BENV0096: MSc ESDA Dissertation

"SDG 7 INTERLINKAGES ON A LEVEL"

by

NQMJ9

01/09/2025

Paper submitted in part fulfilment of the
Degree of Master of Energy Systems and Data Analytics

Energy Institute
University College London

Word count: 10,233

UCL Energy Institute

Coursework Submission

Title

SDG 7 INTERLINKAGES ON A LOCAL LEVEL

Student name **NQMJ9**

Student number (This can be found on your student identity card)

Module title MSc ESDA Dissertation

Module Code BENV0096

Submitted to UCL Energy Institute, Bartlett School of Energy, Environment and Resources

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ABSTRACT

This dissertation examines how interlinkages between Sustainable Development Goal 7 (Affordable and Clean Energy) and other SDGs manifest at the city level. Using over 10,000 indicators from 120 Voluntary Local Reviews, a novel methodology was developed combining semantic embeddings, probabilistic clustering, large language models, progress scoring, and causal discovery. Sentence embeddings were grouped with Gaussian Mixture Models, labelled using Gemini 2.5 Flash, and tracked over time with normalised progress scores. Causal dependencies were inferred with the PC algorithm across rolling windows, with link strengths evaluated using BIC scores and stability tested via bootstrap resampling.

Results show SDG 7 as both a driver and recipient of progress. Outward links highlight how energy access and decarbonisation support health, infrastructure, and climate, while inward links show how education, economic development, and sustainable consumption enable energy transitions. Second-order pathways reveal cascading nexus effects across urban systems. The study concludes that local energy action is central to sustainable development but contingent on progress in other domains.

Keywords: SDG Interlinkages, LLMs, Bayesian Networks, sustainable energy

ACKNOWLEDGEMENTS

I would like to give thanks to my Supervisor, Manos, who has supported me in the implementation of the project, providing insights and useful tips. I would also like to thank my family and friends who helped in proofreading my work, as well as the entire UCL Bartlett fraternity for their continued mentorship throughout my program. It is my wish that my findings yield positive outcomes for future research at the Bartlett and the wider Energy Institute at UCL.

1. INTRODUCTION

The Sustainable Development Goals (SDGs) adopted by the UN General Assembly in 2015 represented a coherent way to address the 2030 agenda by entwining diverse paradigms of economic, social, and environmental targets in the 17 SDGs as an 'indivisible whole' (Nillson et al, 2016). The seventh sustainable development goal to 'Ensure access to affordable, reliable, sustainable, and modern energy for all' (United Nations, 2015) emerged as a key anchor for sustainable development in health and education, spurring industrial and economic growth, while having potential tradeoffs with environmental sustainability, highlighting the importance of renewables uptake and improvements in energy efficiency (IEA et al., 2023).

Despite the recognition of the integrated nature of sustainable development, most evidence of interlinkages is at global and national scales, with an evidence gap at the local/city scale where the implementation happens (OECD, 2020). Furthermore, there is a descriptive bias in the literature, with most studies incorporating associations, including statistical ones such as correlations (Pradhan et al., 2017), and expert judgements while causal evidence of the interlinkages, however, remains scarce, especially for cities, presenting a challenge for urban policymakers who need directional insights and not just correlational ones, to prioritise interventions and avoid unintended trade-offs (Moreira et al., 2025). These challenges are further exacerbated by local-level monitoring hurdles, including heterogeneous indicator sets across cities and sparse time series data, which complicates classic econometric approaches. However, the heterogeneous indicator sets and the diverse nature of subject matter in SDG interlinkages literature lend themselves to semantic methods to uncover underlying themes or topics. Indeed, there are studies using advanced natural language processing methods (NLP) such as word embeddings and Large Language Models (LLMs) with a focus on mapping text, such as corporate documents, or journal abstracts to one or multiple SDGs to gauge their level of alignment with the 2030 agenda (Chen et al., 2022; Vanderfeesten et al., 2022).

While there are studies that have attempted to thematically cluster locally reported indicators across different cities (Stamos et al., 2024), few studies have furthered the analysis by integrating the semantic understanding of local-level indicators with quantitative causal discovery to determine levers for progress and potential hurdles between different progress indicators, including energy-related measures of sustainable development. As such, this study aims to posit an integrative, data-driven pipeline to uncover plausible causal pathways among local SDG themes using city-reported indicators, with a focus on SDG 7. More formally, the study aims to answer the following research questions:

1. What thematic/topical clusters of indicators related to SDG 7 emerge in local-level monitoring and reporting?
2. What progress have cities made in the different thematic areas of SDG 7-related indicators?
3. What are the causal mechanisms for SDG progress at the local level - what are the potential levers and hurdles in achieving SDG 7 at the local level, and what role does the achievement

of this goal play in the wider sustainable development agenda?

To answer the research questions, the study follows the high-level methodological pipeline outlined. An urban SDG corpus of over 10,000 indicators is assembled from 120 Voluntary local reviews (VLRs) published by 93 cities, aligning names, units, and directionality. The indicators are coherently clustered semantically using sentence embeddings, and Large Language Models (LLMs) are used to label and interpret the thematic indicator clusters (e.g., clean cooking, urban mobility). Cluster progress is computed using baseline-relative, direction-aware scoring at the city-year level, and the cluster-level panel progress scores are used to infer causal structure among clusters using Bayesian networks (BN), with an emphasis on SDG 7. The causal links discovered are validated and interpreted against prior literature and urban context to identify synergies, tradeoffs, and policy levers. The robustness of the results is tested through sensitivity tests, including bootstrapped network edges.

The study offers several contributions and research significance. To the best of the author's knowledge, this presents the first empirical city-scale mapping of directional causal interlinkages between SDG 7 clusters and other urban SDG themes. It demonstrates methodological novelty in an integrated pipeline linking semantic clustering with causal discovery on urban indicators. The study's results present substantive policy implications, identifying leverage points where energy progress likely catalyses (or hinders) other outcomes, and vice versa. The results are reproducible, with a transparent workflow that encompasses data harmonization, embedding, clustering, scoring, and causal discovery, enabling future city replication.

The remaining sections of the paper are organised as follows. Chapter 2 - The Literature review discusses SDG interlinkages concepts; provides a review of qualitative/NLP + LLM methods as well as quantitative methods and causal discovery; presents a concise SDG 7 nexus synthesis, and highlights the research gaps identified. Chapter 3 - The Methodology outlines the analysis pipeline from text embedding, clustering, and labelling, to progress scoring, BN methods, and robustness checks, Chapter 4 - The Results, presents the cluster taxonomy, progress patterns, and causal graphs whose causal links are interpreted with literature in Chapter 5 - The discussion, highlighting potential synergies, trade-offs, and policy implications as well as pointing out the methodological limitations and future research opportunities. Chapter 6 - The Conclusion summarizes the findings and contributions, offers recommendations to cities, and provides closing reflections.

2. LITERATURE REVIEW

2.1. THE ROLE OF LOCAL-LEVEL REPORTING

Following the adoption of the SDGs, reporting mechanisms were established at global, national, and local scales. At the local level, the focus of this study, reporting is coordinated by municipalities and regional governments, often in partnership with civil society, academia, or the private sector. Cities publish Voluntary Local Reviews (VLRs), the local counterpart to Voluntary National Reviews (VNRs), providing data and narratives tailored to urban contexts.

Local reporting captures the nuanced dimensions of sustainable development. Some indicators are adapted from national or global frameworks, but many reflect specific urban or regional priorities. The importance of local governments in implementing the 2030 Agenda is widely recognised: the UN Secretary-General stressed their role during the launch of the Decade of Action (United Nations, Secretary-General, 2019), and it is estimated that 66% of SDG targets require local implementation (OECD, 2022).

VLRs allow cities to align reporting with their capacity and stage of engagement with the SDGs implementation (Pipa and Bouchet, 2020; Ortiz-Moya et al., 2025), offering flexibility amidst the complexity of the UN framework (Taajamaa et al., 2022). They also reveal inequalities masked in aggregated statistics (Stamos et al., 2024). For instance, while a national average may suggest strong progress in renewable adoption, individual cities may still rely entirely on fossil fuels.

2.2. DEFINITIONS, TRENDS, AND POLICY IMPLICATIONS OF INTERLINKAGES

The interlinkages between SDG targets, indicators, policies, and interventions are described as theoretical or evidence-based, qualitative or quantitative, and encompass synergies, trade-offs, associations, or correlations of a positive, negative, or neutral nature (Chaniotakis et al., 2024). Key distinctions arise in the literature between correlative interlinkages that are purely statistical in nature and causal interlinkages that imply a cause-and-effect relationship. Pradhan et al. (2017) use correlations to map synergies/trade-offs, but explicitly caution about not inferring causality. Another distinction of interlinkages is between direct and indirect interlinkages. McCollum et al. (2018) distinguished “direct synergies” (e.g., energy access → education) vs. “indirect/mediated” ones (e.g., through economic growth, i.e. energy access → economic growth → education)). These interlinkages can be further categorized as one-way or two-way interlinkages, with one-way interlinkages described as interactions between a policy/intervention/technology and an SDG goal, target, and/or indicator, and two-way interlinkages described as interactions between the SDG goals, targets, and indicators themselves. (Chaniotakis et al., 2024). Lastly, SDG interactions can be classified as unidirectional, bidirectional, or cyclic. For example, electricity access (target 7.1) is required to power hospitals providing essential healthcare service (target 3.8), but hospitals are not required to provide electricity, thus representing a unidirectional interaction (Griggs et al, 2017).

Because the SDG framework is largely based on advancements evidenced in developed countries (Chaniotakis et al., 2024), the intuitive a priori assumption is that the majority of SDG targets interact synergistically, i.e., actions toward the achievement of one target also progress the accomplishments of other SDG targets, rather than tradeoff interactions where actions toward the achievement of one target detract from the progress on other targets (Anderson et. al., 2021). It is indeed the case that 80-90 % of identified SDG interactions are synergistic; however, this may indicate a bias in reporting on positive links compared to tradeoffs or a lack of available methods to infer the latter (Chaniotakis et al., 2024), and there is general consensus among the research community and policymakers around the potential for conflicts and tradeoffs (IRP, 2015; LeBlanc, 2015).

Understanding the SDG interlinkages is crucial for coherent policy-making. Nilsson et al. ,(2016) note that policymakers and planners often operate in silos with different ministries handling health, education, energy, etc., leaving them lacking the tools to identify the most important interactions or evidence to show what effects policies/interventions directed at certain targets/goals may have on other unseen targets/goals. Horvath et al. (2022) further note that knowledge of interaction at different levels of integration is required to minimise tradeoffs that may manifest when measures applied to achieve progress in one or a few targets compromise progress in others.

2.3. THE SDG 7 NEXUS AND INTERLINKAGES

SDG 7 (Affordable and Clean Energy) is unusually “networked” across the 2030 Agenda. Energy access, reliability, affordability, and decarbonisation simultaneously condition progress in other sustainable development pillars, including health, education, gender equality, industry, cities, and climate. Rather than exhaustively cataloguing every reported linkage, this section distils what the literature broadly agrees on, where it diverges, and where city-scale causal evidence is lacking.

Three nexus traditions dominate and help translate interlinkages into mechanisms - The Water-Energy-Food (WEF) nexus, the Energy-Climate-Industry nexus and the Energy-Cities nexus. Within the (WEF) nexus, Energy systems both demand water (thermal cooling, hydropower) and supply the electricity for water treatment, pumping, and cold chains (Acheampong et al., 2017; Zhang et al., 2018). Furthermore, unconventional water sources such as desalination that are energy intensive can either present challenges by additional demand on the grid or offer opportunities to integrate intermittent renewables (Parkinson et al., 2016; Yillia, 2016)). Efficiency and diversification (e.g., non-thermal renewables, demand-side management) are repeatedly identified as synergy levers that reduce water intensity while safeguarding food systems. Modern energy access is critical to enhance agricultural productivity, and best-practice production methods, such as rice intensification, can reduce energy demand in the agricultural sector. On the contrary, bioenergy and food production may compete for scarce land and other inputs (Kline et al., 2017; Rasul, 2016).

Within the Energy-Climate-Industry nexus, clean power and electrification (transport, heat, industry) align SDG 7 with achieving the SDG 9 target of upgrading energy infrastructure and making the energy industry more sustainable (Bhattacharyya et al., 2016). Furthermore, with regard to SDG 13 on climate action, meeting the renewable energy and energy efficiency targets of SDG7 is a necessary, but not entirely sufficient, condition for long-term temperature stabilization below 2 ° C. Importantly, the timing and sequencing of grid decarbonisation vs. end-use electrification determine whether early-stage emissions spike or decline whereas industrial policy on innovation, standards, and finance modulates whether benefits diffuse or concentrate. (Kriegler et al., 2013; Vuuren et al., 2015).

Within the Energy-Cities nexus, at the local level/urban scale (SDG 11), energy interlinks with land use, mobility, buildings, and slum upgrading (Haines et al., 2017) whereas distributed renewables, efficient buildings, and clean transit consistently show multi-goal synergies with air quality, health, and equity, while still requiring institutional capacity, stable tariffs, and inclusion to avoid unintended consequences suhs as green gentrification(Raji et al., 2015)

Beyond the energy nexuses discussed, multiple other interactions exist between SDG 7 and other paradigms of sustainable development, including education, health and sustainable consumption and production, and it is indeed the case that many such interactions at the local level are encountered in the results of this study. The three aforementioned nexuses, however, suffice to describe the high-level systemic interactions between energy and the 2030 agenda encountered in the literature.

2.4. METHODOLOGIES FOR IDENTIFYING INTERLINKAGES

With an understanding of interlinkages, their definitions and policymaking implications, as well as the high-level interactions of the energy nexus, the next section reviews the broad categories of methods used to infer interlinkages, including their areas of applicability, assumptions, and data requirements.

2.4.1. Quantitative methods overview

Quantitative methods are widely applied in SDG interlinkage research for exploratory or confirmatory analysis, as well as for scenario testing and projections. These include statistical techniques such as correlation and regression, and modelling approaches such as structural equation models (SEMs) or Integrated Assessment Models (IAMs). For example, Anderson et al. (2021) used correlation analysis to examine interactions between SDG targets, highlighting governance and institutional drivers of progress, while Ament et al. (2020) applied regression analysis to explore synergies and trade-offs among the 17 goals. In contrast, modelling approaches have been used to simulate system dynamics and policy impacts. Barbier and Burgess (2019) employed scenario modelling to investigate interlinkages across the SDGs, and Engström et al. (2019) developed a simulation framework to assess the effects of local climate and energy policies on water and land use.

While valuable for identifying statistical patterns and conceptual interactions, quantitative approaches face notable limitations. They are less effective at capturing qualitative aspects of sustainable development, including local socioeconomic and political contexts. A key shortcoming is their limited ability to establish causality; most methods are not designed to assess the effects of specific policies or interventions (Chaniotakis et al., 2024). Furthermore, their applicability depends heavily on the availability and quality of data, which is often inconsistent across contexts. For these reasons, quantitative methods are best complemented by qualitative approaches to build a more holistic understanding of SDG interlinkages (Chaniotakis et al., 2024).

2.4.2. Causal Discovery and Network Analysis Methods

Although most quantitative methods in the literature fail to capture causal effects, a growing body of work implements causal discovery techniques to infer interlinkages between SDG indicators, targets, and interventions. Broadly, these approaches can be grouped into time-series causality methods and graphical methods.

Among time-series approaches, Granger regression is the most commonly applied. Granger causality assesses whether past values of one variable improve the prediction of another (Granger, 1969). If the predictive model of x regressed on its own lags performs worse than when lags of y are added, then y is said to “Granger-cause” x. Importantly, this is not “true causality” but rather a proxy based on predictive power. The method, which relies on autoregressive models, performs poorly on short or sparse time series (Ospina-Forero et al., 2022), which is often the case for SDG data. It is also sensitive to time aggregation and subsampling errors. Despite these challenges, Granger causality has been used effectively: Ngarava et al. (2019) examined lagged relationships between agricultural CO emissions and income in South Africa, while Dörgő et al. (2018) applied it to 801 SDG indicators across 283 regions, uncovering about 4,000 causal links.

The second family, graphical methods - commonly implemented as Bayesian networks - represents variables as nodes and edges as dependencies, quantified through conditional probability distributions (Requejo-Castro et al., 2020). Edges are directed in such a way as not to form cycles, which would imply self-causality that is difficult to interpret, and the resulting Directed Acyclic Graph (DAG) encodes probabilistic and causal assumptions (Friedman Koller, 2003).

Graphical approaches are divided into constraint-based and score-based algorithms. Among the former, the PC algorithm (Spirtes et al., 2001) is widely cited. It begins with a fully connected graph, removes edges through conditional independence tests, and then orients edges where collider structures are detected. The result is a Completed Partially Directed Acyclic Graph (CPDAG). While highly influential, the detailed mechanics of collider orientation and propagation rules are beyond the scope of this review, and full details are available in (Spirtes et al., 2001); what is of importance is that PC identifies plausible causal structures without predefined assumptions.

Score-based approaches, such as Greedy Equivalence Search (GES) (Chickering, 2003), take a different route: starting with an empty graph, they iteratively add or remove edges to maximize a fit criterion like the Bayesian Information Criterion (BIC) (Glymour et al., 2019). These methods are flexible and efficient in high-dimensional contexts, but can be computationally intensive.

Both constraint-based and score-based methods face challenges when applied to SDG time series. Indicators exhibit temporal dependence, meaning today’s values depend on previous ones. Mitigation strategies include partitioning into time windows and treating each as an independent analytic unit, though this risks omitting cross-window relations, and results may vary with window size (Glymour et al., 2019). Data sparsity, irregular reporting, and aggregation at multiple scales further complicate inference (Ospina-Forero et al., 2022). Non-stationarity, where causal relations themselves evolve, poses another obstacle. Nonetheless, compared to Granger regression, Bayesian networks handle sparse data better and allow integration of qualitative and quantitative evidence (Coccoli et al., 2018).

Several studies illustrate their value. Requejo-Castro et al. (2020) used structure learning and independence tests to map SDG 6 interlinkages within the 2030 Agenda. Moreira et al. (2025) showed their policy relevance by contrasting Bayesian networks with regression in socioeconomic contexts. De Cock et al. (2022) applied Bayesian belief networks to analyse the contested role of hydropower in Ecuador’s agro-food-fisheries nexus.

Extensions such as Dynamic Bayesian Networks (DBNs) incorporate time explicitly, combining an initial network with transitional probabilities (P(Xt+1|Xt)). Franco-Gaviria et al. (2022) employed DBNs to assess socio-ecological resilience in the Colombian Andes. While data-intensive, these models capture temporal causality more directly than static networks.

In summary, causal discovery methods offer powerful alternatives to correlation-based analyses. Granger regression remains widespread but is limited by data quality and interpretability. Graphical approaches, particularly Bayesian networks, provide richer representations, integrate multiple data types, and are more robust to sparsity, though they also face challenges of temporal dependence, non-stationarity, and computational complexity. For analysing VLRs, where datasets are short with missing gaps from the irregular nature of local-level monitoring and reporting, and wide heterogeneity in the indicators reported across different cities, Bayesian networks represent a promising approach.

A natural extension of causal discovery is network analysis, since multiple graphs often arise from different entities, methods, or bootstrap/time-window sampling. Comparing such networks requires topological metrics: connectivity metrics quantify nodal discrepancies, while structural metrics assess internal communities. Ospina-Forero et al. (2022) applied four causal discovery methods, including the PC algorithm and Sparse Bayesian Networks, to data from four countries, generating sixteen SDG networks and comparing them via measures such as Hamming distance. Similarly, Zhou et al. (2017) analysed SDG interlinkages across 51 indicators in nine countries, using centrality measures (degree, eigenvector, betweenness, closeness) to identify key SDG targets.

2.4.3. Qualitative Approaches

Qualitative methods have been proposed as a way to bypass the influence of data and assumptions inherited in the use of quantitative methods (Chaniotakis et al., 2024). Including methods such as system dynamics, case studies, and content analysis, these methods provide the necessary flexibility to capture the SDG interlinkage particularities that emerge at various scales, i.e., as subnational, national, and international contexts.

While a myriad of qualitative methods exist, those of particular interest to this study are within the Natural Language Processing (NLP) family of methods - namely word-to-vector embeddings and Large Language Models (LLMs). Word embeddings convert words into dense vectors that capture semantic relationships, while LLMs are advanced deep learning models for NLP used to understand, generate, and manipulate text at the sentence, paragraph, or document level. Given the lack of a framework for SDG reporting at the local level and the heterogeneity in indicators reported between different cities and local authorities, word embeddings offer an avenue to cluster local-level SDG indicators semantically, identifying thematic areas, while LLMS can generate content such as labels and descriptions of the given clusters of word embeddings.

In the study of SDG interlinkages thus far, word embeddings and LLMs have been predominantly used to map text, usually documents or abstract summaries, to SDG goals, targets, and indicators. Matsui et al. (2024) use bidirectional encoder representations from transformers (BERT) embedding models developed by Devlin et al. (2019) to build a classifier capable of semantic mapping of practices and issues in the SDGs context, as well as a visualizing method of the SDGs nexus based on the co-occurrence of goals. Vanderfeesten et al. (2022) trained the BERT multi-language model for classification and mapping to the 169 individual SDG Targets, based on the English abstracts in the corpus of 1.4 million research papers. To map the Sustainable Development Goals in science, technology, and innovation, Hajikhani and Suominen (2022) performed SDG classification of scientific publications to compile a machine learning model that classifies the SDG relevance in patent documents, thereby revealing the extent to which the SDGs are addressed in patents. In a similar vein, Chen et al. (2022) leverage word-to-vector embeddings, logistic regression, and support vector machine models (SVMs) in the analysis of the Corporate Social Responsibility reports of Russell 1000 companies between 2010-2019 to classify the companies' alignment with SDGs over time.

The above studies represent supervised learning approaches where labelled texts, e.g., a publication abstract explicitly labelled as being associated with an SDG goal, are used to train machine learning models for classification before being applied to classify unseen data in the form of the word-embeddings of new text inputs. In the complementary paradigm of unsupervised techniques, algorithms such as K-means or Gaussian mixture models (GMMs) are usually applied to the word embeddings of SDG-related texts to cluster semantically related texts. Indeed, unsupervised topic modelling is emerging as an important tool in the scoping and thematic analysis of SDG literature. Invernici et al. (2025) used BERTopic applied to a large corpora of scientific publication abstracts to capture insights on the evolution of the attitude toward SDGs within scientific abstracts in the 2006-2023 time span.

On a local level, Stamos et al. (2024) used sentence transformers (SBERT), and the K-means algorithm to cluster 10,506 indicators compiled from 120 VLRs to establish what variations exist across different world regions and types of local governments, whether local indicator frameworks mirror institutional (UN, EU) SDG indicators, and whether the semantic analysis of VLRs indicators align with the 17 SDGs, or if new clusters of interest emerge. This study builds on the work of Stamos et al. (2024), leveraging the same they compiled, with an adjusted focus of discovering local interlinkages as opposed to analysing local SDG monitoring trends and their alignment with the SDGs, as was the focus of Stamos et al. (2024)

2.5. RESEARCH GAPS

Given the context of local SDG monitoring and reporting, and the inference of localized interlinkages, this study aims to fill three key research gaps.

1. First, there is limited literature on semantic grouping or thematic clustering of SDG indicators at the local/city level.
2. Secondly, Few studies apply causal discovery methods to urban SDG datasets, and by extension, there is limited empirical causal mapping of SDG 7 interlinkages at the local level
3. Lastly, this study fills a methodological gap in attempting to overcome the challenges in integrating qualitative and quantitative approaches. Novelty is introduced by combining text embedding, clustering, progress scoring, and causal inference into a single pipeline for SDG analysis.

3. EXPLORATORY DATA ANALYSIS

3.1. DATA SOURCES & INCLUSION CRITERIA

This study builds on the dataset assembled by Stamos et al. (2024), who provide full details on data sources, extraction protocols, and harmonisation. The data was primarily drawn from Voluntary Local Reviews (VLRs) published between 2016 and 2024. Of the 325 VLRs available worldwide at the time, only those published in English were included, reducing the corpus to 190. A further criterion excluded VLRs reporting only qualitative information without quantitative SDG indicators, leaving a final dataset of 120 VLRs.

The data were structured into a database capturing each VLR's official title, document link, issuing city and country, year and language of publication, and classification as quantitative, qualitative, or hybrid. For each indicator, canonical variables recorded included the full name and units, associated SDG goal or target (author-curated where not explicitly reported), and time-series data for 2008-2022. A directionality variable, "Higher Means", was also introduced to distinguish whether higher indicator values signified progress (e.g. percentage of dwellings connected to electricity) or regression (e.g. average electricity interruptions per customer per year).

In total, the database contained 10,506 indicators across the 120 VLRs, providing a comprehensive, harmonised source of city-level SDG monitoring data (Stamos et al., 2024).

Table 1 summarizes the columns of importance extracted from the database for this study's analysis.

Table 1: Data Description

Variable	Description
Goal_curated	The SDG goal associated with the indicator as stated in the VLR or curated by the authors (Stamos et al., 2024).
Target_Curated	The SDG target associated with the indicator as stated in the VLR or curated by the authors (Stamos et al., 2024).
HigherNumberMeans	Indicates whether a higher number of the indicator variable results in good or bad sustainable development outcomes.
Indicator.name	Name of the indicator as stated in the VLRs.
Unit_Curated	Units of the indicators as stated in the VLR or curated by the authors (Stamos et al., 2024).
Location	The local governing authority issuing the VLRs e.g. cities/districts/municipalities.
Country	The Country which the city belongs to.
VLR.Title	Official Title of the VLR.
Year.of.publication	Year of publication.
Time series data (2008-2022)	Fifteen columns showing the timeseries data of the reported indicators between 2008-2022.

3.2. EXPLORATORY DATA ANALYSIS SUMMARY

The data was explored at the goal level, identifying how indicators and cities are distributed across the SDG goals. Figure 1 shows, for each goal, the number of cities and countries reported, as well as the total indicators per goal and the number of non-null values across the time series data for all indicators associated with that goal. This provided a measure of the extent of reporting on each goal at the local level. Some indicators were flagged as not having an obvious SDG goal alignment.

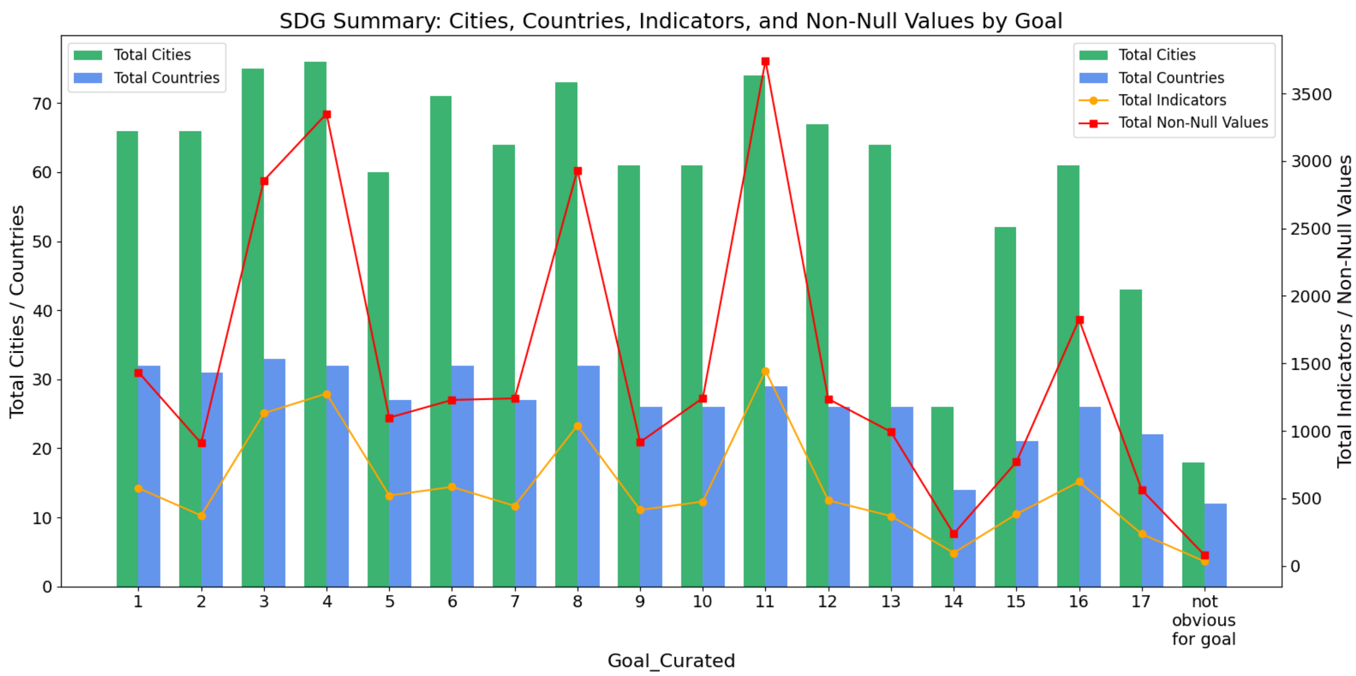


Figure 1: ***Exploratory Data Analysis summary:*** City/Country distributions and number of indicators/ non-null values across all 17 SDGs

Figure 1 shows that SDG 11 is the most reported on among SDG goals, reflecting cities' prioritization of making urban and human settlements inclusive, safe, resilient, and sustainable. SDG 7, the focus of this study, was fairly well represented with 444 indicators across 64 cities. This represented approximately two-thirds of all cities in the database, as seen in Figure 2.

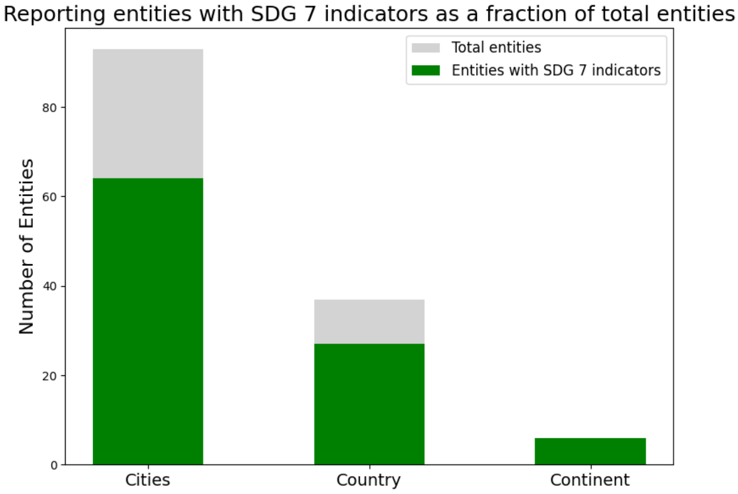


Figure 2: ***Number of Entities reporting SDG 7 indicators:*** Reporting entities with SDG 7 indicators as a fraction of total entities

3.3. MISSING DATA EXPLORATION

Missing data was analyzed in three dimensions. First, the time series evolution of missing data in each year across all goals was inspected, as seen in Figure 3. The general trend shows a sharp increase in local-level reporting following the adoption of the SDGs in 2015. This same trend is evident in the second dimension of exploration, where missing data in each year is analyzed across the 64 cities with SDG 7 indicators reported, as shown in Figure 4. The general high values of missing data are a result of both sparse reporting and heterogeneous indicators across cities.

