A Novel Automatic Reflective Indexing (ARI) method to create a World Peace Index

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Declaration

I confirm that this is my own work and the use of all material from other sources has been properly and fully acknowledged.

Yiran Wei

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I want to say thank you to all the people I have met during my PhD study. My supervisor Prof. Yinshan Tang has guided me kindly and patiently, not only the academics, but also the view of seeing the world, and the attitude of living a life. I believe his guidance will be a treasure throughout my life. Cindy is a warm person who has helped me a lot during the tough covid time. Without her help, I can't imagine how much trouble I would have got into. I have also spent some great time with my PhD colleagues, they have made my PhD study such an interesting and colorful journey.

I want to say thank you to my parents who have constantly encouraged and supported me for so many years. I love you, always and forever.

Abstract

The negative peace and positive peace are the core concepts of the peace research. The Global Peace Index (GPI) and Positive Peace Index (PPI) try to measure the levels of negative and positive peace respectively and support the relevant empirical researches. However, the influences of GPI and PPI are very limited in empirical peace research. The literatures ascribed the unpopularity of the GPI to its low credibility caused by its embedded "inappropriate subjectiveness", which is an ambiguous statement since no concrete limitations of GPI and PPI were revealed. The aim of this research is to identify the concrete limitations of the GPI and PPI methods which reduce their credibility, and then develop a new peace indexing method to solve these limitations. We dig into the methods of GPI and PPI and conclude four concrete limitations in terms of the target aggregation, the indicator validation, the indicator weighting (PPI), and the missing value estimation which can reduce the credibility of GPI and PPI. Then, we design a new peace indexing method called the automatic reflective indexing (ARI) and demonstrate its theoretically advantages by solving the concrete limitations of the methods of GPI and PPI. To evaluate the practical performance of the ARI, we use the ARI to establish specific peace indexes, the Internal Peace Index (IPI) and the External Negative Peace Index (ENPI), and then demonstrate that these indexes indeed no longer suffer from the limitations of GPI and PPI. We also illustrate that the ARI can be useful to study the causes of peace due to its SEM-based characteristics. At the end of this thesis, we summarise the contributions and limitations of the ARI and give an outlook on the future works after this research.

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List of Abbreviations

GPI	Global Peace Index
PPI	Positive Peace Index
ARI	Automatic Reflective Indexing
IPI	Internal Peace Index
IPPI	Internal Positive Peace Index
INPI	Internal Negative Peace Index
EPPI	External Positive Peace Index
ENPI	External Negative Peace Index

Chapter 1 Introduction

1.1 Introduction

In chapter 1, we will introduce the background and motivation of this research. The goal of this chapter is to bring in the gap and formalise it into specific research problems. The research aims and objectives will be proposed as well. At the end of this chapter, we will list an outline to briefly illustrate the structure of this thesis.

1.2 Background and Motivation

In recent years, due to the ceaseless global conflicts and vulnerable international relations, more and more researchers have started to seek solutions from the peace research, which is a field that aims to identify the violent behaviours and analyse their underlying mechanisms (Dugan, 1989).

To identify the scopes of different types of violence, peace researchers had a fruitful debate over the definition of peace in the 1970s, during which the most well-renowned peace definitions, the negative peace and positive peace, were proposed and accepted (Galtung, 1969). The births of negative and positive peace distinguished peace research from other cognate fields, as they identified the normative target of peace research (Lawler, 2008).

It is an intuitive idea to establish global peace index to measure and visualise the negative and positive peace statuses for countries around the world, since index is a composite statistic to summarise and rank complex observations (Babbie, 2020). In social research, establishing index is a popular method to measure and visualise the complex target. For instance, the Human Development Index (HDI) (Anand & Sen,

1994) was created to measure the level of human development, the Consumer Price Index (CPI) (Greenlees, 1997) was developed to measure the level of average price of goods and services, the Dow Jones Industrial Average (DJIA) (Milne, 1966) was built to measure the average stock price of the US stock market, and the Impact Factor (IF) (Garfield, 1994) was established to measure the academic importance of journal, etc. In general, an indexing method includes five steps: 1) Define the target of the index. 2) Collect indicators for the target. 3) Weight the indicators. 4) Deal with missing values. 5) Compute the index (Babbie, 2020).

In 2009, an Australian think tank called the Institute for Economics and Peace (IEP) developed the first worldwide peace index, the Global Peace Index (GPI, 2019). The aim of GPI is to measure the level of negative peace for countries around the world and support the empirical research of negative peace. The indicators of GPI are collected and weighted subjectively by the expert panel of IEP. GPI has been updated annually and its method hasn't changed since its birth. Then in 2018, the IEP launched another worldwide peace index called the Positive Peace Index (PPI), which has also been updated annually without modifications in method since its birth. The aim of PPI is to measure the level of positive peace for countries around the world and provide data for empirical research of positive peace. The indicators of PPI are collected and weighted via the objective method. So far, GPI and PPI are the only attempts to establish worldwide peace index to measure the levels of negative and positive peace.

