sustainability, resilience, and livability with smart city development: Modelling Interconnections using systems approach, In *Proceedings of the International Conference on Industrial Engineering and Operations Management*, Istanbul, Turkey, March 8 – 10, 2022.

4. **Kutty, A. A.**, Wakjira, T. G., Kucukvar, M., Abdella, G. M., Onat, N. C., (2022). Urban Resilience and Livability Performance of European Smart Cities: A Novel Machine Learning Approach. *Journal of Cleaner Production* (Accepted).

5. **Kutty, A. A.**, Kucukvar, M., Ayvaz, B., Onat, N. C., Abdella, G. M., (2022). A Novel Fuzzy-Expert based Multi-criteria Decision Support Model For Smart City Composite Performance Assessment, *Cities* (under review).