# A Topic Modeling Approach for Extracting Key City Resilience Indicators

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## ABSTRACT

In the field of urban resilience, there is a great diversity of approaches to measuring the level of resilience in cities. This information is scattered among reports and academic articles. In this ongoing research paper, we explore the potential of Topic Modeling to analyze this information, in order to determine cluster indicators for a set of academic papers and resilience frameworks. These clusters are referred to as Key City Resilience Indicators (KCRI), which are used as reference to facilitate the measurement of urban resilience regardless of the context, including all the key dimensions required for cities to achieve resilience. Topic modeling outcomes can be used to generate indicators based on each topic or to automatically classify a new set of indicators in each of the established topics. These results can be applied to any resilience framework.

### Keywords

Urban Resilience, Machine Learning, Indicators, Topic Modeling, KCRI.

## INTRODUCTION

"Urban resilience" has been defined as "the ability of an urban system and all its constituent socio-ecological and socio-technical networks across temporal and spatial scales to maintain or rapidly return to desired functions in the face of a disturbance, to adapt to change, and to quickly transform systems that limit current or future adaptive capacity" (Meroow et al, 2016; p38). Since urban areas are complex and dynamic, this multi-disciplinary concept contemplates different aspects that cities need to face in order to achieve resilience, depending on the perspective of the discipline and hazard considered. Infrastructure (engineering perspective), Ecology (nature-based perspective), Social (community perspective), Economy (focusing on adaptative economic responses and critical resources), and Institutions (considering organization capacities) are examples of the dimensions used by Torabi et al (2020) in a context of climate-related hazards. In a bibliometric analysis, Büyükozkan et al (2022) identified the six most mentioned sub-topics on urban resilience, showing a different approach: Climate change (Kim and Kim, 2016); Urban Planning (Yaman Galantini and Tezer, 2018); Urban Sustainability (Tabibian & Movahed, 2016); Adaptation (Kim and Lim, 2016); Urban Vulnerability (Diaz-Sarachaga and Jato-Espino, 2020) and Smart Cities (Ahvenniemi et al, 2017). Therefore, despite the growing interest in both analytical and conceptual research in many fields, according to Woodruff et al (2021), the literature does not provide an overview but a partial view of the necessary dimensions and effective measurement of urban resilience, which vary depending on the authors consulted. Thus, this lack of consensus on topics to consider developing resilience hampers its operationalization. Sarifi (2020) highlighted the need to develop economic and social dimensions of urban resilience, climate change other than flooding, and resilience assessment tools and methods to adopt a holistic approach. To the best of our knowledge, there is no standardized or comprehensive view of the key topics for the measurement of urban resilience and metrics associated with each dimension.

Thus, there is a great diversity of approaches to measuring the level of resilience in cities. This information is scattered among reports and academic papers. There is a technique from artificial intelligence (AI), from the subfield of machine learning, that can be of great help in classifying these indicators. This is the so-called topic modeling, which is intended to identify, without the help of any dictionary, the main themes contained in a text. In this ongoing study, we explore the potential of Topic Modeling to analyze this information, in order to determine cluster indicators for a set of academic papers and resilience frameworks in Key City Resilience Indicators (KCRI). KCRI are used to facilitate the measurement of urban resilience regardless of the context, including all the key dimensions necessary for cities to achieve resilience. This methodology has been carried out based on already existing frameworks and relevant academic papers that propose resilience measures.

This paper is structured as follows: Section 2 analyzes the literature review process; Section 3 presents the methodology; and Section 4 describes the results. This on-going study ends with the conclusions drawn from the interpretation of the obtained results.

## LITERATURE REVIEW

### Urban resilience frameworks

There are frameworks in the literature that propose dimensions and indicators that should be considered for measuring urban resilience. In this study, we selected four of the most relevant urban resilience frameworks to analyze the diversity of existing indicators to assess resilience in cities: 1) City Resilience Framework (CRF), 2) UNDRS Disaster Resilience Scorecard for cities, 3) City Resilience Program (CRP), and 4) Resilience Assessment Framework (RAF). These four frameworks were selected based on the fact that they are highly recognized in the city resilience field, they were developed by well-known associations in the field of city resilience, and they have been tested and implemented in several cities worldwide.

