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# TEXTS (IGNORE)

# Typology of shocks + indicators

An event can cause a candidate shock when (1) there is a direct or indirect impact on the socio-ecological system (social capital or environment), (2) it is sudden, and (3) that impact is high. Considering that an event can cause a shock, this one can be classified into one of the five types below based on which subsystem impacts (see below). For instance, the political, economic, and social systems are functionally differentiated subsystems of society (Albert, 2022).

The environmental shocks are disasters that occur in the environment (Didenko & Kulik, 2018). Some of these disasters are caused by natural conditions and are referred as *natural disasters,* severe weather with potential to pose a significant threat to human health and safety, property, critical infrastructure, and homeland security (Homeland Security, 2024). In this project, we will call **ecological shocks** such natural disasters that fulfills the three criteria mentioned above. Some examples are hurricanes, tornados, floods (Atkinson, 2013). These shocks depend on variables like the changes in the volume of CO2 in the environment; greenhouse gas emissions from industries into the environment; emissions of greenhouse gases from agriculture into the environment; changes in global temperature of the planet; freshwater resource reduction; changes in forested area (Didenko & Kulik, 2018).

Based on the above, we will analyze environmental indicators sourced from databases such as the World Bank, International Monetary Fund, and Our World in Data. From these data sources, we can obtain ecological indicators regarding environmental quality (CO2 emissions, PM2.5 air pollution, precipitation in-depth) and environmental conservation (Forest area, Total natural resources rents, Terrestrial protected areas, Terrestrial and marine protected areas).

On the other hand, human activities also affect the environment; such events are called technological disasters*.* These are commonly studied under environmental contamination (Ritchie & Gill, 2007), meaning a “man-made contamination of an environment that persists over time”(Ritchie & Gill, 2007). Some examples are dam collapses, explosions, and nuclear accidents, which are commonly called *technological catastrophes* (Baum et al., 1983; Manion & Evan, 2002). In this project, we will call **technological shocks** these technological disasters that fulfill the three criteria mentioned above.

Indicators related to this type of shock can be extracted from the *World Bank* database, which provides indicators regarding agricultural productivity (agricultural land, cereal yield, agriculture, value added per worker), energy sustainability (energy intensity level of primary energy, renewable energy consumption, renewable electricity output, access to electricity, access to clean fuels), urban-rural infrastructure (people using at least basic drinking water services, people using at least basic sanitation services), and water security (renewable internal freshwater resources per capita, annual freshwater withdrawals, water productivity, people using safely managed drinking water services).

On the other hand, **economic shocks** are sudden events causing a significant impact on the local economy (economic system), which may not be economic in nature (Besser et al., 2008). For instance, while events like a tornado or the construction of a highway are not considered to be economic in nature, their impact on the economy can be considered shocks.

These economic shocks will be identified through economic capital indicators extracted from the World Bank Group measuring economic activity, and Organization for Economic Co-operation and Development (OECD) Main Economic Indicators (MEI). These indicators fall into two subcategories economic structure and growth (GDP growth or contraction, unemployment rate, inflation, and government decisions on budget and public debt, etc.) and labor productivity (Unemployment, value added per agriculture worker, value added per industry worker, etc.).

Following a similar principle, political shocks have been defined as “dramatic change in the international system or its subsystems that fundamentally alters the processes, relationships, and expectations that drive nation-state interaction” (Goertz & Diehl, 1995), or as a “sudden, violent change in a host country’s political or institutional contexts” (Darendeli et al., 2021). In this project, a **political shock** will be any event that causes dramatic changes in the political system of a country. Territorial changes, alterations in international power distribution, civil wars, and national independence are examples of this.

The identification of political shocks will be aided by indicators that measure safety and security, social polarization, trust in institutions, and quality of life. Some of these are closely related to societal factors, so the assignment to either political, social shock, or both will depend on what each individual metric measures. These indicators will be obtained from the United Nations Development Programme (UNDP), OECD, World Bank, and The Social Progress Imperative. Examples are the Global Residence Index, Global Peace Index, political polarization, Worldwide Governance Indicators (WGI), and Social Progress Indexes.

