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Development of a Natech Social Vulnerability Index: A Comprehensive Multi-Hazard Risk Assessment for a Case Study in Colombia

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Abstract Natech refers to complex scenarios where secondary technological accidents are triggered by natural disasters, having the potential to cause severe societal loss, especially in developing countries such as Colombia, potentially due to its vulnerable social system (De Souza Porto & De Freitas, 2003; Ran et al., 2020). However, one major identified research gap is the lack of a specific approach to assess the Natech social vulnerabilities. A popular vulnerability assessment tool: social vulnerability index, widely used for natural and industrial hazards, shows promising usability for Natech vulnerability assessment. The current study has proposed a novel methodology to assess Natech social vulnerability by establishing a Natech social vulnerability index based on identification of the Natech scenarios and investigation of multi-hazard intercorrelations.

To verify the introduced methodology, the author utilized rainfall-induced, landslide-triggered chemical Natech incidents in Colombia as a representative case. The study identified hazards present in varying Natech situations to determine which social factors amplify vulnerability. Subsequently, social vulnerability indices were constructed to quantitatively aggregate social factors. These were applied to 3 vulnerability conceptual frameworks and then refined and scrutinized using Structural Equation Modelling (SEM). The outcomes, illustrated via GIS,

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generally agrees with preceding studies. Nonetheless, certain fit index values signal potential ambiguities in model alignment.

The paper concludes into the challenges of the new methodology. Based on these analyses, policy recommendations for the Colombian government's vulnerability assessment have been proposed. These include refining the national census, databases, and Natech reports. Additionally, future research directions have been highlighted to address the acknowledged research gaps.

In summary, this research, with its novel methodology, findings, and policy suggestions, serves as an important reference for succeeding investigations on social vulnerability assessments related to Natech and other multi-hazard events.

Keywords: Natech, Social Vulnerability Index, multi-hazard risk assessment, climate change and disaster risks, industrial and societal vulnerability, risk management

1. INTRODUCTION

Natural disasters can trigger severe technological accidents termed as Natech, which include explosions, toxic gas release, fires, and contamination (Krausmann et al., 2017).

Conventional disaster prevention tactics may be insufficient when it comes to Natech, because these accidents have significant societal, economic, and environmental consequences globally, often intensifying the effects of natural disasters (United Nations Office for Disaster Risk Reduction (UNDRR), 2017; Araki et al., 2021). This highlights the need of specialized approaches (Krausmann et al., 2017). The Fukushima nuclear catastrophe of 2011 serves as an important example, where an earthquake and ensuing tsunami precipitated a subsequent nuclear crisis. Climate change and a rise in extreme weather events may increase Natech's prevalence (Luo et al., 2020). External factors like industrial evolution and heightened societal vulnerabilities might compound this impact (UNDRR, 2017). Particularly, developing nations with rapid industrial growth, like Colombia, are especially at risk due to their inherent vulnerabilities (Naudé et al., 2009).

Colombia, with its geological diversity, has vast energy resources (Etter et al., 2017). It is South America's second-largest oil producer with substantial oil and gas infrastructure (U.S. Energy Information Administration, 2022; U.S. Commercial Service, 2023). Cenit, a major

Colombian company, manages about 9,000 km of this infrastructure, including 'OCENSA' pipeline (U.S. Energy Information Administration, 2019). Unfortunately, Colombia is also landslide-prone, especially in the Andean region, where many of the pipelines are located (Aristizábal & Sánchez, 2020; Sepúlveda & Petley, 2015). 92% of these landslides are propelled by rainfall, and climate shifts further exacerbate this issue, intensifying landslide occurrences (Cullen et al., 2022; Herzog et al., 2011). Natech accidents resulting from these rain-induced landslides have been on the rise (Parra & Cruz, 2022). Such accidents, like the tragic event in Dosquebradas, Risaralda, where 31 people died and thousands lost their homes, can cause devastating societal consequences (El Colombiano, 2011).

Furthermore, societal vulnerabilities can magnify Natech's impact. The Dosquebradas catastrophe showed the repercussions of local vulnerabilities, such as the strain placed on medical resources (El Espectador, 2011). Colombia, facing substantial challenges in healthcare and poverty, requires a thorough assessment of these vulnerabilities to accurately gauge the social impacts of Natech (Red Cross Red Crescent Climate Centre (RCCC) & International Committee of the Red Cross (ICRC), 2021). Unique Natech-specific vulnerabilities also exist; the undisclosed pipeline locations can potentially heighten community vulnerability. Moreover, Colombia's pronounced wealth inequality, as indicated by its high GINI index (measuring the extent of income distribution inequality) (Central Intelligence Agency, 2022), which underscores the need to understand regional vulnerabilities and their distribution for effective risk management (Red Cross Red Crescent Climate Centre (RCCC) & International Committee of the Red Cross (ICRC), 2021).

In conclusion, it is important to understand Natech risks and their potential impacts, especially in regions like Colombia. By identifying both general vulnerabilities and those specific to Natech, decision-makers can more effectively address these risks, and help to ensure the safety and well-being of affected communities.

Despite numerous studies on social vulnerabilities in natural and technological disasters, there is a notable gap in research specific to Natech vulnerabilities. The variety of methodologies used in existing studies further complicates the situation. This study aims to bridge this gap by introducing a novel methodology for Natech vulnerability assessment using Colombia's rainfall-induced landslide incidents as a case study. It ultimately aims to enhance Natech Risk Assessment and guide informed policymaking.

2. LITERATURE REVIEW

2.1 Origin, Definitions, and Complexities of Social Vulnerability

Historically, disaster analyses predominantly adopted a naturalistic view, which tends to attribute risks to technological shortcomings (Blaikie, 2004; Burton et al., 1993). This perspective might put limited emphasis on the varying societal conditions that influence disaster impacts. The concept of vulnerability emerged as a bridge between society and nature during hazards (Emrich & Cutter, 2011). Today, vulnerability is important in risk analysis for both natural disasters and industrial accidents (Dintwa et al., 2019; Fatemi et al., 2017a). However, its definition varies widely, ranging from focusing solely on the inherent conditions of those at risk to a more multidimensional approach incorporating various aspects such as coping capacities and exposure (Birkmann & Wisner, 2006). Despite this variation, all studies agree that vulnerability shapes risk.

According to the United Nations Office for Disaster Risk Reduction (UNDRR), disaster risk is defined as potential losses due to hazards over a given time (UNDRR, 2015). In this research, this definition is narrowed down to the social risks linked to Natech which emphasizes societal losses and assets crucial to human well-being. We also exclude indirect environmental damage in the definition.

2.2 Social Vulnerability Index for Social Vulnerability Assessment

Various methodologies are adopted for assessing social vulnerability, with the Social Vulnerability Index (SVI) being particularly prominent.

Reality is often understood through models. While these models do not fully capture the complexities of the real world, they serve as frameworks that reflect aspects of nature and researchers' perspectives (Nardo et al., 2005a). Vulnerability, being intangible, cannot be directly measured like physical entities such as mass. To bridge this gap, functions are created to tie observable indicators with theoretical concepts, known as composite indicators or indices (Hinkel, 2011). These methodologies have gained widespread use across various fields, such as poverty measurement and human development analysis (Baptista, 2014). The SVI connects indicators to social vulnerabilities, and it can be mathematically expressed as in equation (1) below, mapping indicators (I) to vulnerability (V) (Hinkel, 2011):

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$$F: I \rightarrow V$$

$$I = \begin{bmatrix} I_1 \\ I_2 \\ I_3 \\ \dots \end{bmatrix}; \ V = \begin{bmatrix} V_1 \\ V_2 \\ V_3 \\ \dots \end{bmatrix} \tag{1}$$

As pioneers of this concept, Cutter et al. in 2003 introduced the SVI by employing county-level data to discern 11 independent indicators, which were then utilized in an additive model to calculate the Social Vulnerability Index (SoVI) (Cutter et al., 2003).

SVI helps policymakers in recognizing the most vulnerable populations or regions, thereby eases disaster planning and resource distribution (Rufat et al., 2015; Nardo et al., 2005b). In recent times, SVI has emerged as a preferred tool for vulnerability assessment, bridging the gap between academic research and policymaking (Hinkel, 2011). It has been used by organizations like CDC & ATSDR (Centers for Disease Control and Prevention (CDC), 2024), Caribbean Development Bank (Ram et al., 2019), and the United Nations (United Nations, 2024). In this research, we also use Social Vulnerability Index for vulnerability assessment.

There is a surge in research regarding the social vulnerability index primarily focusing vulnerabilities to natural hazards. According to a comprehensive literature review by Fatemi et al., a significant majority (83%) of these indices are designed for natural disasters, while only 7% address industrial accidents. A mere 10% cover both natural and industrial incidents (Fatemi et al., 2017b). Notably, research on social vulnerability related to Natechs is scarce.

2.3 Review on Methodologies

Our current case study area is Natech hazards within Colombia. Through a rigorous literature review, we have found that Khazai et al. (2013) did delve into the secondary effects of natural calamities on the industrial sector. Their emphasis, however, lay broadly on the interplay between industrial activity and social vulnerability. On the other hand, there also exist dedicated studies evaluating social vulnerabilities to either natural or industrial disasters in South American nations, such as Brazil (De Loyola Hummell et al., 2016), Argentina (Gentili et al., 2018), and Colombia (Roncancio et al., 2020) using the social vulnerability index. Among these, Roncancio et al. have targeted natural hazard-induced social vulnerabilities in Colombia at the municipal scale (Roncancio et al., 2020), but not focusing mainly on industrial threats, instead of Natech. Their reliance on the PCA technique for multivariate analysis also differs from this study's aim, as detailed in next section.

Creating a social vulnerability index involves several steps. Although many scholars describe similar procedures, like the 11 steps delineated by Tate (2012), these methodology are not agreed universally (Nardo et al., 2005b; Hagenlocher et al., 2016). Therefore, in real-world applications, these steps are also not always strictly adhered. In this section, the methodology is simplified into three primary steps: (1) Conceptual Framework Selection, (2) Indicator Selection, and (3) Data Processing. Given the study's focus on Natech accidents, which differ from most research, an introductory "STEP 0" examining hazard intercorrelations will be detailed in Section 3.

Review on Conceptual Framework Selection

Vulnerability framework selection is crucial as the framework defines what the index measures (Tate, 2012). We focus on 2 prevalent frameworks: The IPCC's Conceptual Framework and the MOVE Framework. The IPCC's Framework, updated in 2015, defines vulnerability and includes adaptive capacity and sensitivity components (Sharma & Ravindranath, 2019; Pachauri et al., 2015). This framework views risk as a product of vulnerability, hazard, and exposure, as illustrated in Figure 1. On the other hand, the MOVE Framework, proposed by the European Commission, is a comprehensive model used across various hazards (Birkmann et al., 2013). A modified version by Hagenlocher et al. (2016), aligning with the 2015 IPCC update, is utilized in this study. Different from IPCC Framework, it divides vulnerability domain into two categories, Susceptibility and Lack of Resilience, which further consists lack of 3 capacities: anticipate, cope and recover.

As far as the authors reviewed the available literature, limited studies have examined or compared the model fit of vulnerability frameworks; and especially, no study was found comparing the revised IPCC and MOVE frameworks. One of the research goals of the current study is to apply both conceptual frameworks on the Natech social vulnerability, then compare their different results.