Goal_Curated	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
1	98	97	91	94	93	91	87	66	77	72	65	66	74	89	93	100	99
2	98	98	91	94	92	90	85	74	75	76	60	64	76	90	94	100	99
3	99	98	90	92	94	88	89	68	76	69	73	62	72	84	93	97	99
4	99	99	92	90	91	90	90	75	65	71	65	59	78	85	88	97	100
5	99	98	94	97	97	89	92	73	84	76	76	59	79	84	93	98	99
6	99	99	93	95	93	95	91	73	81	78	76	66	72	86	93	98	100
7	98	98	88	91	86	83	78	64	73	70	73	72	68	87	93	99	99
8	97	97	86	89	91	90	88	63	77	68	65	61	71	82	94	99	99
9	97	98	90	92	94	91	91	66	78	77	72	71	81	87	94	99	99
10	98	98	89	92	92	91	90	69	77	69	61	65	76	79	94	99	99
11	97	96	89	91	91	90	88	73	79	71	64	71	69	80	92	99	99
12	98	95	92	92	91	92	89	72	80	69	64	62	72	85	92	99	98
13	98	95	90	91	86	88	83	65	76	66	67	76	72	85	93	98	99
14	97	100	97	100	91	94	91	68	70	73	71	67	65	79	93	99	99
15	99	97	93	96	91	95	94	74	85	81	76	71	74	81	93	99	99
16	98	99	92	92	93	92	83	67	75	62	55	50	73	83	92	98	99
17	100	100	93	94	94	94	90	69	81	79	78	57	69	78	87	96	97

Figure 3: ***Evolution of missing data across goals:*** Missing data for each goal

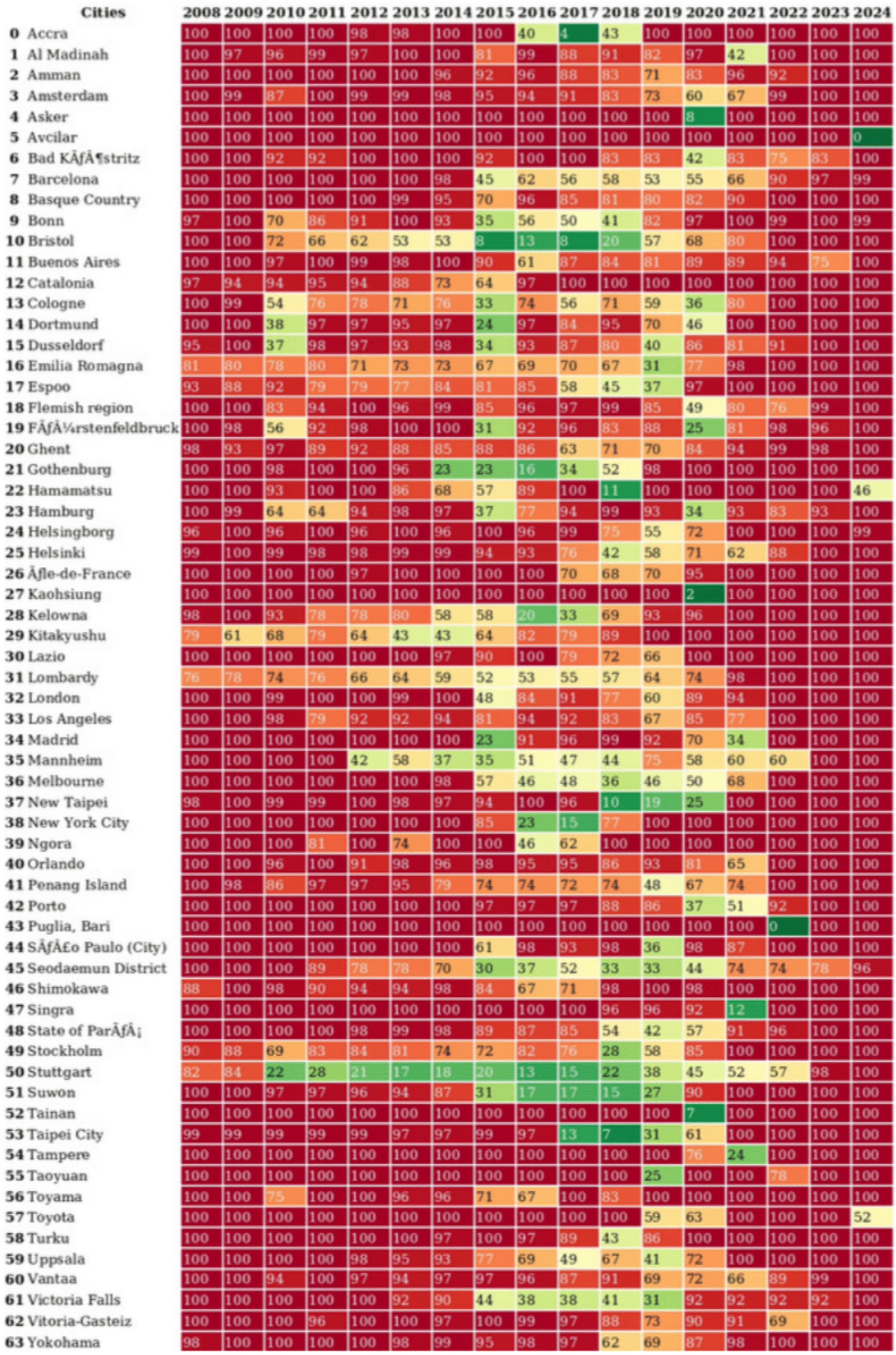


Figure 4: ***Evolution of missing data across cities:*** Missing data for each city

In the final dimension of exploration, cities were explored to see the raw number of indicators reported across the goals, as seen in Figure 5. In general, every city reported equally across all goals, with Ghent, Stuttgart, and Barcelona being the top 3 cities reporting the highest number of SDG7 indicators.

Goal_Curated_norm	City	SDG01	SDG02	SDG03	SDG04	SDG05	SDG06	SDG07	SDG08	SDG09	SDG10	SDG11	SDG12	SDG13	SDG14	SDG15	SDG16	SDG17
0	Accra	6	3	9	10	5	0	2	7	3	1	0	0	0	0	0	0	1
1	Al Madinah	5	0	8	8	5	6	3	7	1	0	27	2	0	0	0	1	0
2	Amman	0	0	15	0	0	1	4	0	2	0	0	2	0	0	0	0	0
3	Amsterdam	36	1	9	21	3	7	6	55	0	50	56	17	4	0	3	9	0
4	Asker	4	1	15	5	0	13	10	6	4	1	43	0	0	0	0	7	5
5	Avcilar	7	1	3	4	4	1	1	3	3	5	6	6	2	1	2	5	4
6	Bad KÃƒÂ¶stritz	0	0	0	1	0	0	4	0	0	0	5	1	1	0	0	0	0
7	Barcelona	40	17	98	62	49	46	24	69	27	60	86	28	34	18	26	46	27
8	Basque Country	20	15	32	15	11	16	20	31	20	18	11	15	16	11	11	20	14
9	Bonn	14	2	9	16	6	11	11	22	5	5	51	11	8	0	8	5	2
10	Bristol	7	4	32	52	6	3	9	25	16	25	25	10	7	10	4	18	0
11	Buenos Aires	10	4	69	158	32	8	14	26	16	9	45	13	10	0	8	18	15
12	Catalonia	22	22	54	20	28	22	11	53	28	4	28	24	6	7	26	24	0
13	Cologne	8	4	16	13	4	7	8	14	4	5	50	12	7	0	6	10	6
14	Dortmund	4	1	1	5	3	2	2	4	0	2	9	0	0	0	3	1	0
15	Dusseldorf	6	1	12	5	9	4	1	6	3	3	16	7	1	1	8	3	0
16	Emilia Romagna	1	6	11	10	3	12	2	7	13	1	10	6	4	2	2	10	3
17	Espoo	7	0	16	9	14	3	2	1	0	1	7	3	1	0	2	7	0
18	Flemish region	2	3	3	5	8	6	6	6	0	3	20	0	2	1	0	3	3
19	FÃƒÂ¼rstenfeldbruck	2	1	1	0	0	8	8	2	2	0	21	2	1	0	0	0	0
20	Ghent	50	17	60	55	30	16	45	68	30	15	101	24	20	3	4	53	0
21	Gothenburg	2	2	0	4	4	4	3	3	3	5	11	3	3	0	1	8	0
22	Hamamatsu	0	1	3	1	0	3	3	4	1	0	2	1	4	0	0	2	2
23	Hamburg	5	2	10	31	5	5	8	12	6	4	19	3	6	0	9	8	4
24	Helsingborg	3	4	8	8	4	8	4	6	4	4	4	8	3	4	4	4	0
25	Helsinki	11	2	12	32	8	6	1	53	0	46	17	9	7	2	4	13	1
26	Kaohsiung	11	9	10	15	9	13	2	2	3	5	30	21	11	5	14	8	6
27	Kelowna	5	2	5	3	2	1	4	2	8	2	2	2	3	1	1	1	1
28	Kitakyushu	0	0	0	0	3	0	5	4	11	0	0	5	0	0	0	0	0
29	Lazio	1	2	2	2	2	2	2	1	2	1	3	3	0	2	2	2	0
30	Lombardy	4	6	6	5	3	4	4	4	5	4	4	4	3	0	2	0	0
31	London	16	20	20	33	18	10	9	27	9	12	17	18	4	0	9	11	2
32	Los Angeles	5	5	1	11	0	2	5	9	3	1	2	3	0	0	0	0	1
33	Madrid	6	4	10	4	6	4	3	13	6	4	12	5	2	0	3	6	4
34	Mannheim	2	1	1	9	1	0	1	8	0	4	12	2	1	0	1	12	0
35	Melbourne	7	10	48	28	23	10	5	28	13	16	30	9	6	3	7	31	0
36	New Taipei	1	3	20	4	6	4	4	4	3	5	31	6	2	2	3	7	1
37	New York City	0	0	0	0	0	3	1	0	0	0	4	2	0	0	3	0	0
38	Ngora	2	6	18	3	13	6	7	18	6	0	0	0	0	0	1	13	3
39	Orlando	0	10	7	0	0	7	9	0	0	5	3	10	6	0	0	0	0
40	Penang Island	0	2	13	3	8	0	3	1	4	0	4	10	8	0	2	0	0
41	Porto	7	5	11	15	0	9	11	15	1	2	37	11	12	1	4	1	0
42	Puglia, Bari	10	9	30	28	12	13	8	20	13	10	19	19	2	4	6	13	8
43	Seodaemun District	1	0	3	3	0	1	1	4	0	1	6	3	1	0	0	3	0
44	Shimokawa	2	3	2	3	2	6	4	4	4	2	4	4	2	1	3	3	0
45	Singra	0	0	0	0	2	7	3	0	0	0	12	0	1	0	0	0	0
46	State of ParÃƒÂ¡	10	20	21	19	8	24	8	16	9	4	34	2	12	0	53	9	4
47	Stockholm	9	9	3	3	1	2	11	19	3	10	2	2	4	0	1	13	0
48	Stuttgart	25	10	51	73	14	10	28	40	7	17	60	14	16	0	15	27	23
49	Suwon	15	10	4	1	0	24	12	24	0	11	29	5	0	0	13	9	0
50	SÃƒÂ£o Paulo (City)	16	24	39	35	41	36	12	44	25	16	61	0	0	0	64	52	32
51	Tainan	0	0	3	7	0	9	5	1	2	0	10	6	9	0	1	0	3
52	Taipei City	2	0	23	22	17	20	11	17	8	1	22	11	16	0	0	1	2
53	Tampere	0	1	1	2	0	1	1	1	1	1	1	1	1	2	1	1	1
54	Taoyuan	3	0	4	4	3	6	3	5	1	0	12	4	2	2	2	3	4
55	Toyama	0	2	0	0	0	5	3	0	3	0	4	6	0	0	1	0	0
56	Toyota	0	0	12	0	1	0	3	3	2	0	2	1	1	0	0	0	2
57	Turku	4	0	2	3	0	3	3	4	4	2	3	4	2	0	0	3	0
58	Uppsala	1	1	13	15	4	0	1	17	0	5	6	5	0	0	0	15	0
59	Vantaa	9	6	42	45	9	11	23	14	2	11	14	2	4	0	5	10	1
60	Victoria Falls	7	1	12	1	4	2	1	1	1	0	6	0	0	0	0	2	1
61	Vitoria-Gasteiz	2	8	4	2	2	2	4	26	7	4	31	4	3	0	6	4	6
62	Yokohama	15	9	23	43	9	19	10	13	14	13	47	2	3	1	5	14	5
63	Ãƒle-de-France	1	1	4	2	1	2	2	5	0	1	4	4	4	0	2	4	0

Figure 5: ***Number of raw indicators in city across all goals:*** Ghent, Stuttgart, and Barcelona were the top 3 cities reporting the highest number of SDG7 indicators

Comprehensive details on techniques of handling missing data, including interpolation and imputation, are discussed in the methodology section.

4. METHODOLOGY

4.1. RESEARCH DESIGN & OVERVIEW

At a high level, the research design comprised three stages. First, a data assembly and harmonisation stage collected more than 10,000 city-level indicators from 120 VLRs (Stamos et al, 2024). Second, qualitative analysis was conducted through the semantic clustering of word embeddings, utilizing large language models to interpret and label the resulting clusters. Third, progress scoring of these thematic clusters was performed, followed by causal discovery of interlinkages using Bayesian Networks. Identified links were validated against existing literature and tested for stability through robustness checks, including frequency counts across time-sliced, bootstrap-sampled networks. The unit of analysis throughout is the city-year, indexed by the progress of indicator clusters reported in local-level SDG data.

4.2. QUALITATIVE ANALYSIS - SEMANTIC REPRESENTATION & CLUSTERING

4.2.1. Word embeddings

With the database in hand, the first step of the analysis involved qualitative clustering of SDG indicators to identify underlying themes in local-level reporting. Each indicator was converted into a vector embedding using Sentence Transformers. Sentence embeddings transform sentences or short texts into numerical vectors that capture semantic meaning. Unlike vanilla BERT, which processes text word by word, SBERT (Sentence-BERT) considers full sentence context and outputs fixed-length vectors representing semantic similarity. Related indicators, therefore, produce embeddings that are close in vector space and can be grouped into coherent clusters. This study utilized the all-MiniLM-L6-v2 model from the Sentence-Transformers library, which strikes a balance between quality and efficiency by producing compact 384-dimensional vectors at approximately five times the speed of larger models, such as all-mpnet-base-v2 (Reimers and Gurevych, n.d.). These embeddings are optimised for clustering and semantic similarity tasks (Red and Green, 2024). The model is open-source and locally deployable, avoiding the costs and access restrictions associated with proprietary services, such as OpenAI embeddings, which require API keys and token-based billing. HuggingFace Transformers were also considered, but using them directly requires custom pooling and normalisation (Hugging Face, n.d.), whereas Sentence-Transformers abstracts this complexity with ready-to-use pooling strategies.

4.2.2. Semantic Clustering

The next step was to semantically cluster these embeddings to reveal thematic similarities across indicators. Several algorithms were evaluated, including K-means, DBSCAN, and Gaussian Mixture Models (GMMs). K-means has been used in prior SDG embedding studies, such as Stamos et al. (2024), who set 17 clusters to align with the 17 SDGs. However, K-means assumes spherical clusters of similar size (MacQueen, 1967; Jain, 2010), which is unlikely in high-dimensional spaces. Density-based approaches, such as DBSCAN, can detect non-spherical clusters and manage outliers (Ester et al, 1996), and have been applied in NLP pipelines, including BERTopic (Grootendorst, 2022). Yet DBSCAN requires sensitive hyperparameters (the epsillon distance and minimum cluster size) that are difficult to calibrate across more than 10,000 indicators and tend to underperform in high dimensions (Campello et al, 2015). For these reasons, GMMs were selected. GMMs enable elliptical clusters with varying covariance structures and provide probabilistic (soft) assignments, which better reflect the possibility that indicators overlap across themes (McLachlan and Peel, 2000; Fraley and Raftery, 2002). In this framework, data are modelled as generated from a mixture of Gaussian distributions, each representing a latent cluster. Probabilities of membership are then estimated, though in this study, each indicator was assigned to the cluster with the highest probability. Prior to clustering, embeddings were reduced in dimensionality using Principal Component Analysis (PCA), retaining 90% of the variance to reduce noise and computational burden while preserving most of the information in the embedding space.

In their study, Stamos et al. (2024) clustered the dataset at the raw indicator level, linking each to its relevant SDG goal and target (from the VLR or author-curated). This study extends their pipeline by first grouping indicators by their associated goal and then clustering at the goal level to identify thematic clusters within each. To determine the optimal number of clusters, Gaussian Mixture Models (GMMs) were fitted across a bounded range of 3-10 clusters. For each candidate model, the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) were computed, normalised to a [0,1] scale, and combined as a weighted average.

The weighting was set at 0.6 for AIC and 0.4 for BIC, slightly favouring AIC. This reflects a preference for retaining more clusters to capture the heterogeneity of indicators across cities, while still constraining against overfitting through BIC. Increasing the AIC weight generally favours larger partitions, whereas stronger emphasis on BIC penalises complexity. An optional penalty discouraged very small k values, while the bounds of 3-10 were chosen to avoid degenerate single-cluster outcomes or excessive fragmentation.

This approach provided a transparent and reproducible mechanism for cluster selection, balancing model fit and simplicity while maintaining flexibility in interpreting thematic groupings. The methodology aligns with established clustering frameworks (McLachlan Peel, 2000; Fraley Raftery, 2002).

4.2.3. Cluster interpretations

With each local-level SDG indicator assigned a cluster label, the final stage of qualitative analysis involved cluster interpretation, producing a concise 4-6 word label and short description for each cluster. Generative Pre-trained Transformers (GPTs) were tested for this task, including models from OpenAI and Google Gemini. The Gemini 2.5 Flash model, accessed via Google AI Studio, was ultimately selected. It was preferred over OpenAI's models for cost reasons - Gemini offers a free tier - and because it generated concise, domain-appropriate labels during pilot testing.

For each cluster, the 20 most frequent indicator names were compiled into a short prompt requesting (i) a label under six words and (ii) a one-two sentence description. Outputs were parsed programmatically into a table (Cluster ID, Label, Description) and lightly post-edited for consistency (capitalisation, duplicate removal). To remain within API rate limits, calls were throttled, while prompts and sampling settings were fixed to ensure reproducibility. All outputs were human-reviewed for accuracy and bias before use. Appendix B presents the exact prompt used.

To complement this interpretation, the most representative indicators were identified using cosine similarity to cluster centroids in semantic space, while top word frequencies were visualised as word clouds.

The final output of the qualitative analysis consisted of thematic cluster assignments for the local-level indicators, accompanied by human-readable labels, brief descriptions, the most representative indicators per cluster, and cluster statistics, including the number of indicators per cluster, the most frequently reported indicators per cluster, the cities in which they were reported, and so on. Figure 6 illustrates the comprehensive methodological pipeline for qualitative analysis, outlining the high-level steps and specific models/methods employed

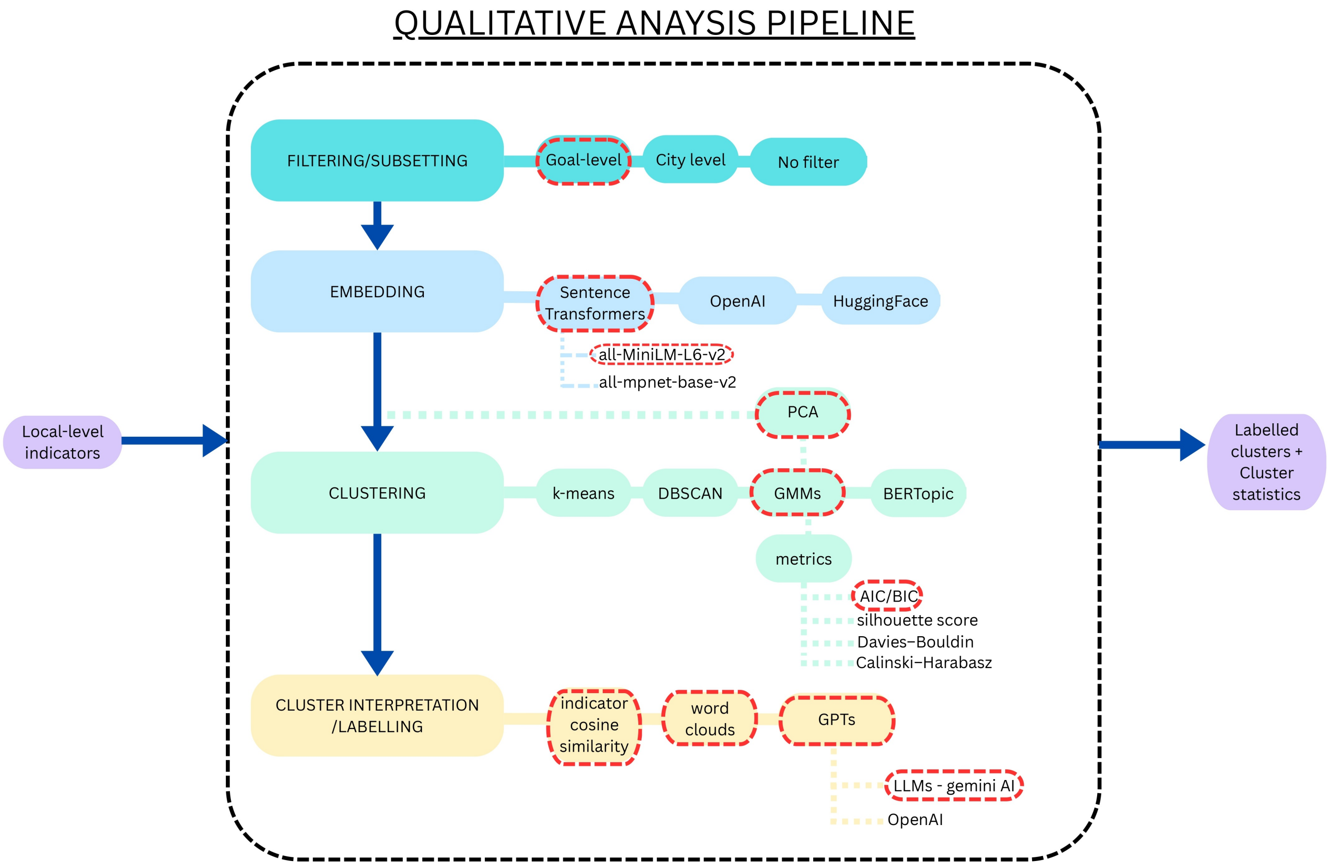


Figure 6: ***Qualitative analysis pipeline:*** Outputs thematic labels for local-level indicators

4.3. QUANTITATIVE ANALYSIS - PROGRESS SCORING AND CAUSAL DISCOVERY

4.3.1. Cluster progress scores at the city-year level

The thematically labelled indicators served as the input to the quantitative pipeline. The first step was to construct a cluster-level panel of indicators aggregated at the city-year level. To track the evolution of SDG indicators over time, progress scoring was implemented using rolling time windows (sustainable development lifecycles) of 3-7 years, spanning local-level data from 2008 to 2022.

To address sparsity and missing data within each window, linear interpolation was applied. Indicators with fewer than two values for a city in a given window were dropped, as they could not be interpolated. For each window, only the top 30 cities with the highest number of non-null values were included in progress scoring.

Within each window, the data was filtered by city to obtain the reported indicators. Individual progress scores were then calculated separately for each city. For each indicator, the first year in the window served as the baseline, and values were normalised using min-max scaling to handle differing units. Directionality adjustments were applied using the "Higher Means" column, with inverted scores for indicators where higher values represent worse outcomes. For example, the indicator proportion of households unable to maintain adequate temperatures was inverted so that progress increased as the proportion declined.

Finally, progress scores were aggregated at the cluster level for each city and year, using the thematic clusters defined in the qualitative analysis. Median aggregation was applied to limit the influence of outlier indicators that would bias mean scores. The output of this step was a tidy city-year-cluster panel of progress scores, which formed the input for causal discovery.

4.3.2. Causal Discovery

To infer causal interdependencies between the clustered progress scores, constraint-based graphical models were employed, specifically the PC algorithm. For each time window, the clustered progress scores of all cities were concatenated into a single dataframe, which served as the input to learn conditional dependencies within that period. A model dictionary was developed for each window size, storing the directed acyclic graphs (DAGs) learned from the data (e.g. the three-year model dictionary was keyed by values '2008-2010', '2009-2011', '2010-2012', and so on, while the seven-year dictionary was keyed by '2008-2014', '2009-2015', etc.).

Graphical causal discovery methods were chosen over time-series approaches such as Granger regression because the local SDG data are sparse, irregularly reported, and relatively short. Granger methods typically require long, continuous time series and perform poorly in the presence of missing data (Ospina-Forero et al, 2022), whereas graphical approaches can infer conditional dependencies from short panels by leveraging independence testing.

Within the family of graphical methods, the PC algorithm was selected over score-based alternatives such as Greedy Equivalence Search (GES). While both are widely applied in Bayesian network structure learning, in this study, PC consistently produced a greater number of interpretable links that aligned with plausible SDG interdependencies. By contrast, GES tended to yield sparser graphs with fewer substantively meaningful connections. The use of PC thus reflected a balance between model interpretability and empirical plausibility, while still grounding inference in a rigorous constraint-based framework (Spirtes et al, 2000).

Once conditional dependencies were identified, each DAG was evaluated by fitting a Bayesian network to estimate parameters and compute Bayesian Information Criterion (BIC) scores. For each edge, the BIC value was calculated by comparing the fit of the model with and without that edge, providing a post hoc measure of causal strength. These BIC scores were then normalised within each network to facilitate comparison across time windows. To supplement causal strength analysis, Pearson correlation coefficients were also calculated between clusters using the same city-year panels. Finally, the frequency of each link across all time windows was computed as a measure of stability, providing a robustness check on the persistence of inferred interdependencies.

4.3.3. Causal links results synthesis

To synthesise causal links, three complementary approaches were applied. The first examined outward first-order links from SDG 7 clusters. For each network, time slice, and window size, links with SDG 7 clusters as parent nodes were filtered and ranked by the cumulative sum of their normalised BIC scores, capturing both causal weight and frequency across windows. The top 30 outward links were then assessed to understand how progress in SDG 7 clusters acted as drivers of other goals, highlighting potential policy levers within the energy domain.

The second approach focused on inward links, selecting the top 30 connections where SDG 7 clusters were child nodes. This analysis revealed how progress in non-energy clusters contributed to sustainable energy outcomes, identifying levers outside the energy domain that can accelerate SDG 7.

The third approach synthesised results using a fixed five-year window size. Directed acyclic graphs (DAGs) from rolling windows (2008-2012 to 2018-2022) were analysed to highlight persistent causal structures, while incorporating second-order links to capture potential cascading effects.

Causal inference was complemented by a longitudinal analysis of cluster progress. For each SDG, rolling linear regressions were fitted to centred five-year windows (e.g. 2011-2015 for 2013). Regression slopes provided smoothed estimates of progress rates, reducing noise and enabling comparison of trajectories across clusters between 2010 and 2020. This analysis was applied to all clusters and city rankings.

The outputs included causal graphs (inward and outward links), longitudinal trends in cluster progress, and city progress rankings. Figure 7 illustrates the complete analysis pipeline.

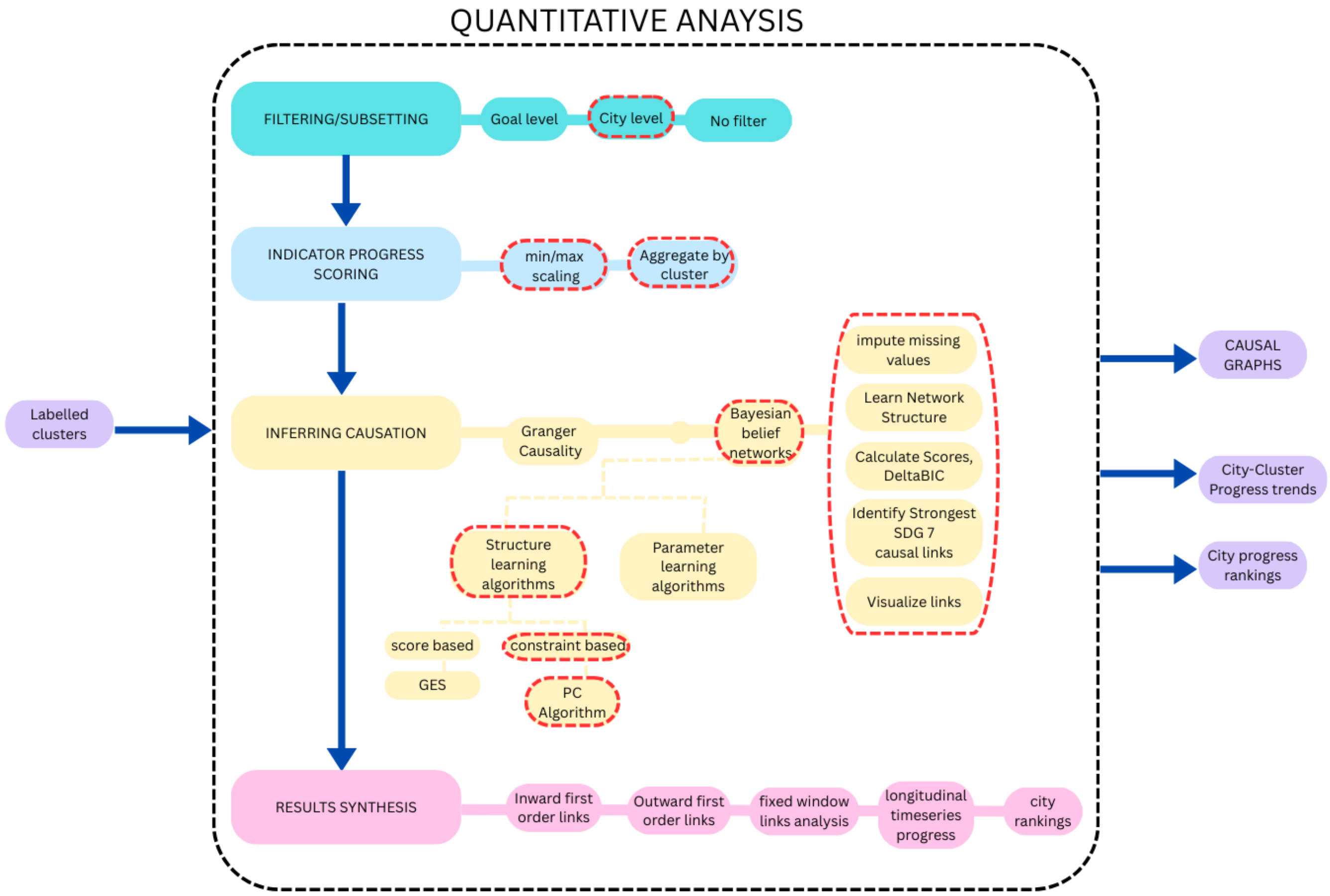


Figure 7: ***Quantitative analysis pipeline:*** Outputs Causal graphs, city-cluster progress trends and city rankings

5. ANALYSIS AND DISCUSSION

5.1. QUALITATIVE ANALYSIS RESULTS

5.1.1. Optimal cluster selection

The word embeddings of the local level indicators for each SDG goal were clustered using GMMs with the optimal number of clusters automatically selected using the combined normalized AIC and BIC scores. The slightly higher weighting of 0.6 for the normalized AIC and 0.4 for the normalized BIC favoured a higher number of clusters. Figure 8 shows nine as the optimal number of thematic clusters for SDG 7 indicators. The optimal number of clusters for all other goals can be seen in Appendix A

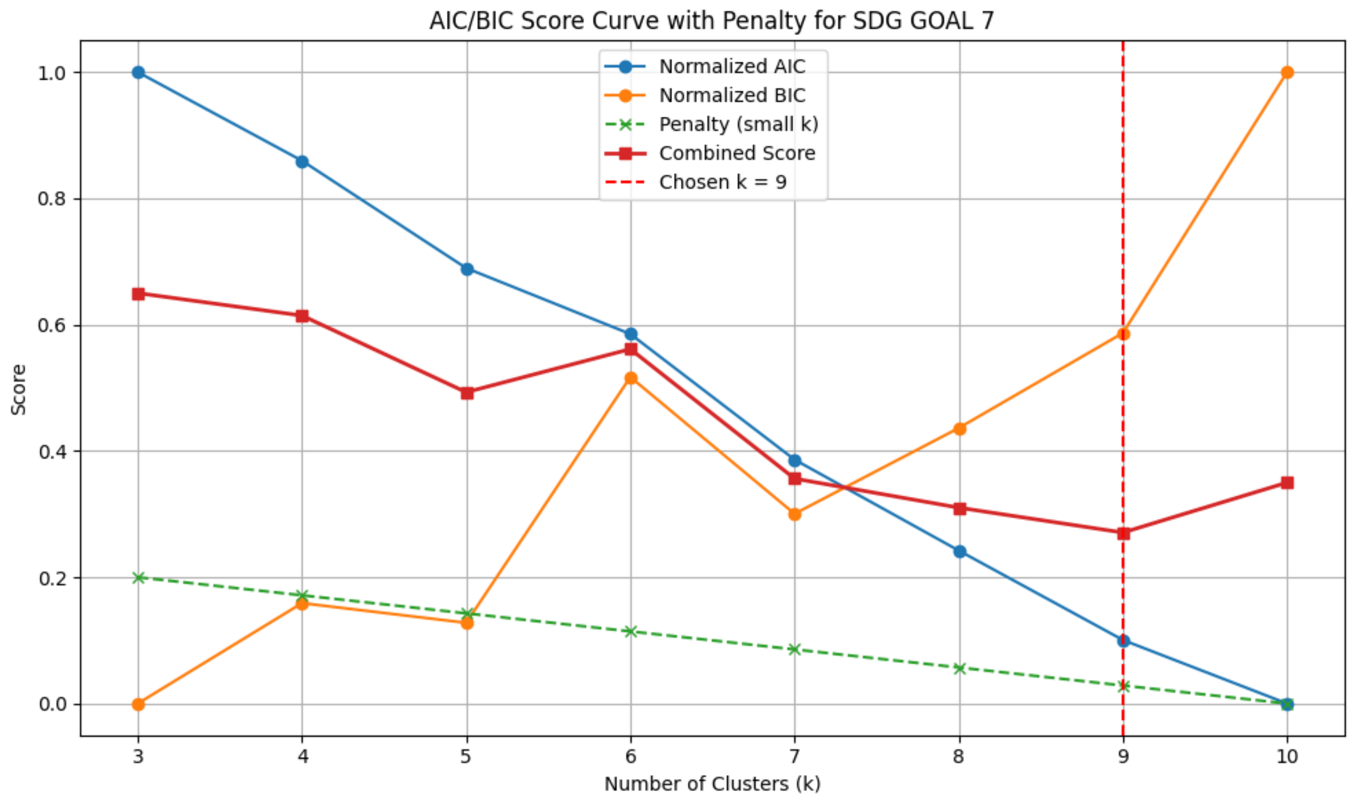


Figure 8: ***Optimal number of SDG 7 Clusters:*** Chosen at lowest combined score

5.1.2. Word cloud interpretations

As a first attempt of semantic understanding, the top words (highest occurring among the local level indicators) were visualized in word clouds. Figure 9 shows the top words per cluster for SDG 7

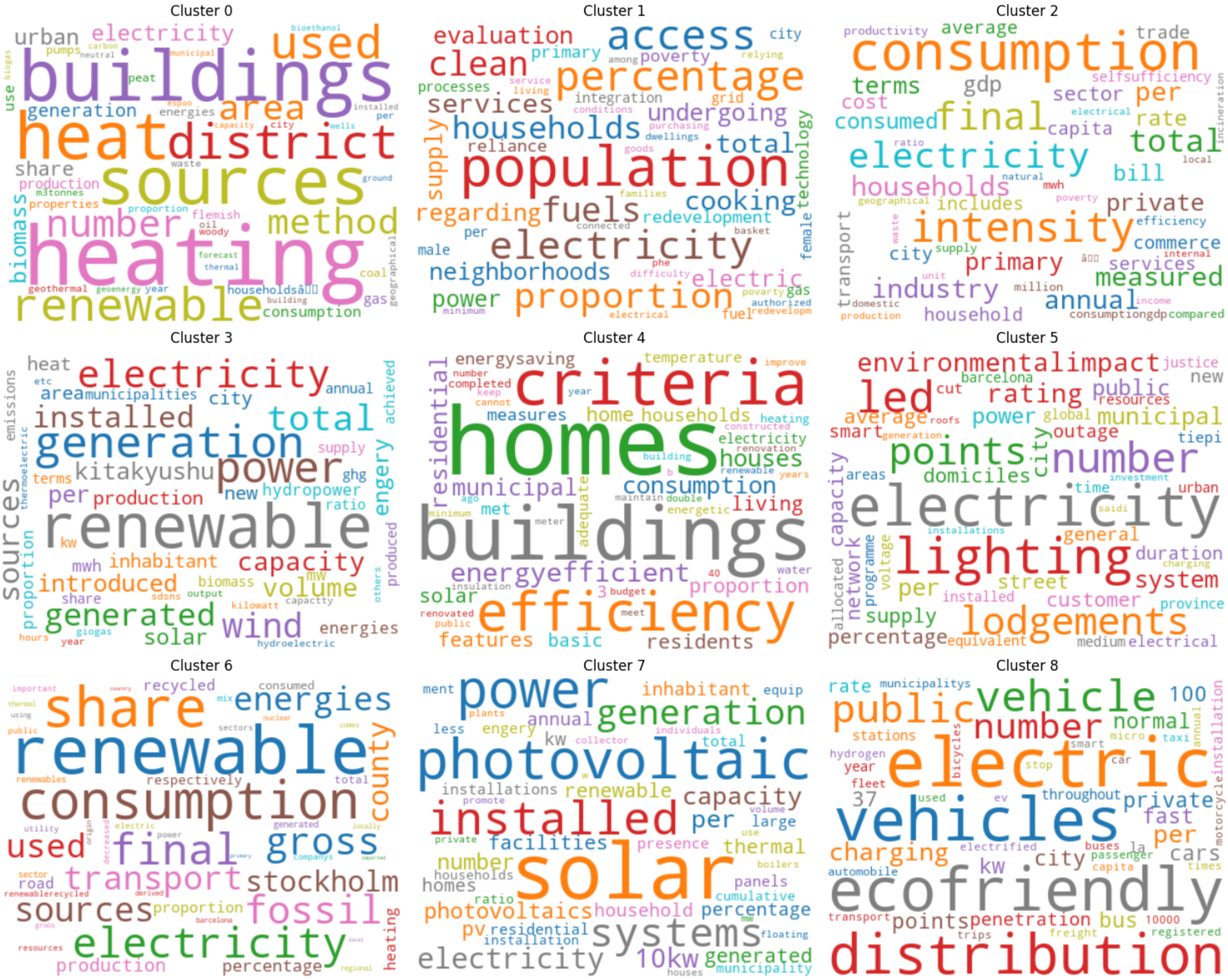


Figure 9: ***Word cloud of SDG 7 Clusters:*** Displays the individual words with the highest frequency occurrence in the names of VLR indicators within each cluster

5.1.3. Generative Pretrained Transformer (GPT) interpretations

To complete the interpretation of clusters, Google AI's GPT model Gemini Flash 2.5 was leveraged, with prompts to provide cluster labels and descriptions of the given indicator clusters. Table 2 shows the Gemini cluster labels and interpretations for the SDG 7 clusters and the modal associated SDG targets. More details on the most representative indicators per cluster (using the embeddings' cosine similarity to cluster centroids), the most reported indicators per cluster, as well as the complete cluster interpretations for all SDG goals are presented in Appendix B.