CRF was developed by Arup with support from the Rockefeller Foundation in 2014, and it was tested in the 100 cities selected in the 100 Resilience Cities initiative. This framework allows cities to facilitate a common understanding of what resilience is and the different aspects that contribute to increasing the city resilience level, combining physical aspects of cities with less tangible aspects associated with human behavior. The key elements defined by this framework are 12 goals, 4 categories, 7 qualities, and 52 indicators. The goals describe the main outcomes of a resilient city, such as minimal human vulnerability, effective safeguards to human health and life, and a sustainable economy, among others. These goals have been classified based on four dimensions: 1) health and well-being of individuals; 2) urban systems and services; 3) economy and society; and 4) leadership and strategy. In addition, the goals are complemented by 7 qualities, which are relevant for preventing breakdown or failure, or enabling appropriate and timely action to be taken. Finally, the 12 indicators help to assess the performance of the 12 goals.

The second selected framework is the Disaster Resilience Scorecard, which was developed by the United Nations Office for Disaster Risk Reduction (UNDRR) in 2017. The Scorecard supports cities in establishing a baseline measurement of their resilience level based on the Ten Essentials for Making Cities Resilient, which cover issues such as governance and financial capacity, planning and disaster preparation, and disaster response and recovery. The Scorecard can be used applying two levels of detail. A preliminary level has 47 questions, which are answered with a 0-3 score, whilst the detailed assessment includes 117 indicators measured with a score of 0-5. This Scorecard has already been used in several case studies around the world.

The third framework is the City Resilience Program (CRP), which is an initiative aimed at increasing financing for urban resilience promoted by the World Bank Group since 2017. This program defines three strategic pillars: (i) Planning for Resilience, (ii) Finance for Resilience, and (iii) Partnership for Resilience. For each pillar, CRP defines a set of intermediate outcomes that are measured using quantitative results indicators, which allow cities to assess the results of the implemented actions to reach the strategic pillars and to establish specific targets. This program has engaged more than 90 cities around the world, helping them with the development of investment programs to increase their current resilience level.

Finally, the RAF framework was developed in the context of the RESCCUE project, funded by the Horizon 2020 program in 2020. This framework helps cities to assess their level of resilience to climate change, with a special focus on the water cycle. This framework considers five dimensions (spatial, organizational, physical, functional, and time), and a set of medium-long-term resilience objectives are assessed using metrics, which are defined by questions or specific indicators. This framework has been applied in Bristol (UK), Barcelona (Spain), and Lisbon (Portugal).

Although the objective of these frameworks is similar, there is a lack of consensus on the selected dimensions and on the number of indicators (Table 1). The four frameworks propose a diversity of 21 subdimensions, which do not match completely, although they are not mutually exclusive. This prevents the categorization of measures by dimension, making it difficult to obtain a global perspective of resilience dimensions and measures. Furthermore, the indicators' target or goal is different depending on the context.

**Table 1. Dimensions, Subdimensions, and Indicators by framework**

| | **Dimensions** | **Number of indicators** | **Subdimensions** | **Num of indicators/ subdimension** |
|---|---|---|---|---|
| **CRI (City Resilience Index)** | Human behavior and Infrastructure | 52 | Economy and society<br>Health and well-being<br>Infrastructure and environment<br>Leadership and strategy | 13<br>14<br>13<br>12 |
| **CRP (City Resilience Program)** | Planning, capital mobilization, and partnership | 15 | Financial advisory support<br>Partnership for Resilience<br>Planning for Resilience | 5<br>4<br>6 |
| **UNDRS (Disaster Resilience Scorecard)** | Corporate and city governance, planning integration, and response planning | 47 preliminary assessment | Ensure Effective Disaster Response<br>Expedite Recovery and Build Back Better<br>Identify, Understand, and Use Current and Future Risk Scenarios<br>Increase Infrastructure Resilience<br>Organize for Resilience<br>Pursue Resilient Urban Development<br>Safeguard Natural Buffers to Enhance the Protective Functions Offered by Natural Ecosystems<br>Strengthen Financial Capacity for Resilience<br>Strengthen Institutional Capacity for Resilience<br>Understand and Strengthen Societal Capacity for Resilience | 7<br>2<br>5<br>9<br>3<br>4<br>3<br>4<br>6<br>4 |
| **RAF (Resilience Assessment Framework)** | Governance, Social Infrastructure, spatial, built environment and Environmental | 719 | Functional<br>Organizational<br>Physical<br>Spatial | 346<br>74<br>270<br>29 |

For example, CRI includes aspects associated with human behavior (economy, well-being, and leadership and strategy) and infrastructure (reference); The DRS "ten essentials" highlight strategic areas related to corporate and city governance (organization, scenarios, financial capacity), planning integration (urban development and design, natural ecosystems, institutional and societal capacity, and infrastructure) and respons planning (disaster response, recovery, and build); CPR focuses on planning, capital mobilization, and Partnership; and RAF focuses on the assessment of urban resilience to climate change with a focus on physical, spatial and functional matters and their interdependencies with other urban services, but also organizational aspects.