Besides IPCC and MOVE Frameworks, other similar conceptual frameworks have been proposed, e.g., Social Vulnerability Index (SoVI) (Cutter et al., 2003), Social Vulnerability Index (SVI) (Centers for Disease Control and Prevention (CDC), 2024), etc. However, as far as the authors have done the literature review, limited studies have examined or compared the model fit of these constructs; and especially, no study has examined the revised IPCC and MOVE frameworks. One of the research goals of the current study is to apply both conceptual frameworks, inspect their results, and evaluate their model fit.

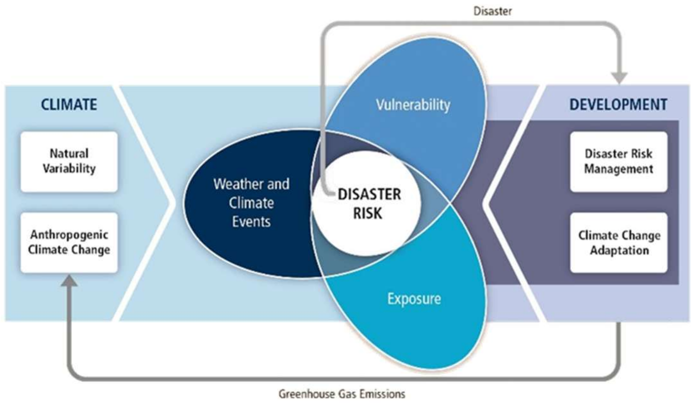

Figure 1. IPCC conceptual framework of risk. Adapted from IPCC (n.d.)

Review on Indicator Selection

The validity of the social vulnerability index is directly linked to its indicators. Selection methods include knowledge-based, where researchers use established knowledge; value judgement-based, which integrates stakeholder or researcher perspectives; and data-driven, derived from available datasets (Hinkel, 2011; Niemeijer, 2002). This study proposes a multi-criteria selection method, which is elaborated in Section 3.

Review on Data Processing

Before analysis, indicators require preprocessing to manage missing data and ensure consistency in scales. The specific methods employed will be detailed in the Methodology Section.

Lastly, to avoid redundancy and extract meaningful information, multivariate analysis, like Principal Component Analysis (PCA) and Structural Equation Modelling (SEM), is crucial (Nardo et al., 2005b). While PCA is ideal for data reduction, SEM delves deeper, seeking underlying constructs in data (Chumney, 2012; Ringnér, 2008; Alavi et al., 2020). Given the study's focus on examining conceptual frameworks like IPCC and MOVE, we decide to adapt SEM as our research methodology.

2.4 Research Objective

The primary objective of this research is to develop a novel methodology to assess social vulnerability for Natech accidents, specifically focusing on rainfall-induced landslide-triggered events in Colombia as a case study. Addressing the existing research gaps, the study will follow these steps:

- Natech Scenario Identification Model: Identify different risk scenarios and investigate the interactions among multiple hazards. This step aims to create a new multi-hazard scenario identification model specific to rainfall-induced landslide-triggered Natech accidents.

- Conceptual Framework Selection: Choose suitable conceptual frameworks to define the dimension of vulnerability for current study.

- Indicator Selection: Adopt a multi-criteria approach, incorporating various indicator selection strategies, to determine the most relevant indicators for the social vulnerability index.

- SEM Analysis: Prepare the data and conduct Structural Equation Modelling (SEM) analysis. This step will analyze correlations among the various indicators.

- Result Interpretation: Visualize, interpret, and discuss the results derived from the SEM analysis.

The five-step methodology does not only complements existing research but also presents a valuable tool for Natech Risk Assessment. This tool is expected to be helpful for policymaking, which aligns with the mainobjective of this research.

3. METHODOLOGY

3.1 Natech Scenario Identification Model

While most prior studies on the social vulnerability index focus on specific hazards (e.g., flooding) or a category of hazards (e.g., natural hazards), they are often not focusing on the complex interplay between multiple hazards. This is particularly relevant in the context of our study on the rainfall-caused landslides which leads to a pipeline-based Natech accident.

Examining causality in the Natech sequence allows us to understand event timelines among diverse hazards. As illustrated in Figure 2, a sequence might unfold as follows: rainfall causes debris flow, which leads to pipeline damage, resulting in the release of toxic gas. While each hazard in this sequence might be familiar, the combination and interaction between them result in a unique social risk. For instance, a poorly constructed house is not just vulnerable to flooding, but also to landslides and explosions. In a Natech scenario involving all these hazards, the house faces increased vulnerability due to the combined impact of these risks.

In assessing vulnerability in Natech scenarios, it is necessary to consider how these hazards relate and amplify one another. However, aggregation of hazards is just one of many inter-correlations to consider. Drawing from a review by Tilloy et al. (2019), we can categorize hazard relationships into five types:

- Independence/Aggregation: Hazards that co-occur in time or space without a causal relationship, sometimes referred to as "Aggregation" (Drakes & Tate, 2022).
- Cascading/Triggering: A primary hazard setting off a secondary one.
- Change Conditions: One hazard altering the conditions or dynamics of another.
- Compound: Multiple hazards stemming from a shared primary source.
- Mutual Exclusion: Hazards that cannot coexist or are inversely related (Tilloy et al., 2019).

Worth noting is that Drakes, in a multi-hazard context literature review, defines "compound risk" differently. Such definition implies the emergence of novel hazards due to the compounded effects of primary ones (Drakes & Tate, 2022).

When discussing about "Change Conditions," Tilloy et al. provide an example where a fire eliminates vegetation, which in turn increases the flood risk (Drakes & Tate, 2022). In the framework of our study, the changed condition here relates more to physical vulnerability rather than the hazard itself. For consistency in our study, we will use "Change of Condition" to also signify change in "exposure" and "vulnerability".Considering the various type of multi-hazard interaction in the Natech event, as mentioned above, the current study has developed a new Natech Scenario Identification Model. If we denote N as natural and, T as technological hazard, and NT stands for Natech multi-hazard accident, we can symbolize the current multi-hazard accident as below:

Triggering: $\boldsymbol{N \rightarrow T}$

Change Condition: $\boldsymbol{N' = f(N)}$**.** Function f changes the original event N into N'.

Aggregation: $\boldsymbol{NT_1 = N' \cup T}$.

Compound: $\boldsymbol{NT_2 = N' \cap T}$

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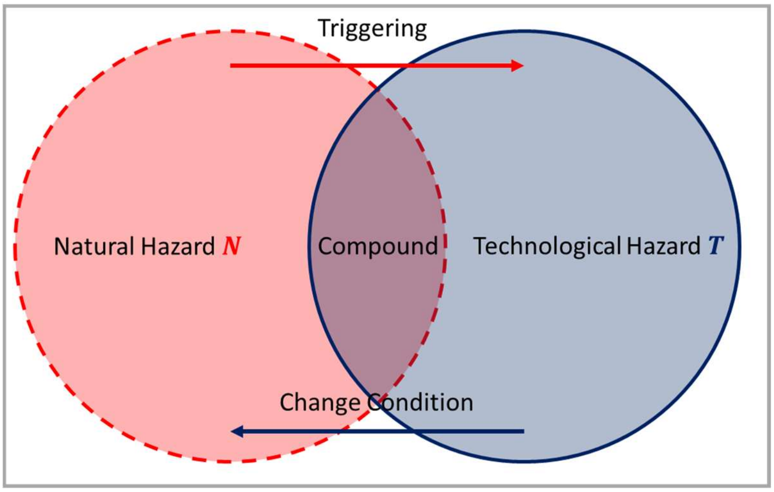

Figure 2. Intercorrelations among hazards involved in the rainfall-induced landslide-triggered Natech accident

Table 1 describes the significance of various hazard intercorrelations with respect to social vulnerability assessment. It details types of intercorrelations, their symbolic representations, and the resultant scenarios in terms of social risk and vulnerability. While "Triggering" does not create new social vulnerability scenarios, "Change Condition" and "Compound" requires to consider vulnerability in new scenarios, and "Aggregation" requires summing up vulnerabilities of all specific vulnerabilities. Therefore, the current model considers the "Change Condition," "Compound" and "Aggregation" effects of the hazards.

Table 1. Significance of the hazard intercorrelations to social vulnerability assessment

Interrelation	***Significance***	***Symbolic Representation***	***New Vulnerability Scenarios***
Triggering	Reflects the internal link between different hazards.	$\boldsymbol{N \rightarrow T}$	Does not directly create new scenarios for social risk and vulnerability.
Change Condition	Change exposure and vulnerability conditions of hazards	$\boldsymbol{N' = f(N)}$	Create new vulnerabilities.
Compound	Magnifying the current hazards.	$\boldsymbol{NT_1 = N' \cup T}$	Create new vulnerabilities.
Aggregation	Summation of all occurred hazard.	$\boldsymbol{NT_2 = N' \cap T}$	Adding up existing vulnerabilities.

Table 2 presents real and hypothetical examples of risk scenarios stemming from these intercorrelations, supported by literature references where applicable. The table aims to contextualize the theoretical intercorrelations from Table 1 with risk scenarios.

Table 2. Risky scenarios created from various types of hazards intercorrelations

Intercorrelations		***Examples of Risk Scenarios***	***Literature Support***
Triggering	TRG1	The rainfall triggers landslide.	92% landslides in Colombia are induced by rainfall (Aristizábal & Sánchez, 2020).
	TRG2	The landslide triggers pipeline failure.	(Parra & Cruz, 2022)
	TRG3	Intense rainfall can trigger flooding.	(NSSL - National Severe Storms Laboratory, 2024)
	TRG4	Pipeline failure can trigger toxic gas, fire, explosion, and pollution.	(Parra & Cruz, 2022)
	TRG5	Landslide dam triggers flood	(Hermanns, 2013)
Change Condition	CC1	Flood triggered toxic gas release affects flood evacuation process	Hypothetical scenario
	CC2	Rain-induced debris flow triggers explosion destroying community emergency shelters	Hypothetical scenario
Compound	COM1	Flooding spreads pollution.	(Misuri, 2020)
	COM2	Debris flow spreads pollution.	Hypothetical scenario
	COM3	Flooding spreads fire.	(El Colombiano, 2011)
Aggregation	AGG1	The summation of all occurred hazard, and ultimately creates social risk on exposed, vulnerable population.	-

3.2 Indicator Selection

The current study develops a 7-step procedure to select the indicators, which aims to both consider the different hazard interrelations across multiple Natech scenarios and combine the advantages of existing indicator selection strategies. Each step in the proposed procedure is shown in Figure 3 below and explained in the following sections.