However, Keith Gottschalk (2015) noticed that the influence of GPI in empirical peace research was very limited. To update his observation and study the recent influence of GPI and PPI in empirical peace research, we use Google Scholar to count the annual publications of relevant literatures according to different keyword settings between 2016 and 2022 (see figure 1-1). Since 2016, the annual publications of empirical peace research have experienced a rising trend, yet the usage of either GPI or PPI remains at the low level. Figure 1-1 demonstrates that both GPI and PPI fail to achieve their goals of providing influential measurements for empirical research of negative and positive peace.

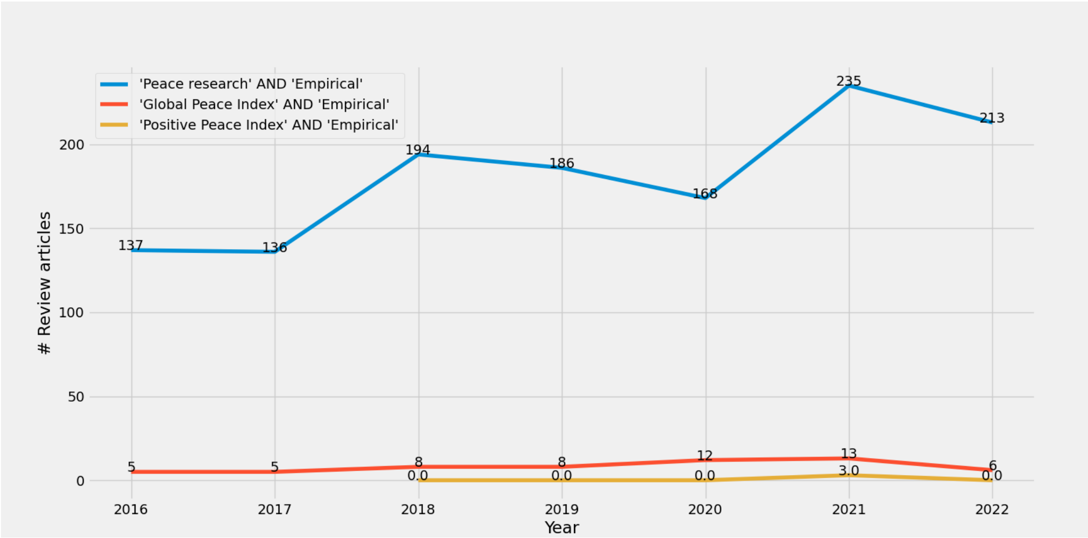


Figure 1-1. Google Scholar Keyword Search

The unsatisfied status quo of GPI and PPI motivates us to think about why peace researchers hardly use these tools to conduct their research. Keith Gottschalk (2015) ascribed the unpopularity of GPI to its low credibility caused by the embedded “inappropriate subjectiveness” in its indicator collection and weighting methods. He listed some dubious countries in the GPI ranking to challenge the credibility of GPI and suggested that researchers should read GPI with scepticism.

However, Keith didn’t illustrate how the subjectiveness in GPI method damaged its credibility, as he didn’t propose any concrete limitations of the GPI. Thus, Keith’s charge is ambiguous and not persuasive enough.

1.3 Research Problem

From section 1.2, we know that the research gap has yet been identified, as the concrete limitations of the GPI and PPI methods have yet been revealed. Keith’s argument about the “inappropriate subjectiveness” is superficial, otherwise PPI who was created by the objective indicator collection and weighting methods should have achieved greater influence, which apparently not (see figure 1-1). In this research, we propose the following research problems:

1) What are the concrete limitations of GPI and PPI that reduce their credibility?

2) How can we develop a peace indexing method to establish the peace indexes without the limitations of GPI and PPI?

The first research problem is trying to identify the gap and clarify the weaknesses of current solutions (GPI and PPI). The second research problem is about designing a new peace indexing method to fix these weaknesses.

1.4 Research Aim & Research Objectives

The research aim is to create the peace indexes without the concrete limitations of the GPI and PPI to measure the levels of the negative and positive peace. To achieve this research aim, we propose the following research objectives:

1) To review the GPI and PPI methods in detail and figure out their concrete limitations. Criteria that our peace indexing method should meet will need to be proposed in this process.

2) To obtain the knowledge of the indexing methods and look for one that meets the criteria. If there exists an indexing method which can meet all the criteria, then we can directly use it as our peace indexing method. Otherwise, we will need to develop a new one to meet the criteria.

3) To demonstrate the theoretical advantages of our peace indexing method by solving the concrete limitations of GPI and PPI.

4) To use our peace indexing method to establish practical peace indexes to measure the levels of negative and positive peace as the evaluation to our peace indexing method.

1.5 Thesis Outline

There are five chapters left in this thesis. We give a brief outline about what will be discussed in each following chapter. In chapter 2, we will review GPI and PPI methods in detail and figure out their concrete limitations to identify the research gap. Criteria of the peace indexing method will be proposed in this chapter. In chapter 3, we will talk about the research methodology of this thesis, the design science research (DSR), to illustrate how this research will be conducted step by step. In chapter 4, we will search for the knowledge of existing indexing methods, techniques, and theories to set up our peace indexing method. We will demonstrate the theoretical advantages of our indexing method by comparing it to the methods of GPI and PPI. In chapter 5, we will use our peace indexing method to establish concrete peace indexes to measure the levels of negative and positive peace. The goal of this chapter is to evaluate the practical performance of our peace indexing method, to see whether the produced indexes are indeed free of the limitations of GPI and PPI. In chapter 6, we will conclude the contributions and limitations of this research, and then give an outlook to the future works following this research.