Table 2: Gemini AI cluster labels and descriptions

Cluster ID	Thematic Label	Short Description	Modal SDG target
0	Renewable Heat Production and District Energy	This cluster tracks the production and use of heat from various renewable energy sources like biomass, solar, geothermal, and heat pumps. It also covers the role of district heating in sustainable energy provision and overall heat consumption in urban areas.	7.2
1	Household Energy Access and Poverty	This cluster assesses the extent of household access to modern energy services, including electricity and clean cooking fuels, and various dimensions of energy poverty, such as affordability and ability to keep homes adequately warm.	7.1
2	Energy Use, Affordability, and Efficiency	This cluster encompasses indicators related to the consumption volume and intensity of various energy types, especially for households. It also covers the economic aspects of energy, including costs, affordability, and overall energy efficiency.	7.3
3	Renewable Energy Generation and Capacity	This cluster measures the installed capacity, actual generation, and overall share of electricity from various renewable energy sources. It also tracks progress towards renewable energy goals.	7.2
4	Building Energy Efficiency and Thermal Comfort	This cluster focuses on energy consumption, efficiency, and renovation in residential and public buildings. It also addresses thermal comfort and energy poverty, including the use of renewable heating systems.	7.3
5	Energy Grid Performance and Modernization	This cluster measures energy supply performance, reliability, and modernization. It includes indicators on grid quality, smart technologies, charging infrastructure, access, and investment.	7.1
6	Renewable Energy Consumption Share	This cluster quantifies the proportion of total energy and electricity consumed that is derived from renewable sources, including those generated locally.	7.2
7	Solar Power Generation and Capacity	This cluster measures the deployment and output of solar energy, encompassing both photovoltaic and thermal systems. It includes indicators for installed capacity, electricity generation, and system presence across residential and large-scale installations.	7.2
8	Sustainable Urban Mobility Progress	This cluster measures the progress in transitioning to electric and eco-friendly vehicles, developing their necessary charging infrastructure, and improving the adoption of public and active transportation modes within urban areas.	7.a

Table 2 presents the nine thematic clusters of SDG 7 indicators reported at the local level, showing their alignment with the three main SDG 7 targets: energy access, renewable integration, and energy efficiency. The column Modal SDG target records the most frequently associated SDG target for each indicator, based on the original dataset compiled by Stamos et al. (2024), which mapped indicators from VLRs or author-curated sources.

Indicators in the clusters Household Energy Access and Poverty and Energy Grid Performance and Modernization are predominantly linked to target 7.1, which focuses on improving energy access. The clusters Renewable Heat Production and District Energy, Renewable Energy Generation and Capacity, Renewable Energy Consumption Share, and Solar Power Generation and Capacity are most often linked to target 7.2, which aims to increase substantially the share of renewable energy in the global mix. In contrast, Energy Use, Affordability, and Efficiency and Building Energy Efficiency Thermal Comfort align with target 7.3, which calls for doubling the global rate of energy efficiency improvement by 2030. Notably, the cluster on Sustainable Urban Mobility Progress is associated with target 7.a, which promotes international cooperation on clean energy technologies.

Figure 10 summarises statistics for these clusters, including the number of indicators and reporting cities. Energy Use, Affordability, and Efficiency was the most widely reported, with 87 indicators across 34 cities, while Sustainable Urban Mobility Progress was the least reported, with 17 indicators across 6 cities.

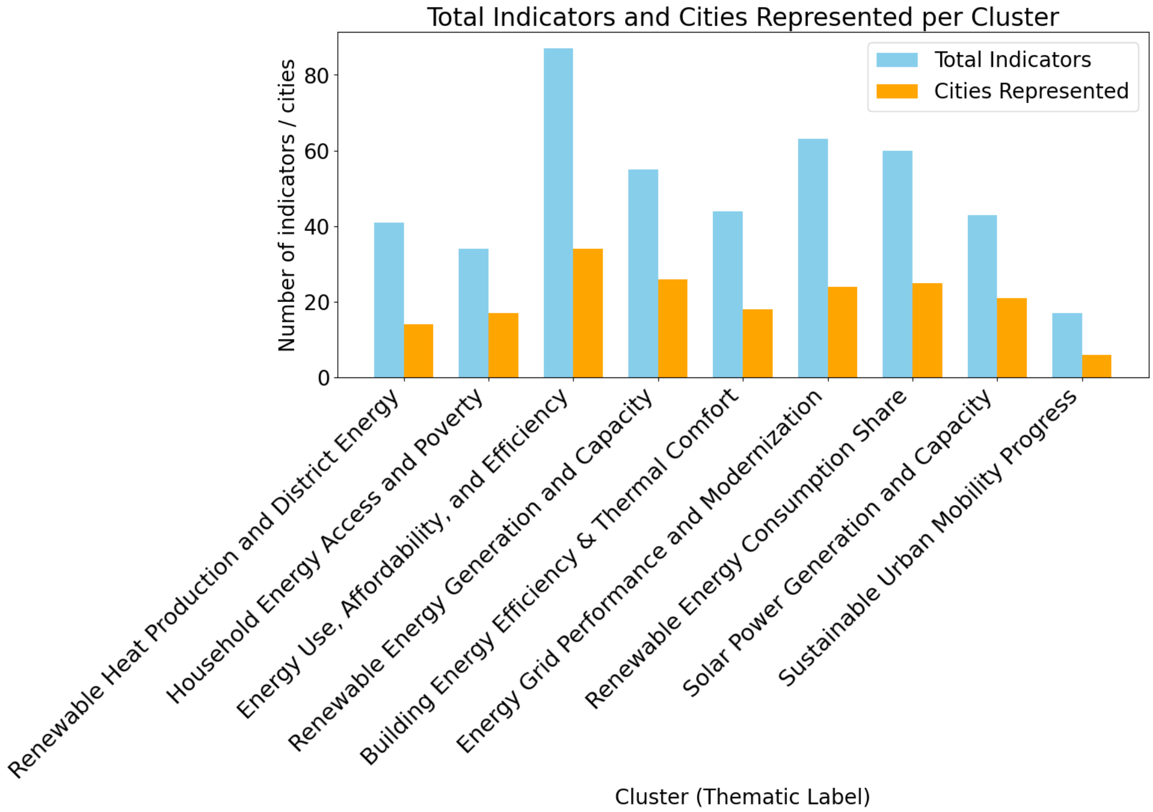


Figure 10: ***SDG 7 Cluster Statistics:*** Number of indicators and cities represented per thematic cluster

5.1.4. Semantic space visualization

To visualize the clusters in the semantic space, the vector embeddings of the indicators were reduced to two dimensions using PCA. This allowed for the assessment of cluster coherence and the identification of overlapping themes across clusters. Figure 11 shows the SDG 7 clusters in the semantic space.

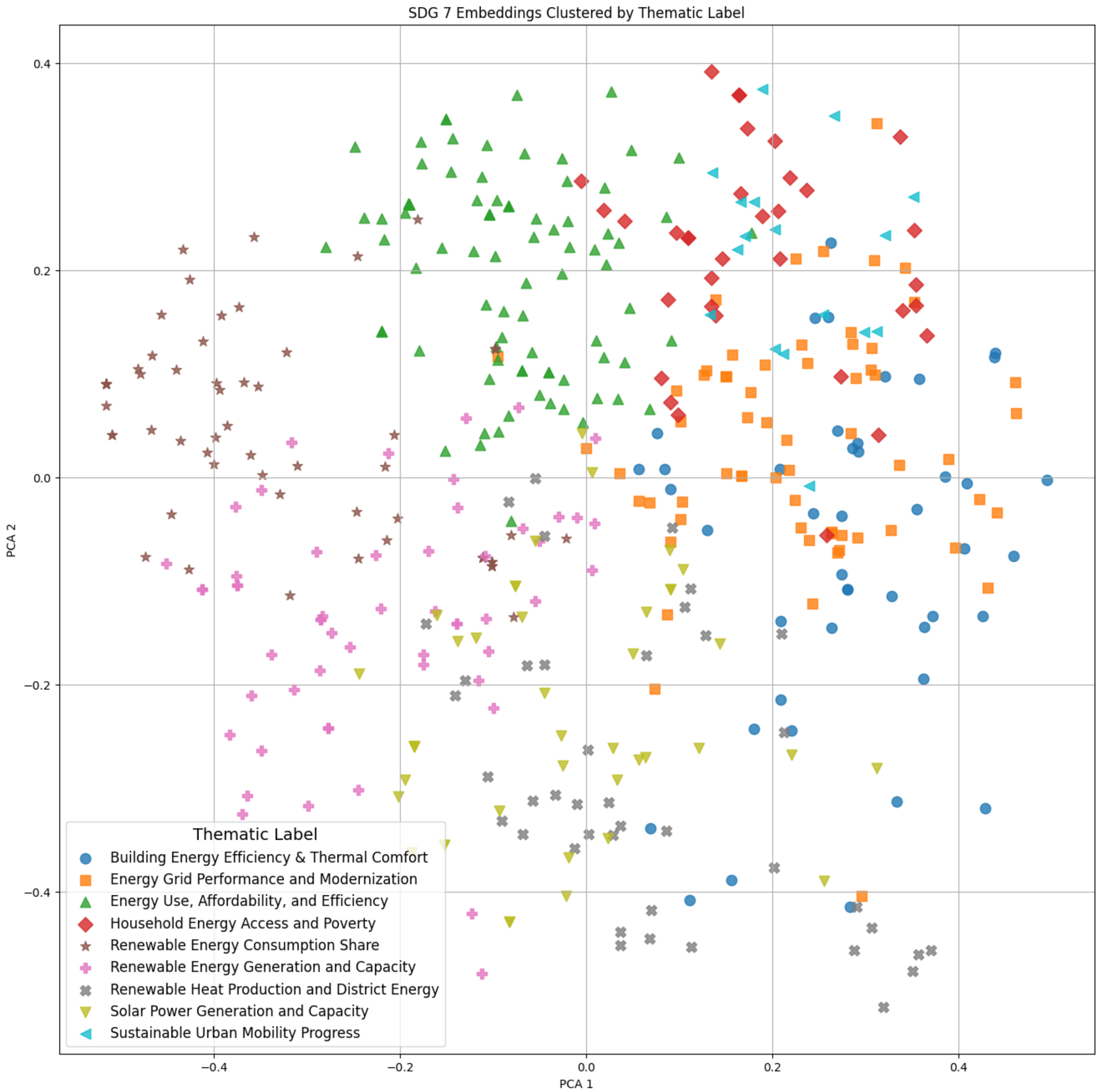


Figure 11: ***SDG 7 clusters in semantic space:*** coherent clusters are more compact, closlely related clusters overlap

From Figure 6, the cluster "Energy Use, Affordability, and Efficiency" is the most coherent with closely clustered indicators and few overlaps with other clusters. As expected, the clusters "Renewable Energy Generation and Capacity", "Renewable Energy Consumption Share", and "Solar Power Generation and Capacity" are closely related with multiple overlaps in the semantic space. Equally as expected, the clusters "Building Energy Efficiency & Thermal Comfort" and "Renewable Heat Production and District Energy" have semantic overlaps. Lastly, the clusters "Household

Energy Access and Poverty", "Energy Grid Performance and Modernization", and "Sustainable Urban Mobility Progress" are semantically clustered together, reflecting their thematic overlaps and overarching target of improving energy access and quality.

Semantic space clustering for the local-level indicators other than SDG 7 are presented in Appendix C.

5.2. QUANTITATIVE ANALYSIS RESULTS

5.2.1. Longitudinal progress analysis

Time series analysis was conducted for progress in all cities (median aggregated) across the reported indicators in the SDG 7 clusters. Figure 12 illustrates the changes in rates of progress reported across the SDG 7 thematic clusters for the years 2010-2020. Values below the zero mark line indicate decreasing progress/regression in the indicators reported across the decade 2010-2020.

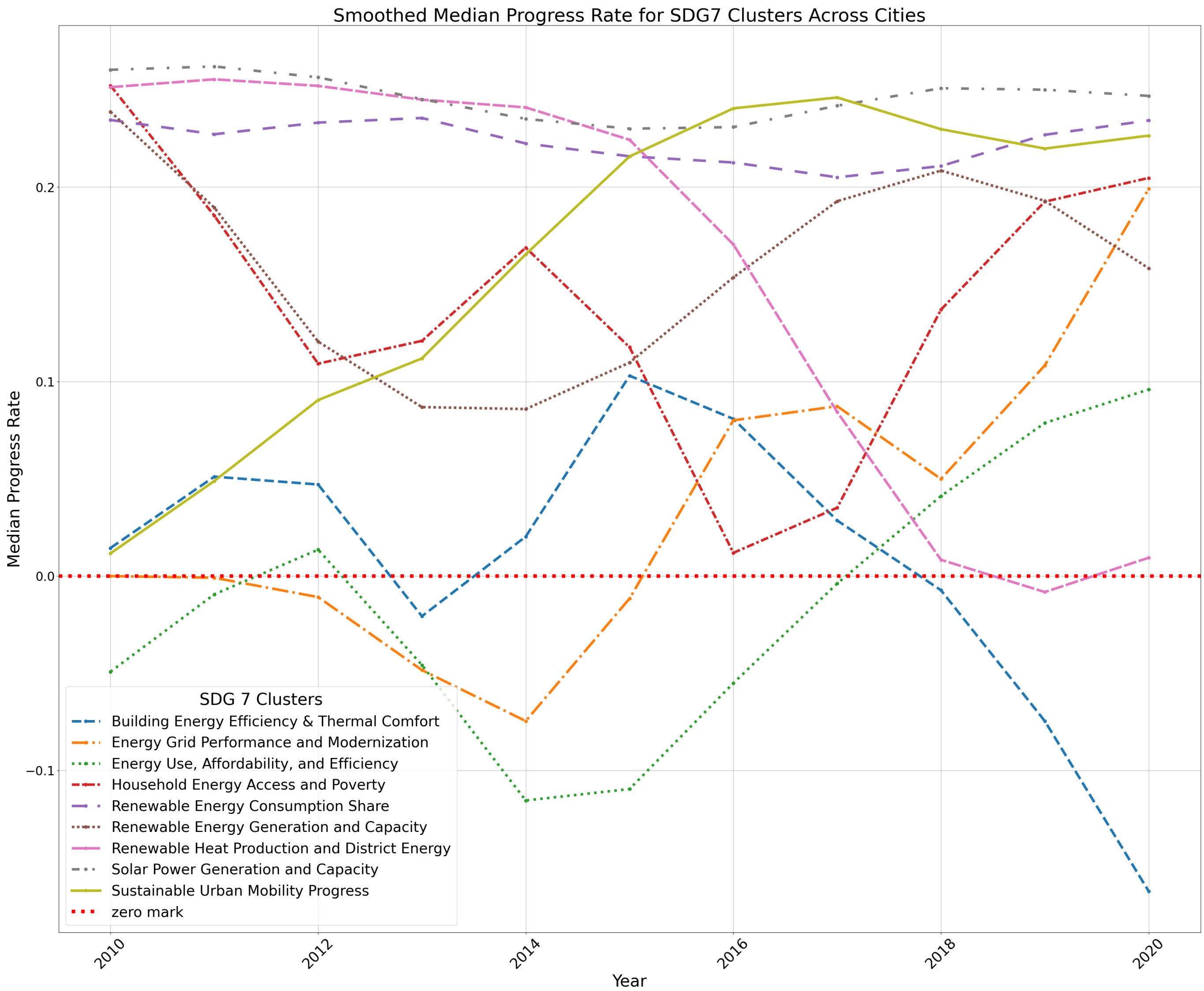
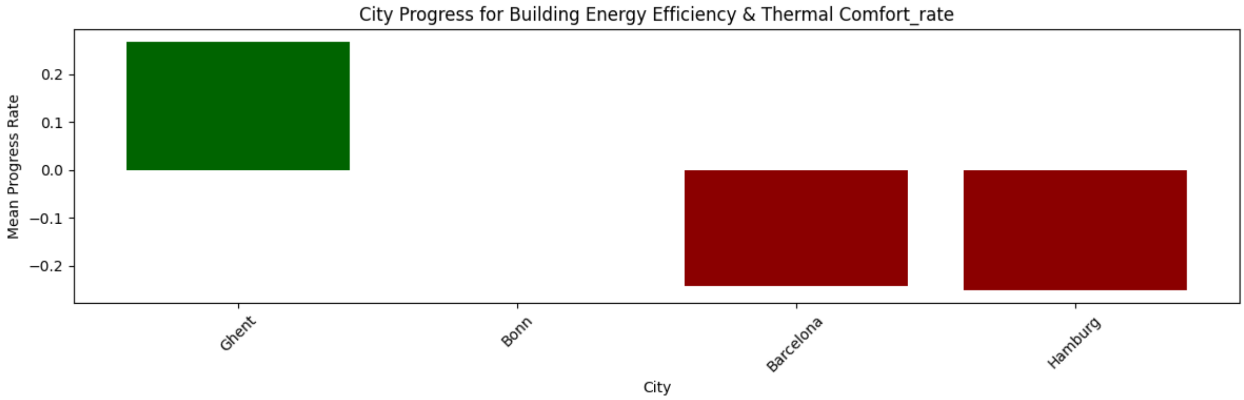


Figure 12: ***Time series progress in SDG clusters:*** Rates of progress calculated by fitting linear regression models for each indicator (subsequently aggregated to clusters) for 5-year time windows centered around each year from 2010 to 2020

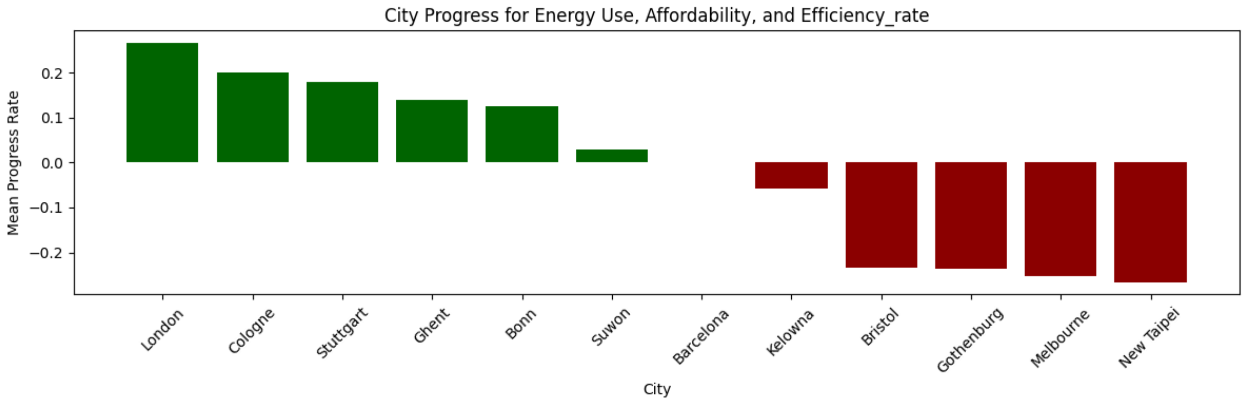
Between 2010 and 2020, progress across SDG7 clusters followed divergent trajectories. Renewable energy consumption share and solar power generation maintained steady gains, while sustainable urban mobility showed the most consistent upward trend, becoming the strongest performer in 2016. Energy use, affordability and efficiency and energy grid performance also improved markedly after 2014. In contrast, renewable heat and district energy declined sharply from 2012 onward, with only marginal recovery. Building energy efficiency and thermal comfort also trended downward after 2016, reaching negative territory by 2020. Household energy access and renewable generation capacity exhibited fluctuating but modest improvements overall.

5.2.2. City rankings across clusters

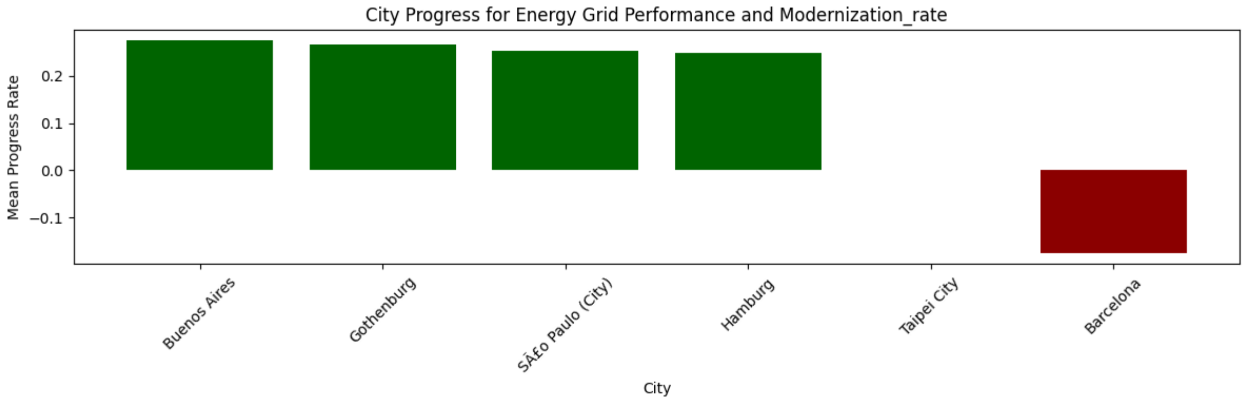
To complement the longitudinal time series analysis and contextualize the causal discovery results, the cities were ranked according to progress made in the SDG 7 thematic clusters. The results are illustrated in Figure 13 for each SDG 7 cluster. City rankings for progress in other SDG clusters are illustrated in appendix D.



(a) Building Energy Efficiency and Thermal Comfort progress rates

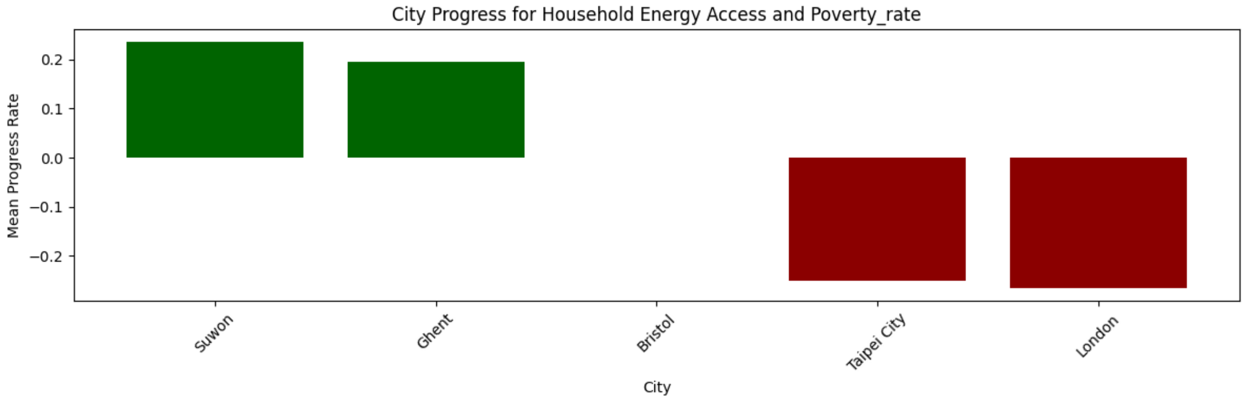


(b) Energy use, affordability, and efficiency progress rates

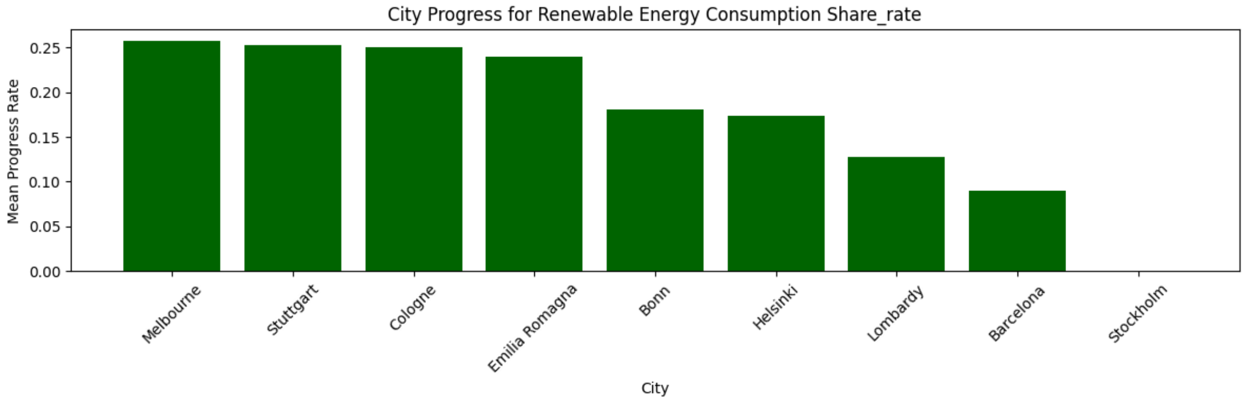


(c) Grid performance and modernization progress rates

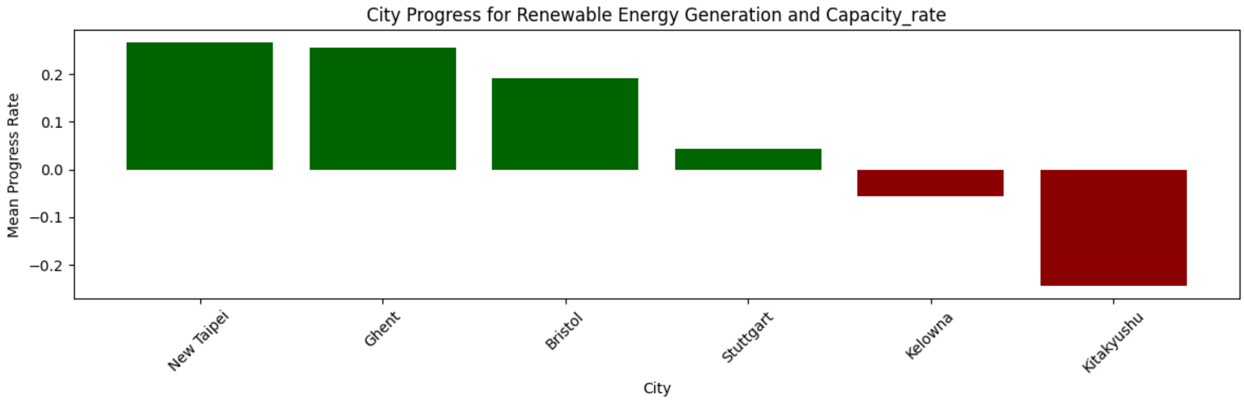
Figure 13: City cluster progress rankings



(d) Household energy access progress rates

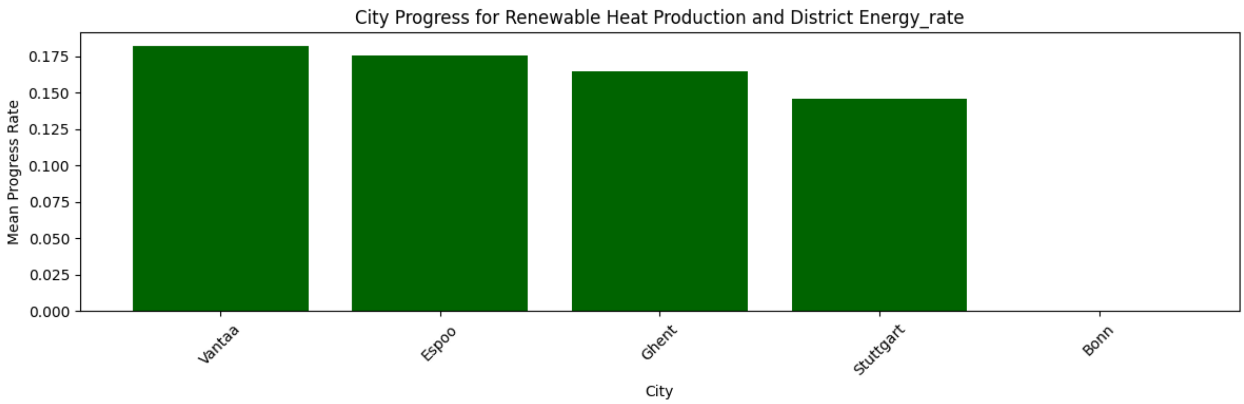


(e) Renewable energy consumption share progress rate

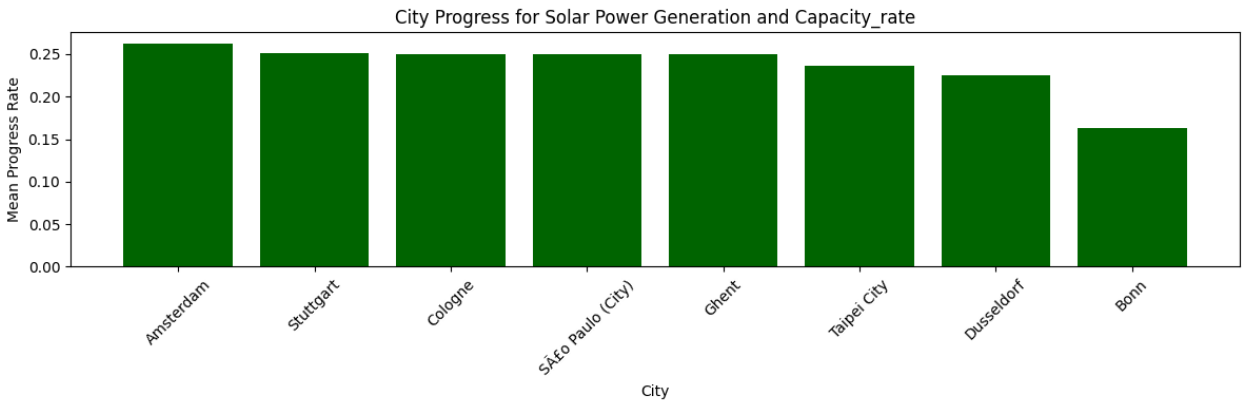


(f) Renewable Generation capacity progress rates

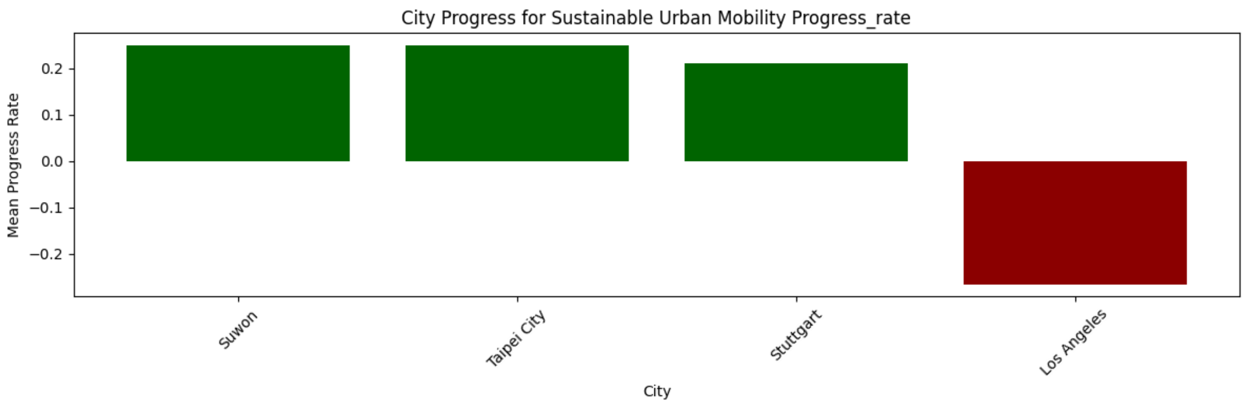
Figure 13: City cluster progress rankings



(g) Renewable heat and District Heating progress rates



(h) Solar power generation capacity progress rates



(i) Sustainable Urban mobility progress rates

Figure 13: City cluster progress rankings

5.2.3. Causal Discovery results summary

The results of the causal links were synthesized by the three high-level approaches described in section 3.4.3. In the first high-level approach to determine how progress in SDG 7 clusters caused progress in other indicator clusters, the top 30 outward first-order SDG 7 links (ranked by the cumulative sum of their normalised BIC scores) were filtered and analyzed as seen in Figure 14. These comprised all the links for each network (rolling time-window slice,e.g., 2015-2022,) for every time window size (3-year to 7-year windows)

The edge colours correspond to the Pearson's correlation coefficients between the median cluster progress scores, whereas the edge widths correspond to the sum of the delta BIC values for the causal links across all networks. As seen in the markers of Pearson's correlation scale in Figure 14, only positive correlations were associated with the causal links, indicating that all the uncovered dependencies were synergies and no tradeoffs were encountered. This is in line with literature findings on the dominance of synergies over tradeoffs (Anderson et. al., 2021). The label of each edge represents the number of networks it was present in, while the size of each node is proportional to its nodal influence, defined as the sum of the delta BIC values for all edges connected to that node (both inward and outward pointing)

In the second high-level complementary approach to determine how progress in other indicator clusters caused progress in SDG 7 clusters, the top 30 inward first-order SDG 7 links were filtered and analyzed, as seen in Figure 15.