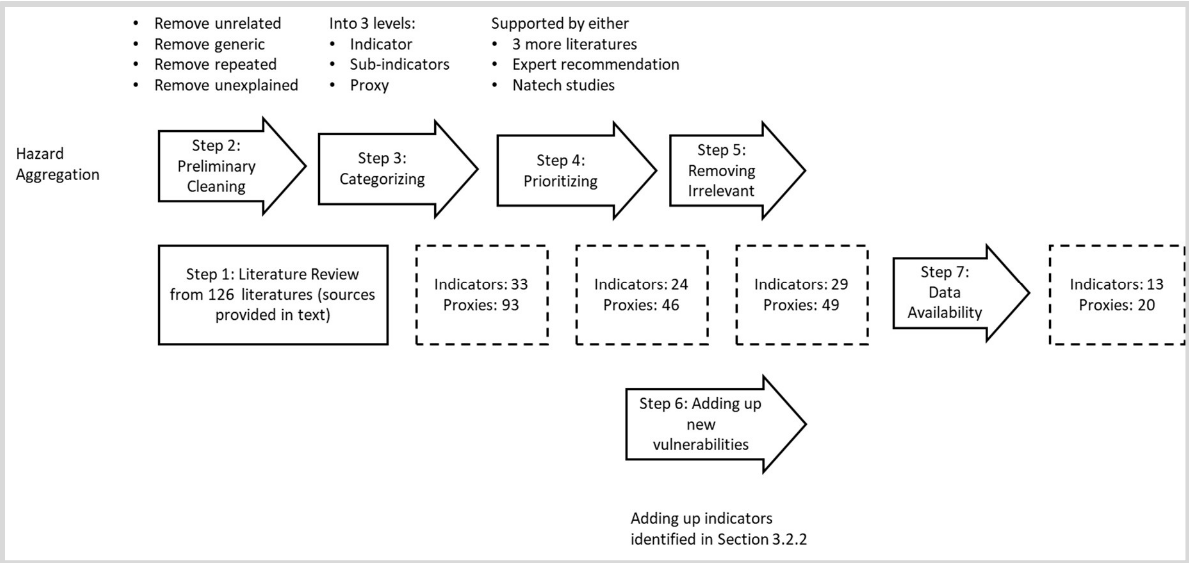

Figure 3. Flow chart of the indicator selection process

Step 1-5: Identify Social Vulnerabilities from Hazard Aggregation[3]

- The initial step involved aggregating social vulnerabilities of Natech-related hazards, beginning with a literature review of vulnerability candidates. This review encompassed:

- Hazard-Specific Studies (n=10): Covering a range of hazards such as landslides, flooding, pollution, explosions, and fires, with notable studies by Xiao et al. (2022), Lianxiao and Morimoto (2019), and others.

- Non-Hazard Specific Studies (n=6): Addressing both natural and technological hazards, with contributions from Mavhura and Manyangadze (2021) and Roncancio et al. (2020), among others.

- Literature Reviews (n=110): Focusing on flooding and general hazards, including Fatemi et al. (2017b) and Rufat et al. (2015).

The process is illustrated in Figure 4 below.

[3] More details of the indicator selection process are included in the Appendix.

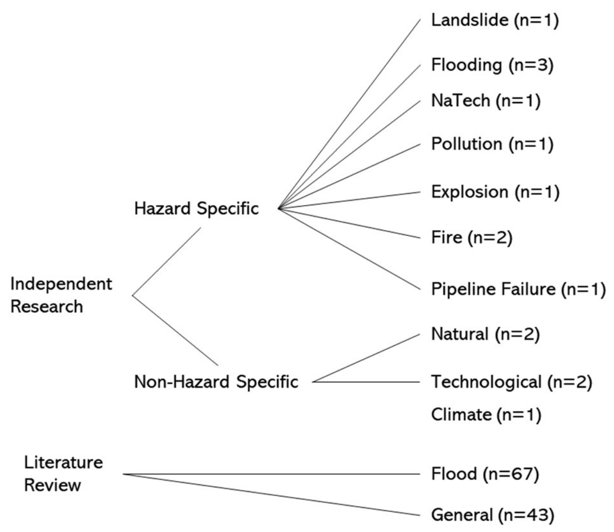

Figure 4. Illustration of the Literature Review Process

However, direct application of these variables was limited due to irrelevance, duplication, or insufficient explanation. The authors refined these variables by removing unrelated or vague concepts. We select one variable from similar concepts, and discard poorly explained variables. This led to the identification of 33 indicators with 96 proxies.

To manage the excessive number of variables, a re-evaluation was conducted based on three criteria: frequency in literature, relevance to both natural and technological hazards, and expert opinions. Some indicators were further excluded for not fitting the study's focus, including national-level indices like GDP.

Step 6: Identifying Social Vulnerabilities from Compound or Changing Conditions

Investigating specific Natech scenarios highlighted two types: evacuation and magnifying scenarios. Due to limited literature, seven hypothetical indicators were selected based on value judgment. These include mitigation measures like Natech Plan and Early Warning, as well as socioeconomic factors like governance and civil participation, informed by studies such as work by OECD & Economic Commission for Latin America and the Caribbean (2014) and Araki et al. (2021). SEM analysis was proposed to validate the impact of these indicators.

Step 7: Data Availability and Selection

From available data, 20 proxies across 13 indicators were chosen for analysis. Two indicators—access to health services and social security—were excluded due to data interpretation challenges and the complexity of Colombia's SISBEN system. The selected indicators were then categorized into sensitivity/susceptibility and resilience/adaptive capacity

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groups, as per the IPCC and MOVE Frameworks. These include key socio-demographic factors like gender, age, housing quality, and education levels. For instance, gender (represented by the female population percentage) highlights socioeconomic challenges in recovery, as discussed in studies like De Loyola Hummell et al. (2016). Similarly, housing quality is examined through indicators like the condition of exterior walls (Suda, 2017), linking to increased vulnerability. Each indicator is categorized under sensitivity/susceptibility and resilience/adaptive capacity groups, as per the IPCC and MOVE frameworks. A detailed breakdown of these indicators, including their sources and literature support, is provided in Appendix, Supplementary Table 1.

3.2.1 Sensitivity/Susceptibility

According to the previous studies that have used the MOVE framework, people who are at a vulnerable age, minority groups, living in an inadequate housing, and or dependent are classified into this category, since the source of vulnerability is related with the subject's internal predisposition (Hagenlocher et al., 2016) when exposed to rainfall induced pipeline chemical accident. Nevertheless, the categorization of indicators into the sensitivity/ susceptibility class as compared to other classes, such as capacity to cope is not straight forward. For example, being aged is an internal predisposition of a person. However, an aged person might be less mobile, which would also contribute to their lack of coping capacity. In the present study, to avoid such ambiguity, age is considered only as one factor for susceptibility. This classification method follows a common practice from previous studies (Lianxiao & Morimoto, 2019; Prasetyo et al., 2020). Similarly, the gender indicator using the proxy of being female is removed; though Lianxiao & Morimoto (2019) have consider gender indicator to be one component of the susceptibility, however, the disadvantage of being a female is not an internal predisposition, but a socially constructed disadvantage; moreover, the social-economical disadvantages accompanied with being a female could be directly measure by other indicators, such as unemployment. Therefore, in the current study, the indicator is discarded.

3.2.2 (Lack of) Resilience and Adaptive Capacity

As mentioned above, unlike IPCC, which does not make further distinction inside Adaptive Capacity, the MOVE framework further divides it into capacity to anticipate, cope and recover. Note that some indicators are connected to more than one dimension.

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3.2.3 Vulnerability Modelling

After finishing the categorization, the models based on the selected indicators in IPCC and MOVE Frameworks with the explanation of the proxies are presented in Figure 5-6. The red arrows represent the "Marker Indicators" for the SEM analysis, which will be explained in the next section.