1.6 Conclusions

In this chapter, we show the unappealing status quo of the Global Peace Index (GPI) and Positive Peace Index (PPI) in empirical peace research. The current “inappropriate subjectiveness” criticism does not touch the concrete limitations of GPI, therefore is not persuasive enough to explain the low credibility of GPI.

We propose two research problems to formalise this gap. We will need to figure out what concrete limitations the GPI and PPI methods have, and then find out a solution to deal with these limitations.

We propose a research aim with four research objectives. The aim of this research is to create the peace indexes without the limitations of GPI and PPI to measure the levels of the negative and positive peace. To achieve this aim, we will need to review the GPI and PPI methods, figure out their concrete limitations, and set up criteria that the peace indexing method should meet. According to the criteria, we will search for the knowledge of the indexing methods and then develop our peace indexing method. Afterwards, we will need to demonstrate the theoretical advantages of our peace indexing method by solving the limitations of GPI and PPI methods, and then evaluate its practical performance by creating peace indexes to measure the levels of negative and positive peace.

At last, the thesis outline has been listed to illustrate the structure of this research.

Chapter 2 Literature Review

2.1 Introduction

In this chapter, we will review the information of the Global Peace Index (GPI) and the Positive Peace Index (PPI) in detail, including their backgrounds, aims, methods, and applications. Afterwards, we will try to analyse the concrete limitations of the GPI and PPI methods to explain their low credibility. Some criteria of peace indexing method will also be set up.

2.2 Global Peace Index (GPI) & Positive Peace Index (PPI)

An Australian think tank called Institute for Economics and Peace (IEP) developed the Global Peace Index (GPI) in 2009, aiming to provide a measurement of negative peace for nations around the world and support empirical research of negative peace. In 2018, IEP established another worldwide peace index called Positive Peace Index (PPI), which aims to measure the level of positive peace for nations around the world and facilitate empirical research of positive peace. GPI and PPI are the only existing attempts on measuring their targets (worldwide negative / positive peace).

2.2.1 Definition of Peace

Before diving into the GPI and PPI methods, we will review the development of peace definitions to understand the targets that GPI and PPI try to measure.

Peace research is a relatively new field compared to other mainstream social sciences. Most researchers would agree that peace research was deemed as an independent field from international relation studies only after World War II. Stephenson (2008) made a chronicle of peace research, stating that the peace research has experienced five phases. This chronicle was made according to both academic and educational progresses. To highlight the development history of the peace definition, we reorganise these five phases and condense them into three.

During the first phase (1950-1969), peace research gradually became an independent research field separated from international relation studies. Since early peace research was still heavily influenced by international relation studies, the peace research during this period mainly focused on negative peace, which is defined as the absence of direct violence. All actions realised as doing physical harm to human beings can be seen as cases of direct violence, such as crime, war, etc.

In the second phase (1970s), the focus of peace research had gradually shifted from negative peace to positive peace. Johan Galtung (1969) introduced the concepts of structural violence and positive peace. Positive peace is defined to be the absence of structural violence, which refers to the unjust structures and mechanisms embedded in society that indirectly harm people. Sexism, racism, and economic inequality can all be regarded as examples of structural violence. Galtung (1975) claimed that researchers should put more efforts into positive peace, as it is the fundamental reason leading to high-level negative peace and the real way to achieve sustainable peace in the long run.

The debate over negative peace and positive peace dominated the peace research context during 1970s. Boulding (1977) in his paper “Twelve friendly quarrels with Johan Galtung” held that Galtung’s idea of broadening the concept from negative peace to positive peace reduced the clarity of peace definition, since the scope of structural violence can be too large and ambiguous to be determined compared to narrow concepts such as direct violence. He criticised Galtung for having biased favour towards positive peace research. Even so, Boulding still acknowledged the value of positive peace in his stable peace theory (Boulding, 1978), in which he noted that the social justice forms an important aspect of peace. Some other dissenters of positive peace as well as advocators of negative peace also agreed that peace research community should put more attention on studying the relationship between negative peace and positive peace, rather than being doctrinaire in peace definition (Bönisch, 1981; Kelman, 1981). At the end of the second phase, the value of positive peace has been widely acknowledged by the peace research community.

The third phase has spanned from 1980 to nowadays, during which the focus of peace research has shifted from peace definitions to peace approaches. Only a few of new peace definitions were created during this phase, and neither of which have significant influence compared to negative peace and positive peace. Johan Galtung proposed a new concept called cultural violence (Galtung, 1990; Galtung, 1996) as a complement to his peace framework, which refers to the cultural aspects that can be used to legitimise the direct violence and structural violence. Anderson (2004) proposed a composite peace definition which is defined as a two-dimensional construct with aligned objective and subjective measures.