**Societal shocks** are events that impact the societal system, affecting the capacity of societies to maintain their core social functions, mainly through effects on society’s health, and increased social inequalities (Wernli et al., 2021). Examples of societal shocks affecting societies’ health are disease epidemics (Cook et al., 2019), famines (Vågerö et al., 2013), and genocide (Keinan-Boker, 2014). Other events like armed conflicts create spatial inequalities through structural destruction (e.g. demolition of agricultural land, hospitals, markets, roads, schools, etc.), and events of massive international migration also hold the potential for value/normative transformations in society (Portes, 2010). Considering that social changes might be gradual, these events will only be considered societal shocks if their impact is sudden and elevated, as stated in the three criteria for shock identification.

Several data sources, including the World Bank, the World Happiness Report, the United Nations Development Programme, Our World in Data, Freedom House, and IDMC, provide indicators concerning societal shocks. These sources encompass indicators reflecting household, business, and citizen perceptions of governance quality. Additionally, indicators such as the Happiness Index, the Human Development Index, the Healthcare Access and Quality Index, Freedom Rates, and internal displacements are also considered.

# social capital index over the years

Global indexes like the Social Capital Index (SCI) give a base for comparison between countries over the years. shows the SCI index captured by Solability (2024) for 180 countries in 2019 and 2023. This index measures health, security, freedom, equality, and life satisfaction within a country, and was captured based on 190 quantitative indicators derived from international organizations like the World Bank, IMF, and UN (Solability, 2024). Like this, a Global Index of Collapse will be built with to quantify how close are countries to collapse, or if they have reached it, make comparisons between countries and over time, and which shocks influenced it. One can also make comparisons with other indexes like the SCI, natural capital, resource efficiency & intensity, social cohesion, economic sustainability, and governance efficiency among countries, which also hold the potential to numerically establish that a shock affects countries differently depending on its characteristics. For example, a flood might not have the same impact in a Scandinavian country (highest SCIs in the rank) as a country in East Africa (SCIs below average), and that difference can be indirectly assessed with these and other indexes and assess their relationship with the Global Index of Collapse.

The existing literature on resilience predominantly concentrates on communities, organizations, and cities, with a particular emphasis on factors such as disaster risk assessment, urban infrastructure, and community resilience (Hao & Wang, 2023; Jamali et al., 2023; Rezvani et al., 2023). While various studies have explored resilience using different frameworks and models, there is a notable gap in the application of advanced methods like Machine Learning (ML) to study resilience, especially on a global scale (Hassan & Megahed, 2022; Krakovská et al., 2024). The use of ML, as a form of artificial intelligence, remains underutilized in enhancing urban energy resilience and overall resilience strategies, indicating a potential area for further research and development in the field of resilience studies.

Natural language processing (NLP) can indeed contribute to building a dictionary of terms related to social resilience and collapse, this was made in the context of resilience (Kang et al., 2022; Schweitzer et al., 2022). This can be achieved by analyzing a large amount of text data, such as online interviews, news articles, and academic papers. Through this analysis, the NLP pipeline can identify and extract relevant terms and reveal the relationships between these terms (Rösiger et al., 2016; Wichmann, 2021). To create a dictionary of social resilience and collapse, we need to follow these steps:

1. **Preprocessing the text data**. Includes removing punctuation, stop words, and irrelevant information, which is a crucial step in text mining and natural language processing (Bhattacharjee et al., 2013; Tang et al., 2005).
2. **Identify core themes for social resilience and collapse**. This could be done using topic modeling, a statistical technique for identifying groups of words that frequently co-occur in the text data. Barde (2017) provides comprehensive overviews of topic modeling methods, including Latent Semantic Analysis (LSA), Probabilistic Latent Semantic Analysis (PLSA), Latent Dirichlet Allocation (LDA), and Correlated Topic Model (CTM).
3. **Conceptualize social resilience and collapse indicators**. A list of resilience indicators can be developed based on the core themes. These indicators could then be used to create a dictionary of terms related to social resilience and collapse.