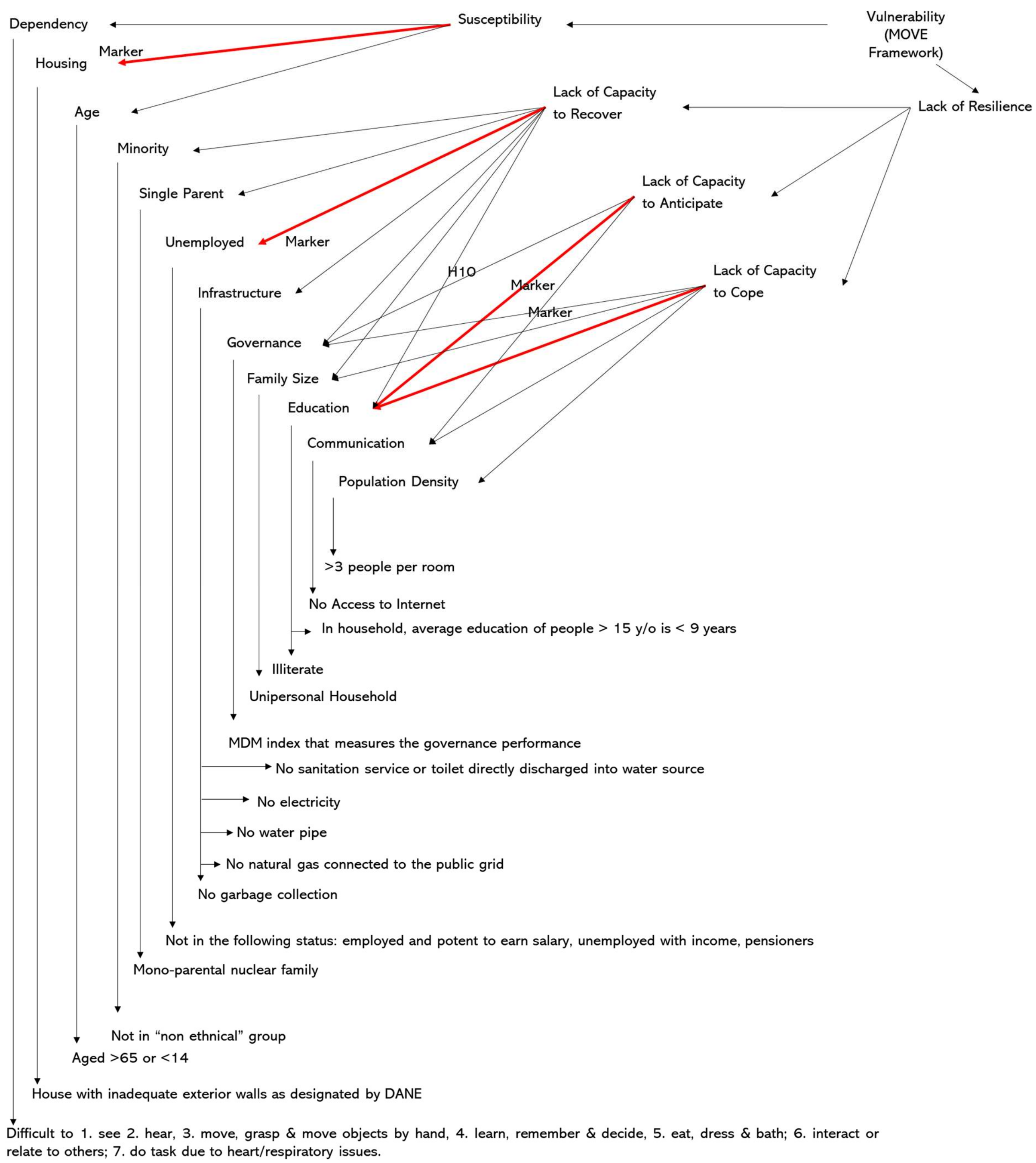

Figure 5. Vulnerability model based on the MOVE framework

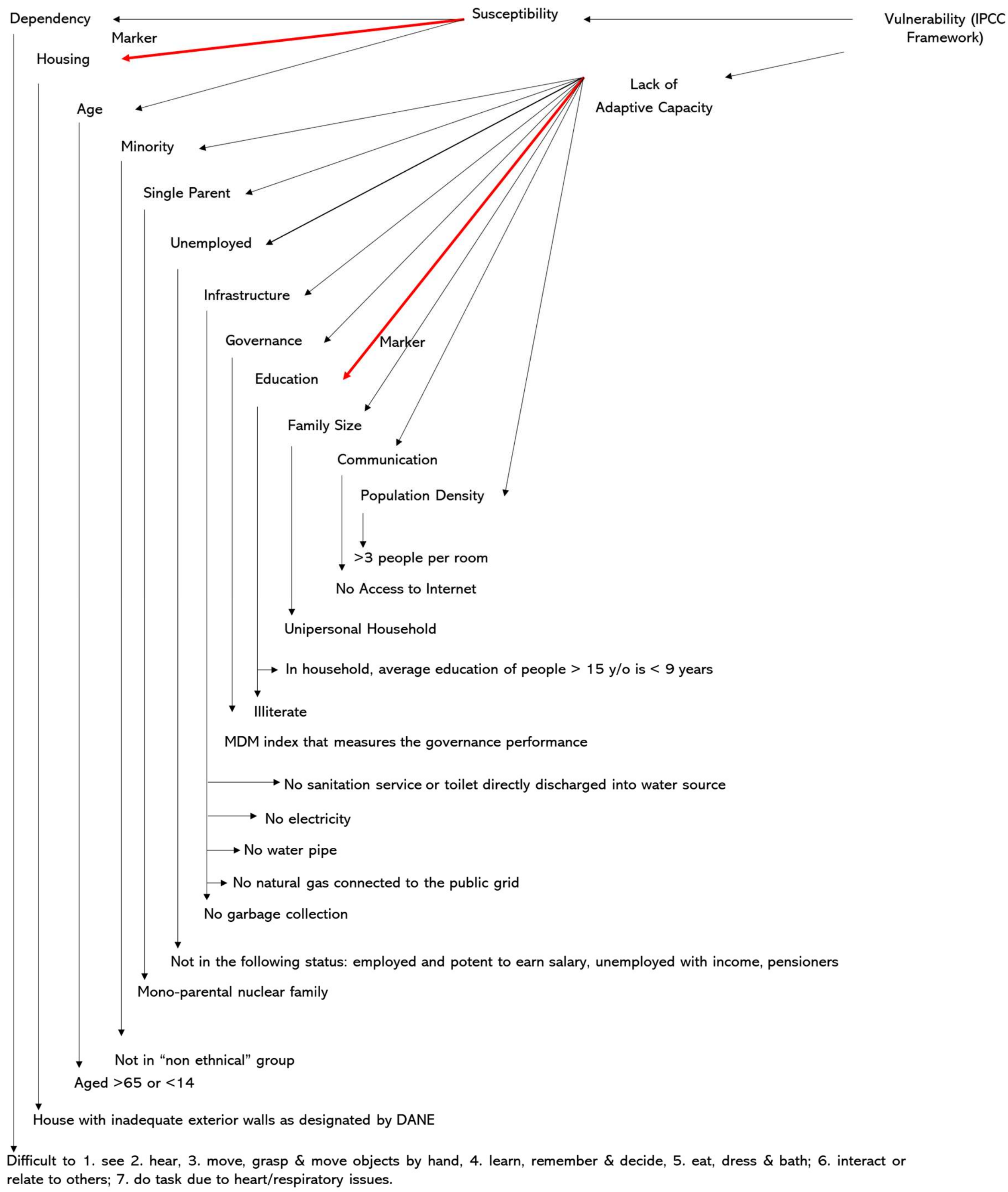

Figure 6. Vulnerability model based on the IPCC framework

3.3 Structural Equation Modelling (SEM)

3.3.1 Structural Equation Modelling (SEM)

The study utilizes SEM to examine relationships between vulnerability, sub-groups, and indicators, as detailed in the literature review. SEM analysis focuses on: (1) the variance of indicating variables explained by latent variables (e.g., sensitivity), indicating factor loadings, and (2) the fit of vulnerability frameworks with selected indicators, assessing model fit.

3.3.2 Factor Loading (FL)

FL, set at a 0.5 cutoff following (Prasetyo et al., 2020), helps validate the hypothetical indicator selection and improve model generalizability. Latent variable scales are defined by fixing one observed indicator's scale, based on Brown's recommendation (Brown & Little, 2015). This study selects markers with strong literature backing for scale definition, shown in red in Figure 5-6.

3.3.3 Measuring Model Fit by Fit Indices

Fit indices guide model-data fit evaluation, with each index having unique benefits and issues (Peterson et al., 2020; Newsom, 2023; Schermelleh-Engel et al., 2003). This study employs six indices (CFI, GFI, AGFI, NFI, TLI, RMSEA) with established cutoffs (Hooper et al., 2008) to evaluate vulnerability index models.

3.3.4 Dataset and Pre-processing

Data from 1,122 Colombian cities were sourced from DANE and DNP (DANE, 2018; DNP, 2018). Missing data in 21 cities was handled via mean imputation. Data normalization used z-scores (Pongas & Leulescu, 2011), with outlier handling and SEM analysis exclusions for cities with populations under 10,000. Indicator values were adjusted to align positively with social vulnerability.

SEM analysis used Semopy (Georgy & Anna, 2019) on Python 3.9 with Spyder, employing default sequential least squares programming.

3.3.5 Procedure

The study's procedure, outlined in Table 3: 1) Testing the original construct's fit. 2) Applying SEM to each sub-group, reducing variables with $FL<0.5$ or $p>0.05$, and updating the model. 3) Identifying multicollinearity using VIF, with a 5.0 cutoff based on Hagenlocher et al. and OECD (Hagenlocher et al., 2016; Nardo et al., 2005b). This led to retaining "Education" and removing other high-VIF indicators for the final SEM analysis.

The progression from Figure 7 (SEM Analysis of the MOVE-Initial Model) to Figure 14 involved refining our model through several stages. Initially, we tested the fit of the MOVE-Initial Model. Subsequently, we applied Structural Equation Modeling (SEM) to various subgroups, adjusting variables based on factor loadings and p-values. During this process, we identified multicollinearity using the Variance Inflation Factor (VIF), excluding high-VIF indicators, except for 'Education.' The intermediate steps, detailed in Figures 7-14, present the final, optimized SEM model. The optimization of additional models is provided in the Appendix.

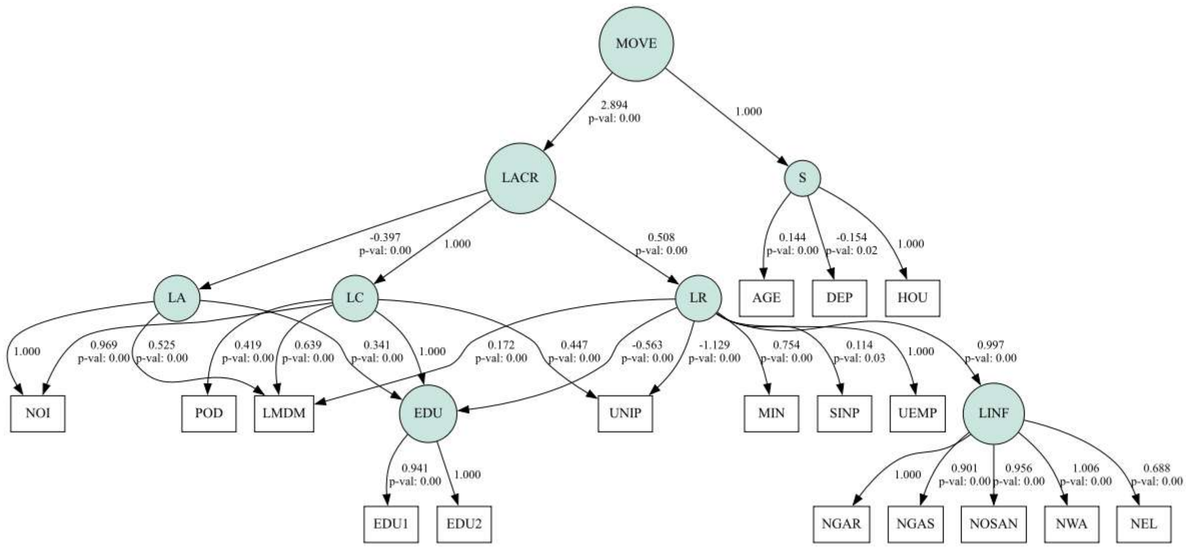

Figure 7. SEM analysis of the MOVE-initial model

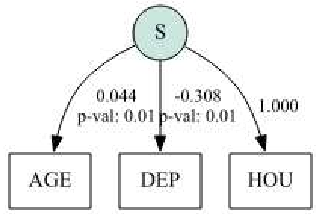

Figure 8. SEM analysis of the susceptibility sub-group of the MOVE-initial model

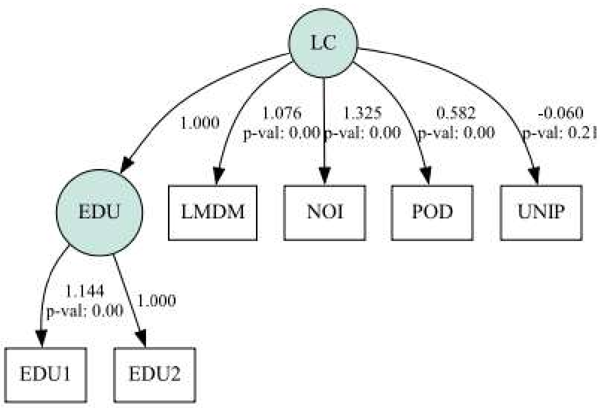

Figure 9. SEM analysis of the lack of capacity to cope sub-group of the MOVE-initial model

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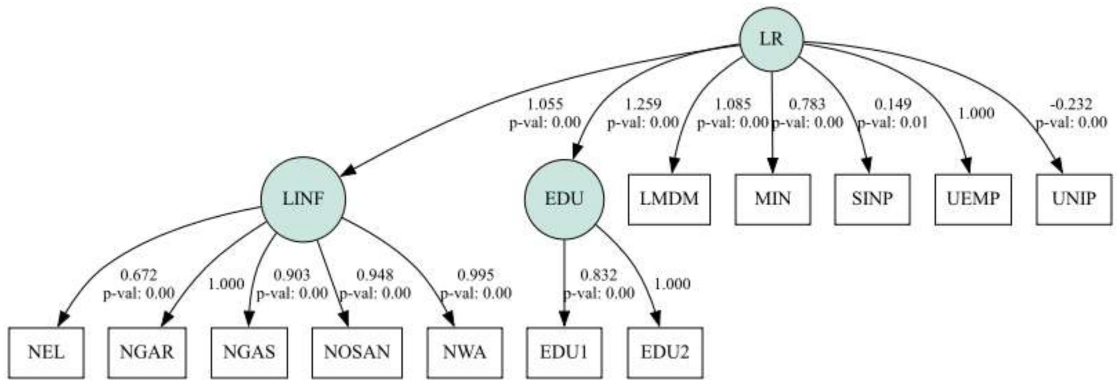

Figure 10. SEM analysis of the lack of capacity to recover sub-group of the MOVE-initial model

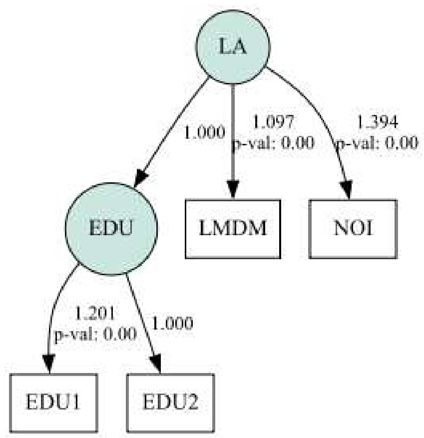

Figure 11. SEM analysis of the lack of anticipate sub-group of the MOVE-initial model