To sum up, after being independent from international relation studies, peace research gradually set up its unique feature by grinding the peace definitions. The negative and positive peace are the milestones of peace research, which are still the most accepted and influential peace definitions nowadays.

2.2.2 Global Peace Index (GPI) Method

GPI was created by IEP to measure the level of negative peace for global nations and support empirical research of negative peace, for example, Dogan (2019) used GPI to study the gender determinants of direct violence.

Since 2009, the IEP expert panel has been publishing the GPI ranking every year without changing GPI indexing method of GPI. We take GPI 2019 as an example to illustrate the method of GPI (GPI, 2019). The indicator set of GPI 2019 is shown in figure 2-1 and the information of GPI 2019 is stored in table 2-1.

ONGOING DOMESTIC & INTERNATIONAL CONFLICT

- **Number and duration of internal conflicts**
  Uppsala Conflict Data Program (UCDP) Battle-Related Deaths Dataset, Non-State Conflict Dataset and One-sided Violence Dataset; Institute for Economics & Peace (IEP)
- **Number of deaths from external organised conflict**
  UCDP Georeferenced Event Dataset
- **Number of deaths from internal organised conflict**
  UCDP Georeferenced Event Dataset
- **Number, duration and role in external conflicts**
  UCDP Battle-Related Deaths Dataset; IEP
- **Intensity of organised internal conflict**
  Qualitative assessment by EIU analysts
- **Relations with neighbouring countries**
  Qualitative assessment by EIU analysts

SOCIETAL SAFETY & SECURITY

- **Level of perceived criminality in society**
  Gallup World Poll, IEP estimates
- **Number of refugees and internally displaced people as a percentage of the population**
  Office of the High Commissioner for Refugees (UNHCR) Mid-Year Trends; Internal Displacement Monitoring Centre (IDMC)
- **Political instability**
  Qualitative assessment by EIU analysts
- **Political Terror Scale**
  Gibney, Mark, Linda Cornett, Reed Wood, Peter Haschke, Daniel Arnon, and Attilio Pisanò. 2021. The Political Terror Scale 1976-2019. Date Retrieved, from the Political Terror Scale website: http://www.politicalterrorscale.org.
- **Impact of terrorism**
  IEP Global Terrorism Index (GTI)
- **Number of homicides per 100,000 people**
  United Nations Office on Drugs and Crime (UNODC) Surveys on Crime Trends and the Operations of Criminal Justice Systems (CTS); EIU estimates
- **Level of violent crime**
  Qualitative assessment by EIU analysts
- **Violent demonstrations**
  Armed Conflict Location and Event Data Project (ACLED); IEP
- **Number of jailed population per 100,000 people**
  World Prison Brief, Institute for Criminal Policy Research at Birkbeck, University of London
- **Number of internal security officers and police per 100,000 people**
  UNODC CTS
- **Ease of access to small arms and light weapons**
  Qualitative assessment by EIU analysts

MILITARISATION

- **Military expenditure as a percentage of GDP**
  The Military Balance, IISS, EIU Estimates
- **Number of armed services personnel per 100,000 people**
  The Military Balance, IISS
- **Volume of transfers of major conventional weapons as recipient (imports) per 100,000 people**
  Stockholm International Peace Research Institute (SIPRI) Arms Transfers Database
- **Volume of transfers of major conventional weapons as supplier (exports) per 100,000 people**
  SIPRI Arms Transfers Database
- **Financial contribution to UN peacekeeping missions**
  United Nations Committee on Contributions; IEP
- **Nuclear and heavy weapons capabilities**
  Military Balance+, IISS; IEP

Figure 2-1. Indicators of GPI 2019

Table 2-1. Information of GPI 2019

	Global Peace Index
Claimed target	Overall negative peace
Covering states/territories	172
Number of indicators	23
Internal / External	14 / 9
Indicator collection	Robust debate by IEP experts
Indicator weighting	Robust debate by IEP experts
Missing value estimation	Replaced by historical value

The indexing method of GPI is slightly overwhelmed, so we are going to review it following Babbie's five general indexing steps (Babbie, 2020), namely defining the indexing target, collecting indicators for the target, weighting the indicators, dealing with missing values, and computing the index. The indexing method of GPI is shown in table 2-2.

Table 2-2. The indexing method of GPI

1. Define the target of GPI. IEP experts claim that GPI aims to measure the level of overall negative peace, which refers to the aggregation of internal negative peace and external negative peace. Internal negative peace refers to the negative peace within the border of each country, external negative peace refers to the negative peace beyond the border (foreign relations).
2. Collect the indicators for GPI. Three dimensions are formalised to construct GPI, namely 'Ongoing domestic & international conflict', 'Societal safety and security', and 'Militarisation'. Through "robust debate", IEP experts collected 23 GPI indicators, 14 are internal indicators and 9 are external indicators.
3. Weight the indicators of GPI. The weights of GPI indicators are also determined through 'robust debate' by IEP expert panel. In addition, 60% weights are applied on internal indicators and 40% weights are applied on external indicators. IEP experts consider that high-level internal peace can lead to high-level external peace, therefore internal indicators should be more important and deserve higher fraction in the aggregated peace index.
4. Deal with the missing values of GPI. For every indicator of each country, the missing values are filled with the nearest historical value.
5. Compute GPI. The value of GPI is computed by the weighted average of 23 GPI indicators.