Social Resilience: Literature Review Analysis

# Introduction

Resilience can be conceptualized as a process, an attribute, and an outcome at the individual, family, and community levels (Aburn et al., 2016; Laksmita et al., 2020; Pfefferbaum et al., 2015; Southwick et al., 2014). Community resilience is distinguished from personal resilience in that community members, bolstered by available physical and social conditions and structures, work together to respond to and recover from the community's hardships and adversities. Community resilience is grounded in the ability of community members to take meaningful, deliberate, and collective action (Pfefferbaum et al., 2015). Community resilience thus enhances disaster preparedness and recovery (Pfefferbaum et al., 2015; West et al., 2020). In total, 199,253 publications related to resilience were identified in Scopus. The publication period was between 1851 and 2024. A peak of publications was reached in 2023 (n = 29,691), and around half of the publications reached in 2024 (n = 10,455). Most are articles (n = 135,007), conference papers (n = 27,060), book chapters (n = 14,668), and reviews (n = 12,997). The other document types, such as books, editorials, notes, conference reviews, letters, erratum, short surveys, data papers, retracted reports, and others, are limited in numbers (all less than three thousand). Most of the subject areas are social sciences (n = 49,912), engineering (n = 39,562), environmental science (n = 38,823), medicine (n = 36,130), and computer science (n = 28,276).

The concept of social resilience is quite complex and requires a deep understanding of various domains. It is a multidimensional subject and is the focus of cross-disciplinary research. Despite its challenging nature, exploring social resilience can help us better understand how communities and societies can adapt and recover from different challenges and crises. A bibliometric analysis was conducted. This analysis helped us to identify influential research and emerging trends (Merigó & Yang, 2017). The data for this analysis were retrieved from Scopus on April 18, 2024. Scopus was chosen as a search engine because it extensively covers STM journal articles and references, allowing forward and backward searches (Burnham, 2006). The term “social resilience” is identified in the title, the abstract, and/or the keywords of the publications. However, certain words such as "mental health," "pharmaceutical," and "aviation were excluded from the final query. In total, 1,211 publications related to social resilience were identified. The timespan of publication was founded between 1993 and 2024. All types of publications were included in the search. Looking at the document types (see Table 1), the majority are articles (n = 834) and book chapters (n = 129). The other document types, such as conference papers, reviews, editorials, books, notes, letters, conference reviews, erratum, and short surveys, are limited in numbers (all less than a hundred).

# Bibliometric analysis

## Terms analysis

The VOS (Visualization Of Similarities) mapping method was used to calculate and locate each topic in a two-dimensional map so that the distance between two items reflects the similarity or relatedness of the items as accurately as possible (Van Nunen et al., 2018). The VOS clustering method was applied to cluster topics into different groups, where each cluster is marked with a different color (Van Eck et al., 2010; Waltman et al., 2010). The interpretation is as follows: the circles' size and the label's font represent the number of occurrences, the colors represent clusters, and the distance between two circles reveals their relatedness and similarity (Khalil & Crawford, 2015; Rizzi et al., 2014). The x-axis and y-axis have no special meaning; the maps may be freely rotated and flipped (Khalil & Crawford, 2015).

A keyword co-occurrence analysis (co-word analysis) was conducted using the VOS mapping method to visualize the relationships of keywords or topics (Börner et al., 2003; Van Eck & Waltman, 2014). The result of the keyword co-occurrence analysis is presented in. We select a threshold of six keyword occurrences as a minimum number of occurrences. This means that each of the 357 keywords on the co-occurrence network in had appeared in at least six documents. There is no standard threshold for use in co-word analysis (Van Eck & Waltman, 2014). The co-word network map displays the frequency and relationships among 357 social resilience keywords/topics. The size of nodes on the map reflects the level of interest in a particular topic. Smaller nodes represent keywords that were mentioned at least six times in the document database. The positions, links, and proximity between nodes visualize the relatedness of topics studied in the literature. The lines or links between nodes indicate that the two keywords co-occurred, and the density of the lines suggests the frequency of co-occurrence. The proximity of nodes on the map suggests the degree to which nodes were related in the literature.

Based on their conceptual similarity, the keywords have been organized into three clusters, as shown in These clusters can be distilled into three primary domains: (1) the relation between social resilience and climate change-related concerns –­ indicated by the green color; (2) the relation between social resilience and natural disasters in urban areas ­– identified by the blue color; and (3) the relation between social resilience and COVID-19-related issues – identified by the red color.