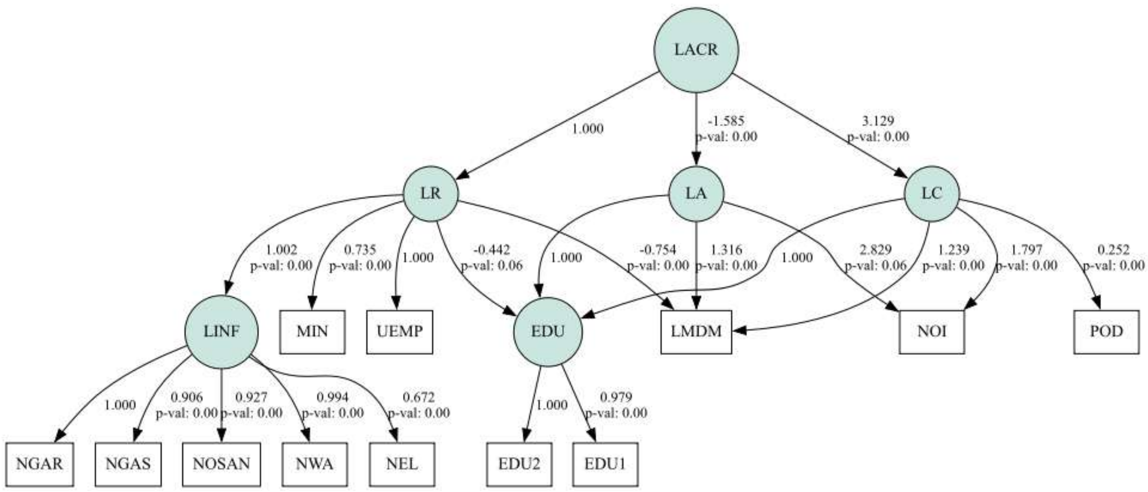

Figure 12. SEM analysis of the lack of capacity sub-group of the MOVE-initial model

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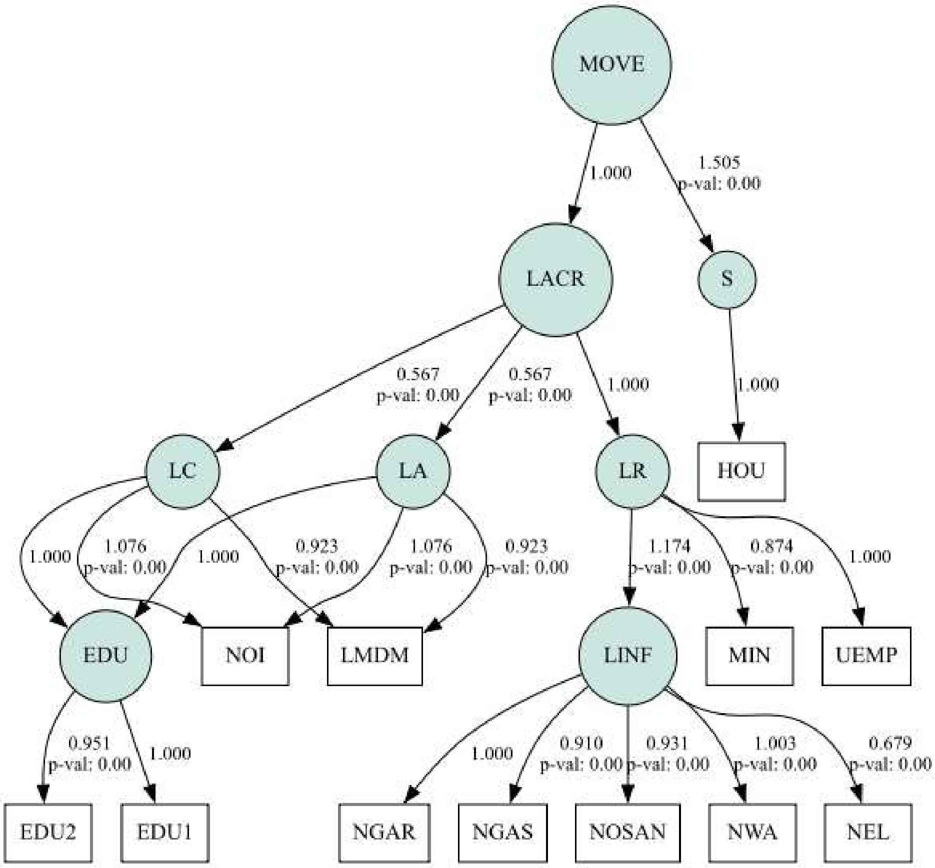

Figure 13. SEM analysis of MOVE-reduced model

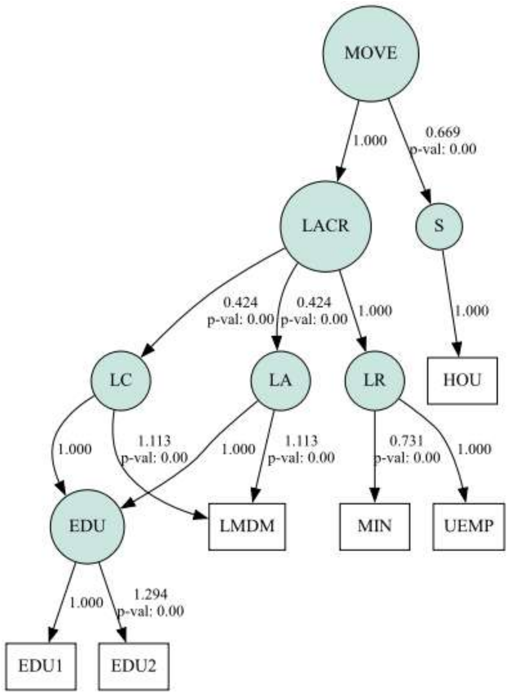

Figure 14. SEM analysis of MOVE-final model

Table 3. Procedure of using SEM to reduce the indicators, with fit indices
Negative values are marked in red.

Model	Marker	Operation	CFI	GFI	AGFI	NFI	TLI	RMSEA
Cut-Off			> 0.90	> 0.90	> 0.95	> 0.95	> 0.95	< 0.08
MOVE-Initial			0.65	0.65	0.55	0.65	0.56	0.21
Susceptibility	HOU		0.89	0.90	N/A	0.90	N/A	inf
		-AGE (FL=0.044) -DEP (FL=-0.308)	-	-	-	-	-	-
Lack of Capacity to Cope	EDU		0.71	0.71	0.45	0.71	0.45	0.37
		-UNIP (FL=-0.060, p=0.21)	0.81	0.81	0.52	0.81	0.52	0.39
Lack of Capacity to Recover	UEMP		0.75	0.74	0.67	0.74	0.68	0.20
		-SINP (FL=0.149) -UNIP (FL=-0.232)	0.82	0.81	0.74	0.81	0.75	0.20
Lack of Capacity to Anticipate	EDU		0.98	0.98	0.89	0.98	0.89	0.21
Lack of Capacity	LR		0.75	0.74	0.62	0.74	0.62	0.24
		LR-MDM (FL=-0.754) LR-EDU (FL=-0.442, P=0.06) LC-POD (FL=0.252)						
			0.79	0.79	0.68	0.79	0.68	0.23
MOVE-Reduced	LACR	VIF (EDU, NOI, INF>5)	0.78	0.77	0.66	0.77	0.66	0.22
MOVE-Final	LACR	Keep EDU	0.92	0.92	(0.25)	0.92	(0.25)	0.48
IPCC-Initial			0.65	0.64	0.57	0.64	0.58	0.20
Sensitivity	HOU		0.89	0.90	N/A	0.90	N/A	inf
		-AGE (FL=0.044) -DEP (FL=-0.308)	-	-	-	-	-	-
Lack of Adaptive Capacity	EDU		0.68	0.67	0.60	0.67	0.61	0.22
		-SINP(FL=-.109) -UNIP (FL=-0.177)	0.74	0.73	0.66	0.73	0.67	0.22
IPCC-Reduced			0.72	0.71	0.63	0.71	0.64	0.22
IPCC-Final		-NOI-INF	0.84	0.84	0.69	0.84	0.70	0.23
Single Factor-Initial			0.66	0.64	0.58	0.64	0.58	0.20
		-DEP (FL=-0.049, p=0.18) -AGE(FL=0.082) -DEP (FL=-0.049, p=0.18) -SINP(FL=0.084)						
Single Factor-Reduced		-UNIP(FL=-0.178)	0.72	0.71	0.65	0.71	0.65	0.22
Single Factor-Final		-NOI-INF	0.84	0.83	0.74	0.84	0.75	0.21

3.3.6 Aggregation and Visualization

Based on the reduced set of indicators, the social vulnerability index SV can be calculated using an additive method, where n represents the number of indicators in each sub-group. Notably, for indicators that contain sub-indicators/proxies, the averages of all the sub-indicators are used to calculate the value for that indicator, as shown in equation (4).

$$SV = \frac{1}{n}\sum_{n=subgroup}\frac{1}{k}\sum_{k=indicator} I_k \tag{4}$$

In the formula shown above, $n,\ k$ represents the number of subgroups and indicators, while I_k represents the value for the indicator k.

4. RESULTS

After the social vulnerability indices were calculated, they are projected to the Colombian municipal level administrative divisions by ArcGIS at the scale of 1:14,000,000, and ranked into 5 groups of vulnerability level, ranged from 1, the least vulnerable, to 5, the most vulnerable, using Jenks natural breaks classification method, as shown in Figure 15 below.

Moreover, the geological distributions of each indicator are included in Figure 16. To see more information about the datasets, please refer to the Appendix.

4.1 Social Vulnerability Distribution in Colombia

From Figure 15 below, we can observe that the 3 models generally agree on each other, in the sense that the cities located in Amazonia, Orinoquia, and Pacifico are relatively more vulnerable than those in Caribe, and the Andes Mountain regions in Central Colombia, which have relatively low vulnerabilities.

The result pattern basically agrees with the precedent social vulnerability index for natural hazards by Roncancio et al. (2020). This is expected to be the case because there is only one Natech related indicator: 'Governance' available for the current study, and since other indicators are selected based on importance, we can assume that the result has generalizability, which should be similar to the non-hazard specific previous study by Roncancio. However, albeit the similarities between the two studies, cities in Pacifico are generally even more vulnerable than those in Amazonia and in Orinoquia. Notably, in the research of Roncancio

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and colleagues, the reduced set of indicators contain twenty-nine variables, while the current study reduces the number of variables down to 6 (MOVE), 7 (IPCC) and 8 (Single factor).