2.2.3 Positive Peace Index (PPI) Method

IEP expert panel claims that PPI aims to measure the level of overall positive peace and support the empirical research of positive peace. The goal of PPI is to measure 'the attitude, institutions, and structures that create and sustain peaceful society'. Some studies have been done according to PPI, e.g., Simangan (2021) used PPI to study the relationship between peace and environmental sustainability.

Since 2018, IEP expert panel has been publishing the PPI ranking every year without changing PPI indexing method. We take PPI 2019 as an example to show the method of PPI. The indicator set of PPI 2019 is shown in figure 2-2 and the information of PPI 2019 is stored in table 2-3.

Pillar	Domain	Indicator	Description	Source	Correlation coefficient (to the GPI)
Acceptance of the Rights of Others	Attitudes	Gender Inequality	The Gender Inequality Index (GII) reflects women's disadvantage in three dimensions: reproductive health, political empowerment and the labour market.	United Nations Development Programme	0.71
	Attitudes	Group Grievance	The Group Grievance Indicator focuses on divisions and schisms between different groups in society – particularly divisions based on social or political characteristics – and their role in access to services or resources, and inclusion in the political process.	Fragile States Index	0.64
	Attitudes	Exclusion by Socio-Economic Group	Exclusion involves denying individuals access to services or participation in governed spaces based on their identity or belonging to a particular group.	Varieties of Democracy (V-Dem)	0.72
Equitable Distribution of Resources	Structures	Inequality-adjusted life expectancy index	Measures the overall life expectancy of a population accounting for the disparity between the average life expectancy of the rich and that of the poor. The smaller the difference the higher the equality and that is a reflection of the equality of access to the health system.	United Nations Development Programme	0.62
	Institutions	Access to Public Services	Measures the discrepancies in access to public services distributed by socio-economic position.	Varieties of Democracy (V-Dem)	0.76
	Attitudes	Equality of Opportunity	Assesses whether individuals enjoy equality of opportunity and freedom from economic exploitation.	Freedom House	0.70
Free Flow of Information	Structures	Freedom of the Press	A composite measure of the degree of print, broadcast and internet freedom.	Reporters Without Borders (RSF)	0.50
	Attitudes	Quality of Information	Measured by Government dissemination of false information domestically: How often governments disseminate false or misleading information.	Varieties of Democracy (V-Dem)	0.60
	Structures	Individuals using the Internet (% of population)	Internet users are individuals who have used the Internet (from any location) in the last three months. The Internet can be used via a computer, mobile phone, personal digital assistant, games machine, digital TV etc.	International Telecommunication Union	0.61
Good Relations with Neighbours	Attitudes	Law to Support Equal Treatment of Population Segments	This is a measure of how population segments interrelate with their domestic neighbours. It assesses whether laws, policies, and practices guarantee equal treatment of various segments of the population.	Freedom House	0.66
	Structures	International Tourism	Number of tourists (Number of arrivals per 100,000 population) who travel to a country (staying at least one night) other than that in which they have their usual residence.	World Tourism Organization	0.63
	Institutions	External Intervention	The external intervention Indicator considers the influence and impact of external actors in the functioning - particularly security and economic - of a state.	Fragile States Index	0.71
High Levels of Human Capital	Structures	Share of youth not in employment, education or training (NEET)	Proportion of people between 15 and 24 years of age that are not employed and are not in education or training.	International Labour Organization	0.75
	Structures	Researchers in R&D	The number of researchers engaged in Research & Development (R&D), expressed as per one million population.	UNESCO	0.67
	Structures	Healthy life expectancy (HALE)	Average number of years that a newborn can expect to live in full health.	World Health Organisation	0.59

Low Levels of Corruption	Institutions	Control of Corruption	Control of Corruption captures perceptions of the extent to which public power is exercised for private gain.	World Bank	0.78
	Attitudes	Factionalised Elites	Measures the fragmentation of ruling elites and state institutions along ethnic, class, clan, racial or religious lines.	Fragile States Index	0.72
	Institutions	Public Sector Theft	Assesses perceptions of how often public sector employees steal, embezzle or misappropriate public funds or other state resources.	Varieties of Democracy (V-Dem)	0.73
Sound Business Environment	Institutions	Regulatory Quality	Captures perceptions of the ability of the government to formulate and implement sound policies and regulations that permit and promote private sector development.	World Bank	0.76
	Institutions	Financial Institutions Index	Part of the financial development index, this indicator measures the quality of the financial institutions, including the depth of the financial sector and the access to financial products.	International Monetary Fund	0.62
	Structures	GDP per capita	GDP per capita (current US$) is gross domestic product divided by midyear population.	International Monetary Fund	0.67
Well-Functioning Government	Institutions	Government Openness and Transparency	Assesses to what extent the Government operations can be legally influenced by citizens and are open to scrutiny from society.	Freedom House	0.63
	Institutions	Government Effectiveness: Estimate	Government Effectiveness captures perceptions of the quality of public services, the quality of the civil service and the degree of its independence from political pressures, the quality of policy formulation and implementation, and the credibility of the government's commitment to such policies.	World Bank	0.79
	Institutions	Rule of Law: Estimate	Rule of Law captures perceptions of the extent to which agents have confidence in and abide by the rules of society, and in particular the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence.	Bertelsmann Transformation Index	0.68