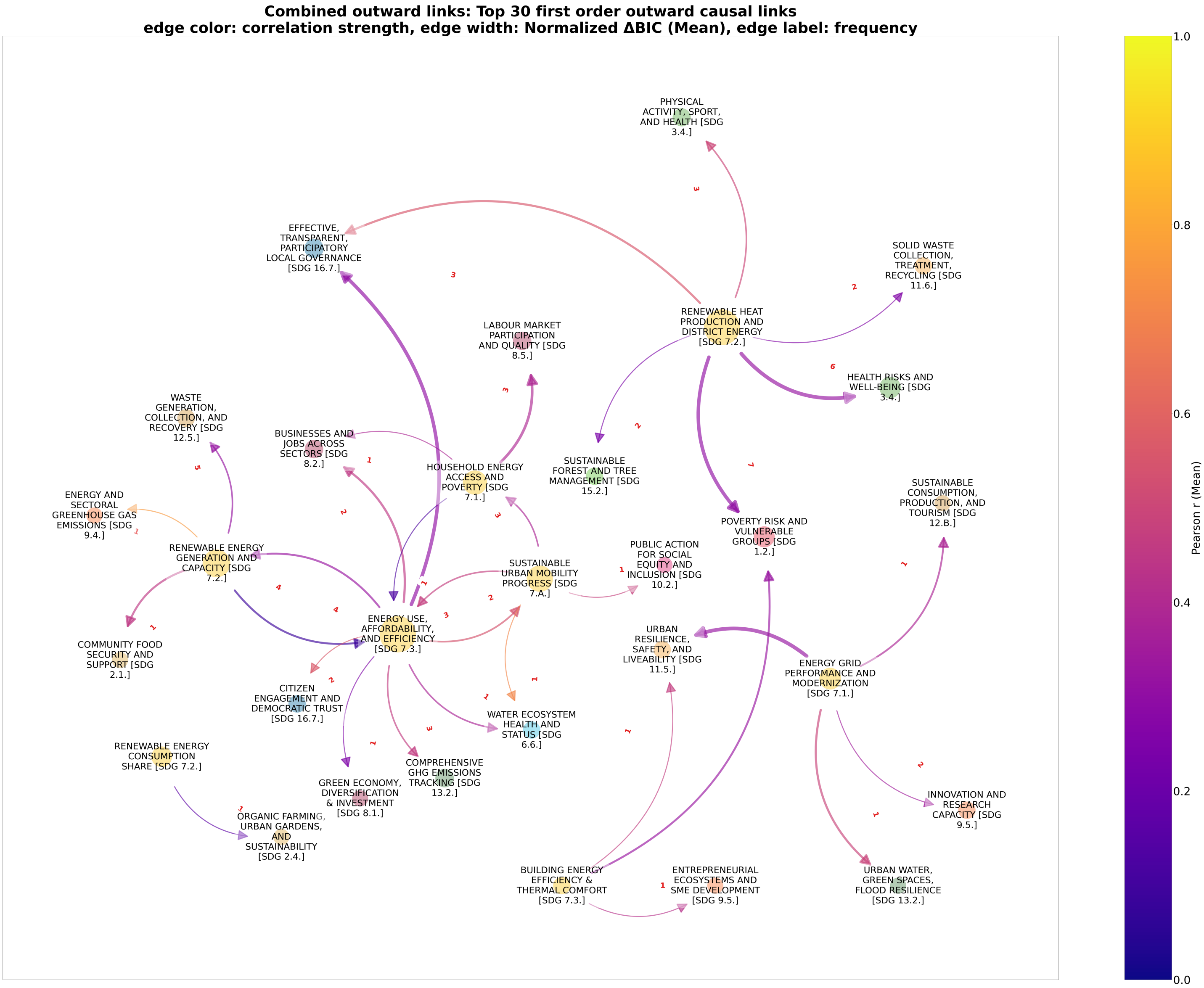


Figure 14: ***SDG 7 clusters as drivers of sustainability progress:*** First-order outward links

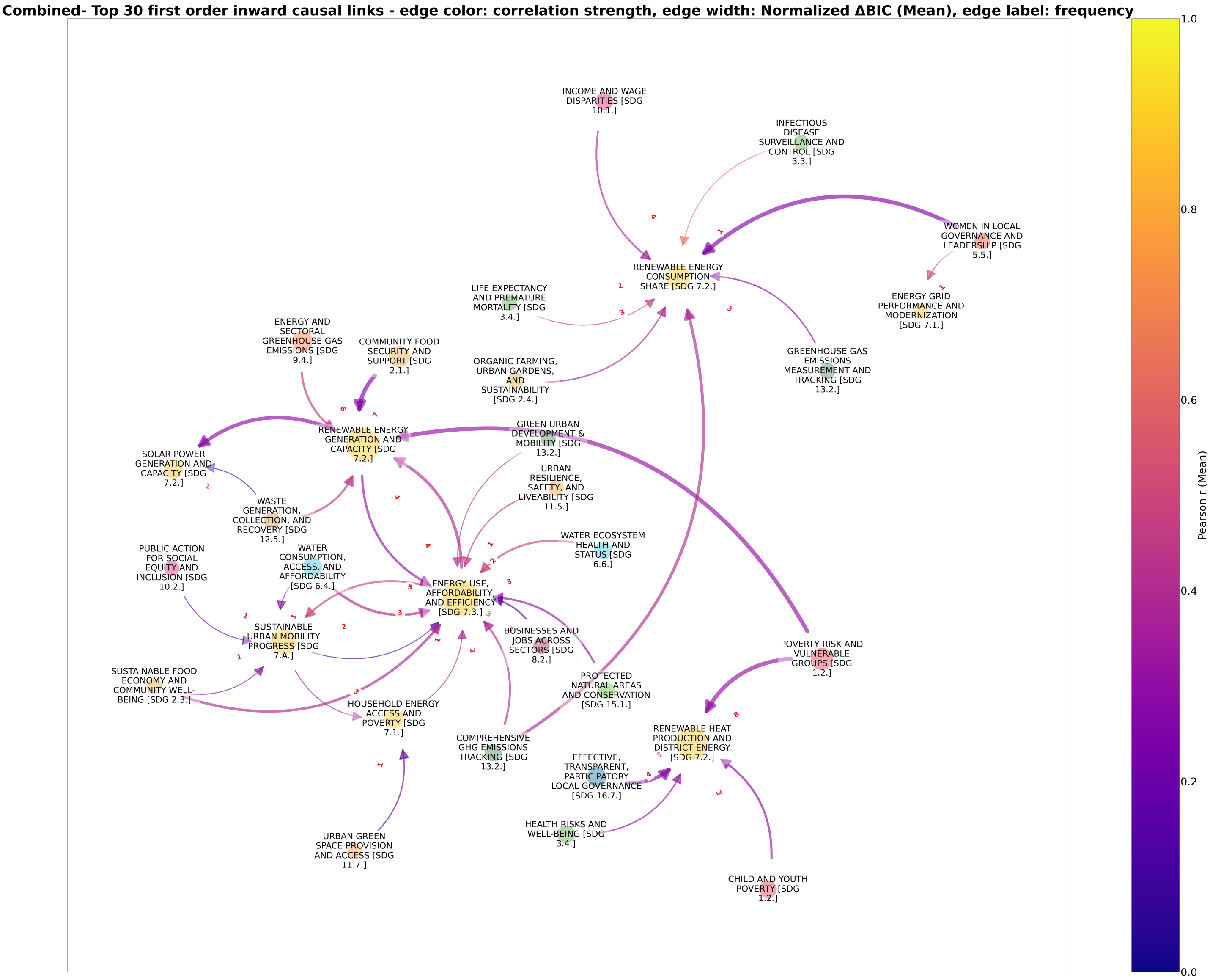


Figure 15: ***Non-SDG 7 clusters as drivers of progress in achieving SDG 7:*** First-order inward links

5.2.4. Local level Drivers of progress in SDG 7 and its role in the 2030 agenda

The first and second high-level approaches yielded causal links seen in Figure 14 and Figure 15 that were validated against the literature based on their broad alignment with the three SDG 7 targets and locally contextualized using the results of city progress rankings across the thematic clusters. Emphasis is laid on strong links with high frequencies.

Energy access and sustainable mobility

As seen in Table 2, the clusters "Household Energy Access and Poverty" and "Energy Grid Performance and Modernization" had most of their indicators associated with SDG target 7.1 on improving energy access. The cluster "Sustainable Urban Mobility Progress", while mostly associated with SDG target 7.a as per the data, is discussed alongside the two aforementioned clusters due to their thematic overlaps as seen in Figure 11.

As seen in Figure 14, a recurring edge appears between Household Energy Access and Poverty, and Labour market participation and quality. This linkage is consistent with a substantial body of evidence showing that improved household energy access can enable employment opportunities and reduce poverty. Access to reliable and affordable modern energy lowers the burden of fuel collection, improves health outcomes, and facilitates education, all of which support greater labour-force participation (Khandker, Barnes, Samad, 2012).

Figure 14 and Figure 15 illustrate that progress in the Sustainable Urban Mobility cluster is bidirectionally linked to improvements in Household Energy Access and Poverty. This connection likely reflects co-movement driven by shared infrastructure investment and planning capacity. For example, Figure 13.d and Figure 13.i, show Suwon as the city that made the highest improvement in both clusters. Suwon's rollout of electric bus charging infrastructure likely necessitated grid upgrades that extend benefits to households through improved connections and reliability (Institute for Global Environmental Strategies, 2022). At the national level, South Korea's greening strategy has emphasised smart grids and microgrids as key enablers of both transport electrification and residential energy access (The Asia Pacific Journal, 2016). Thus, this edge is interpreted not as a unidirectional causal pathway, but as an indicator of integrated energy-mobility planning.

The last cluster within the paradigm of energy access is Energy Grid Performance and Modernization. In Figure 14, grid modernization shows persistent links to Urban Resilience, Safety, and Livability and Urban Water, Green Spaces and Flood Resilience. The former cluster contains indicators on electricity interruptions and modernized LED street lighting, while the latter includes measures such as economic losses from natural disasters and rates of street cleaning (see Appendix B). These relationships are highly plausible. The installation of LED street lighting improves visibility and safety, contributing to reduced crime and enhanced perceptions of security in public spaces (Chalfin et al., 2019). Similarly, reductions in electricity interruptions strengthen resilience by ensuring reliable operation of essential services, including hospitals, water pumping, and communications, during natural disasters (Panteli & Mancarella, 2017). Modernized grids can also lower municipal energy costs, freeing resources for reinvestment in urban services such as street cleaning and waste management.

Figure 14 further shows links between grid modernization and Innovation and Research Capacity, which includes indicators such as patents, researchers, and R&D projects (see Appendix B). As shown in Figure 13.c and Figure 31.a, São Paulo made progress in both clusters, with credible evidence supporting this association. Brazil's electricity regulator ANEEL requires utilities to allocate approximately 1% of operating revenues to R&D, supporting innovation in grid technologies alongside operational upgrades (Pica, 2011). A notable example is AES Eletropaulo's R$75 million smart meter pilot, funded partly by FINEP, which installed 62,000 units and advanced grid management systems (Cisco News Release, 2014). This illustrates how grid modernization can catalyse technological innovation and capacity building within municipalities. Although directionality may also run from innovation ecosystems to grid upgrades, the evidence supports a mutually reinforcing relationship between modernization and innovation.

Renewable energy adoption

Table 2 lists the clusters "Renewable Heat Production and District Energy", "Renewable Energy Generation and Capacity","Renewable Energy Consumption Share" and " Solar Power Generation and Capacity" as having indicators mostly associated with SDG target 7.2 of substantially increasing the share of renewable energy in the global energy mix.

Associations between Renewable energy generation and capacity and other clusters are largely bidirectional. With Energy and sectoral greenhouse gas emissions, the relationship is reinforcing: renewables displace fossil fuels and reduce emissions, while climate and air-quality policies simultaneously drive renewable deployment (IEA, 2022; IRENA, 2021). Similarly, links with Waste generation, collection and recovery reflect co-evolution, as waste-to-energy projects transform municipal waste into renewable supply, while improved collection systems expand capacity (Scarlat et al., 2019). These dynamics highlight how renewable deployment both responds to and catalyses broader sustainability strategies.

This link is exemplified in Ghent, the only city to record progress in both clusters (Figure 13.f; Figure 32.b, Appendix D). The municipal authority IVAGO operates a waste-to-energy plant that incinerates residual waste to generate heat and electricity, supporting both energy supply and waste management (Collectors Project, 2020). At the district level, the Nieuwe Dokken project demonstrates circular ambition, with the DuCoop cooperative capturing organic waste and wastewater to produce biogas for local energy needs (City of Ghent, 2025). These initiatives underscore a mutually reinforcing relationship where improved waste systems enable renewable capacity, and vice versa.

At the same time, Ghent illustrates the potential for confounding effects. It is the only city showing simultaneous progress in Poverty risk and vulnerable groups (Figure 27.a, Appendix D), Renewable energy generation and capacity (Figure 13.f), and Renewable district heating (Figure 13.g). While links between these clusters appear plausible, they may instead be co-driven by Ghent's wealth, institutional capacity, and ambitious sustainability agenda (City of Ghent, 2025). This highlights the need for caution, as strong governance can generate statistical associations that are not necessarily structural causal links.

Despite the confounding causal links with progress in poverty risk and vulnerable groups, Figure 14 and Figure 15 show the cluster "Renewable heat productuion and district energy" exhibited more plausible links grounded in literature, including a bidirectional association with the cluster "Effective, participatory and transparent local governance". From Figure 13.g and Figure 34.b (Appendix D), Espoo and Stuttgart were the only cities to make mutual progress, with Espoo also making progress in "health risks and well-being" (Figure 28.a, Appendix D) and Stuttgart also making progress in "sustainable forest and tree management" (Figure 34.a, Appendix D). On one side, participatory governance and capable administrations are crucial for planning and financing complex infrastructure such as district heating networks (European Commission, 2016). On the other hand, successful deployment of renewable heat projects generates visible public benefits, including lower emissions, better health outcomes, and local jobs that enhance citizen satisfaction with municipal administrations. Espoo's geothermal heating initiatives and Stuttgart's biomass-based district energy, aligned with gains in well-being and sustainable forest management respectively, illustrate how renewable heat and governance can reinforce each other in practice while evidencing progress in sustainable forest management and health risks as seen in Figure 14.

The cluster Renewable energy consumption share emerges as highly influenced, with many inward links (Figure 15) rather than outward drivers (Figure 14). Its progress is strongly connected to Income and wage disparities and Inclusive governance (women in local governance), with Barcelona standing out as the only city advancing in all three clusters (Figures 13.c, 29.a, 31.b). This pattern reflects Barcelona's progressive policy framework, where equity and participatory governance underpin ambitious renewable targets. The city's Climate Plan 2018-2030 explicitly situates renewable deployment within a broader agenda of inclusion and justice (Ajuntament de Barcelona, 2018).

Elsewhere, Inclusive governance links to Energy grid modernization in Hamburg, where participatory planning and robust local institutions have supported smart grid and renewable projects (European Commission, 2011). Yet Barcelona regresses in grid modernization despite progress in renewables, suggesting that its growth has been driven more by socially anchored policies and distributed generation than by technical upgrades. Thus, inclusive governance shapes renewable adoption through divergent city pathways.

Energy Efficiency

The final group of clusters is related to energy efficiency, namely, the clusters "Energy Use, Affordability, and Efficiency" and "Building Energy Efficiency & Thermal Comfort", whose indicators were mostly associated with SDG target 7.3 of doubling the global rate of improvement in energy efficiency, as seen in Table 2.

The cluster "Energy Use, Affordability, and Efficiency" had the most indicators out of all the SDG 7 clusters (Figure 10) and was the most compact, with few overlaps with other clusters (Figure 11), which partly explains why it emerged as the most connected cluster, as seen in Figure 14 and Figure 15. It exhibits bidirectional links with both Renewable energy generation and capacity and Sustainable urban mobility, reflecting the reciprocal relationship between energy efficiency, renewable deployment, and low-carbon transport systems. Efficiency measures reduce overall demand, facilitating renewable integration and enabling sustainable mobility, while advances in renewables and transport electrification create new incentives for efficient energy use. In addition, a unidirectional link from Household energy access and poverty to energy efficiency indicates that expanding access can catalyse subsequent gains in affordability and efficient consumption.

In Figure 15, a causal link is also observed between Water consumption, access and affordability and Energy use, affordability and efficiency, with Bonn and Cologne evidencing progress in both (Figure 13.b and Figure 29.b - Appendix D). This reflects the literature review findings on the water-energy nexus, where improving water systems (through efficiency, metering, and affordability measures) reduces energy demand for pumping, treatment, and distribution, whereas gains in energy efficiency and affordability lower the costs of water provision. The connection highlights the interdependence of resource efficiency measures across utilities.

The Building Energy Efficiency and Thermal Comfort cluster links outward to Urban resilience, safety and livability, Poverty risk and vulnerable groups, and Entrepreneurial ecosystems and SME development, as seen in Figure 14. The connection to resilience and vulnerability reduction is well supported. Efficient and well-insulated buildings mitigate health risks during heat or cold events and contribute to lower peak demand, enhancing overall system resilience (Ürge-Vorsatz et al., 2014; Santamouris, 2016). The link to poverty and vulnerable groups is also plausible, as energy-efficient housing reduces household energy burdens and helps to alleviate fuel poverty (Thomson, Snell &

Bouzarovski, 2017). By contrast, the association with SME development is more tenuous. While retrofit programmes can stimulate demand for specialised firms and skilled professionals in construction and energy services (IEA, 2019), this connection is less direct. Once again, however, given that Ghent is the only city evidencing progress across all three clusters (Figure 13.b, Figure 31.a & Figure 32.a - Apppendix D), these edges may partly reflect confounding by the city's strong institutional capacity and integrated sustainability strategy, rather than generalisable causal pathways.

Second order effects and local level nexuses

While the first two synthesis approaches assessed first-order causal progress between SDG7 and other goals across all time-window sizes, the third approach focuses on potential second-order effects and the energy nexuses that emerge locally. This final synthesis applies fixed rolling windows to identify top links: 5-year windows (2008-2012, 2009-2013, etc.) and 7-year windows over the same 2008-2022 period. By including second-order links, this method highlights possible nexus and chain effects spanning multiple goals. Figure 16 presents the top 30 first- and second-order links for the 5-year windows, while Figure 17 shows results for the 7-year windows.

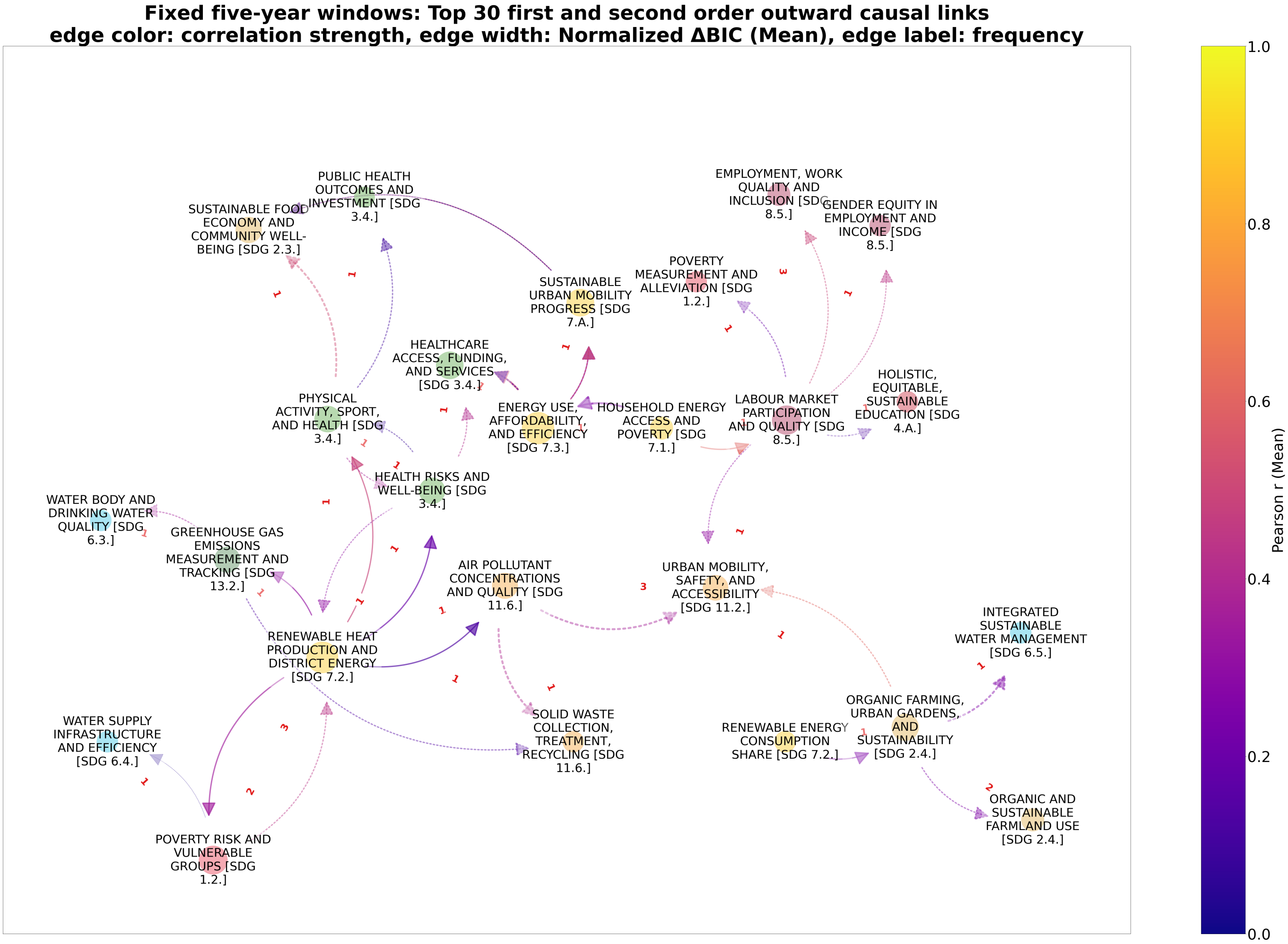


Figure 16: ***Causal links across Fixed 5-year time windows:*** First and second order outward links

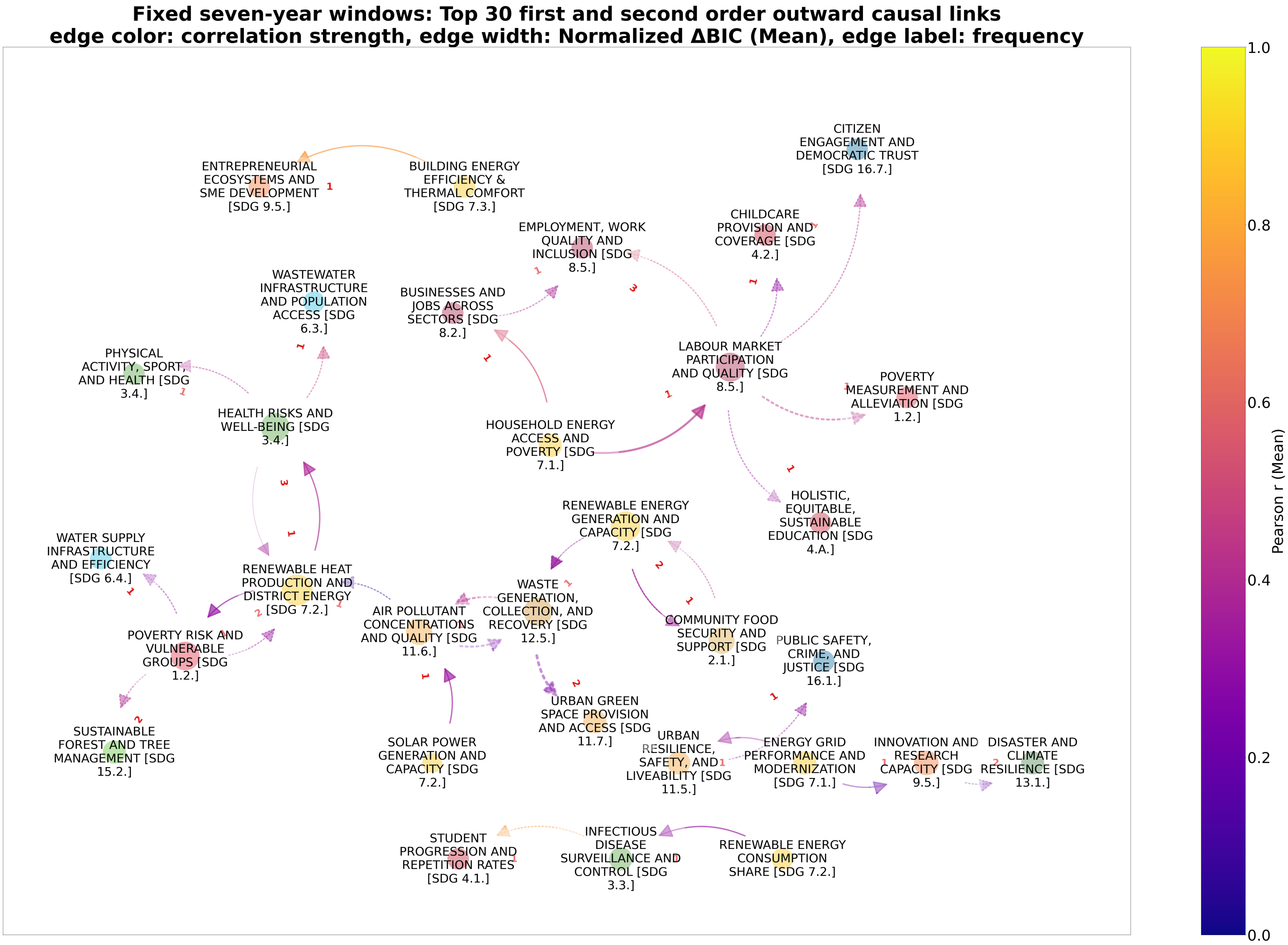


Figure 17: ***Causal links across Fixed 7-year windows:*** First and second order outward links

Several nexus relationships emerge in Figures 16 and 17. The water-energy-food nexus appears where renewable energy consumption interacts with organic farming, urban gardens, and sustainable farmland use, which in turn links to integrated sustainable water management.

The energy-cities nexus is illustrated through multiple pathways. Renewable heat production and district energy reduce air pollution concentrations, with second-order effects on the safety of urban mobility (Figure 16). Similarly, improvements in waste generation and collection through waste-to-energy programmes enhance renewable generation capacity, reduce open-air burning, and improve both air quality and the provision of urban green spaces (Figure 17). Within this nexus, energy grid modernization also drives progress in urban resilience and safety-such as through smart LED lighting that improves public safety-while simultaneously strengthening innovation and research capacity. These innovation gains, in turn, reinforce disaster preparedness and climate resilience (Figure 17).

An energy-health nexus is also evident: healthcare access and funding advance indirectly via reduced health risks from renewable district heating, and directly through gains in energy efficiency (Figure 16). Finally, an energy-economy nexus emerges, as improved household energy access enhances labour market participation and quality, generating second-order benefits in poverty alleviation and equitable education outcomes.

5.2.5. Links analysis across time window sizes

To analyze the links' stability, trends of link frequency variation were assessed across different time window sizes. Figure 18 shows, for each window size from three to seven, the total edges and unique edges across all time slices.

As seen in Figure 18, both the total number of edges and the unique edges across all time slices for each window size decrease as the window size increases. This is to be expected, as within a fixed time frame of 2008-2022, the total number of networks/rolling time window slices decreases as the window size increases.

Figure 19 shows the average link frequency for each unique link. It is to be noted that the edges in both Figure 18 and Figure 19 represent all the network edges present in the networks between all SDG goals and not only the filtered first and second order SDG 7 links. Figure 20, on the other hand shows the first and second order SDG 7 links across all time window size.