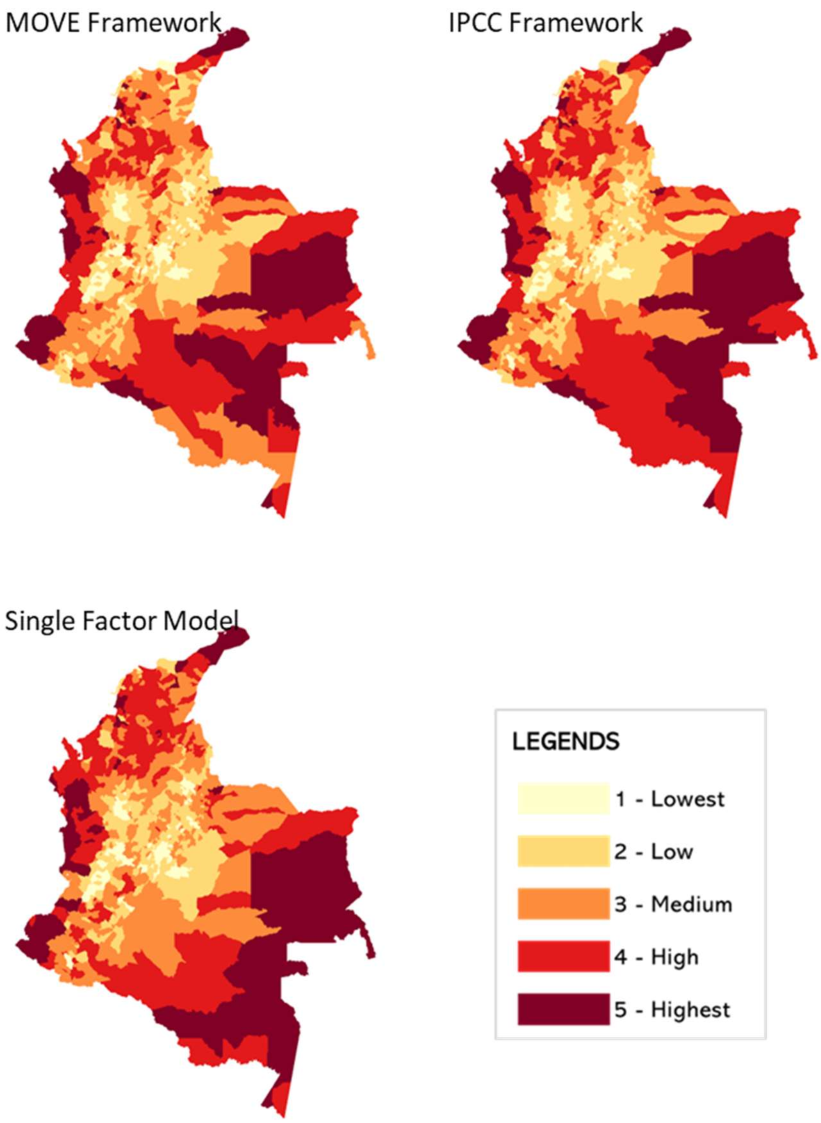

Figure 15. Geological distribution of social vulnerability indices

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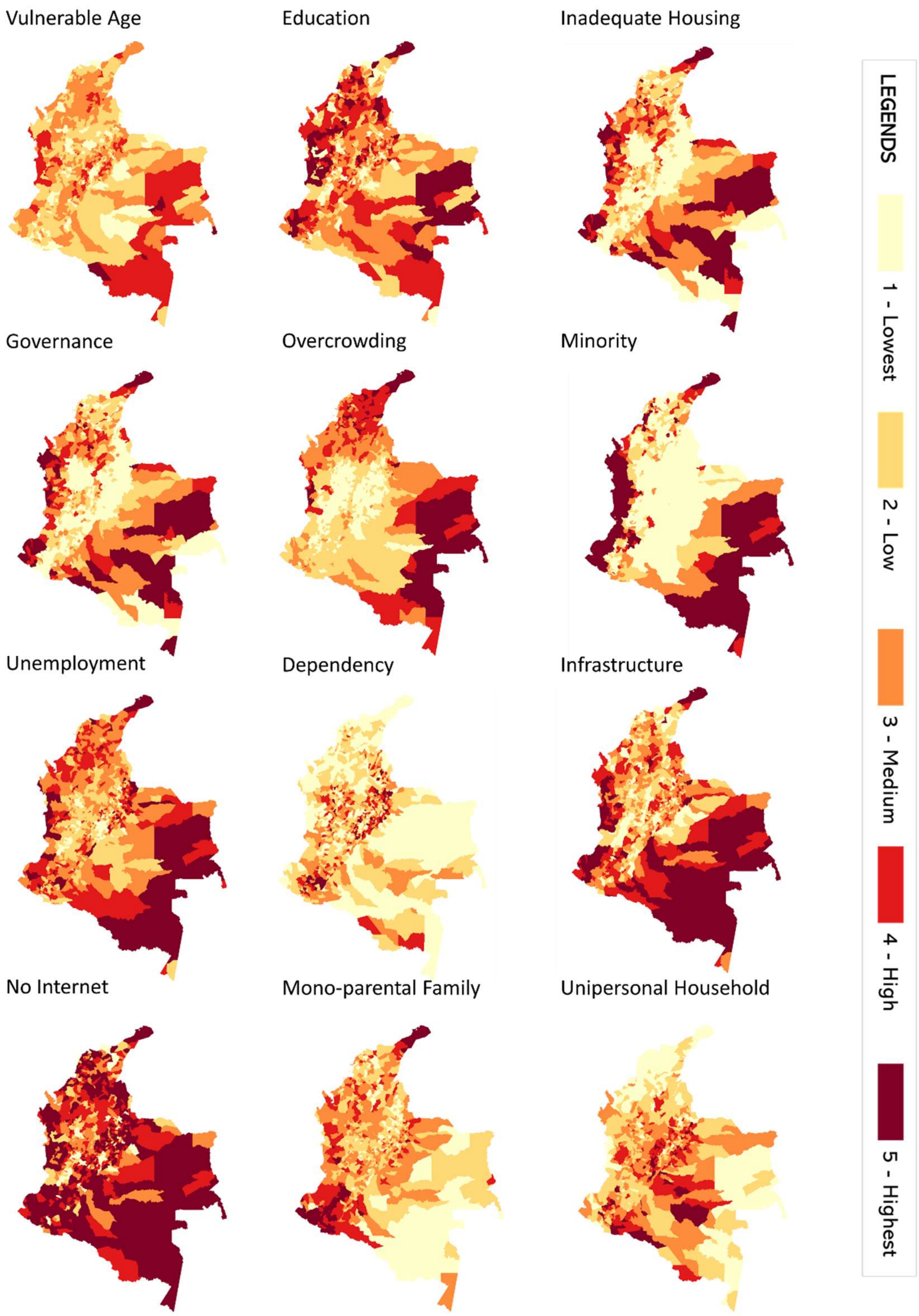

Figure 16. Geological distribution of each social vulnerability indicator

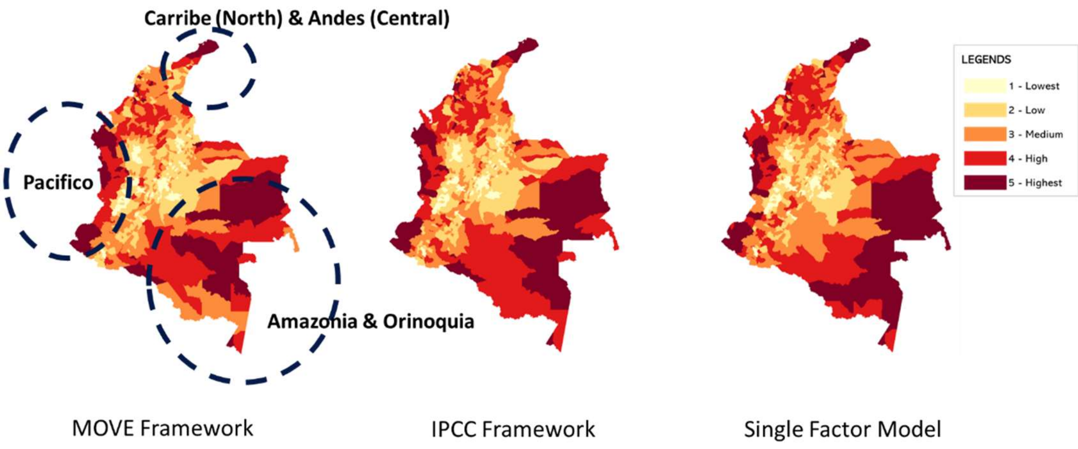

Figure 17. 3 Identified vulnerable regions in Colombia

In addition to the comparison with previous study, if looking at the geological distribution of each variable in Colombia (Figure 17), the pattern of indicators "Mono-parental Household", "Unipersonal Household" and especially the "Dependency" is significantly distinct from other indicators. This might explain why they have very low factor loadings in all frameworks examined before reduced.

4.2 Evaluation of the Models

As mentioned above, multiple fit indices should be used to evaluate the model fit. From Table 4, we could observe that after reducing the indicators with low factor loadings, the fit indices other than RMSEA have been improved. After removing the factors with high global correlations, IPCC and Single factor-based model's indices also significantly increased, except for RMSEA. The optimization has slightly increased the RMSEA, which is unfavorable. Moreover, though CFI, GFI, NFI have been improved, the RMSEA of MOVE model has significantly increased, while AGFI and TLI becomes negative, potentially connected to its extremely low degree of freedom. In addition, a high RMSEA value might be connected to overfit (Peterson et al., 2020; Curran et al., 2003), which might explain why it becomes unfavorable after optimization; however, since not all other fit indices do not suggest a strong fit, this hypothesis is not strong.

Comparing the model fit among the 3 models, it could be observed that applying IPCC and MOVE conceptual frameworks does not fit the model better, compared to the single factor model. In addition, it is important to mention that the data does not clearly support the latent construct of the 3 models, since the fit indices do not have common agreements. However, it does not mean that the models are "bad" or rejected. A more detailed discussion of the results is included in the next section.

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Table 4. Summary for the fit of all models. Negative values are marked in red.

Model	***CFI***	***GFI***	***AGFI***	***NFI***	***TLI***	***RMSEA***
Cut-Off	>0.90	>0.90	>0.95	>0.95	>0.95	< 0.08
MOVE-Initial	0.69	0.69	0.59	0.69	0.60	0.20
MOVE-Reduced	0.78	0.77	0.66	0.77	0.66	0.22
MOVE-Final	0.92	0.92	(0.25)	0.92	(0.25)	0.48
IPCC-Initial	0.65	0.64	0.57	0.64	0.58	0.20
IPCC-Reduced	0.72	0.71	0.63	0.71	0.64	0.22
IPCC-Final	0.84	0.84	0.69	0.84	0.70	0.23
Single Factor-Initial	0.66	0.64	0.58	0.64	0.58	0.20
Single Factor-Reduced	0.73	0.72	0.66	0.72	0.67	0.20
Single Factor-Final	0.84	0.83	0.74	0.84	0.75	0.21

5. DISCUSSION

While acknowledging of the potential limitations illustrated above, it is important to emphasize that model fit indices are only one aspect of evaluating the result. The current study has solid theoretical foundations, and the results align with previous studies in Colombia by Roncancio and colleagues (Roncancio et al., 2020). While aiming to address these constraints, the current findings still offer valuable insights for policy-making processes.

The results of the constructed social vulnerability indices have shown similarities across different models. All 3 models also show similar results with the index based on SOVI Framework by Cutter et al. Notably, even after doing indicator reduction, and even the number of the indicators are around 6-8, approximately ¼ of that from the previous study, suggesting high generalizability.

Several challenges have been identified when implementing the methodology to the study area.

Data Quality

<u>Data Availability Issues</u>: A notable data gap is the lack of available information on personal income level distribution in Colombia. This limitation impacts the number of total indicators used for SEM. This could be a contributing factor for Sensitivity/Susceptibility subgroups

containing only one variable, and for the Lack of Capacity to Cope and Anticipate subgroups sharing the same variables in the MOVE Framework, potentially decreasing model fit.

Data Sources and Potential Errors: With 17 out of the 18 variable datasets being generated by DANE, there are uncertainties about potential common measurement errors. This might necessitate the incorporation of residual covariance relations between factors in the SEM.