Figure 2-2. Indicators of PPI 2019

Table 2-3. Information of PPI 2019

	Positive Peace Index
Claimed target	Overall positive peace
Covering states/territories	163
Number of indicators	24
Internal / External	21 / 3
Indicator collection	Strongest correlation with internal GPI
Indicator weighting	Regression coefficients with internal GPI
Missing value estimation	Replaced by historical value

Same as the GPI, we review the method of PPI in table 2-4 according to Babbie's five general indexing steps.

Table 2-4. The indexing method of PPI

1. Define the target of PPI. IEP experts claim that PPI measures the level of overall positive peace, which refers to the aggregation of internal positive peace and external positive peace. Internal positive peace refers to the positive peace within the border of each country, external positive peace refers to the positive peace beyond the border (foreign relations).
2. Collect the indicators for PPI. IEP experts analyse over 24700 data series from open sources and then compute their correlations with the internal GPI, keeping 24 data series with the highest correlations left as the indicators of PPI. Among these 24 indicators, 21 are internal and 3 are external. IEP experts group these 24 indicators into eight pillars, namely "Acceptance of the rights of others", "Equitable distribution of resources", "Free flow of information", "Good relations with neighbours", "Level of human capital", "Level of corruption", "Sound business environment", "Well-functioning government", each of which is measured by three indicators. Amadei (2020) provided a system thinking to explicitly account for the relationships between these eight PPI pillars.
3. Weight the indicators of PPI. The weights of PPI indicators are determined by their correlation coefficients with the internal GPI.
4. Deal with the missing values of PPI. For every indicator of each nation, the missing value slots are filled with the nearest historical value. This missing value estimation method is applied on all 24 indicators to ensure the feasibility of PPI computation.
5. Compute PPI. The value of PPI is computed by the weighted average of 24 PPI indicators.

2.3 Concrete Limitations of GPI and PPI methods

Keith Gottschalk's criticism towards GPI ascribed its unpopularity to the subjectiveness of IEP experts embedded in the indicator collection and weighting steps (Gottschalk, 2015). However, he didn't illustrate why the subjectiveness can damage the credibility of GPI, as he didn't reveal any concrete limitations of GPI. In this section, we will come up with some concrete limitations of GPI and PPI methods, list them according to the five general indexing steps, and figure out how they can damage the credibility of GPI and PPI.

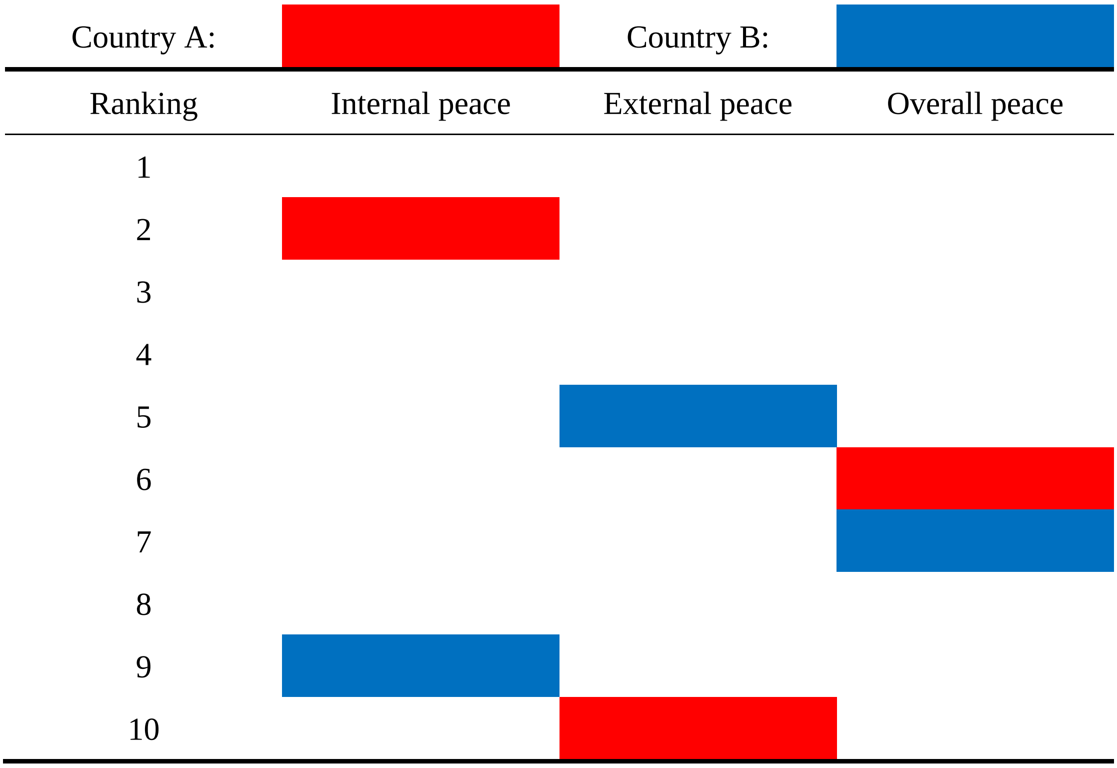
2.3.1 Define the targets of GPI and PPI: Debatable target aggregation