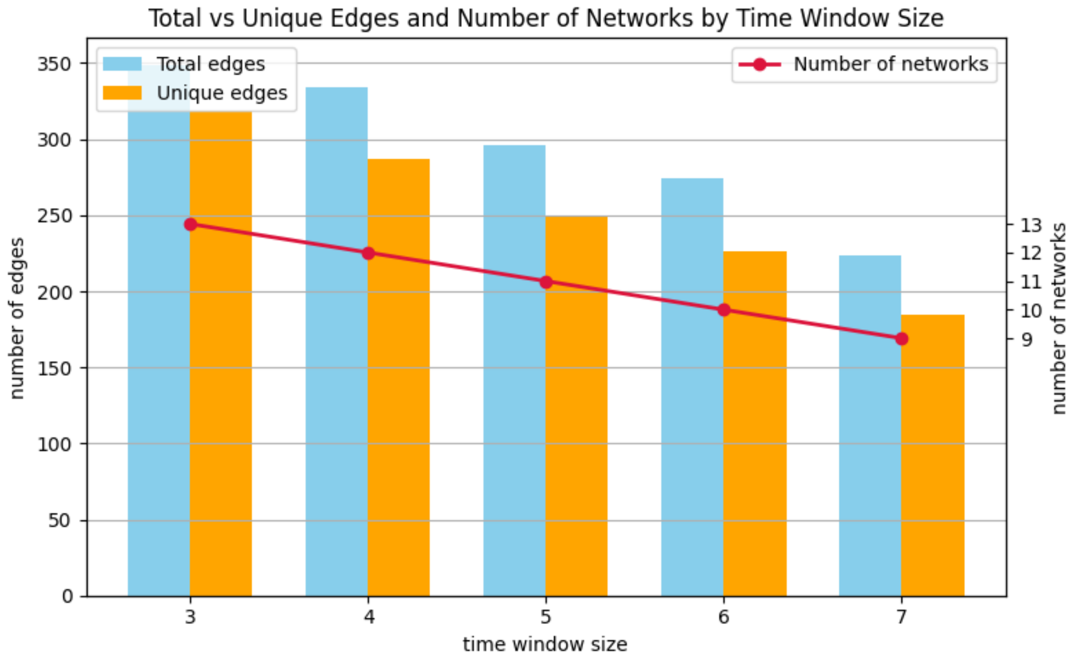


Figure 18: ***Total and unique links across time windows:*** Trends from three to seven year windows with link frequencies across all rolling time windows

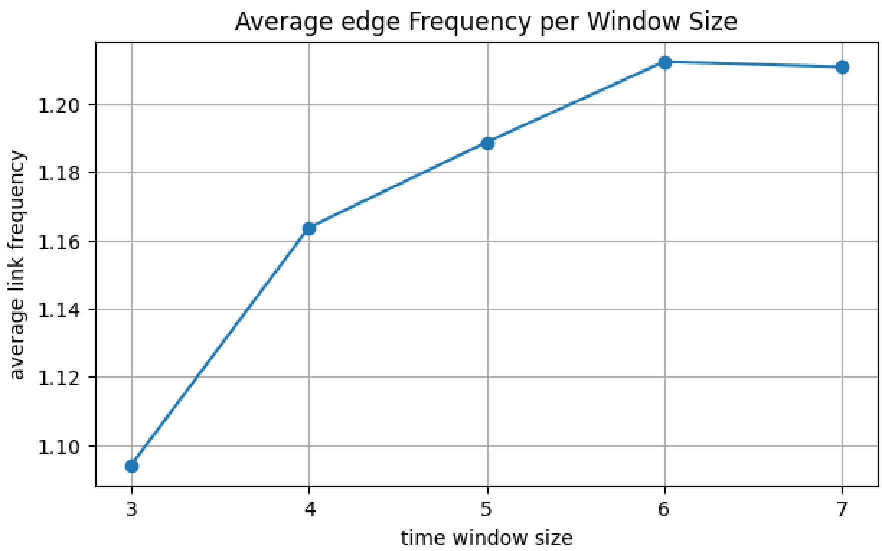


Figure 19: ***Average link frequency for each unique link:*** Trends from three to seven year windows with link frequencies across all rolling time windows

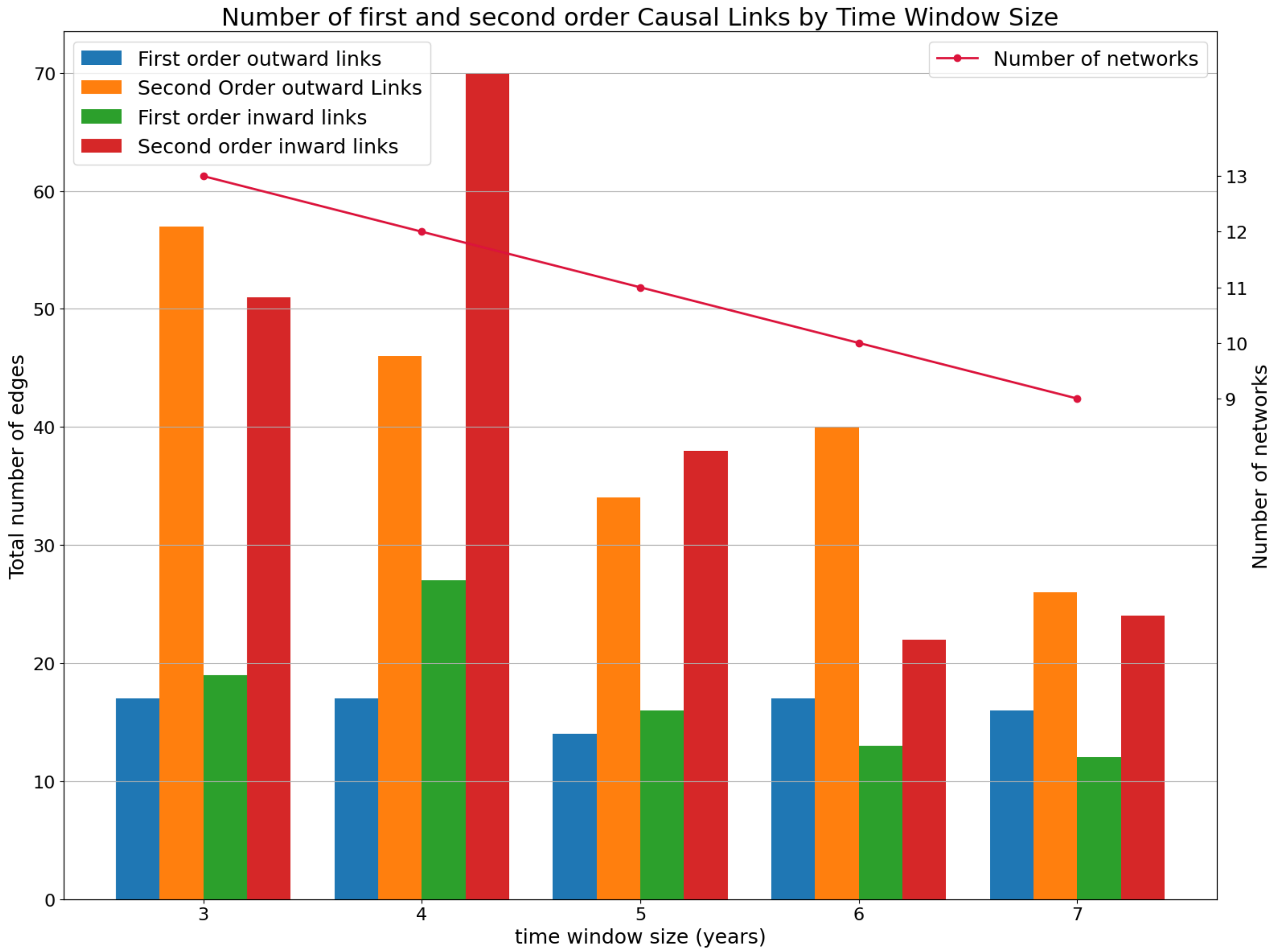


Figure 20: ***Number of First and second order SDG 7 links across time-window sizes:*** Trends from three to seven year windows with link frequencies across all rolling time windows

6. CONCLUSION

6.1. KEY FINDINGS ON SDG 7 PROGRESS AND INTERLINKAGES

This study addressed three research questions on SDG 7 at the local level. First, semantic analysis identified nine thematic clusters of SDG 7 indicators, broadly aligned with its global targets. Second, longitudinal analysis and city rankings revealed varied progress across clusters, highlighting leaders and laggards in the local energy transition. Third, causal discovery demonstrated that SDG 7 is a highly interconnected goal. Outward links showed energy access, efficiency, and renewable adoption as key drivers of progress in other domains, including sustainable cities (SDG 11), climate action (SDG 13), health (SDG 3), and infrastructure (SDG 9). Inward links revealed that non-energy clusters such as responsible consumption (SDG 12), education (SDG 4), and economic growth (SDG 8) enabled energy progress by providing efficiency gains, institutional capacity, and skilled labour. Finally, time-windowed analysis uncovered second-order cascading effects, such as grid modernization improving urban livability and safety. Together, these findings confirm energy's dual role as both driver and recipient of sustainable development.

6.2. CRITICAL REFLECTION ON METHODS

Several methodological strengths underpin these findings. The use of semantic embeddings and clustering allowed diverse, city-specific indicators to be grouped into interpretable thematic clusters, overcoming the heterogeneity of VLR reporting. Incorporating LLM-based labelling ensured clusters were intelligible while preserving their data-driven basis. Progress scoring with rolling time windows enabled dynamic tracking of change while accounting for reporting irregularities, and the use of graphical causal discovery methods allowed directional interdependencies to be inferred even with sparse, short time series.

Robustness was strengthened through multiple safeguards, including cluster stability checks, dimensionality reduction with PCA to minimise noise, the use of both outward and inward analyses to validate directionality, and bootstrap stability checks across time windows. These design features enhance the credibility of the results and position the study as a replicable framework for local SDG analysis.

6.3. LIMITATIONS AND ASSUMPTIONS

Nonetheless, several limitations and assumptions must temper the conclusions. First, the choice of embedding and clustering methods involved subjectivity. While Gaussian Mixture Models were selected for their flexibility and probabilistic assignments, the bounds of three to ten clusters and the weighting of AIC/BIC criteria were partly arbitrary. These decisions may have influenced the granularity and thematic composition of clusters.

Second, LLM-based interpretation introduced potential bias. While prompts were standardised and outputs human-reviewed, semantic labelling remains sensitive to model behaviour and context, and alternative formulations might yield different thematic labels.

Third, the progress scoring framework relied on min-max normalisation and directionality adjustments. This standardisation was necessary to compare heterogeneous indicators but may have obscured nuances in scale or intensity of progress. The assumption that the first year in each window serves as a valid baseline also imposes path dependency.

Finally, causal inference was constrained by data sparsity. The PC algorithm was chosen over GES for producing more plausible links, but this introduces dependence on algorithmic behaviour. Moreover, causal discovery cannot establish definitive causality; rather, it suggests plausible dependency structures conditional on observed data. Missing variables and unobserved confounders may have influenced the learned graphs.

These assumptions affect both the strength and interpretation of the findings. Arbitrary cluster bounds and labelling choices may shape which interlinkages appear most prominent. Normalisation decisions affect the comparability of progress measures, and causal discovery results must be interpreted as indicative rather than definitive. Importantly, while the results reveal consistent synergies and trade-offs, they should be seen as mapping potential causal pathways, not as final proof of causal mechanisms.

6.4. POTENTIAL IMPROVEMENTS AND FUTURE WORK

Several avenues could strengthen this work. Data quality remains the largest barrier: improved frequency, standardisation, and coverage of VLR indicators would enable more precise longitudinal analysis. Future research could extend this approach to Dynamic Bayesian Networks, which incorporate explicit temporal ordering, or to hybrid methods combining constraint-based and score-based algorithms. Incorporating additional robustness checks, such as comparing multiple embedding models, could reduce sensitivity to representation choices.

Qualitative validation is another important improvement. Engaging local policymakers or domain experts to review cluster labels and inferred links could enhance interpretability and policy relevance. Finally, expanding the dataset beyond VLRs to include other local sustainability reports or administrative data could enrich the analysis and address biases in self-reported indicators.

7. REFERENCES

REFERENCES

Acheampong M, Ertem F C, Kappler B and Neubauer P 2017 In pursuit of sustainable development goal (SDG) number 7: will biofuels be reliable? Renew. Sustain. Energy Rev. 75 927–37

Ajuntament de Barcelona 2018, Climate Plan 2018–2030, Barcelona City Council, Barcelona, viewed 30 August 2025, https://ajuntament.barcelona.cat/emergenciaclimatica/sites/default/files/climate_plan_barcelona_2018-2030.pdf.

Ament, J.M., Freeman, R., Carbone, C., Vassall, A. and Watts, C. (2020) 'An empirical analysis of synergies and tradeoffs between Sustainable Development Goals', Sustainability, Vol. 12, p.8424.

Anderson, C.C., Denich, M., Warchold, A., Kropp, J.P. and Pradhan, P. (2021) 'A systems model of SDG target influence on the 2030 Agenda for sustainable development', Sustain. Sci., Vol. 17, pp.1459–1472.

Barbier, E.B. and Burgess, J.C. (2019) 'Sustainable development goal indicators: analyzing trade-offs and complementarities', World Development, Vol. 122, pp.295–305, https://doi.org/10.1016/j.World Development.2019.05.026.

Bhattacharyya A, Meltzer J P, Oppenheim J, Qureshi Z and Stern N 2016 Delivering on better infrastructure for better development and better climate.

Campello, R.J.G.B., Moulavi, D. and Sander, J. (2015) 'Density-based clustering based on hierarchical density estimates', Advances in Knowledge Discovery and Data Mining, pp. 160–172.

Chaniotakis, E., Siragusa, A., Tzanis, D. and Stamos, I. (2024) 'Scoping SDG interlinkages and methods to infer them', Int. J. Sustainable Development, Vol. 27, No. 5, pp.1–54.

Chalfin, A., Hansen, B., Lerner, J. & Parker, L. 2019, Reducing Crime Through Environmental Design: Evidence from a Randomized Experiment of Street Lighting in New York City, NBER Working Paper No. 25798, National Bureau of Economic Research, Cambridge, MA.

Chen, M., Mussalli, G., Amel-Zadeh, A., & Weinberg, M. O. (2022). NLP for SDGs: Measuring Corporate Alignment with the Sustainable Development Goals.

Chickering, D. M. (2003). Optimal structure identification with greedy search. J. Mach. Learn. Res. 3, 507–554. doi: https://doi.org/10.1162/153244303321897717.

Chou, Jyh-Rong. (2021). A Scoping Review of Ontologies Relevant to Design Strategies in Response to the UN Sustainable Development Goals (SDGs). Sustainability. 13. 10012. https://doi.org/10.3390/su131810012.

Cisco News Release 2014, AES Eletropaulo Chooses Cisco Technology for the Most Innovative Smart Grid Project in Brazil, Newsroom Cisco, 26 November, viewed 30 August

2025,
https://newsroom.cisco.com/c/r/newsroom/en/us/a/y2014/m11/aes-eletropaulo-chooses-cisco-technology-for-the-most-innovative-smart-grid-project-in-brazil.html.

City of Ghent 2025, Renewable Energy – Ghent's Climate Actions, City of Ghent, viewed 30 August 2025,
https://stad.gent/en/city-governance-organisation/city-policy/ghents-climate-actions/renewable-energy.

Coccoli, C., Galparsoro, I., Murillas, A., Pınarbaşı, K., and Fernandes, J. A. (2018). Conflict analysis and reallocation opportunities in the framework of marine spatial planning: A novel, spatially explicit Bayesian belief network approach for artisanal fishing and aquaculture. Mar. Policy 94, 119–131.doi:https://doi.org/10.1016/j.marpol.2018.04.015.

Collectors Project 2020, Case Study Summary – Ghent, COLLECTORS Project, Europe, viewed 30 August 2025,
https://www.collectors2020.eu/wp-content/uploads/2020/08/Case_Integration_Summary_Ghent.pdf.

De Cock, A., Forio, M. A. E., Dominguez-Granda, L., & Goethals, P. L. M. (2022). Bayesian belief networks for the analysis of the controversial role of hydropower development in the antagonistic agrofood-fisheries nexus: A potential approach supporting sustainable development in the Guayas river basin (Ecuador). Frontiers in Environmental Science, 10, 980442.

De Paiva Seroˆa Da Motta, R., 2019. The sustainable development goals and 1.5 ◦C climate change. World Rev. Sci. Technol. Sustain. Dev. 15, 123–144.

Devlin J, Chang M-W, Lee K, Toutanova K (2019) BERT: pre-training of deep bidirectional transformers for language understanding.

Dörgő, G., Sebestyén, V., & Abonyi, J. (2018). Evaluating the Interconnectedness of the Sustainable Development Goals Based on the Causality Analysis of Sustainability Indicators. Sustainability, 10(10), 3766.

Ester, M., Kriegel, H.P., Sander, J. and Xu, X. (1996) 'A density-based algorithm for discovering clusters in large spatial databases with noise', Proceedings of the 2nd International Conference on Knowledge Discovery and Data Mining (KDD), pp. 226–231.

European Commission 2011, Smart Grids: From Innovation to Deployment, European Commission, Brussels, viewed 30 August 2025,
https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:52011DC0202.

European Commission 2016, An EU Strategy on Heating and Cooling, European Commission, Brussels, viewed 30 August 2025,
https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A52016DC0051.

Eurostat, 2024. Sustainable development in the European Union: Monitoring report on progress towards the SDGs in an EU context – 2024 edition. Flagship publication

KS-05-24-071, European Commission. Luxembourg: Publications Office of the European Union. ISBN 978-92-68-11724-8. doi:https://doi.org/10.2785/98370.

Fraley, C. and Raftery, A.E. (2002) ‘Model-based clustering, discriminant analysis, and density estimation’, Journal of the American Statistical Association, 97(458), pp. 611–631.

Franco-Gaviria, F., Amador-Jiménez, M., Millner, N., Durden, C., & Urrego, D. H. (2022). Quantifying resilience of socio-ecological systems through dynamic Bayesian networks. Frontiers in Forests and Global Change, 5, 889274.

Friedman N and Koller D (2003) Being bayesian about network structure. A bayesian approach to structure discovery in Bayesian networks. Machine Learning 50, 95–125.

Glymour, C., Zhang, K., & Spirtes, P. (2019). Review of Causal Discovery Methods Based on Graphical Models. Frontiers in Genetics, 10, 524.

Granger, C. Investigating Causal Relations by Econometric Models and Cross-Spectral Methods. Econometrica 1969, 37, 424–438.

Griggs, D., M. Stafford Smith, J. Rockström, M. C. Öhman, O. Gaffney, G. Glaser, N. Kanie, I. Noble, W. Steffen, and P. Shyamsundar. 2014. An integrated framework for sustainable development goals. Ecology and Society 19(4): 49.

Griggs et al. (2017). A guide to SDG interactions: From science to implementation. International Council for Science (ICSU).

Grootendorst, M. (2022) BERTopic: Neural topic modeling with class-based TF-IDF and topic distributions. arXiv preprint arXiv:2203.05794. Available at: https://arxiv.org/abs/2203.05794 (Accessed: 25 August 2025).

Haines A et al 2017 Short-lived climate pollutant mitigation and the sustainable development goals Nat. Clim. Change 7 863–9.

Hajikhani, A., & Suominen, A. (2022). Mapping the sustainable development goals (SDGs) in science, technology and innovation: Application of machine learning in SDG-oriented artefact detection. Scientometrics, 127(11), 6661–6693.

Horvath, S.-M., Muhr, M.M., Kirchner, M., Toth, W., Germann, V., Hundscheid, L., Vacik, H., Scherz, M., Kreiner, H., Fehr, F., Borgwardt, F., Gühnemann, A., Becsi, B., Körfgen, A. and Gratzer, G., 2022. Handling a complex agenda: A review and assessment of methods to analyse SDG entity interactions. Environmental Science and Policy, 131, pp.160–176.

Hugging Face. (n.d.). Pooling layer documentation for Sentence-Transformers.

IEA 2022, Renewables 2022: Analysis and forecast to 2027, International Energy Agency, Paris, viewed 30 August 2025, https://www.iea.org/reports/renewables-2022.

IEA, IRENA, UNSD, World Bank, WHO (2023). Tracking SDG 7: The Energy Progress Report.

Invernici, F., Curati, F., Jakimov, J., Samavi, A., & Bernasconi, A. (2025). Capturing research literature attitude towards sustainable development goals: An LLM-based topic modeling approach. Journal of Big Data, 12(1), 139.

Institute for Global Environmental Strategies (IGES) 2022, Suwon Sustainable Development Goals Report 2022, IGES, Hayama, viewed 30 August 2025.

International Energy Agency (IEA) 2019, Energy Efficiency 2019, IEA, Paris, viewed 30 August 2025, https://www.iea.org/reports/energy-efficiency-2019.

IRENA 2021, World Energy Transitions Outlook 2021, International Renewable Energy Agency, Abu Dhabi, viewed 30 August 2025, https://www.irena.org/publications/2021/Jun/World-Energy-Transitions-Outlook.

IRP, 2015. Policy coherence of the sustainable development goals – a natural resource perspective. United Nations Environment Programme – International Resource Panel (IRP).

Jain, A.K. (2010) 'Data clustering: 50 years beyond K-means', Pattern Recognition Letters, 31(8), pp. 651–666.

Khandker, S. R., Barnes, D. F., & Samad, H. A. (2012). The welfare impacts of rural electrification in Bangladesh. Energy Journal, 33(1).

Kriegler E et al 2013 What does the 2 ◦C target imply for a global climate agreement in 2020? The limits study on Durban action platform scenarios Clim. Change Econ. 04 1340008.

Le Blanc, D., 2015. Towards integration at last? The Sustainable Development Goals as a network of targets. United Nations Department of Economic and Social Affairs (UN-DESA), Working Paper No. 141.

Lenton, T. M. 2011. Beyond 2°C: redefining dangerous climate change for physical systems. Wiley Interdisciplinary Reviews: Climate Change 2(3):451-461.

MacQueen, J. (1967) 'Some methods for classification and analysis of multivariate observations', Proceedings of the 5th Berkeley Symposium on Mathematical Statistics and Probability, 1, pp. 281–297.

Matsui, T., Suzuki, K., Ando, K., Kitai, Y., Haga, C., Masuhara, N., & Kawakubo, S. (2022). A natural language processing model for supporting sustainable development goals: Translating semantics, visualizing nexus, and connecting stakeholders. Sustainability Science, 17(3), 969–985.

McLachlan, G. and Peel, D. (2000) Finite Mixture Models. New York: Wiley.

Moreira, C., Nguyen, N. L. C., Francis, G., Mohasel Afshar, H., Lopatnikova, A., Cripps, S., & Marchant, R. (2025). Bayesian causal discovery for policy decision making. Data & Policy, 7, e26.

Ngarava, S., Zhou, L., Ayuk, J., & Tatsvarei, S. (2019). Achieving Food Security in a Climate Change Environment: Considerations for Environmental Kuznets Curve Use in the South African Agricultural Sector. Climate, 7(9), 108.

Nilsson, M., Griggs, D. and Visbeck, M. (2016) ‘Policy: map the interactions between Sustainable Development Goals’, Nature, Vol. 534, pp.320–322.

OECD. (2020). A Territorial Approach to the Sustainable Development Goals: Synthesis report (OECD Urban Policy Reviews). OECD Publishing.

Ortiz-Moya, F., Yoshida, T., and Kataoka, Y. 2025. State of the Voluntary Local Reviews 2025: At a Crossroads for Local SDG Action. Institute for Global Environmental Strategies. doi: https://doi.org/10.57405/iges-14390.

Ospina-Forero, L., Castañeda, G., & Guerrero, O. A. (2022). Estimating networks of sustainable development goals. Information & Management, 59(5), 103342.

Panteli, M. & Mancarella, P. 2017, ‘The grid: stronger, bigger, smarter? Presenting a conceptual framework of power system resilience’, IEEE Power and Energy Magazine, vol. 13, no. 3, pp. 58–66.

Parkinson S C et al 2016 Impacts of groundwater constraints on Saudi Arabia’s low-carbon electricity supply strategy Environ. Sci. Technol. 50 1653–62.

Pearl, J. (2000). Causality: Models, Reasoning, and Inference. Cambridge: Cambridge University Press.

Pica, C. Q. 2011, An Overview of Smart Grids in Brazil, Energy 2011: First International Conference on Smart Grids, Green Communications and IT Energy-aware Technologies, IARIA.

Pipa, T., & Bouchet, M. (2020). Next generation urban planning: Enabling sustainable development at the local level through voluntary local reviews (VLRs). Brookings Institute.

Pradhan, P., Costa, L., Rybski, D., Lucht, W., & Kropp, J. P. (2017). A Systematic Study of Sustainable Development Goal (SDG) Interactions. Earth’s Future, 5(11), 1169–1179.

Raji B, Tenpierik M J and van den Dobbelsteen A 2015 The impact of greening systems on building energy performance: a literature review Renew. Sustain. Energy Rev. 45 610–23.

Red and Green, 2024. What are some popular pre-trained Sentence Transformer models and how do they differ (for example, all-MiniLM-L6-v2 vs all-mpnet-base-v2).

Reimers, N. and Gurevych, I. (n.d.) Sentence Transformer Pretrained Models.

Requejo-Castro, D., Giné-Garriga, R., & Pérez-Foguet, A. (2020). Data-driven Bayesian network modelling to explore the relationships between SDG 6 and the 2030 Agenda. Science of The Total Environment, 710, 136014.

Sachs, J. D., Lafortune, G., & Fuller, G. (2024). The SDGs and the UN Summit of the Future. Sustainable Development Report 2024. Dublin: Dublin University Press.

Santamouris, M. 2016, ‘Innovative retrofitting strategies to increase resilience and energy efficiency of existing residential buildings’, Energy and Buildings, vol. 123, pp. 82–90.

Scarlat, N., Motola, V., Dallemand, J.F., Monforti-Ferrario, F. & Mofor, L. 2019, ‘Evaluation of energy potential of Municipal Solid Waste from African urban areas’, Renewable and Sustainable Energy Reviews, vol. 50, pp. 1269–1286.

Spirtes, P., Glymour, C., and Scheines, R. (2001). Causation, Prediction, and Search, 2nd edn. Cambridge, MA: MIT Press.

Stamos, I. et al. (2024) ‘What Does SDG Monitoring Practice Tell Us? An Analysis of 120 Voluntary Local Reviews’, Sustainability, 16(23), p. 10649.

Sustainable development in the European Union—Monitoring report on progress towards the SDGs in an EU context (2024 edition). (n.d.).

Taajamaa, V., Joensuu, M., Karanian, B., & Bettencourt, L. (2022). Seven Steps to Strategic SDG Sensemaking for Cities. Administrative Sciences, 12(1), Article 1. https://doi.org/10.3390/ admsci12010033.

The Asia Pacific Journal 2016, Korea’s Greening Strategy: The Role of Smart Microgrids, The Asia-Pacific Journal: Japan Focus, 15 December, viewed 30 August 2025, https://apjjf.org/2016/24/Lee.html.

Thomson, H., Snell, C. & Bouzarovski, S. 2017, ‘Health, well-being and energy poverty in Europe: A comparative study of 32 European countries’, International Journal of Environmental Research and Public Health, vol. 14, no. 6, 584.

United Nations (2015). Transforming our world: the 2030 Agenda for Sustainable Development. A/RES/70/1.

United Nations General Assembly, 2000. United Nations Millennium Declaration, resolution A/RES/55/2, adopted 8 September 2000, United Nations.

United Nations General Assembly, 2012. The future we want (A/RES/66/288). Outcome document of the United Nations Conference on Sustainable Development (Rio+20), Rio de Janeiro, Brazil, 20–22 June 2012. United Nations.

United Nations, 2024. Global indicator framework for the Sustainable Development Goals (after 2022 refinement). United Nations Statistics Division.

United Nations, 2025. UN global indicator database. United Nations Statistics Division.

United Nations, Secretary-General, 2019. Remarks to High-Level Political Forum on Sustainable Development, 24 September. United Nations.

Ürge-Vorsatz, D., Cabeza, L.F., Serrano, S., Barreneche, C. & Petrichenko, K. 2014, ‘Heating and cooling energy trends and drivers in buildings’, Renewable and Sustainable Energy Reviews, vol. 41, pp. 85–98.

van Vuuren D P et al 2015 Pathways to achieve a set of ambitious global sustainability objectivesby 2050: explorations using the IMAGE integrated assessment model Technol. Forecast. Soc. 98 303–23.

Vandemoortele, J. 2011. If not the Millennium Development Goals, then what? Third World Quarterly 32(1):9-25.

Vanderfeesten, M., Jaworek, R., & Keßler, L. (2022). AI for mapping multi-lingual academic papers to the United Nations’ Sustainable Development Goals (SDGs) (Version 1.0). Zenodo.

Xiao, H., Liu, Y. and Ren, J. (2022) ‘Synergies and trade-offs across Sustainable Development Goals: a novel method incorporating indirect interactions analysis’, Sustainable Development, Vol. 31, pp.1135–1148.

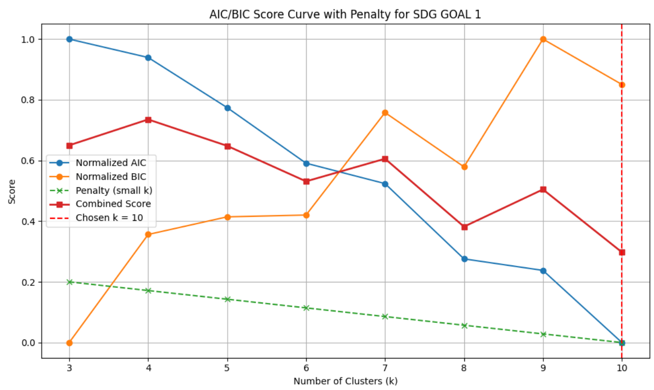
Yillia P T 2016 Water-Energy-Food nexus: framing the opportunities, challenges and synergies for implementing the SDGs Osterreichische Wasser- und Abfallwirtschaft 68 86–98.

Zhang X et al 2018 Impacts of climate change, policy and water-energy-food nexus on hydropower development Renew. Energy 116 827–34.

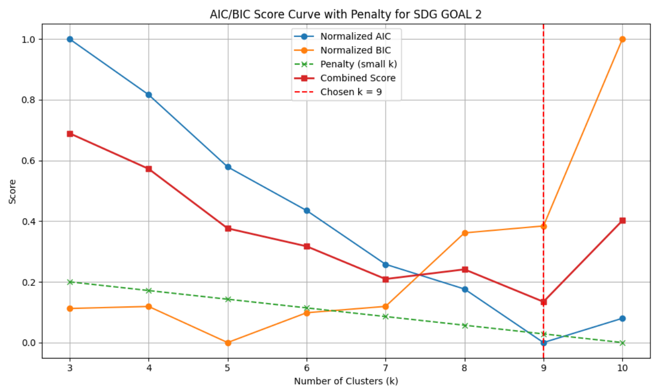
Zhou X, Moinuddin M (2017) Sustainable development goals interlinkages and network analysis: a practical tool for SDG integration and policy coherence. Institute for Global Environmental Strategies (IGES), Research Report. Hayama.

8. APPENDICES

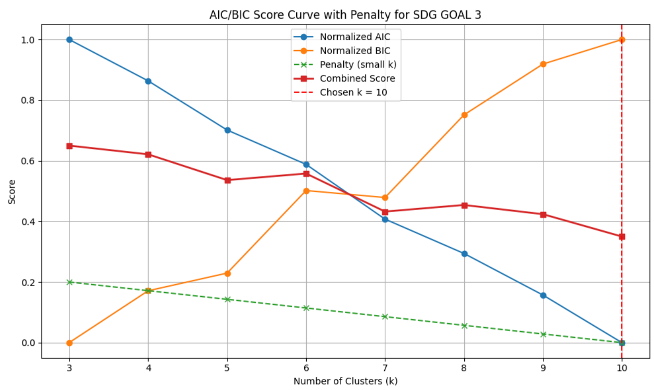
8.1. APPENDIX A: OPTIMAL CLUSTER NUMBER SELECTION



(a) SDG 1



(b) SDG 2



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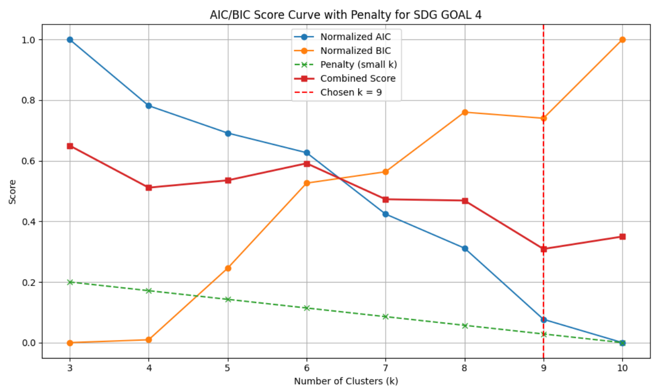

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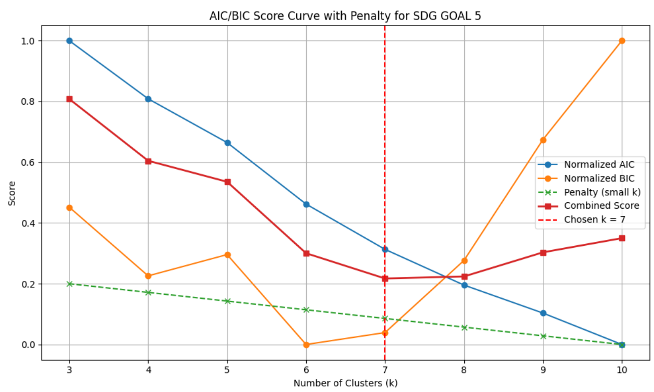
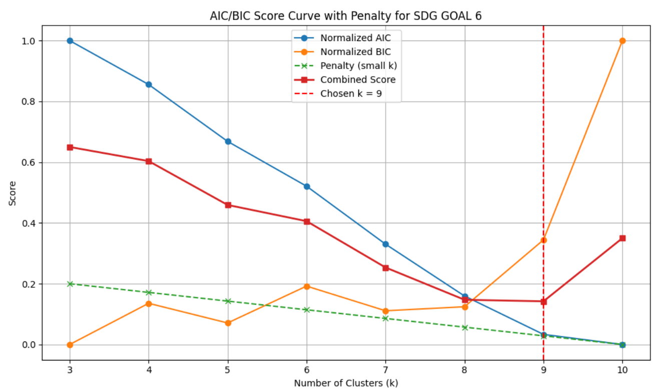
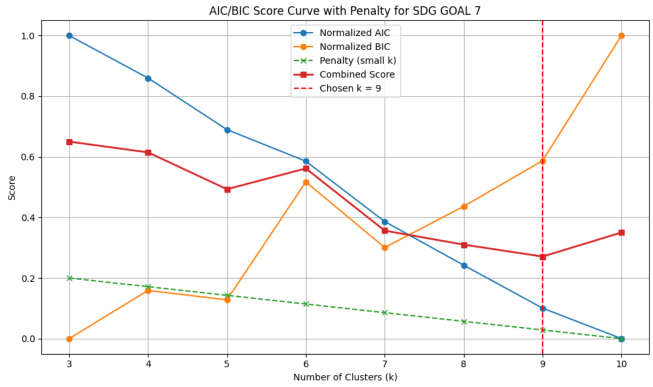


(e) SDG 5

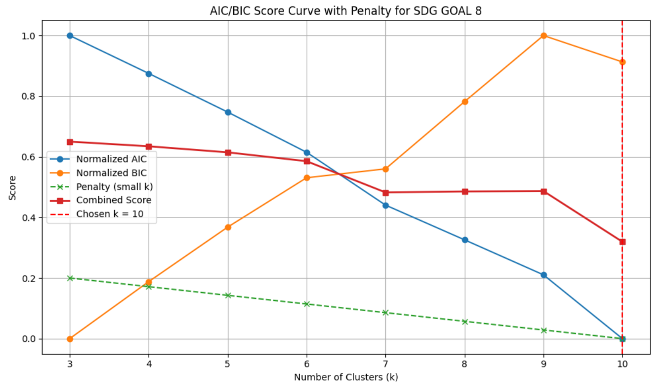


(f) SDG 6

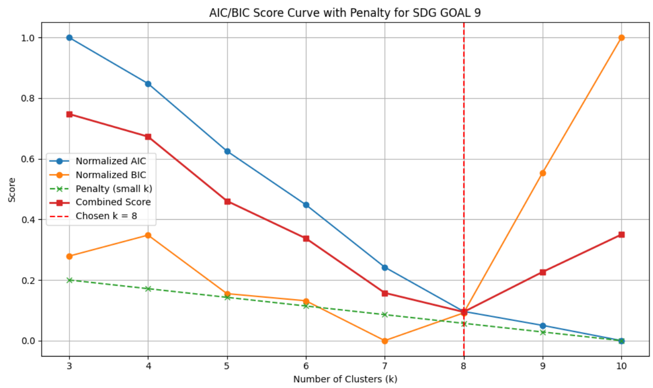
Figure 21: Optimal cluster selection: SDGs 1-6.