Data Resolution Concerns: The study's reliance on municipality-detailed data assumes homogeneity within each municipality. Goodman et al. have argued that this is merely an approximation of personal-level data, and inherent heterogeneity within cities could lead to inaccuracies (Goodman et al., 2021).

Literature Review Process

Manual Literature Review: This process, undertaken manually, is prone to human error, especially when terminologies across different studies diverge. Ambiguities stemming from the absence of a universal identification criterion might introduce subjective biases. The challenges underline the need for a more systematic, AI-based literature review process. Adapting advanced techniques like the Semi-Intelligent Natech Identification Framework (SINIF) proposed by Luo et al. might offer potential improvements (Luo et al., 2020).

Natech Risk Report Scarcity: Making the social vulnerability index specific to Natech risk is challenging due to the paucity of comprehensive accident reports. The current study can only draw upon news and data records of losses, which may not capture all local vulnerabilities.

Conceptual Framework Ambiguities

Indicator Selection based on Global Evidence: While a global approach offers comprehensive insights, it also poses challenges. The debate on the regional specificity of social vulnerability indices, as discussed by Goodman et al. (2021), suggests that global sources might not be entirely aligned with Colombia's unique context.

Conceptual Frameworks: Though these frameworks guide indicator selection, they often lack specificity for real-world data analysis applications. This could inadvertently exclude crucial factors from the study, such as the mobility effect on the latent factor Lack of Capacity to Cope.

Lack of Validation of Index

A gap in the research field is the scarcity of studies validating the results of indices by examining their relationship with actual disaster impacts (Barankin et al., 2021). Future Natech-specific studies related to hazards can potentially yield a more evidence-driven approach to vulnerability assessment, as provided by Schmidtlein and colleagues (Schmidtlein et al., 2011).

Predictivity

This study relies on historical census data, which might not accurately reflect future social economic scenarios. Shared Socioeconomic Pathways (SSP) projections, such as those made by IIASA, can fix this gap by providing future demographic data estimates under different social economic scenarios (Gidden et al., 2019; Riahi et al., 2017; Rogelj et al., 2018).

Regardless of the potential limitations outlined earlier, it is essential to emphasize 2 things.

Firstly, beyond the fit indices itself, having theoretical and logical supports is also important (Cho et al., 2020). Since the current study has selected only the common and explainable indicators and frameworks for analysis, it contains the required theoretical foundations in line with UN and European Commission. This is important for authorities to have standard consistency with international organizations.

Secondly, the foundational methodologies and research outcomes provide valuable insights for shaping policies. Policy suggestions in this study are informed by both the findings of the research and the challenges identified during the research process, such as data availability issues. This dual perspective ensures that the recommendations are both grounded in current evidence and considerate of future research and application needs. By understanding these challenges, policymakers can make more informed, context-sensitive decisions. Furthermore, the challenges identified in this research shed light on areas where policy interventions can support future research, such as enhancing data availability and resolution. The subsequent section delves into specific policy recommendations that aim to mitigate social vulnerabilities.

Therefore, despite the outlined limitations, our research provides key insights for policy development. Recommendations are shaped by both the study’s findings and the identified challenges, like data availability. This ensures the suggestions are evidence-based while addressing future research needs. The upcoming section offers specific policy recommendations to address social vulnerabilities.

6. CONCLUSION AND POLICY SUGGESTIONS

This study introduced a novel methodology to delineate social vulnerability concerning Natech risks. By establishing a newindicator selection strategy, which factored in multi-hazard interrelations, and adapting three conceptual frameworks, the research used SEM for model reduction and fit analysis based on Colombian datasets. Visualization was achieved through GIS. The vulnerability distribution aligns with and supports prior studies. Notably, the proposed Governance indicator was authenticated by SEM as a pivotal explanatory variable for latent variables. However, the result fit for MOVE, IPCC, and single-factor models remains mixed.

Considering these findings, we recommend the following policy directions for future vulnerability analysis:

(1) Natech Regulation: Given the apparent lack of comprehensive Natech event reports in existing literature, policy measures should:

- Mandate timely, detailed, and publicly transparent accident reports to understand indicators for social vulnerabilities.
- Require at-risk companies to obtain Natech certifications, such as the Natech RateME Framework.
- Ensure regular submission of detailed ESG reports in alignment with GRI and TCFD standards.

(2) Data Standardization and Enhancement: Addressing the lack of uniform and essential data by instituting standardized reporting guidelines, centralizing data, and refining census details.

(3) Localized Vulnerability Framework: Given the shortcomings of general vulnerability frameworks, as supported by our discussions, there's a need to integrate qualitative analysis and Bayesian networks for a more nuanced understanding.

This study also suggests refining the research methodology by exploring measurement errors among variables and authenticating results through an evidence-based approach. The latter might involve referencing projected future losses and incorporating real-time demographic and economic data. We also noted challenges with the conceptual frameworks, particularly concerning clarity and model fit, emphasizing the necessity for researchers to re-evaluate their utility in data-centric research.

Despite the identified limitations, this research presents a pioneering methodology for developing sets of Natech social vulnerability indicators, marking a significant step in understanding the social vulnerabilities associated with Natech and multi-hazard incidents.

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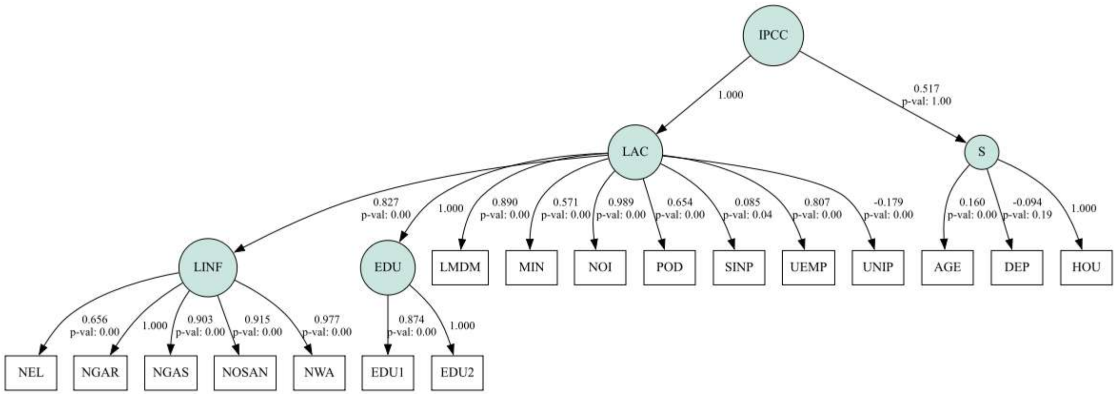
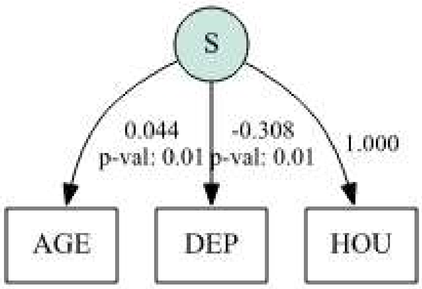
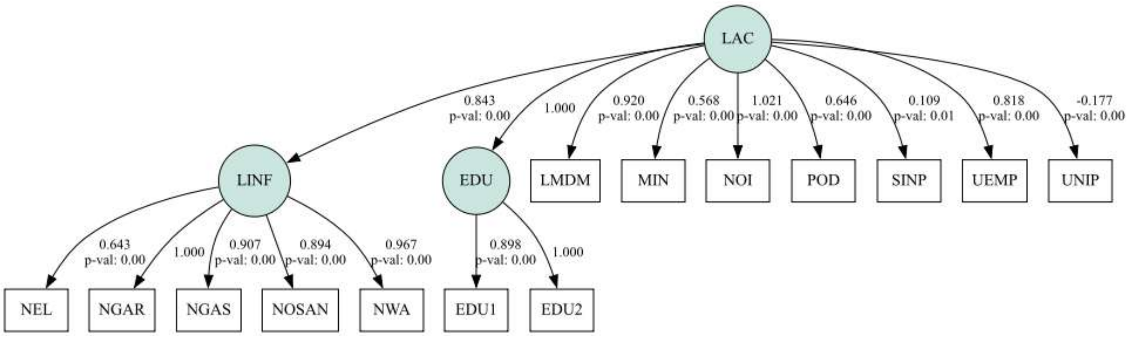
APPENDIX



Supplementary Figure 1. SEM analysis of the IPCC-initial model



Supplementary 2. SEM analysis of the sensitivity sub-group of the IPCC-initial model



Supplementary 3. SEM analysis of the lack of adaptive capacity sub-group of the IPCC-initial model

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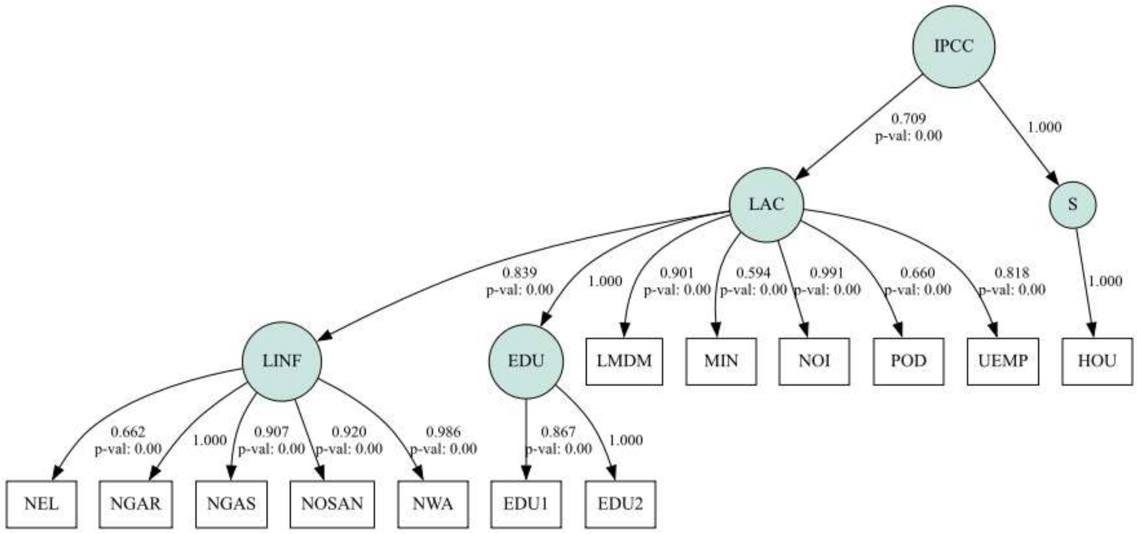
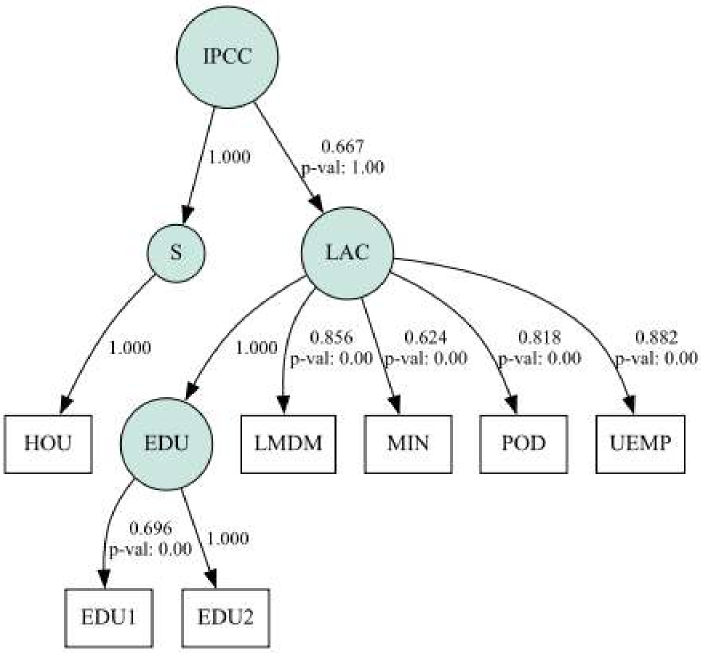