When defining the targets of GPI and PPI, IEP experts decided to measure overall peace status, which aggregates both internal and external aspects. This decision may cause a concern. Kacowicz (1997) observed that some west African countries with widespread internal violence however had peaceful relationships with their neighbours. He suggested that peace researchers should evaluate a country's internal and external peace separately, rather than combined, since the underlying mechanism to treat countrymen and foreigners could be different. The key point here is to figure out whether the phenomenon observed by Kacowicz appears in countries across the world, or in other words, whether the overall correlation between internal and external peace is indeed negative.

If the correlation between internal and external peace is negative, then overall peace index will lose information and can be misleading. In table 2-5, we display a numerical example to illustrate this situation. Supposed that there are two countries, country A and country B. Red slots represent the rankings of country A, blue slots represent the rankings of country B. Country A has high-level internal peace but low-level external peace, while country B has low-level internal peace but medium-level external peace.

The overall peace ranking is computed by the average of internal and external peace, in which country A is at a slightly higher position than country B.

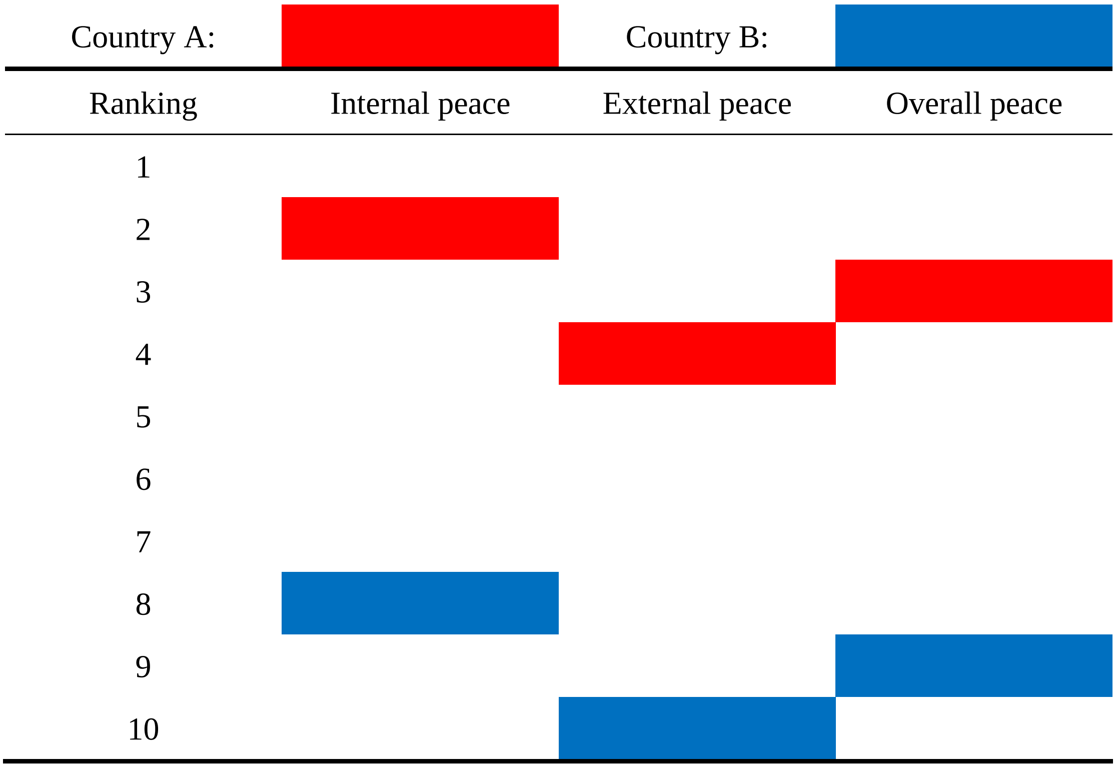
Table 2-5. Negative correlation between internal and external peace



If the correlation between internal and external peace is negative, then country A and B will be common cases in the ranking, and the rankings of internal peace, external peace, and overall peace will be significantly different from each other. In this situation, the overall peace index will not be a credible measurement since we don't know how much of it should be attributed to internal or external aspects, and it will be a must to measure internal and external peace separately, otherwise a bellicose country (such as invading other countries could have a decent overall peace ranking due to its peaceful internal environment, or a chaotic country (such as experiencing a civil war) could have a decent overall peace ranking by sharing peaceful relationships with other countries, neither of these two cases should be allowed in a credible peace index.