Regarding the nature of indicators, most of the frameworks use qualitative measures defining a five-point scale ranging from excellent to poor, or a 0-3 score scale showing incremental progress. CRP uses quantitative results indicators based on the number of activities related to achieving their strategic pillars and, in the case of RAF, this framework combines qualitative and quantitative indicators that can be measured in days, % of customers, or %

of the city area, but mainly in those indicators related to urban services. Additionally, there is no consensus on the number of indicators needed to measure urban resilience, having a range of indicators between 15 for CRP and more than 719 for RAF.

Additionally, the level of aggregation of these indicators is also a difference worth highlighting, since CRI uses a high aggregation level to define an indicator (for example, 12.3 Appropriate land use and zoning), while UNDRR's framework has the essential 4 indicators that cover four issues in this regard, and RAF framework has 7 indicators related to Resilient urban development included in the Spatial Risk Management objective. In the case of CRP, this aspect is not measured.

### Research and technical papers

As a complement to the four frameworks mentioned above, a review of the literature on resilience indicators was carried out. The search strategy used was: indicators AND "urban resilience", limited to the fields of Title and Abstract. The sources used for the selection of articles were: ScienceDirect, Association for Computing Machinery (ACM), Institute of Electrical and Electronics Engineers Digital Library (IEEE Xplore), Information Systems for Crisis Response and Management Digital Library (ISCRAM DL), and Google Scholar. These sources were expected to provide scientific and practical information about resilience indicators, as they cover: technical publications (ScienceDirect); computer research and practices (ACM); engineering and innovation (IEEE Xplore); and research promoted by the largest learning society database for people working in the field of Systems for Crisis Response and Management (ISCRAM DL). As a result, 45 records were identified. All of them were analyzed to detect not only the indicators but also the specific information about their operationalization. Finally, 24 documents met the requirements and were included in the study (Table 2).

**Table 2. Number of Indicators by source**

| ID Article | Author | Number of Indicators |
|---|---|---|
| 1 | Angeon and Bates, 2015 | 20 |
| 2 | Esposito and Chiodelli, 2020 | 5 |
| 5 | Zhang et al, 2019 | 5 |
| 6 | Chlör et al, 2018 | 50 |
| 7 | Cutter et al, 2014 | 47 |
| 8 | Yan et al, 2018 | 18 |
| 9 | Serre and Heinzlef, 2018 | 14 |
| 10 | Moghadas et al, 2019 | 13 |
| 11 | Scherzer et al, 2019 | 21 |
| 12 | Siebeneck et al, 2015 | 6 |
| 14 | Shirgir et al, 2019 | 6 |
| 16 | Abbas, 2019 | 12 |
| 20 | Antoniucci and Marella, 2016 | 9 |
| 23 | Cai et al, 2015 | 25 |
| 26 | Marsal-Llacuna, 2015 | 2 |
| 27 | Chen et al, 2019 | 62 |
| 29 | Heinzlef et al, 2020 | 19 |
| 31 | Cai et al, 2018 | 16 |
| 35 | Kontokosta and Malik, 2018 | 25 |
| 37 | Bates and Angeon, 2013 | 38 |
| 39 | Shim and Kim, 2015 | 16 |
| 41 | Cutter, 2016 | 38 |
| 42 | Cutter et al, 2010 | 61 |
| 45 | ISO 37123:2019 Report | 94 |
| | | **622** |

## METHODOLOGICAL FRAMEWORK

### Topic Modeling

Topic modeling is a machine-learning technique for text mining and pattern identification that extracts the underlying topics (latent themes) from text documents (Pramanik and Jana, 2022). Topic Models, exemplified by Latent Dirichlet Allocation, are useful, as they help us to discover groups of terms that often appear together in indicators. The terms that appear most frequently in an indicator show what the topic is about. In addition, each indicator can be represented as a mixture of these terms, or as a low-dimensional abbreviation to represent what a document is about. The strength of topic models is that they are unsupervised, that is, they do not require a priori annotations (Hu et al, 2014).

### Corpus transformation

The corpus was prepared using Excel 365, Oracle Database 12c, and Orange DM 3.32. The components of the original corpus were 1452 records, originally sentences, formed by indicators' names and their descriptions concatenated in an excel column. After extracting data from the sources, the dataset was imported in ORACLE BBDD from an EXCEL workbook, dumping the DESCRIPTION and INDICATOR columns to a table, and adding a unique identifier to each loaded record. The destination table was named ORIGIN.