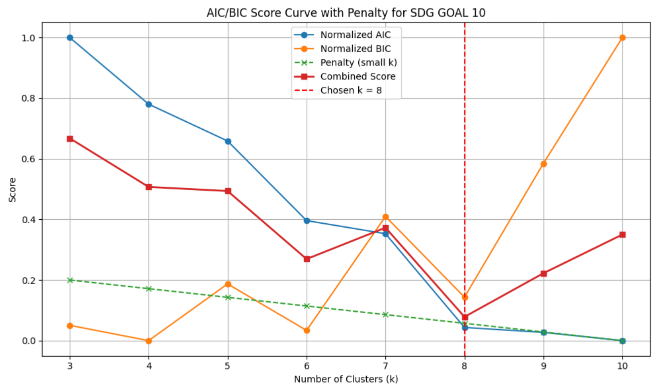
(a) SDG 7



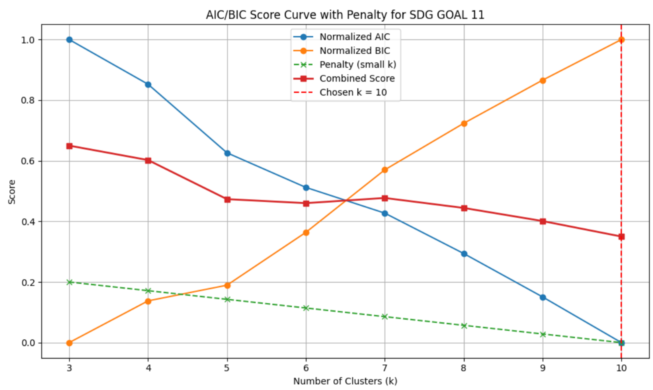
(b) SDG 8



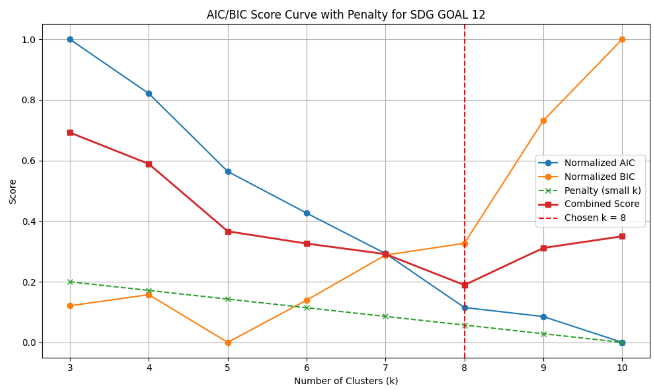
(c) SDG 9



(d) SDG 10

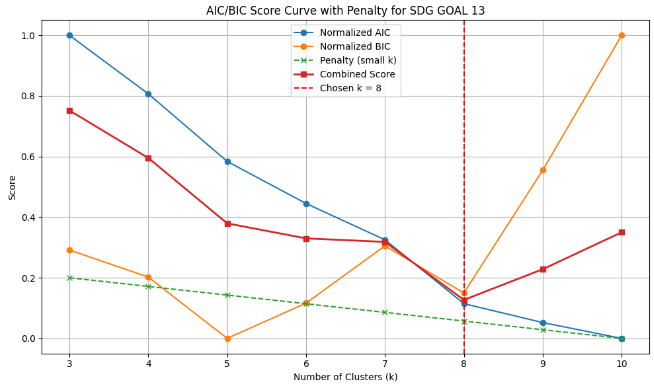


(e) SDG 11

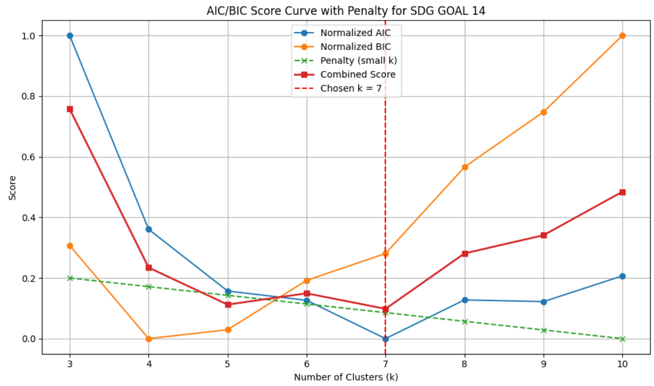


(f) SDG 12

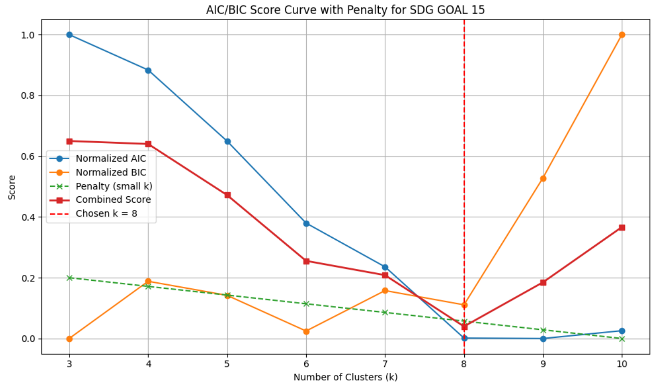
Figure 22: Optimal cluster selection: SDGs 7-12



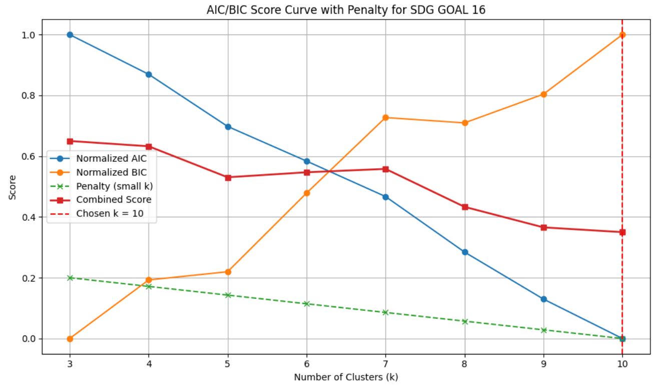
(a) SDG 13



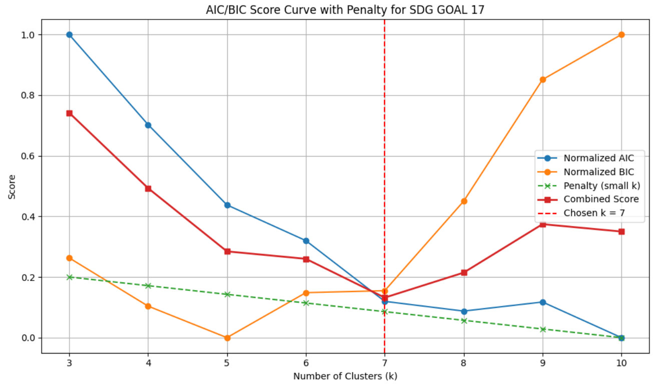
(b) SDG 14



(c) SDG 15



(d) SDG 16



(e) SDG 17

Figure 23: Optimal cluster selection: SDGs 13-17

8.2. APPENDIX B: MOST REPRESENTATIVE AND MOST REPORTED INDICATORS PER SDG 7 CLUSTER

The complete interpretations for all SDG clusters in all goals are available as a scrollable HTML file here: https://drive.google.com/file/d/1rp7kq41pTZ4kIw_h3tv5oN2a2HAIITuK/view?usp=sharing

The prompt given to Gemini flash 2.5 in python programming is as follows:

prompt = f""" I have grouped SDG indicators into semantic clusters. Here are the indicators in one cluster:

indicators

Please return: 1. A short thematic label (max 6 words) 2. A 1-2 sentence description of what this cluster is about.

Format your response as: Label: <label> Description: <description> """

Table 3: Most frequently reported and most representative SDG 7 indicators

Cluster ID	Thematic Label	Most representative indicators	Most reported indicators (non-null values)
0	Renewable Heat Production and District Energy	['Energy use in urban properties (heat) - district heating', 'Energy sources of district heating - gas', 'Energy sources used for heating buildings - gas', 'Heat and electricity generation from renewable energies in the urban area (heat)', 'Energy sources of district heating - coal', 'Energy sources used for heating buildings - coal', 'Energy sources used for heating buildings - biomass', 'Energy sources of district heating - biomass', 'District heating production of renewable energy sources at heat plants in the geographical area, percentage (%)', 'Heat and electricity generation from renewable energies in the urban area (electricity)']	['annual heat generation from renewable energies in the urban area', 'Energy sources of district heating - gas', 'Energy sources of district heating - biomass', 'Energy sources of district heating - waste', 'Energy sources of district heating - oil', 'Energy sources of district heating - coal', 'Energy sources of district heating - peat', 'NUMBER OF GEOENERGY WELLS FOR GROUND SOURCE HEAT PUMPS', 'Generation of renewable energy in the city area (Heat generation from renewable energy in the city area)', 'Heat and electricity generation from renewable energies in the urban area (electricity)']

Continued on next page

Table 3 (continued)

Cluster ID	Thematic Label	Most representative indicators	Most reported indicators (non-null values)
1	Household Energy Access and Poverty	['Proportion of population with access to electricity', 'Proportion of population with access to electricity', 'Proportion of population with access to electricity - total', 'Proportion of population with access to electricity - female', 'Proportion of population with access to electricity - male', 'Proportion of population with primary reliance on clean fuels and technology - total', 'Percentage of population with access to electricity, in neighborhoods undergoing redevelopment and', 'Percentage of population with access to electricity, in neighborhoods undergoing redevelopment and integration processes', 'Access to electricity by population', 'Percentage of households with grid electricity']	['Self-sufficiency rate of households', 'Proportion Living in Fuel PHE Povarty (%)', 'Number of Participants in Climate Change Education Centers', 'Proportion of population with access to electricity', 'Energy poverty among households: budget meters â\{}x1a\{}x1a natural gas', 'percentage of families or dwellings connected to electricity', 'Total municipal solid waste generation per capita per year (ton/person-year)', 'Reduce the city greenhouse gas emissions by 80 percent by 2050 relative to 2005 levels', 'Proportions of households in fuel poverty', 'Percentage of households with grid electricity']
2	Energy Use, Affordability, and Efficiency	['Per capita energy consumption', 'Electricity Consumption', 'Final energy consumption (by industry, commerce, trade and services)', 'final energy consumption compared to GDP', 'Total electricity consumption', 'Total electricity consumption', 'Energy productivity', 'Energy productivity', 'Energy productivity', 'Final energy consumption for the entire city']	['Final energy consumption in commerce, trade, services and industry', 'Final energy consumption transport', 'Final energy consumption of private households', 'Final energy consumption for the entire city', 'Energy productivity', 'Total GHG Emissions', 'Final energy consumption by private households', 'Final energy consumption by the city as a whole', 'energy from waste incineration', 'Final energy consumption (by industry, commerce, trade and services)']
3	Renewable Energy Generation and Capacity	['power generated from renewable sources', 'Proportion of renewable energies in electricity generation.', 'Electricity from renewable sources', 'total renewable energy', 'Total renewable energy ', 'Total renewable energy - Electricity ', 'Total renewable energy - Electricity ', 'Electricity from renewable sources per capita', 'total production of renewable energy', 'power generated from renewable sources - hydroelectric']	['annual electricity generation from renewable energies in the urban area', 'total production of renewable energy', 'onshore wind energy', 'total renewable energy', 'Total renewable energy - Electricity ', 'Generation of renewable energy in the city area (Power generation from renewable energy in the city area)', 'renewable engery generated - Heat pumps', 'renewable engery generated - wind', 'Total renewable energy - Heat ', 'Total renewable energy ']

Continued on next page

Table 3 (continued)

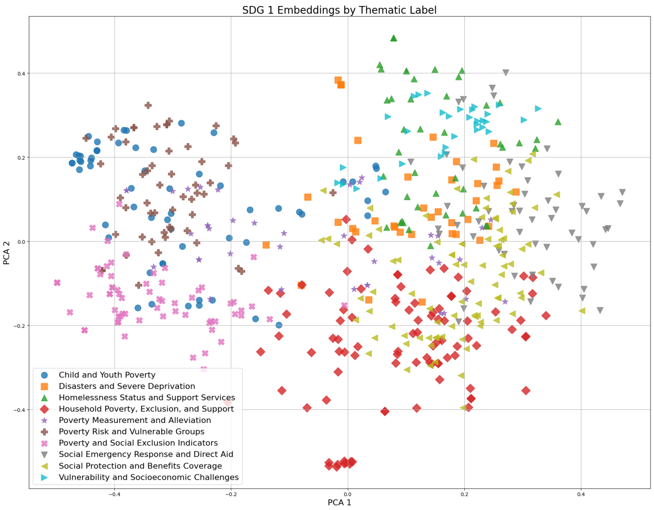
Cluster ID	Thematic Label	Most representative indicators	Most reported indicators (non-null values)
4	Building Energy Efficiency	This cluster focuses on energy consumption, efficiency, and renovation in residential and public buildings. It also addresses thermal comfort and energy poverty, including the use of renewable heating systems.	Thermal Comfort
5	Energy Grid Performance and Modernization	['Community electricity consumption - Services and construction', 'Energy consumption of the municipal public lighting network', 'The City LED Lighting System energy savings (%)', 'electricity used in City Council buildings which is renewable', 'Percentage of total electrical energy consumed that is generated by municipal photo-voltaic installations', 'Percentage of remotely managed public lighting points (%)', 'The City LED Lighting System energy savings (GWh)', 'investment in replacing city lighting with more efficient solutions', 'Capacity (kW) of Energy Saving Power Supply (LED Street lighting)', 'The City LED Lighting System deduction on carbon emissions (metric tons)']	['SAIDI (System Average Interruption Duration Index)', 'TIEPI Duration of power cut equivalent to the installed capacity at medium voltage in urban areas in the Province of Barcelona', 'Capacity (kW) of Energy Saving Power Supply (LED Street lighting)', 'Number of new LED street lighting points (absolute number).', 'Charging point infrastructure per capita', 'Planned investment in the MIP 2020-2023 for SDG 7', 'Publicly accessible normal and fast charging points from 3.7 kilowatts', 'Lodgements by environmentalimpact rating: B', 'Power outages, average downtime per customer (longer than 3 min), minutes / customer', 'Lodgements by environmentalimpact rating: C']
6	Renewable Energy Consumption Share	['Renewable energy share of energy consumed', 'Share of renewable energies in the gross final consumption of energy', 'Share of renewable energies in the gross final consumption of energy', 'Share of renewable energies in the gross final consumption of energy', 'Share of renewable energies in the gross final consumption of energy', 'Share of renewable energies in the gross final consumption of energy', 'Share of energy from renewable sources in gross final consumption of energy', 'Share of renewable energies in final energy consumption', 'Share of renewable energies in final energy consumption', 'Share of electricity from renewable energies in gross electricity consumption']	['Share of renewable energies in final energy consumption', 'Share of renewable energies in final energy consumption', 'Renewable energy share in transport sector (in the groos final energy consumption) (%)', 'Renewable energy share in the groos final energy consumption (%)', 'Regional share of renewable energy in total consumption', 'Proportion of renewable energy in final energy consumption', 'Percent of electricity from renewable sources', 'electric energy consumed of renewable origin', 'consumed energy generated with local renewable resources', 'electricity consumption from renewable sources']

Continued on next page

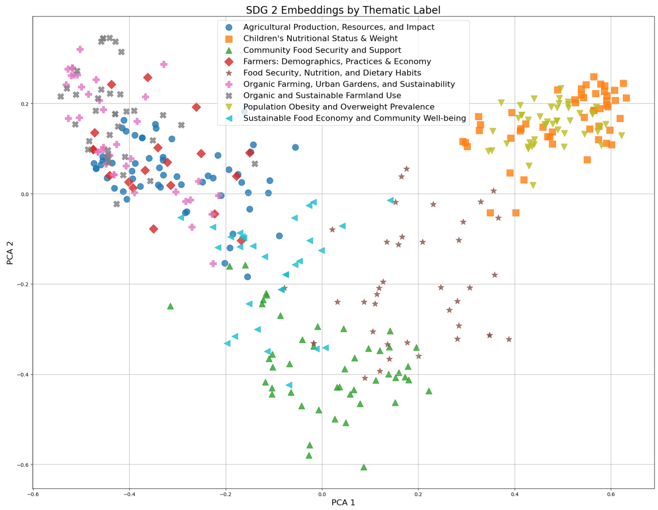
Table 3 (continued)

Cluster ID	Thematic Label	Most representative indicators	Most reported indicators (non-null values)
7	Solar Power Generation and Capacity	['Solar power (Photovoltaic)', 'Solar power (PHOTOVOLTAIC)', 'Power from photovoltaics', 'Electricity from photovoltaics', 'Electricity from photovoltaics', 'Electricity from photovoltaics', 'Electricity from photovoltaics', 'Photovoltaic power installed per inhabitant', 'Electricity generated by photovoltaic plants', 'Promote photovoltaic facilities']	['Electricity from photovoltaics', 'Power from photovoltaics', 'PV >10kW (large installations)', 'PV <10kW (private individuals)', 'solar boilers', 'renewable engery generated - Large photovoltaic installations (>10kW)', 'renewable engery generated - Residential photovoltaic (<10kW) ', 'Electricity from photovoltaics', 'Cumulative installed capacity of solar photovoltaic energy equip- ment (kW)', 'energy from photovoltaic (W per inhabitant)']
8	Sustainable Urban Mobility Progress	['Distribution of Eco-friendly Vehicles (electric bus)', 'Distribution of Eco-friendly Vehicles (Electric passenger car)', 'Distribution of Eco-friendly Vehicles (Electric taxi)', 'Distribution of Eco-friendly Vehicles (Electric freight vehicle)', 'Distribution of Eco-friendly Vehicles (Electric motorcycle)', 'Distribution of Eco-friendly Vehicles (Micro EV)', 'Distribution of Eco-friendly Vehicles (Hydrogen vehicle)', 'Number of Registered Eco-friendly Vehicles', 'Public and private normal and fast charging points from 3.7 kW per 100 electric cars', "Municipality's automobile fleet electrified"]	['Public and private normal and fast charging points from 3.7 kW per 100 cars', 'Public and private normal and fast charging points from 3.7 kW per 100 electric cars', 'Number of Registered Eco-friendly Vehicles', 'Electric Vehicle Charging Stations Throughout L.A. City By Year Of Installation', 'Distribution of Eco-friendly Vehicles (Electric motorcycle)', 'Penetration rate of smart bus stop signs (%)', 'Number of public bicycles used (10,000 times)', 'Distribution of Eco-friendly Vehicles (Hydrogen vehicle)', 'Distribution of Eco-friendly Vehicles (Micro EV)', 'Distribution of Eco-friendly Vehicles (Electric taxi)']

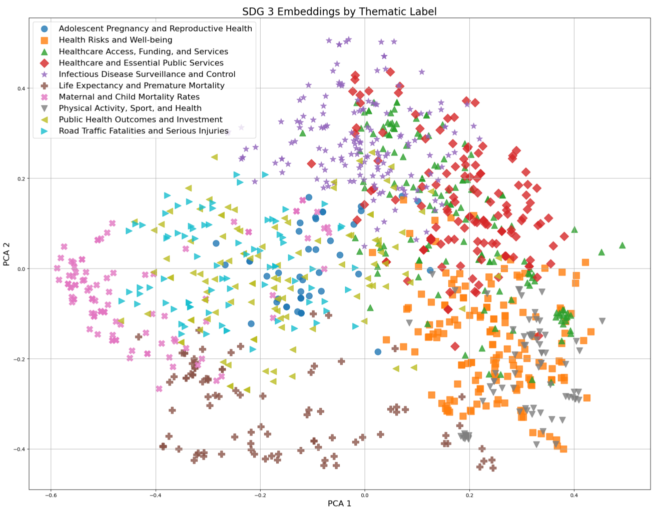
8.3. APPENDIX C: SEMANTIC SPACE CLUSTERS



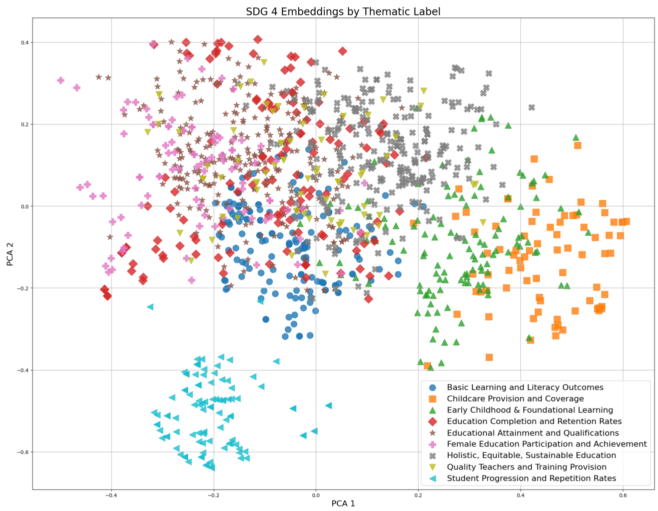
(a) SDG 1



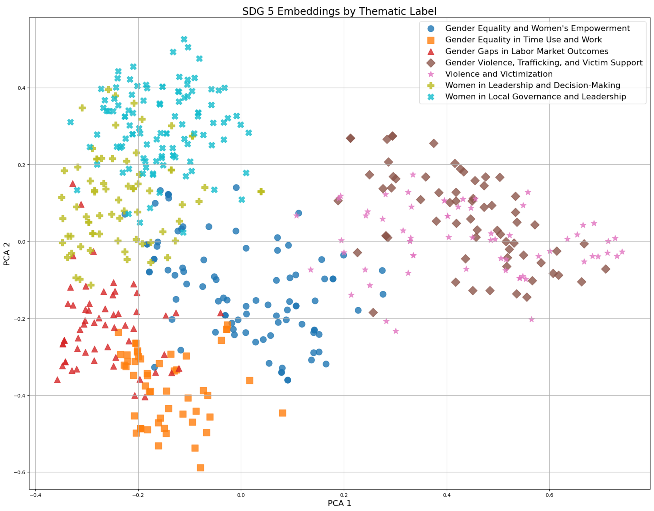
(b) SDG 2



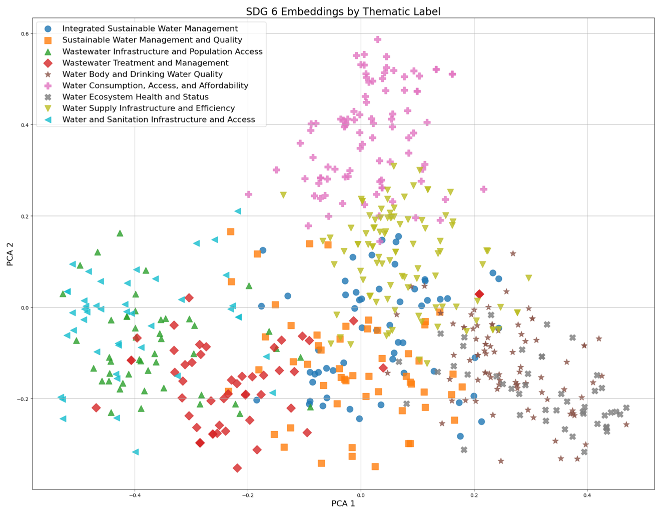
(c) SDG 3



(d) SDG 4

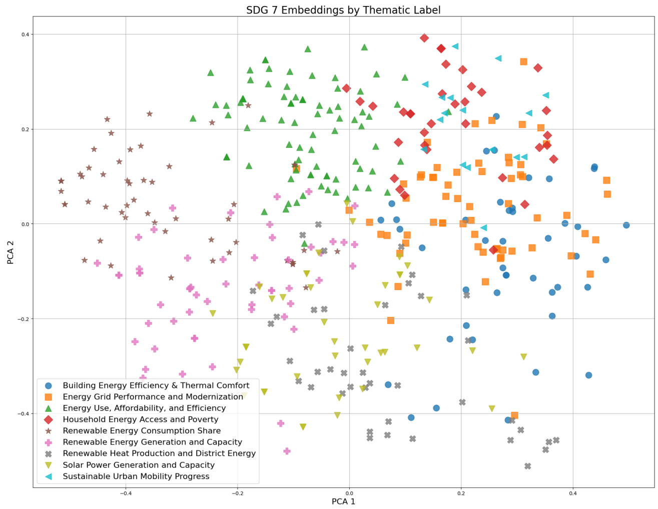


(e) SDG 5

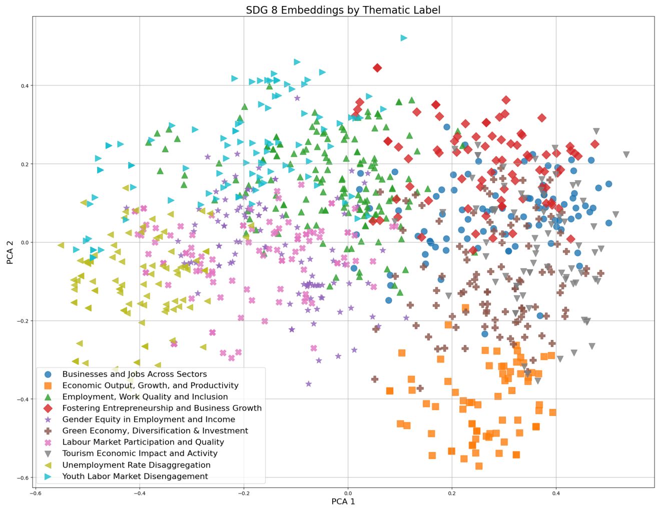


(f) SDG 6

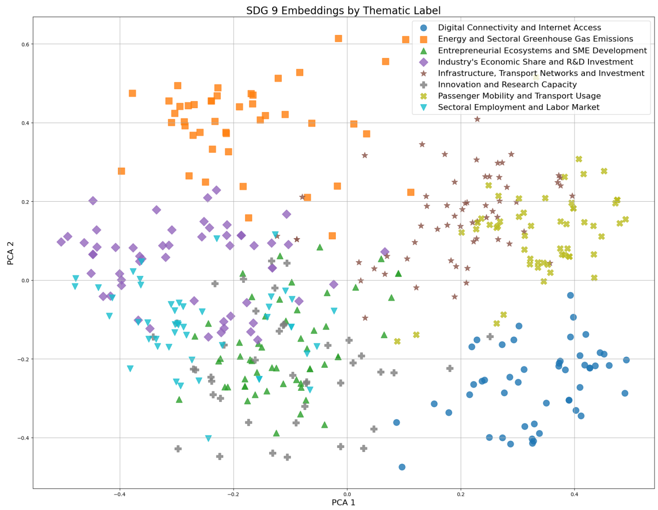
Figure 24: Optimal cluster selection: SDGs 1-6