Supplementary 4. SEM analysis of the IPCC-reduced model



Supplementary 5. SEM analysis of the IPCC-final model

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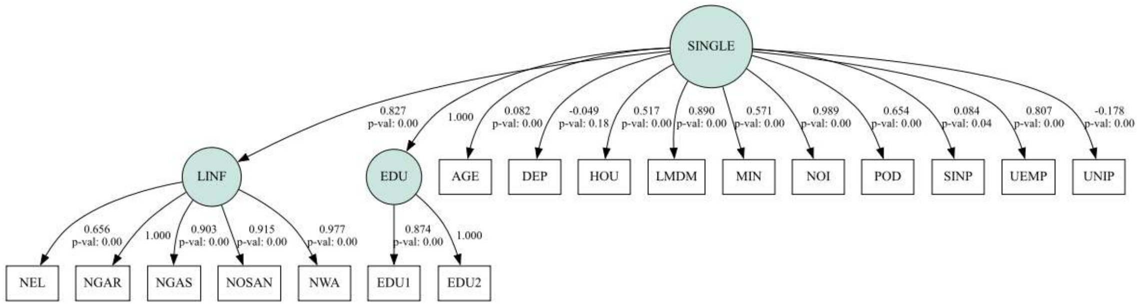
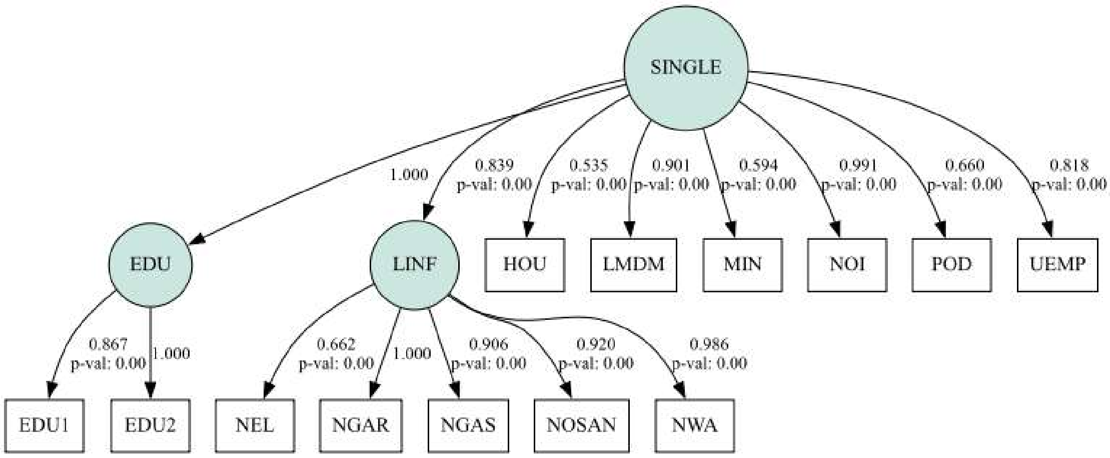
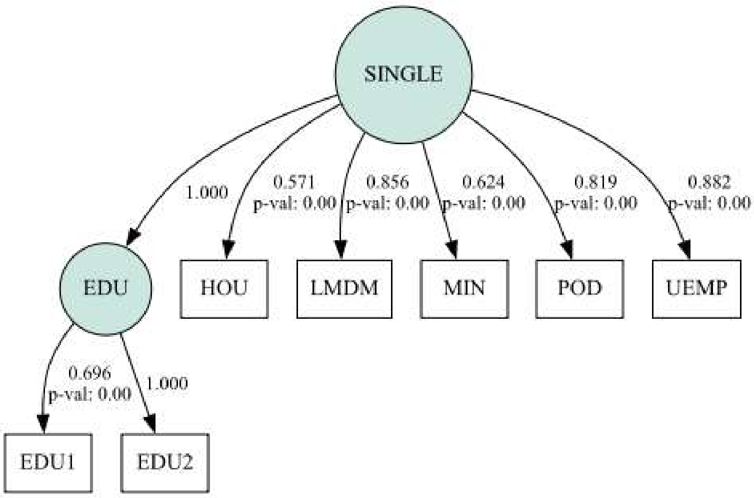


Supplementary 6. SEM analysis of the single factor-initial model



Supplementary 7. SEM analysis of the single factor-reduced model



Supplementary 8. SEM analysis of the single factor-final model

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Supplementary Table 1: Explanation of indicators and classification

Indicator	Proxy	Code	Explanation	Literature	Data Source	Move	IPCC
Gender	Female percentage	GEN1	Disadvantaged social-economic status leads to bad recovery (De Loyola Hummell et al., 2016)	(Fatemi et al., 2017b; Ghorbanzadeh et al., 2019; Hagenlocher et al., 2016; Lianxiao & Morimoto, 2019; Mavhura & Manyangadze, 2021; Roncancio et al., 2020; Rufat et al., 2015; Xiao et al., 2022)	Census 2018	Excluded	Excluded
Housing	House with inadequate exterior walls as designated by DANE	HOU	Inadequate structure makes houses susceptible to destruction. (Suda, 2017)	(Ghorbanzadeh et al., 2019; Mavhura & Manyangadze, 2021; Roncancio et al., 2020; Fatemi et al., 2017b; Rufat et al., 2015)	Multidimension Poverty 2018	Susceptibility	Sensitivity
Minority	Not in “non ethnical group”	MIN	May have “language and cultural barriers that affect access to post-disaster funding” (Cutter et al., 2003)	(Emanuel et al., 2021; Fatemi et al., 2017b; Roncancio et al., 2020; Rufat et al., 2015)	Census 2018	Lack of Capacity to Recover	Lack of Adaptive Capacity
Age	Aged >65 or <14	AGE	Old people might have mobility issues; family having children needs more resources to recover (Cutter et al., 2003); Children have low weight and size, making them easy to be affected (Hagenlocher et al., 2016).	(Carmichael, 2011; Fatemi et al., 2017b, 2017a; Ghorbanzadeh et al., 2019; Hagenlocher et al., 2016; Lianxiao & Morimoto, 2019; Mavhura & Manyangadze, 2021; Roncancio et al., 2020; Rufat et al., 2015; Willis & Fitton, 2016b; Xiao et al., 2022; Yu et al., 2021)	Census 2018	Susceptibility	Sensitivity
Dependency	Difficult to 1. See 2. Hear, 3. Move, grasp & move objects by hand, 4. Learn, remember & decide, 5. Eat, dress & bath; 6. Interact or relate to others; 7. Do task due to heart/respiratory issues	DEP	Disabled people need dedicated disaster plans (Clark et al., 1998).	(Carmichael, 2011; Chas-Amil et al., 2022; Fatemi et al., 2017b, 2017a; Rufat et al., 2015; Willis & Fitton, 2016a)	Census 2018	Susceptibility	Sensitivity
Single Parent	Mono-parental nuclear family	SINP	Might lack financial resource for Recovery (Cutter et al., 2003; Guns & Vanacker, 2014)	(Ghorbanzadeh et al., 2019; Mavhura & Manyangadze, 2021; Roncancio et al., 2020; Emanuel et al., 2021; Khazai et al., 2013; Fatemi et al., 2017; Rufat et al., 2015)	Census 2018	Lack of Capacity to Recover	Lack of Adaptive Capacity
Unemployed	Not in the following status: employed and potent to earn salary,	UEMP	related to low income and difficulties for recovery (Cutter et al., 2003)	(Ghorbanzadeh et al., 2019; Chas-Amil et al., 2022; Willis & Fitton, 2016; Roncancio et al.,	Census 2018	Lack of Capacity to Recover	Lack of Adaptive Capacity

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	unemployed with income, pensioners			2020; Emanuel et al., 2021; Fatemi et al., 2017; Rufat et al., 2015)			
Infrastructure	No garbage collection	NGAR		(Fatemi et al., 2017a; 2017b; Ghorbanzadeh et al., 2019)	Census 2018	Lack of Capacity to Recover	Lack of Adaptive Capacity
	No natural gas connected to the public grid	NGAS		(Fatemi et al., 2017a; 2017b; Ghorbanzadeh et al., 2019)	Census 2018		
	No water pipe	NWA	Expensive to rebuild (Cutter et al., 2003)	(Ghorbanzadeh et l., 2019; Roncancio et al., 2020; Fatemi et al., 2017)	Census 2018		
	No electricity	NEL		(Ghorbanzadeh et al., 2019; Roncancio et al., 2020; Fatemi et al., 2017)	Census 2018		
	No sanitation service or toilet directly discharged into water source	NSAN		(Ghorbanzadeh et al., 2019; Chas-Amil et al., 2022; Roncancio et al., 2020; Rufat et al., 2015)	Census 2018		
Governance	MDM index is created by the Colombian government to measure the governance performance	MDM	Explained in the text	Hypothesis	MDM 2018	Lack of Capacity to Recover, Anticipate	Lack of Adaptive Capacity
Education	Percentage of illiterate people.	EDU1		(Fatemi et al., 2017; Gentili et al., 2018)	Census 2018	LR, LC, LA	AC
	In household, average education of people > 15 y/o is < 9 years.	EDU2	Affects 'people's ability to read warning signs', and links to risky behaviors (Hagenlocher et al., 2016)	(Ghorbanzadeh et al., 2019; Hagenlocher et al., 2016; Andrade et al., 2010; Roncancio et al., 2020; Yu, et al., 2021; Emanuel et al., 2021; Khazai et al., 2013; Xiao et al., 2022)	Multidimension Poverty 2018	Lack of Capacity to Recover, Anticipate, Cope	Lack of Adaptive Capacity
Communication	No Access to Internet	NOI	Related to lack of information (Carmichael, 2011)	(Fatemi et al., 2017; Gentili et al., 2018; Ghorbanzadeh et al., 2019; Carmichael, 2011)	Census 2018	Lack of Capacity to Anticipate, Cope	Lack of Adaptive Capacity
Population Density/ Overcrowding	>3 people per room	POD	Potentially leads to difficulties during evacuation.	(Fatemi et al., 2017a; 2017b; Roncancio et al., 2020; Emanuel et al., 2021; Xiao et al., 2022; Rufat et al., 2015)	Multidimension Poverty 2018	Lack of Capacity to Cope	Lack of Adaptive Capacity
Family Size	Uni-personal family	UNIP	Might be lack of help during the disaster and at the recovery stage (Gentili et al., 2018)	(Fatemi et al., 2017; Gentili et al., 2018; Chas-Amil et al., 2022; Lianxiao & Morimoto, 2019; Mavhuraa & Manyangadze, 2021; Roncancio et al., 2020; Yu, et al., 2021)	Census 2018	Lack of Capacity to Recover, Cope	Lack of Adaptive Capacity