As the first step of data cleaning, irrelevant characters such as punctuation symbols and special characters were replaced from the ORIGIN table with spaces (Table 3).

**Table 3. Example of data cleaning in ORACLE SQL native language**

```
update SOURCE_WORDS_t
set ind = translate(ind, ',().;%":0123456789¿?&*#{}', ' ' ),
    des = translate(des, ',().;%":0123456789¿?&*#{}', ' ' );
```

In the same way, hidden characters that were contained in the excel data, such as carriage returns, tabulations, etc., were replaced with double spaces.

**Table 4. Stemming. SQL**

```
select distinct
d.word,
d2.word
from
(select distinct word from DESTINATION) d
, (select distinct word from DESTINATION) d2
where D.WORD <> D2.WORD
and utl_match.edit_distance_similarity(
D. WORD
,D2.WORD
)>90 --similarity
```

The pre-processing stage includes the tasks of tokenization, stop-word removal, lowercase conversion, and stemming (Uysal and Gunal, 2014). Tokenization is the procedure of splitting a text into words, phrases, or other meaningful parts, namely tokens. A PL/SQL process was launched on the ORIGIN table identifying each word (separated by spaces), inserting them into a DESTINATION table, where each record identified: the Primary Key of the ORIGIN table, the column type DESCRIPTION or INDICATOR where the word was found, the order of the word within the original thread, and the word trimmed in lowercase and without spaces to the right or to the left. The result was 17,036 words, of which 1,334 were different. For stemming, it was considered that derived words were semantically similar to their root forms. On the DESTINATION table, SQL sentences were launched as in Table 4, using the native package utl_match.edit_distance_similarity. It searches for words with different percentages of similarity, which serves to unify words in the one defined as a "base word".

Finally, in every corpus, some words did not provide any useful information to decide which category a text should be classified into, such as prepositions, conjunctions, etc. Those stop-words were removed, resulting in 1,044 different terms. When applying again similarity analyses considering percentages below 80%, the number of words that could not be matched increased significantly.

In addition, to ensure quality data cleaning, the Orange DM Preprocess Text widget automatically repeated the previous stages: transformation (all words were transformed into lowercase, and accents were removed); tokenization (each word was treated as a token by using whitespace and omitting punctuation); normalization (using Porter Steamer); and Filtering (removing the stop-words identified and standard punctuation). As a result, 11,095 tokens were identified.

## RESULTS

As a result of the topic modeling with Orange software, we obtained a classification of the 20 main clusters of topics on urban resilience (Table 5). We determined the number of topics as a function of maximum topic coherence (0.41) and log perplexity (0.82).

**Table 5. Topics**

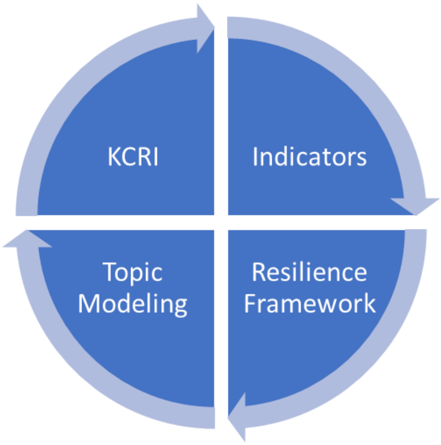
| Num | Keywords |
|---|---|
| 1 | event, climate, scenario, harsher, variables, probable, relevant, failure, days, wastewater |
| 2 | city, annual, disaster, product, frequency, transport, network, case, affordable, people |
| 3 | scorecard, service, adapted, city, failure, plan, emergency, disaster, management, response |
| 4 | service, scenario, plan, climate, change, adequate, vulnerability, capacity, level, emergency |
| 5 | population, year, waste, solid, household, area, collection, city, expected, interruption |
| 6 | scenario, probable, climate, infrastructure, change, operating, service, plan, operation, difference |
| 7 | infrastructure, critical, failure, order, scenario, level, asset, year, event, city |
| 8 | recovery, city, plan, risk, time, restoration, out-of-service, service, infrastructure |
| 9 | water, service, supply, interruption, problems, quality, caused, infrastructure, scenario, exceeding |
| 10 | type, mitigation, address, measure, adaptation, climate, service, change, housing, units |
| 11 | municipal, business, existence, person, consumption, employment, coming, energy, citizen, sector |
| 12 | service, dependence, infrastructure, climate, change, scenario, critical, rescue, base, extent |
| 13 | city, planning, service, sensitive, document, plan, strategy, customers, master, alignment |
| 14 | city, access, vulnerable, population, solution, integration, training, mobility, cities, knowledge |
| 15 | year, regulatory, quality, laboratory, legal, requirements, analysis, sewer, pipe, wastewater |
| 16 | year, infrastructure, city, scorecard, management, expenditure, annual, budget, operation, adapted |
| 17 | city, person, public, organization, infrastructure, resilience, social, expenditure, physician, budget |
| 18 | infrastructure, asset, hazard, risk, identified, critical, data, maps, city, service |
| 19 | infrastructure, time, required, activation, service, population, place, strategy, recovery |
| 20 | service, plan, loss, municipal, damage, infrastructure, place, regularly, city, level |