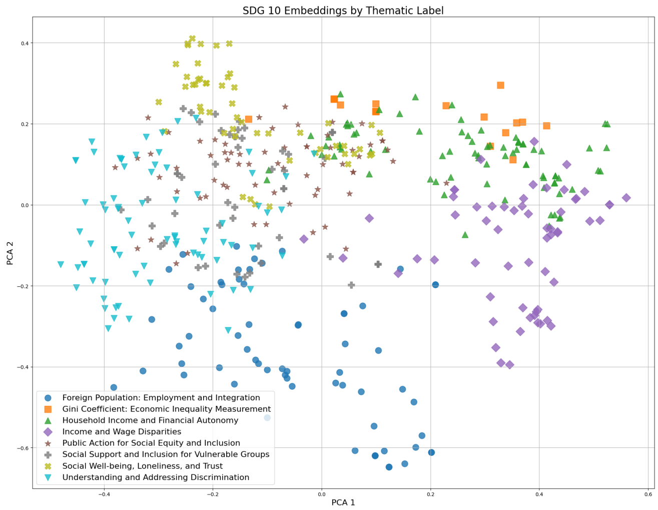
(a) SDG 7



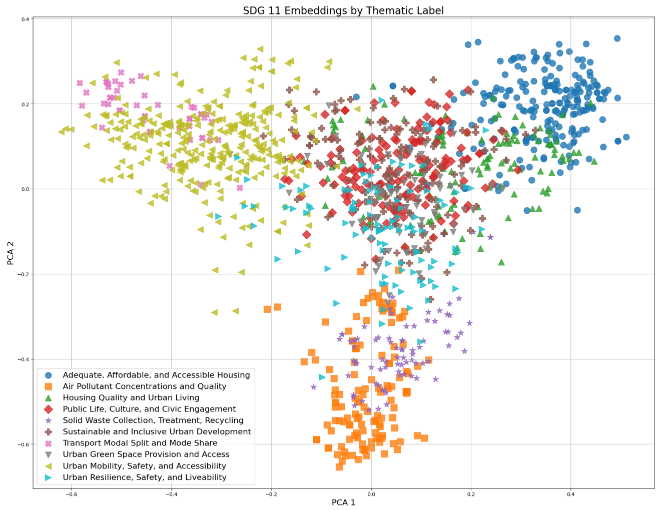
(b) SDG 8



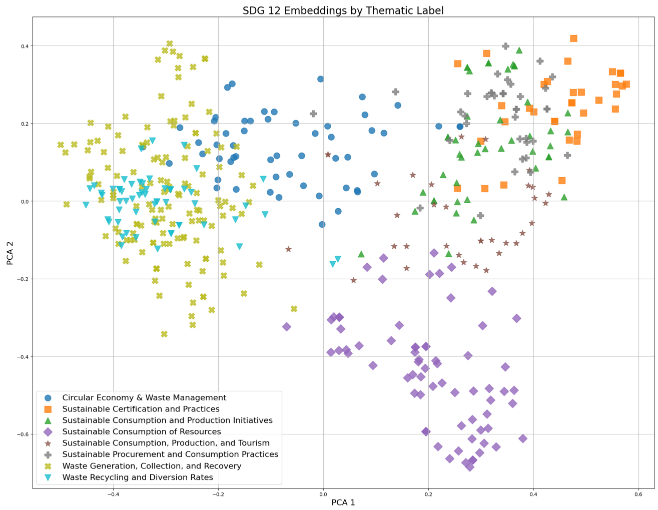
(c) SDG 9



(d) SDG 10



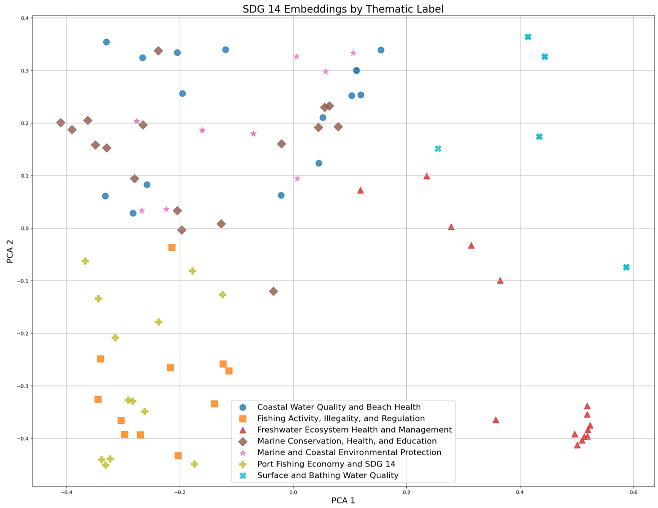
(e) SDG 11



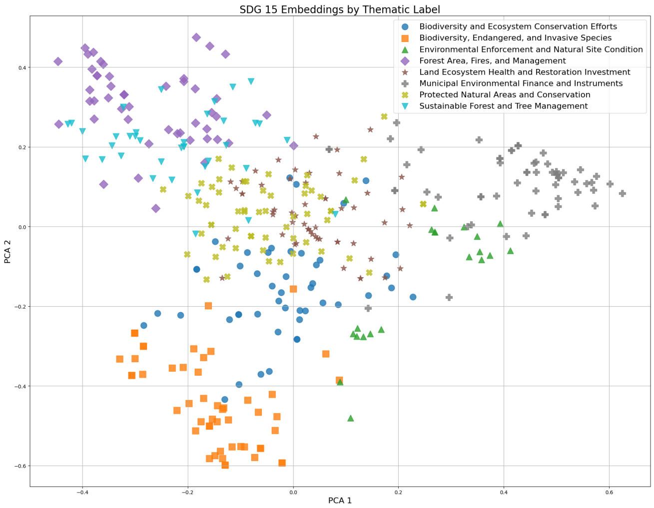
(f) SDG 12

Figure 25: Optimal cluster selection: SDGs 7-12

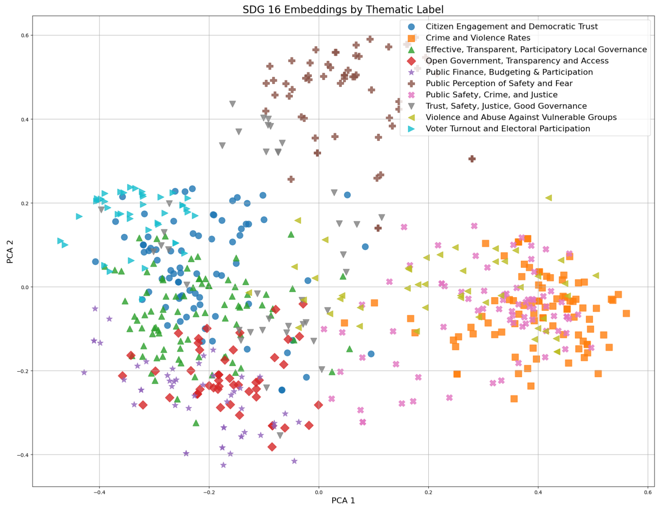
(a) SDG 13



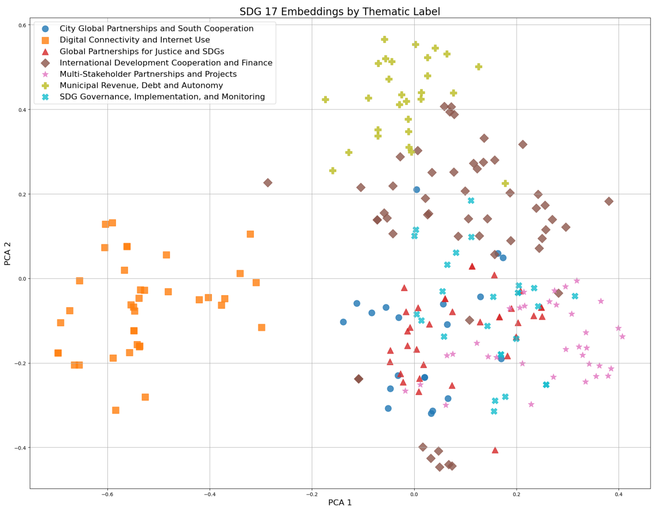
(b) SDG 14



(c) SDG 15



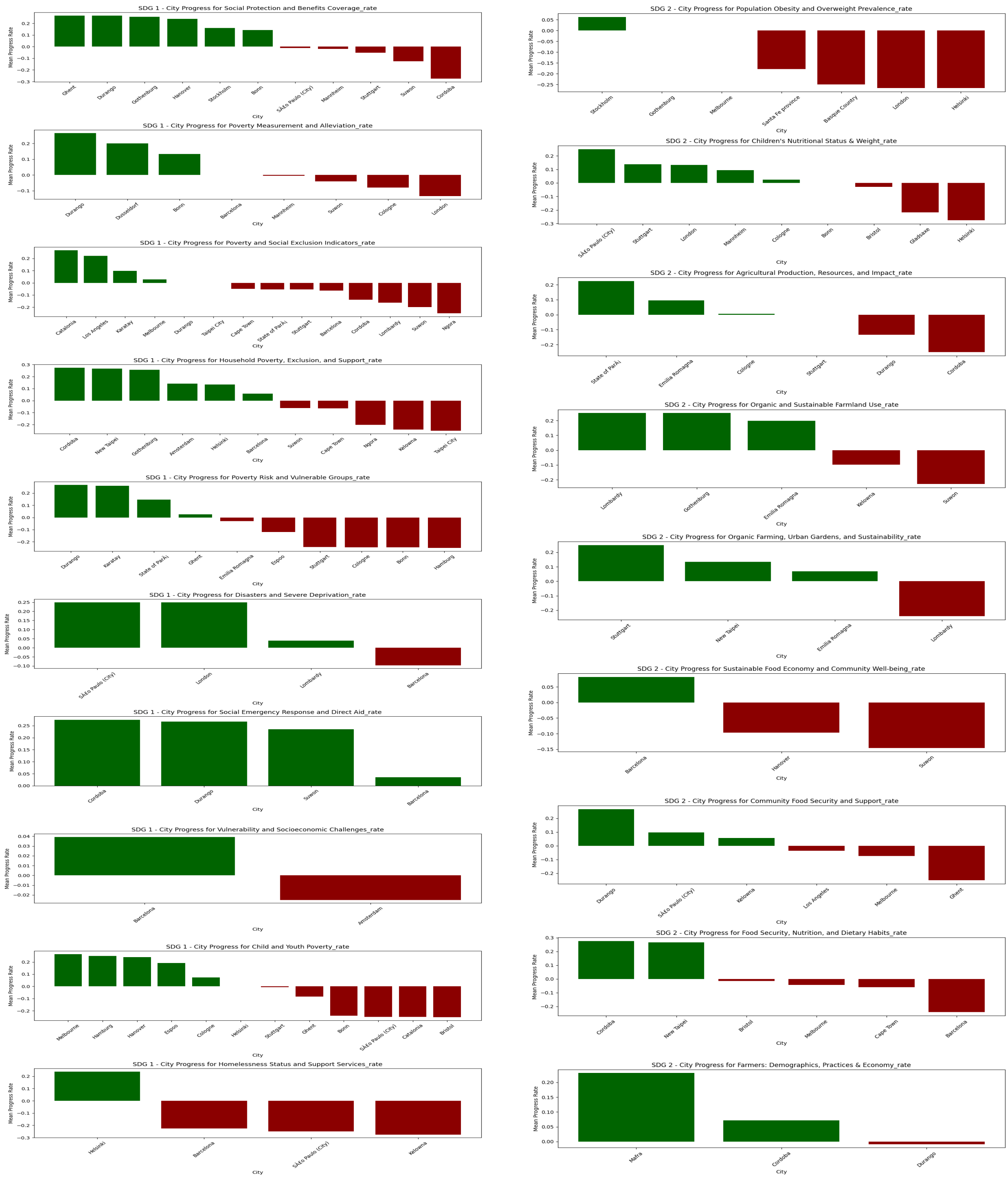
(d) SDG 16



(e) SDG 17

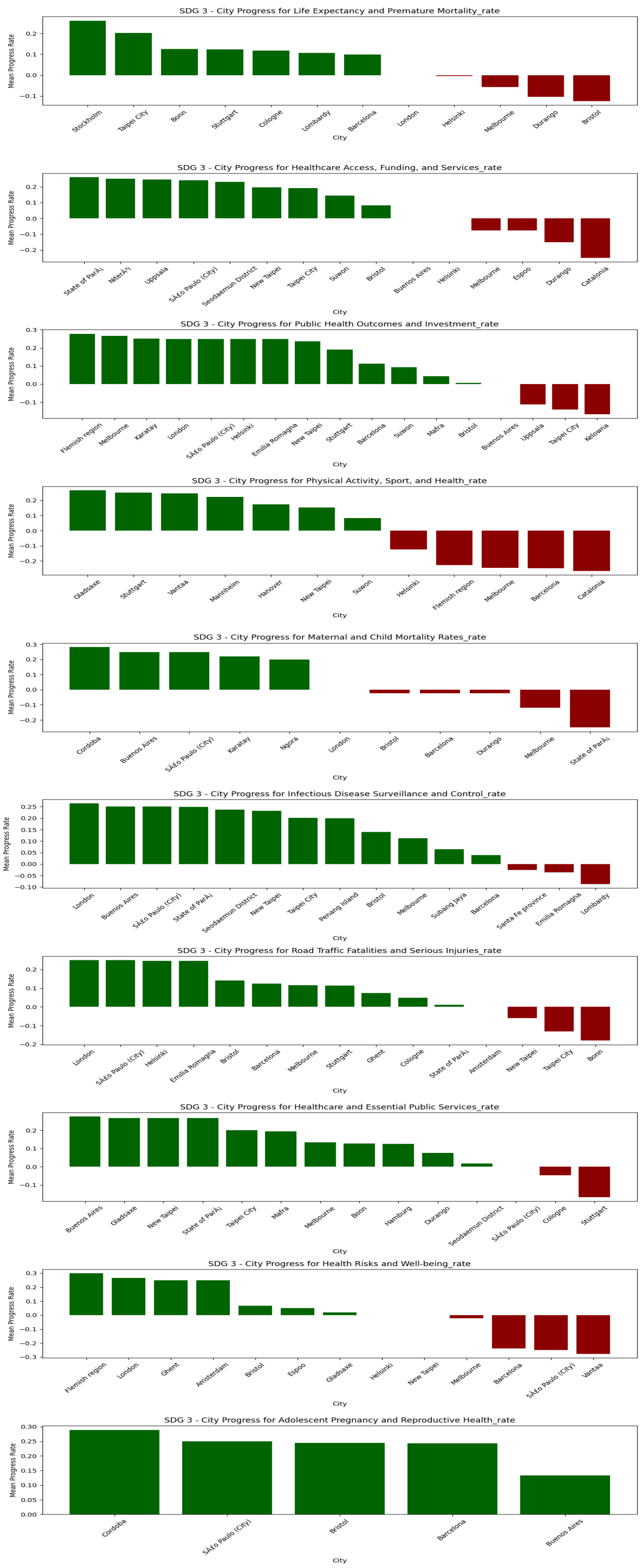
Figure 26: Optimal cluster selection: SDGs 13-17