Cluster 1, researchers have observed that social resilience is interconnected with environmental problems, specifically climate change. Climate change is altering the productivity of natural resources, which has far-reaching implications for resource-dependent industries and communities and the importance of these industries to adapt to a range of climate risks to remain viable (Marshall et al., 2012). The productivity of natural resources has been studied in food security issues such as fishing (Cinner et al., 2011) and agriculture (Abumhadi et al., 2012). Climate change has also been linked to migration decisions (Scheffran et al., 2012; Shi et al., 2019) and social vulnerability (Marshall et al., 2014). Studies that cover these issues mainly focus on ten countries: the United States, the United Kingdom, India, Australia, Brazil, Germany, Mexico, Thailand, and Vietnam. In the United States, efforts have been made to quantify the resilience of communities and infrastructure in the face of climate change and natural disasters (Gerges et al., 2023). In Thailand, the capacity of coastal communities to adapt to various challenges such as environmental degradation, fisheries decline, management interventions, conservation initiatives, new economic opportunities, and climate change has been studied (Bennett et al., 2014).

Cluster 2, it has been observed that social resilience is closely linked to challenges faced by urban populations. Additionally, there is a significant correlation between social resilience and natural disasters such as floods, landslides, and earthquakes, specifically the risk and vulnerability levels of people to these events. Currently, social resilience is understood in the context of community, economic, and ecological resilience. Research on these issues has been conducted mainly in China, Africa, Indonesia, Iran, Japan, New Zealand, and Taiwan.

Cluster 3 shows a correlation between social resilience and its association with health, epidemics, and healthcare, particularly in the context of COVID-19. Additionally, research is being conducted on individuals who are vulnerable to these health issues. Research on these issues has been mainly conducted in China and the United States. Also, social resilience is linked to paying attention to the various obstacles that individuals encounter during their personal growth. These challenges may include issues related to childhood, youth, mental health (e.g., depression, anxiety), pregnancy, and sexuality.

Temporal co-word analysis has been utilized to visualize the progression of research topics based on the frequency of keyword occurrences at different time points. The network shown in can be interpreted by noting that the darker-colored nodes represent keywords or topics of recent interest, while the lighter-colored nodes are associated with topics that were popular earlier in the field's evolution. Additionally, larger nodes indicate the central topics in the field for a specific time period, while relatively smaller nodes represent peripheral topics. A threshold of six keyword occurrences was used to create this network. Since 2022, research on COVID-19 and human problems in cluster 3 has primarily focused on China.

The current research on social resilience primarily focuses on communities, organizations, and cities. It emphasizes factors like disaster risk assessment (Zanuttigh et al., 2014), urban development (Zhou et al., 2021), and community resilience (Gerges et al., 2023). Ecological, infrastructure, and economic components of community resilience are identified as key drivers of differences in resilience fingerprints across hurricanes and other major events, suggesting their significant role in determining community resilience during crises (Rachunok et al., 2019).

Despite various studies examining social resilience using different frameworks and models, there exists a noticeable gap in applying advanced methods like Machine Learning (ML) and Natural Language Processing (NLP). Champlin et al. (2023) used spatiotemporal analysis to measure social resilience in cities during the COVID-19 pandemic and to observe changes in citizen behavior within urban spaces using surveys. Reuter & Spielhofer (2017) investigated citizens’ attitudes towards social media usage in private and emergency situations using qualitative and quantitative analysis on surveys. Meanwhile, Rachunok et al. (2019) introduced the “resilience fingerprint” concept and used Twitter data to compare community resilience components across various event types using data analysis.

The potential of ML as a form of artificial intelligence remains underutilized in enhancing urban energy resilience and overall resilience strategies. This suggests a promising area for further research and development in the field of resilience studies. Furthermore, NLP can contribute to building a dictionary of terms related to social resilience and collapse. This was made in the context of resilience (Kang et al., 2022; Schweitzer et al., 2022). By analyzing a vast amount of text data, such as online interviews, news articles, and academic papers, the NLP pipeline can identify and extract relevant terms, revealing the relationships between them (Rösiger et al., 2016; Wichmann, 2021).