At this level, these topics are too generic, thus the information provided is very limited. Notwithstanding, these cluster topics can be interpreted and assigned to one dimension of an existing framework automatically as KCRI. As a result of this assignment, we can see that these KCRI are connected with infrastructures (7, 9, 18), planning (4, 13), social (14), response (2,3) urban design (5,10), environment (1, 6), recovery (8, 19), legal (15) or economic (11,20). This was the first attempt of our study to extract and normalize a set of topics that are used for measuring urban resilience.

The topic modeling outcomes can be applied in two ways. Firstly, they can be used to generate indicators based on each topic. For example, topic 1 of Table 5 can be taken as a base to generate an indicator including key terms of the topic in the following manner: *Estimated recovery time (days) in the event of a waste service failure due to a probable catastrophic scenario caused by climate change.* It can also be taken as a reference to generate similar indicators. For example, although this topic makes specific reference to wastewater, it could be replaced by energy, mobility, or other essential services related to infrastructure. Likewise, different catastrophic scenarios can be defined. In this way, the combinations are unlimited and fully adaptable to the needs and context.

Secondly, the topic modeling results can be used to automatically classify a new set of indicators in each of the established topics. Both applications are represented in Figure 1, where a continuous cycle is shown in which Topic Modeling and KCRI can serve as a basis both to generate and classify indicators based on a resilience framework of reference. This makes more sense when the classification is done according to a specific dimension of a resilience assessment framework. To this end, this exercise should be carried out taking into account the dimensions of a framework.

**Figure 1. General Schema of KCRI**




For example, using the CRI framework as reference, four sets of KCRI could be generated for "Economy and society", "Health and well-being", "Infrastructure and environment" and "Leadership and strategy". Then we will be able to automatically classify other sets of indicators belonging to other resilience frameworks. This would be one of the most useful applications at the machine learning level, which could be addressed by future research.

## CONCLUSIONS

The popular concept of resilience, especially promoted by international organizations during the last decade, is firmly established in our society and cities as a mechanism for mitigating the effects of disasters and the impacts of social dynamics. Literature has also paid significant attention to the way in which cities prevent, mitigate, and respond to risks, minimizing loss of or damage to life, livelihoods, property, infrastructure, economic activity, and the environment. Recent studies and reviews show the development process of resilience research, which has rapidly increased since 2015, recently focusing on specific aspects such as climate change, frameworks, and urban resilience. Despite the relevance of this topic, there is a lack of studies aimed at standardizing dimensions and indicators. In this on-going study, we propose the use of a machine learning tool called Topic Modeling for extracting KCRI. KCRI are clusters of topics with keywords that can help us to normalize the measurement of urban resilience beyond keywords. The concept of KCRI is the main scientific contribution of this work, serving as the basis for analyzing and generating indicators for any resilience assessment framework. From an applied perspective, based on this machine learning tool, we will be able to automatically classify new papers, frameworks, and indicators attending to our KCRI. In further research, we will apply this methodology to provide the detail of topics into different dimensions and subdimensions of an existing framework, in order to define specific indicators of dimensions.

The main limitation of this on-going study is the lack of specificity in the application of the results. The next step of this research will be the application of this methodology in the project of the Spanish national research plan called INCREMENTAL. The objective of INCREMENTAL is the digital transformation of the Resilience Building Processes to foster significant advances in less time and in greater depth thanks to the use of Information and Communication Technologies. This Project takes as a reference the framework developed in Smart Mature Resilience, a European project funded by the H2020 program, on which the foundations of the resilience-building processes have been laid, and which has recently been qualified by the European Commission as a " Success Story" (a rating that is only granted to projects of great impact). In this sense, we will use Smart Mature Resilience as an application framework. The result will be a set of KCRI based on the dimensions and sub-dimensions of Smart Mature Resilience. These KCRIs will be included in a portal that allows cities to holistically manage their resilience-building process.

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