8.4. APPENDIX D: CITY RANKINGS IN PROGRESS SCORES ACROSS ALL GOALS

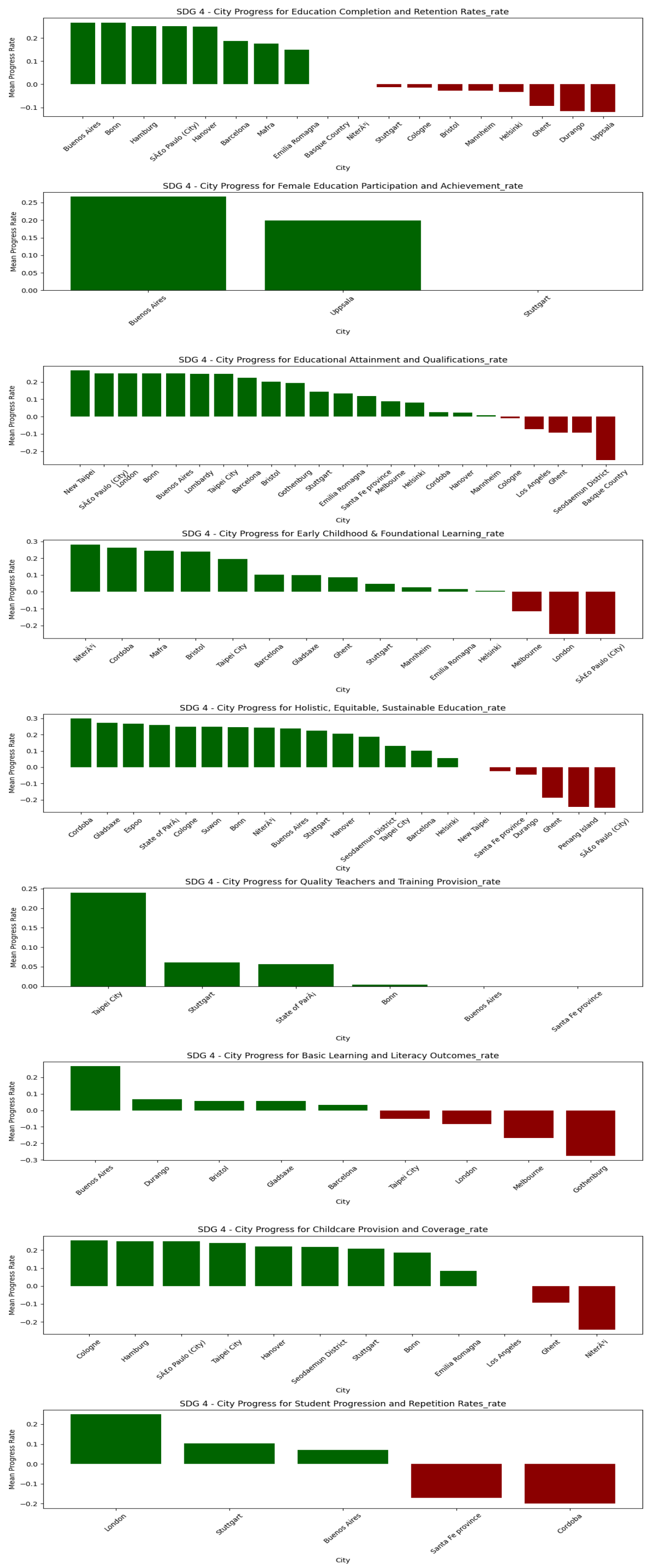


(a) SDG 1 **(b)** SDG 2

Figure 27: City cluster progress rankings SDG 1 & 2

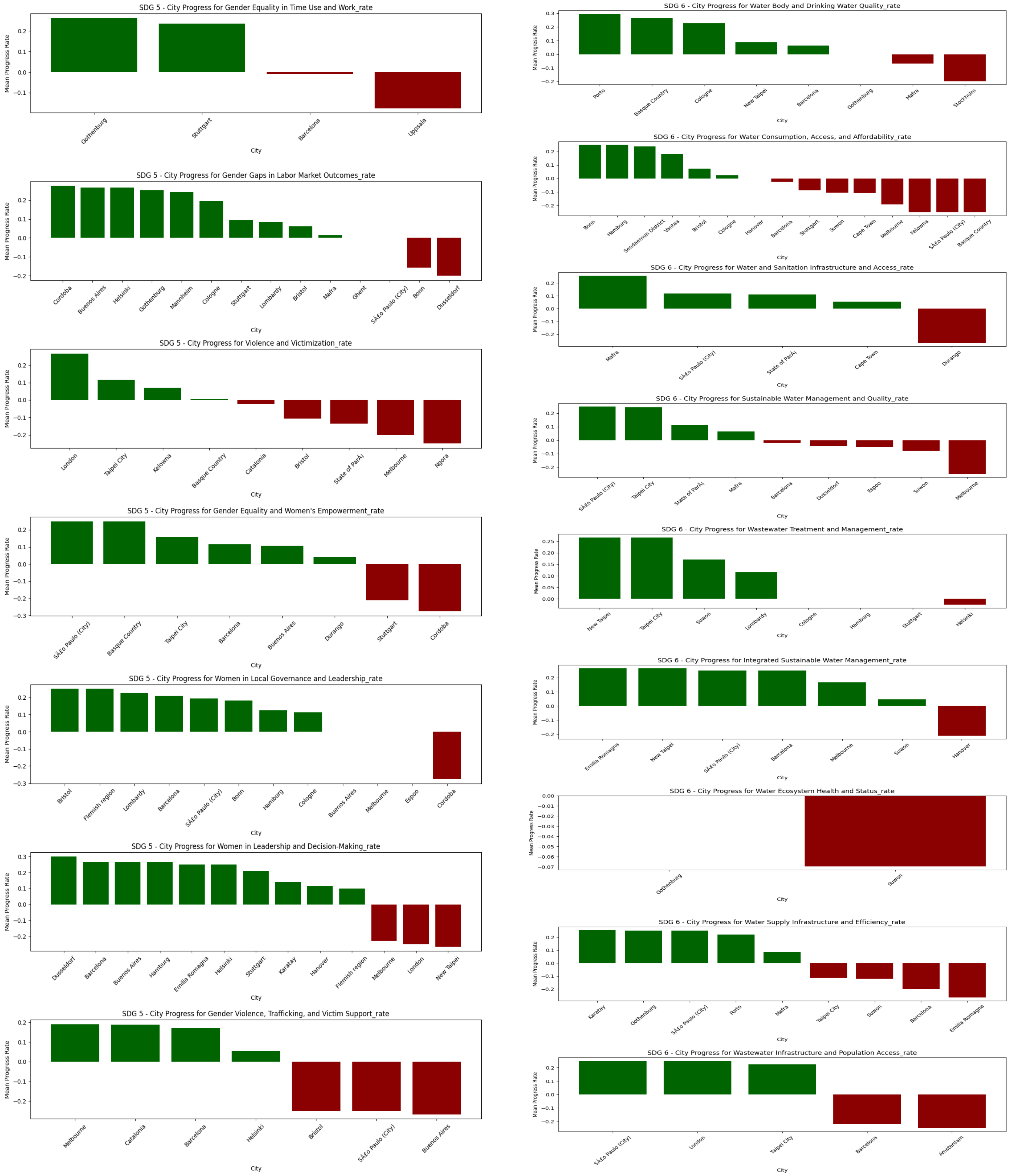


(a) SDG 3



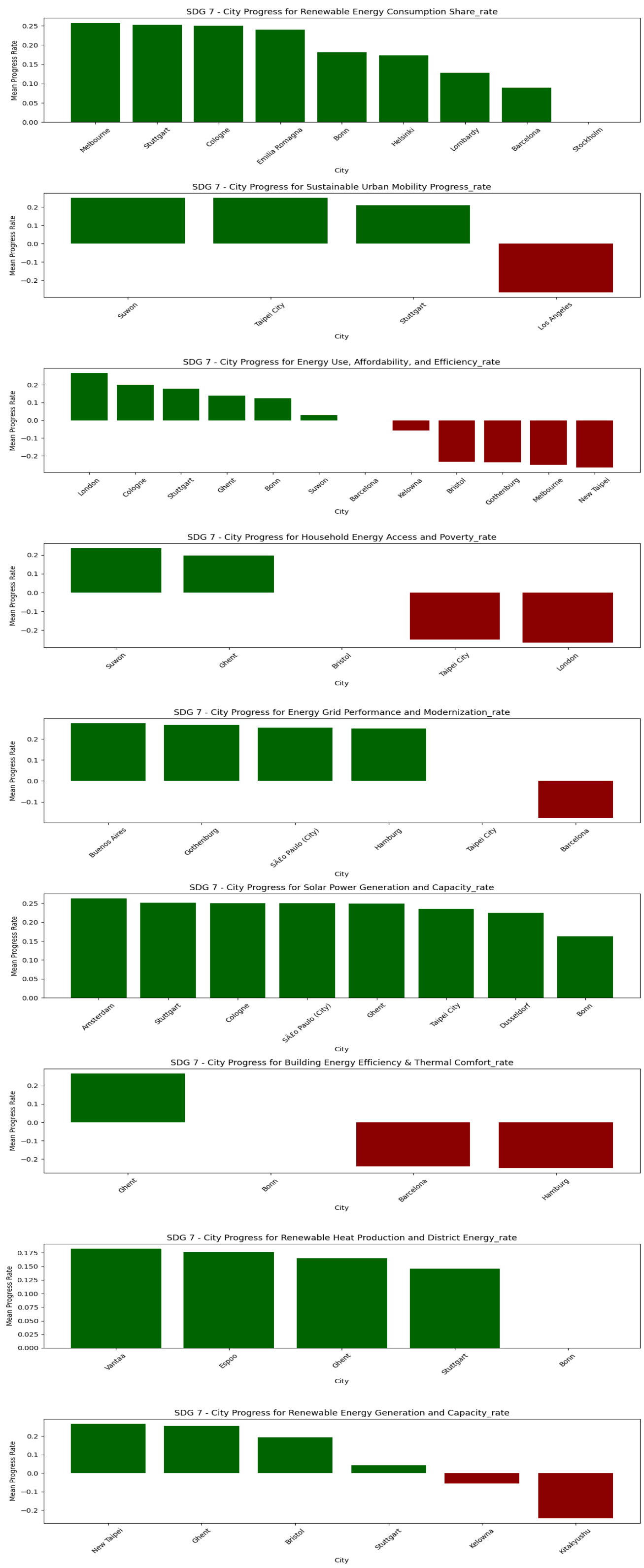
(b) SDG 4

Figure 28: City cluster progress rankings SDG 3 & 4

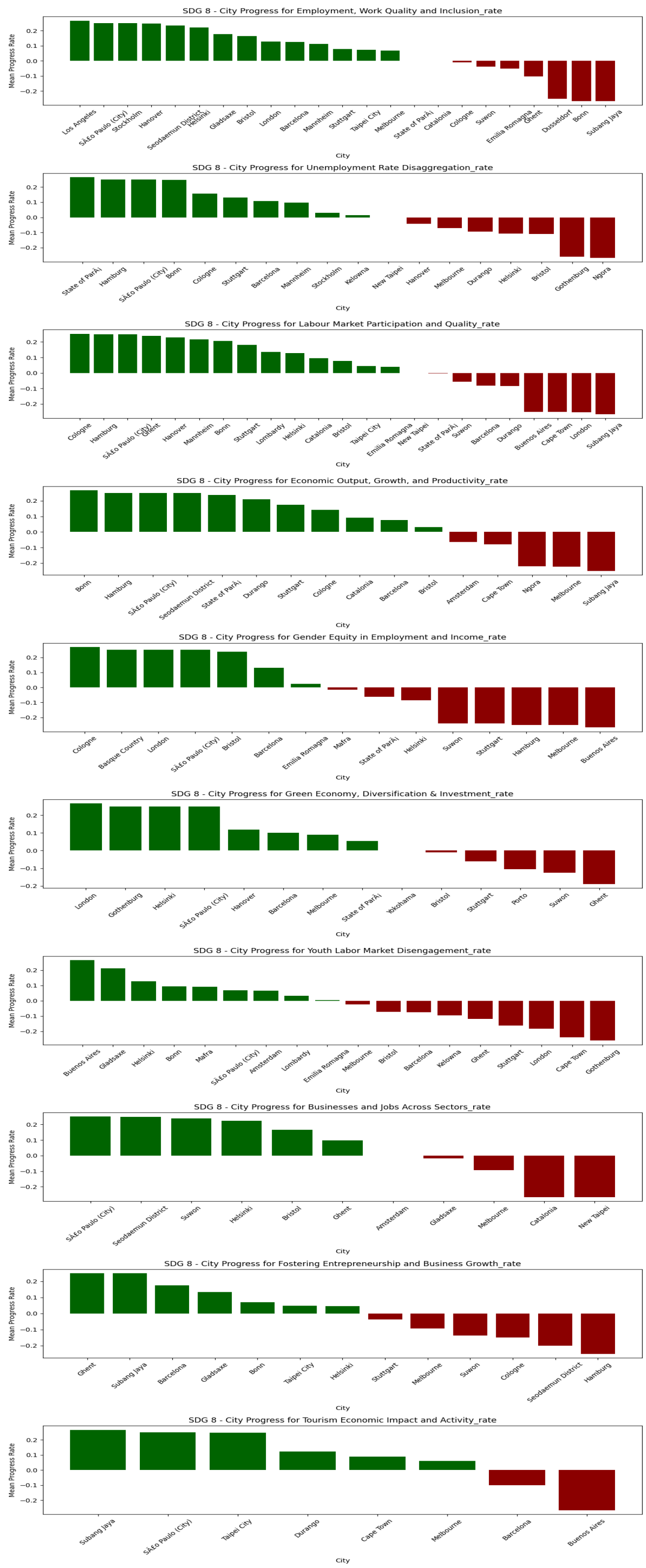


(a) SDG 5 **(b)** SDG 6

Figure 29: City cluster progress rankings SDG 5 & 6

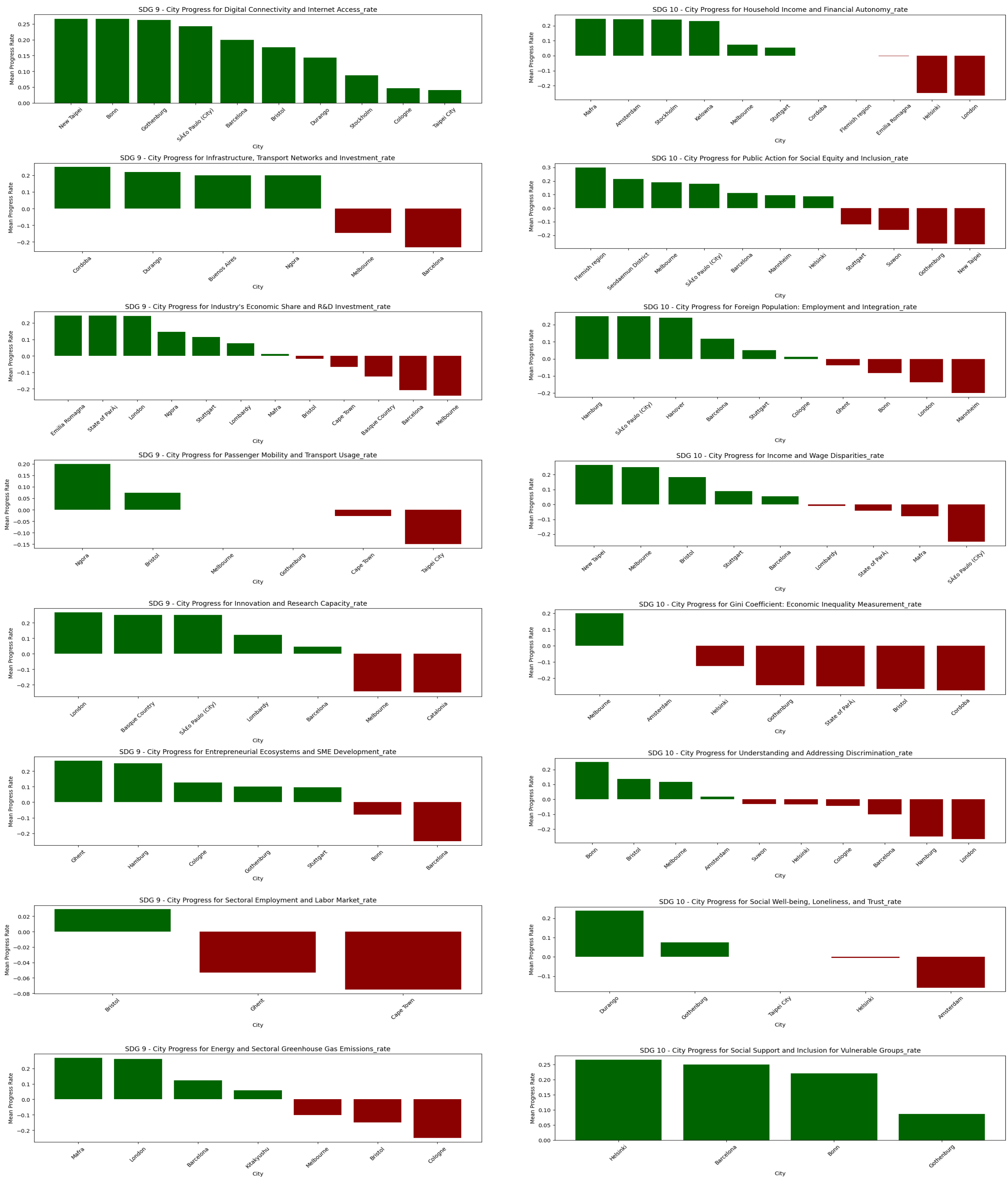


(a) SDG 7



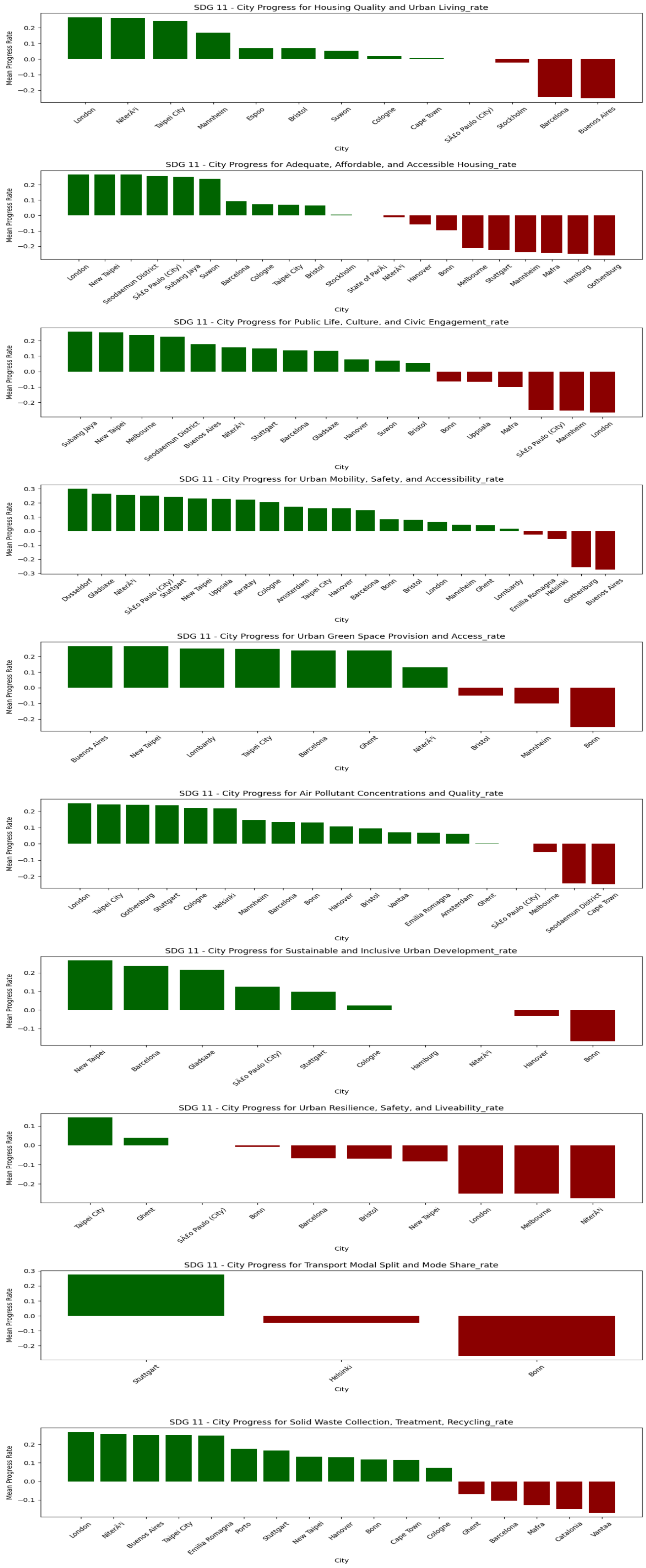
(b) SDG 8

Figure 30: City cluster progress rankings SDG 7 & 8

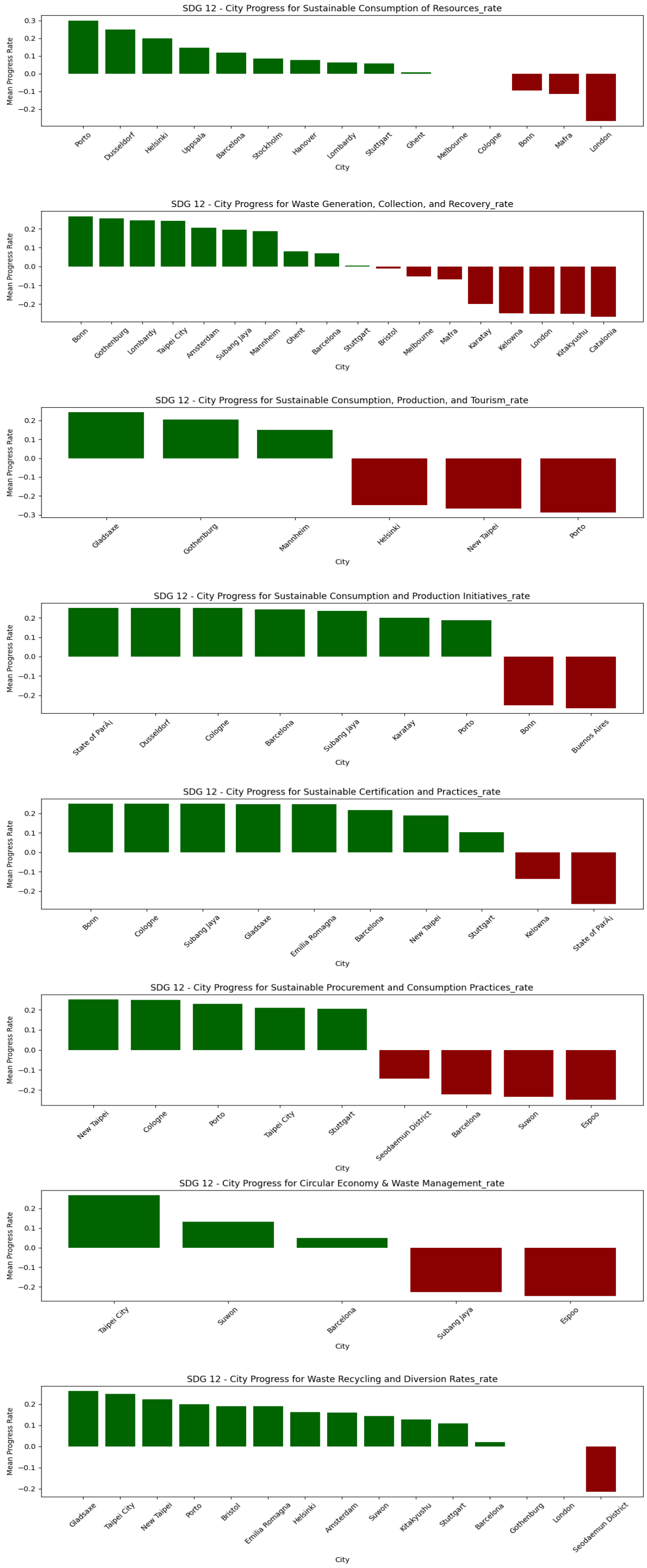


(a) SDG 9 **(b)** SDG 10

Figure 31: City cluster progress rankings SDG 9 & 10

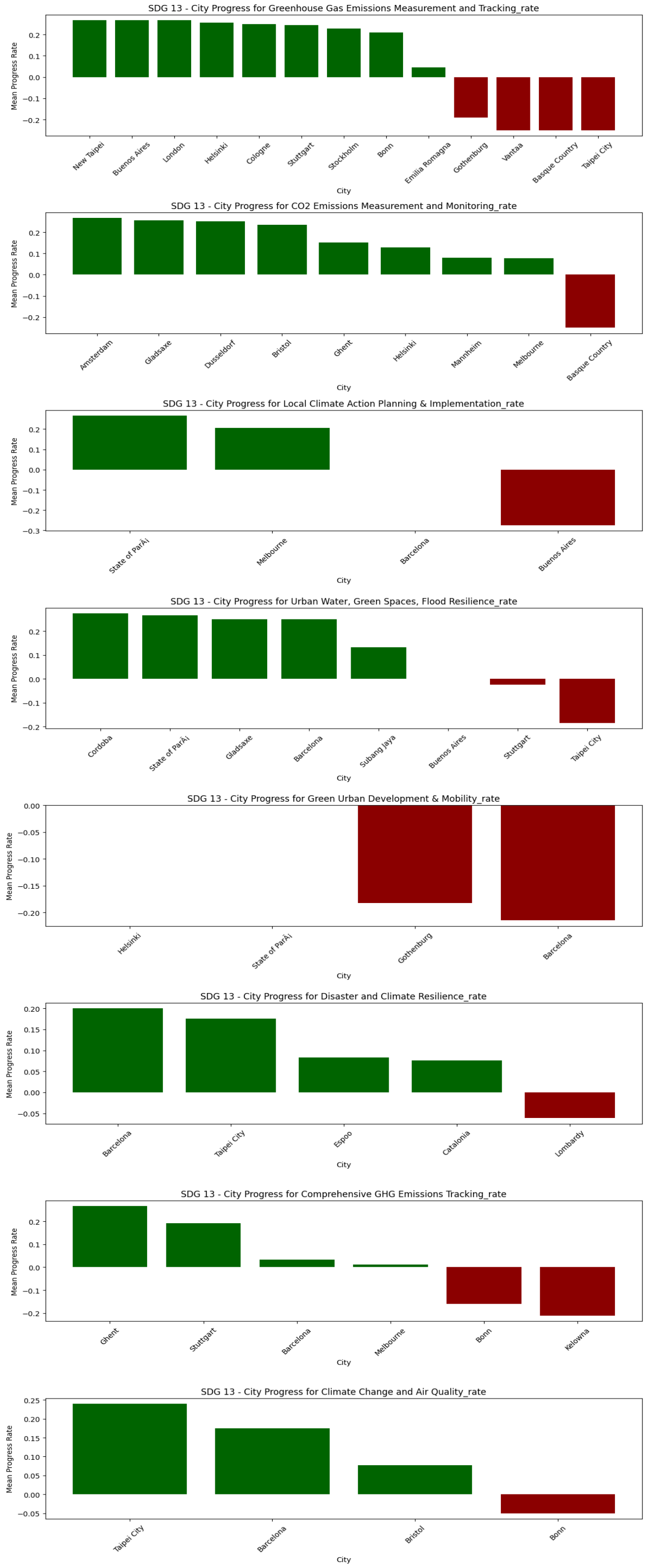


(a) SDG 11

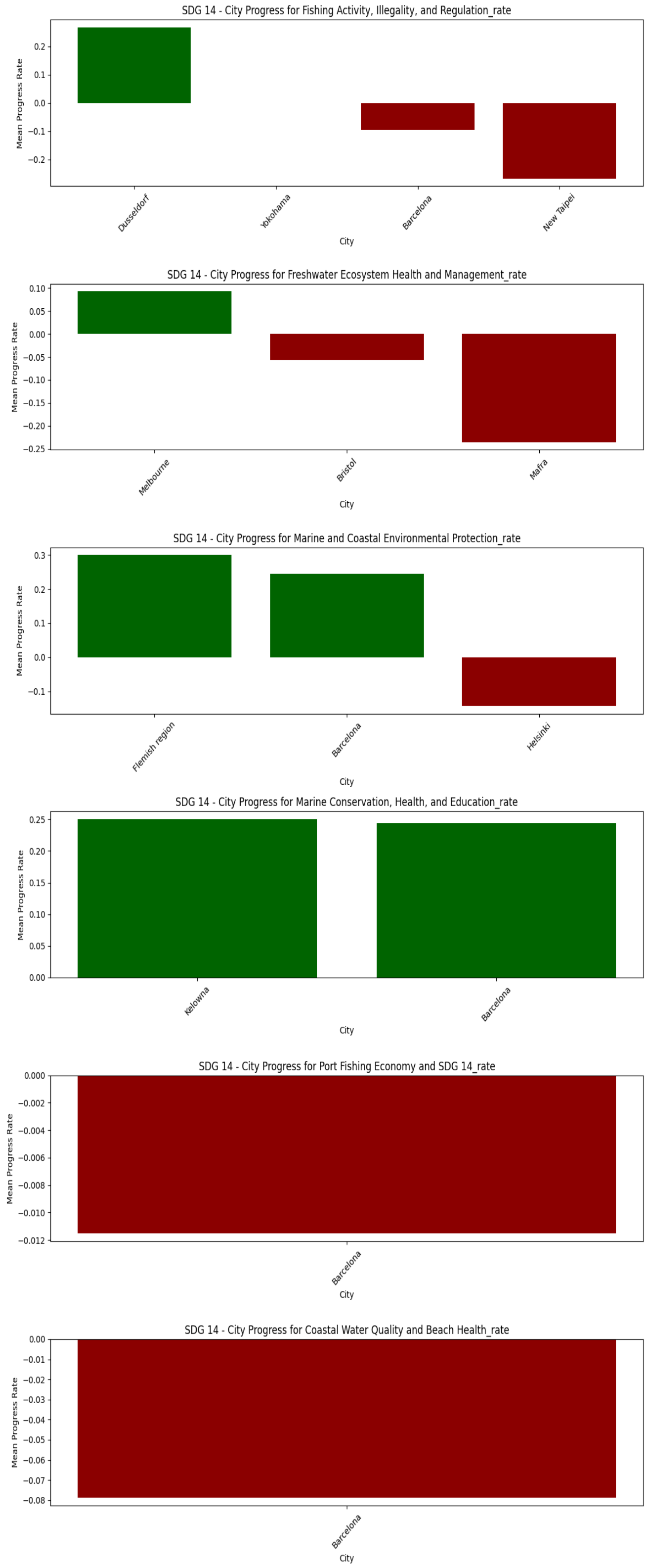


(b) SDG 12

Figure 32: City cluster progress rankings SDG 11 & 12

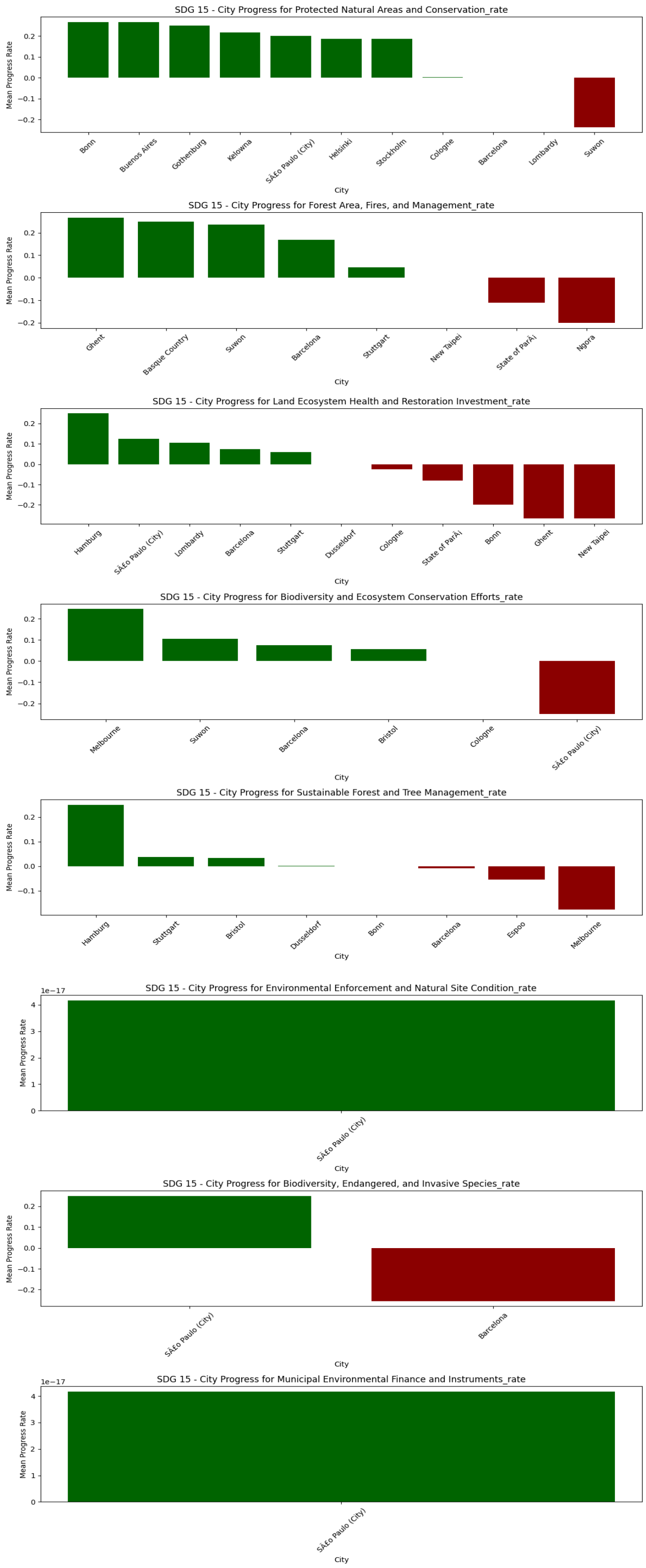


(a) SDG 13

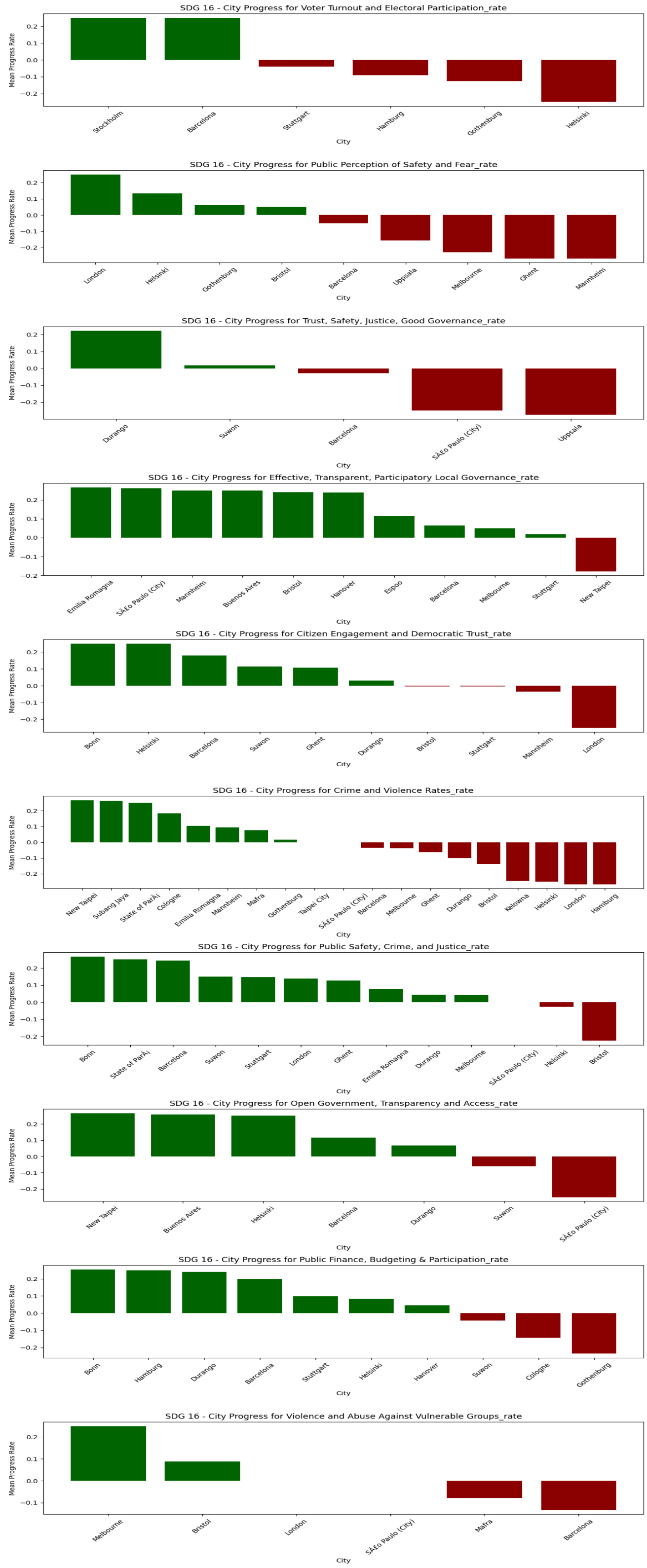


(b) SDG 14

Figure 33: City cluster progress rankings SDG 13 & 14



(a) SDG 15



(b) SDG 16

Figure 34: City cluster progress rankings SDG 15 & 16

MSc ESDA Dissertation Module
Research Ethics, Data Protection & Risk Check
Part A: Declaration of Review Stream Applicable to the Research

This document is for MSc ESDA students to use to determine which ethics stream is applicable to their Dissertation research. It comprises five steps:

- **ALL STUDENTS TO COMPLETE…**
  Step A1 – Does the research require a *Risk Assessment?*
  Step A2 – Does the research require *External* research ethics approval?
- **Where external ethics approval is not required, students complete…**
  Step A3 – Is the research *Exempt* from the need for ethics approval?
- **Where the research is not exempt from the need for ethics approval, students complete…**
  Step A4 – Does the research require *High Risk* ethics approval*?*
- **Where the research is not exempt from the need for ethics approval,**
  but does *not* require high risk ethics approval, students complete…
  Step A5 – Does the research require:
  - Low risk ethics approval for *questions-based methods* – from MSc ESDA.
  - Low risk ethics approval for *other methods* – from BSEER.
- **ALL STUDENTS TO COMPLETE…**
  Step A6 – MSC ESDA Dissertation Ethics *Declaration*
  where students and their supervisors declare
  - Whether or not the research requires a risk assessment, and
  - Which of the following ethics review streams applies to the Dissertation research:
    - External (to UCL) research ethics review.
    - Exempt from the need for research ethics approval.
    - High risk research ethics review from the UCL Research Ethics Committee.
    - Low risk research ethics review for questions-based methods – from MSc ESDA.
    - Low risk research ethics review for other methods – from BSEER.

  The MSC ESDA Dissertation Ethics *Statement* is submitted to the Dissertation module convenor as per their specifications, and included as a Dissertation Appendix, where it will be evaluated by the Dissertation's second marker.

Step A1 – Does the research require a *Risk Assessment?*

UCL has a duty of care to students under the Health and Safety at Work Act.

MSc Esda Students: If you are unsure about answer the below, **consult your Supervisor**.

Evaluate Covid-19 related risks:

Will you conduct any of this research:	**YES**	**NO**
In a way that could breach any relevant Covid-19 laws or guidance?*	☐	☒
In a way that could put you or anyone else at increased risk of Covid-19?*	☐	☒

*Evaluating Covid-19 related risks – UCL resources:

- Evaluating *Fieldwork activity in taught and MRes programmes, 2020-21* – see https://www.ucl.ac.uk/teaching-learning/fieldwork-activity-taught-and-mres-programmes-2020-21
- Risk assessment for return to on-site working at UCL – see https://www.ucl.ac.uk/safety-services/risk-assessment-return-site-working-ucl
- Risk assessments for teaching labs, studios, workshops and other specialist spaces – see https://www.ucl.ac.uk/teaching-learning/education-planning-2020-21/educating-campus-2020-21/risk-assessments-teaching-labs-studios-workshops

If you ticked YES to any of the Covid-19 related risks, your supervisor must complete a RiskNet assessment for this research and you should attach that assessment to this form.

If Covid-19 risks or laws or guidance relevant to the research changes whilst the research is under way, students must immediately discuss this with their supervisors. Students and supervisors should consult the UCL resources above again and decide whether a (new) RiskNet assessment is necessary.

Evaluate laboratory-related risks:

Will you conduct any of this research:	**YES**	**NO**
In a laboratory?	☐	☒

If you ticked YES to conducting any of this research in a laboratory, please explain exactly what risk assessment(s) will be completed prior to the research commencing and (if relevant) prior to each laboratory visit:

Evaluate fieldwork related risks:

Will you conduct any of this research:	**YES**	**NO**
Alone in a non-public place (e.g. dwellings other than those you usually use, workplaces with very few workers present, etc)?	☐	☒
Alone in a public place with few other people present (e.g. quiet park/street)?	☐	☒
In a place where the research topic might be considered sensitive?	☐	☒
Overseas in an area where the UK Foreign and Commonwealth Office (FCO) advises against travel (amber / red on the FCO map of that country)? Note that familiarity with that overseas area is irrelevant to this answer at this stage (see below).	☐	☒

If you ticked YES to ANY of the above, you must complete a Risk Assessment with your supervisor
Your supervisor is responsible for ensuring that any risk assessment necessary for your research is undertaken and completed appropriately. Complete the Department of Geography Dissertation Fieldwork Risk Assessment template under the close supervision of your supervisor. The form and instructions for completing it are available here: https://www.geog.ucl.ac.uk/resources/safety/risk-assessment. Submit an e- copy of your completed and signed Risk Assessment to the Dissertation Module convenor well before undertaking any of the activities covered by the risk assessment. The Dissertation Module convenor or Course Director may need your supervisor to complete a UCL RiskNet risk assessment for your research; if so, you may only undertake the activities covered by the risk assessment once the assessment is approved.

If the risks associated with this research turn out to be higher than expected, or the risks increase for any reason, students must immediately discuss this with their supervisors and decide whether a (new) risk assessment is required.

ALL Students: Proceed to Step A2 – Does the research require external ethics committee approval?

Step A2 – Does the research require *external* ethics committee approval?

MSc ESDA Students: If you are unsure about what to answer, consult your Supervisor.

	YES	NO
1. Is your research social care research funded by the Department of Health? If you ticked YES, you require ethics approval from their authorised ethics committee.	☐	☒
2. **Is your research funded, sponsored or undertaken by the Ministry of Defence?** If you ticked YES, you require ethics approval from their authorised ethics committee.	☐	☒
3. Does the study involve participants lacking the capacity to give informed consent? A person lacks the capacity to give informed consent if at the time when consent is sought they are unable to make a decision for themselves in relation to the matter (i.e. deciding whether to participate) because of an impairment of, or a disturbance in the functioning of, the mind or brain. A person is unable to make a decision for themselves if they are unable: a) to understand the information relevant to the decision, b) to retain that information, c) to use or weigh that information as part of the process of making the decision, or d) to communicate their decision (by talking, using sign language or any other means). If you ticked YES, you require ethics approval from a research ethics committee falling within the UK Health Departments' Research Ethics Service (HRA). UCL committees cannot ethically review research involving participants who fall under the Mental Capacity Act 2005. When unsure please refer to the Mental Capacity Act 2005: • People who lack capacity http://www.legislation.gov.uk/ukpga/2005/9/section/2 • Research http://www.legislation.gov.uk/ukpga/2005/9/part/1/crossheading/research	☐	☒
4. Does your research involve any of the following: • NHS patients and carers • Invasive research involving prisoners • Clinical Trial of an Investigational Medicinal Product • Human tissue requiring ethics approval from 'approved' ethics committee (Human Tissue Act 2004) When unsure please refer to the HRA checklist and the decision tool. If you ticked YES, you require ethics approval through NHS Research Ethics Review (NRES).	☐	☒

If your research DOES require external ethics approval, you must secure this from the relevant authorized ethics committee before data collection starts. **Proceed to Step A6 – *MSc ESDA Dissertation Ethics Declaration*.**

If your research does NOT require external ethics approval, proceed to Step A3 – *Is the research exempt from the need for ethics approval?* (next page).

Step A3 – Is the research *exempt* from the need for ethics approval?

MSc ESDA Students: If you are unsure about what to answer, consult your Supervisor.

Research that is <u>not exempt</u> and requires ethics approval	**YES**	**NO**
1a. Will your research collect / use / store / process personal data? The **legal definition** of Personal Data is any information relating to an identifiable person who could directly *or indirectly* be identified from that information. It includes Personal Data that you are collecting simply to contact your participants. It is data that a motivated intruder or analyst (including you) *could* use to identify someone. This includes if someone could potentially identify individuals from an interview transcript, or from a subsequent report. Examples include: • Name (can be sufficient to ID an individual; usually sufficient if combined with other information) • Email address / Phone number • Home address / Postcode • Photo / Audio / Video → can reveal ID if accessed by someone able to digitally enhance • Location data? EG taxi fleet location data can be processed to reveal identifiable information on individuals • Online identifiers (including IP addresses) • Data derived from electronic sensors or digital 'tracking' tools • Combinations of data that may reveal identifiable data (e.g. Employer + Job Title)	☐	☒
1b. Will your research involve human participants or observing humans? All research involving human participants and/or their data requires ethics approval.	☐	☒
1c. Will your research potentially raise other ethics issues? Research that does not involve human participants and/or their data *may still raise other ethics issues* that require consideration. Below are some examples that will require ethics approval (this list is not exhaustive): • research on terrorism / extreme violence • research on pornography • environmental studies that have the potential to impact on or change the environment • archaeological excavations in disputed territories • studies involving access to sacred sites or the analysis of sacred cultural objects where access is restricted or where there are particular modern sensitivities or issues • access to indigenous communities that have come to insist upon prior permission gained from official or informal indigenous bodies • interpretations of publicly available data that make sensitive or personal claims about individuals. EG analysing speeches and concluding that the language used indicates dementia onset or autistic features	☐	☒

If you ticked YES to ANY of the above, your research IS NOT EXEMPT from the need for ethics approval. Proceed to Question 2, below.

If you ticked NO to ALL of the above, your research IS EXEMPT from the need for ethics approval. **Proceed to Step A6 – *MSC ESDA Dissertation Ethics Declaration*.**

Additional research that is exempt from the need for ethics approval	**YES**	**NO**
2. Is all of your research literary or artistic criticism, or reviews of professional and other publicly-affirmed opinions? If you ticked YES, your research IS EXEMPT from the need for ethics approval. Proceed to Step A6 – *MSC ESDA Dissertation Ethics Declaration*. If you ticked NO, your research IS NOT exempt from the need for ethics approval. Proceed to Step A4 – *Does the research require High Risk ethics approval?*	☐	☐

Step A4 – Does the research require *High Risk* ethics approval?

MSc ESDA Students: If you are unsure about what to answer, consult your Supervisor.

Vulnerability	**YES**	**NO**
1. Will your research involve participants who are particularly vulnerable? For example individuals: • with learning disabilities or a cognitive impairment (see note below) • with emotional and mental health problems (see note below) • who are highly dependent or in unequal positions such as those in care who are unlikely to comprehend the rationale of the research or who are at risk of being traumatised or physically debilitated by it. *A person will not be considered automatically vulnerable if, for example, they are illiterate or have dyslexia or OCD. A vulnerable participant is someone:* - *who is, or may be, in need of community services due to age, illness or a mental or physical disability* - *who is, or may be, unable to take care of himself/herself, or unable to protect himself/herself against significant harm or exploitation.*	☐	☐
2. Will your research include participants who due to their personal circumstances are particularly vulnerable? This includes asylum seekers, people in care facilities, prison, young offenders, refugees (UK and elsewhere), victims of crime, those who have suffered a traumatic event.	☐	☐
Perceived pressure to participate (power relationships)	**YES**	**NO**
3. **Will the project involve researching your own students/clients?** If so, will the research collect personal data that would not otherwise be disclosed during normal relationships/business?	☐	☐
Sensitive Topics	**YES**	**NO**
4. **Will the project cover topics and include the collection of data that would usually be considered as sensitive?** For example: • terrorism / extreme violence (including contact with terrorists, communities in which terrorists are thought to be based or very likely targets of terror), • pornography (to include pornographic materials or contact with persons and organisations that make these materials), • exploration of participants' experiences of violence, abuse or exploitation, • exploration of participants' illegal behaviour (to include direct contact with those persons knowingly engaged in illegal activities).	☐	☐
5. Will the project involve collecting data that, if disclosed outside of the research, foreseeably would place the participants at risk of criminal or civil liability or be damaging to participants' financial standing, employability, reputation or their ties with family or standing in the community?	☐	☐
Risk of Disclosure	**YES**	**NO**
6. Will your research involve a risk of disclosure? In the course of their research, colleagues will sometimes collect information or data that appears to disclose criminal or illegal activity. In some cases there could be a legal obligation to inform the authorities. However, even if there is no legal obligation to report an activity, researchers may still find themselves in possession of information about acts that could potentially harm the participants themselves, specific third parties or the general public. Although it is generally the case that *information should remain confidential there are limits to confidentiality and situations where confidentiality will need to be broken. You must consider beforehand whether the research involves an increased likelihood* of a disclosure happening should a participant tell the researcher something that causes significant concern, or it could be something that is observed during fieldwork such as an illegal activity.	☐	☐

Consent, deception and covert methods	YES	NO
7. Will your research involve an element of deception or covert methods* (observation or other data collection), whereby fully informed consent is not obtained, partial consent is sought or participants are included without their knowledge? **This means situations where it is not appropriate to inform participants either in full or at all about the study as it may either affect the behaviour of participants and/or make it impossible to collect the data.* *This does not include observation of individuals in public spaces.*	☐	☐
Intrusive/Medical Interventions	**YES**	**NO**
8. Will your research involve any of the following intrusive or medical interventions: • taking blood samples • administering drugs or other medicinal products • a medical device • exposure to strong magnetic fields, including Magnetic Resonance Imaging (MRI) and Transcranial Magnetic Stimulation (TMS) • making electrical recordings from muscle (ECG, EMG) or brain (EEG) • use of non-ionising radiation • physically intrusive procedures such as biopsies • DNA / RNA / genetic analysis • samples from participants that could reveal an unknown medical condition	☐	☐
Risk of Harm to Participants	**YES**	**NO**
9. Will your research present a significant risk of harm to the rights and wellbeing of participants; physical, emotional (i.e. distress or humiliation), psychological (i.e. stress or anxiety), reputational, legal or financial beyond the risks encountered in normal life? The answer in this section **should be 'yes'** where there is a risk of participants experiencing psychological stress, anxiety, humiliation, harm or negative consequences as a result of participation and where this risk is significantly greater than anticipated for the participant in their everyday life. For example, the discussion of sensitive topics such as child abuse, terrorism, pornography, eating disorders, suicidal thoughts or sexual or political behaviour, experiences of violence, abuse or exploitation. However, discussing such topics with professionals whose work is related to those areas, such as social workers or psychologists, may not involve an increased risk of them becoming distressed as the nature of their professional lives is that these topics are for them less sensitive than for most people.	☐	☐
Risk of Harm to Researcher/s	**YES**	**NO**
10. Will your research present a real and/or significant risk to a member of the research team? This includes but is not limited to: • working in potentially unsafe environments (e.g. overseas research where the FCO has advised against all travel • lone working such as at night in non-public places where there are other risk elements to consider (for example, the study may be looking at domestic abuse) • engaging with groups or behaviour that could result in harm The Social Research Association highlights these potential risks to researchers: • physical threat or abuse • psychological trauma, as a result of actual or threatened violence or the nature of what is disclosed during the interaction • being in a compromising situation, in which there might be accusations of improper behaviour • increased exposure to risks of everyday life and social interaction, such as road accidents and infectious illness • causing psychological or physical harm to others	☐	☐

If you tick **YES** to **ANY** of the above questions, your research is deemed high risk and you require approval from the UCL Research Ethics Committee (see https://wiki.ucl.ac.uk/display/BI/Ethics). Proceed to Step A6 – *MSC ESDA Dissertation Ethics Declaration*.

If you ticked **NO** to **ALL** of the above questions, your research is not deemed high risk. Proceed to Step A5 —*Check if ESDA or BSEER Low Risk Ethics Review*.

Step A5 – Does the research require MSc ESDA Low Risk Ethics Review for *Questions-based methods* OR BSEER Low Risk Ethics Review for *Other methods?*

This step is for the use of MSc ESDA Dissertation students who have confirmed that their research does not require approval from an external ethics committee (Step A2), that their research is not exempt from the need for ethics approval (Step A3), and that their research will not include any high-risk elements (Step A4). It will help students determine whether they may apply for research ethics approval to the *MSc ESDA* Dissertation module coordinator, or whether they should submit a BSEER Low Risk Ethics application.

MSc ESDA Students: If you are unsure about what to answer, consult your Supervisor.

1. Will you use questions-based methods for your Dissertation?

Interviews are question-and-answer sessions with mostly open answer response options. They can be verbal (e.g. face-to-face, phone) or written (e.g. email, chat) and with either individuals or groups.

Yes ☐ No ☐

Focus groups: where researchers facilitate discussion on a topic among a group of participants.

Yes ☐ No ☐

Social surveys / Questionnaires are highly structured questions with mostly closed answer response options. They can be verbally administered by the researcher (e.g. face-to-face, phone), or written self-completion (e.g. paper, online, via apps).

Yes ☐ No ☐

If you ticked **YES** to **ANY** of the above, proceed to Question 2.

If you ticked **NO** to **ALL** of the above, submit a BSEER Low Risk Ethics application (https://wiki.ucl.ac.uk/display/BI/Ethics) and proceed to Step A6 – *MSC ESDA Dissertation Ethics Declaration*.

2. OTHER THAN these interviews / focus groups / questionnaires, will the research involve human participants?

Yes ☐ No ☐

If **YES**, submit a BSEER Low Risk Ethics application (https://wiki.ucl.ac.uk/display/BI/Ethics). Proceed to Step A6 – *MSC ESDA Dissertation Ethics Declaration*.

If **NO**, proceed to Question 3.

3. Will you collect or use personal data for your Dissertation?

The **legal definition** of Personal Data is any information relating to an identifiable person who could directly *or indirectly* be identified from that information. It includes Personal Data that you are not using as research data – EG personal data you are collecting simply to contact participants. It is data that a motivated intruder or analyst (including you) *could* use to identify someone. This includes if someone could potentially identify individuals from an interview transcript, or from a subsequent report. Examples include:

- Name (can be sufficient to ID an individual; usually sufficient if combined with other information)
- Email address / Phone number
- Home address / Postcode
- Photo / Audio / Video → can reveal ID if accessed by someone able to digitally enhance
- Location data? EG taxi fleet location data can be processed to reveal identifiable information on individuals
- Online identifiers (including IP addresses)
- Data derived from electronic sensors or digital 'tracking' tools
- Combinations of data that may reveal identifiable data (e.g. Employer + Job Title)

Yes ☐ No ☐

If **YES**, go to Question 4.

If **NO**, submit an MSc ESDA Ethics Assessment Part B *Research Ethics Protocol & Application – Methods involving questions.* Proceed to Step A6 – *MSC ESDA Dissertation Ethics Declaration*.

4. Why are you collecting this personal data?

☐ Just for the interviews / focus groups / questionnaires (e.g. to contact participants)
Submit an MSc ESDA Ethics Assessment Part B *Research Ethics Protocol & Application – Methods involving questions.*

☐ For some other aspect of my Dissertation as well / instead.
Submit a BSEER Low Risk Ethics application (https://wiki.ucl.ac.uk/display/BI/Ethics).

Proceed to Step A6 – *MSC ESDA Dissertation Ethics Declaration.*

Step A6 – MSC ESDA Dissertation Ethics Declaration

Statement of Risk Assessment & Ethics Approval Requirements
Student Candidate Number [NQMJ9]: Student Name: [TONY OTIENO]: Student UCL Email Address: [ucbvtot@ucl.ac.uk]: **Supervisor Name:** [Manos Chaniotakis]: Supervisor UCL Email Address: [m.chaniotakis@ucl.ac.uk]: **Dissertation Research Proposal** [FILL IN]: • Title / Topic: SDG Interlinkages on a Local Level: Exploring policy objectives reflection using Large Language Models and Machine Learning Techniques. • Research Question(s) / Aims & Objectives: This work aims at utilising advanced language models and ML techniques to extract interlinkages from data available on a local level. • Data & source (specify all data to be used; if none, explain why): Structured database summarizing SDG indicator progress as reported in 120 Voluntary local reports (VLRs) • Method(s) (specify all methods to be used): Machine learning, large language models, system dynamics modelling
I have read and understood **Step A1 'Does the research require a Risk Assessment?'** and: • This planned research does NOT require a risk assessment.
I have read and understood **Step A2 'Does the research require External research ethics approval?'** and: • This planned research does NOT require external ethics review.
External ethics approval is *not required* and I have read and understood **Step A3 'Is the research Exempt from the need for ethics approval?'** and: • This planned research IS EXEMPT from the need for research ethics approval.
The research is *not exempt* from the need for ethics approval and I have read and understood **Step A4 'Does the research require High Risk ethics approval?'** and: • This planned research is NOT deemed high risk.
The research is *not exempt* from the need for ethics approval, does not require high risk ethics approval and: I have read and understood **Step A5 'Does the research require ESDA low risk ethics review for questions-based methods OR BSEER low risk ethics review for other methods?'** and: [DELETE ONE STATEMENT]: [NOT APPLICABLE] • This planned research requires MSc ESDA Low Risk Ethics approval for questions-based methods and approval will be secured before data collection starts. • This planned research requires BSEER low risk ethics approval (for other methods), which will be secured before data collection starts.
I confirm that: • the information I have provided is accurate to the best of my knowledge. • if the answers to any of these questions changes, I will go through this protocol again.

NEXT STEPS:

- **STUDENT:** Copy the text of the *completed* statement above into an email and email it to your supervisor.
- **SUPERVISOR: Reply to the email confirming your approval of the completed statement, copying the Dissertation PGTA (r.alasmar@ucl.ac.uk). It is the student's responsibility to ensure that happens.**
- **STUDENT:**
    - Include this A6 Statement as a Dissertation Appendix after you have BLACKED OUT YOUR NAME & EMAIL ADDRESS so the second marker can mark anonymously.

The Dissertation mark sheet asks the second marker whether this form was filled out correctly and, if not, what % mark deduction they recommend.