If the correlation between internal and external peace is positive, then the credibility of the overall peace index will suffer less from not separating internal and external peace compared to the situation of negative correlation. Table 2-6 shows a numerical example of positive correlation, in which country A has higher rankings of internal peace, external peace, and overall peace than country B.

Table 2-6. Positive correlation between internal and external peace



In this situation, the rankings of internal peace, external peace, and overall peace will be relatively close to each other, therefore even if we use overall peace ranking to realise the level of internal or external peace, the gap won't be as significant as the situation of negative correlation. There might be some outlier countries, which have high-level internal peace but low-level external peace or low-level internal peace but high-level external peace, however since the correlation of population is positive, these cases are just minority and will only have limited influence on the overall peace index. Certainly, if we want to obtain the accurate peace index, we still need to report internal and external peace separately.

The discussion of internal and external peace aggregation can be transferred to think about negative and positive peace aggregation. Many literatures indicated that the correlation between negative and positive peace is positive (Bönisch, 1981; Boulding, 1978; Galtung, 1969; Kelman, 1981), since a more equal and just society can decrease people's willing of committing direct violence. This judgement also needs to be checked by evaluating the correlation between negative and positive peace. If the correlation is negative, we must separate negative and positive peace as individual peace indexes. If the correlation is positive, aggregating negative and positive peace to form an overall peace index can be an optional choice since it is less harmful compared to the situation of negative correlation.

Now we can apply the above discussions on the credibility analysis of GPI ranking. IEP experts claim that GPI measures the level of overall negative peace. However, the most GPI indicators are internal negative indicators (14 / 23). Moreover, the weights of internal indicators are set to be bigger than the weights of external indicators (60% vs 40%). In fact, the ranking of GPI is highly biased towards internal negative peace. If a causal reader or heedless researcher only reads the claimed target of GPI without reading its method, they will be misled. The credibility of GPI depends on the correlation between internal negative peace and external negative peace. If the correlation is positive, the ranking of GPI can be trusted since internal negative peace ranking (mainly measured target) will be close to overall negative peace ranking (claimed target). If the correlation is negative, the ranking of GPI should not be trusted since the internal negative peace ranking (mainly measured target) will dominate and can be significantly different from the overall negative peace ranking (claimed target).

We can also apply the discussions on the credibility analysis of PPI ranking. IEP experts claim that PPI measures the level of overall positive peace. In fact, 90% indicators (21 / 3) are internal indicators, which means that PPI is highly biased to internal positive peace. Likewise, the credibility of PPI depends on the correlation between internal positive peace and external positive peace. If the correlation is positive, the ranking of PPI can be trusted since internal positive peace ranking (mainly measured target) will be close to overall positive peace ranking (claimed target). If the correlation is negative, the ranking of PPI should not be trusted since the internal positive peace ranking (mainly measured target) will dominate and can be significantly different from the overall positive peace ranking (claimed target).

To conclude this part, the decision of aggregating internal and external peace, negative and positive peace should be made according to the empirical result of regression, instead of subjective judgement.

2.3.2 Collect indicators for GPI & PPI: Invalid indicators

Regardless of using subjective or objective indicator collection methods, both GPI and PPI contain some invalid indicators beyond respective scope of negative and positive peace, which contaminate the purity of indexing targets and reduce the credibility of indexes.

For example, GPI includes an indicator called "Number of internal security officers and police per 100,000 people". According to the definition, police resource is not a kind of direct violence as it is not an action that harms people, therefore should be excluded from negative peace index. In fact, police resource is a cause of direct violence, since it can affect "crime rate" which is a typical direct violence indicator (Machin & Marie, 2005). When comparing different countries' internal peace statuses, if all other violence indicators are at the same levels, then countries with lower crime rates should be considered more peaceful than countries with higher crime rates, no matter how much police resources they have, this is however not guaranteed in GPI due to its invalid indicators. In GPI, if some countries have more security resources but higher crime rates, it will be totally possible for them to have higher GPI rankings than countries which have few security resources but lower crime rates, only due to the gap between their security resources.

PPI also contains some invalid indicators that don't line up with the definition of positive peace. PPI indicators are selected due to their strong correlations with internal GPI, but this method doesn't guarantee the collected indicators to follow the definition of positive peace. Some indicators that are highly correlated with internal GPI but beyond the scope of positive peace also might be collected, e.g., PPI includes "GDP per capita" as an indicator, since prosperity can reduce internal violence by providing abundant security and educational resources (Buonanno, Montolio & Vanin, 2009; Jonathan et al., 2021), but "GDP per capita" is a not a kind of structural violence as it measures the level of economic development instead of unjust social structure, therefore should be excluded from the positive peace index. In fact, "GDP per capita" is a cause of structural violence, since economic development can affect the amount of unjust social structures (Kuttner, 1987). In PPI, countries with more unjust social structures are totally possible to be ranked higher than countries with less unjust social structures, only due to the gap between their economic developments.

IEP experts collected GPI indicators through 'robust debate' and collected PPI indicators by doing regression with internal GPI. No matter subjective or objective the collection method is, both GPI and PPI contain invalid indicators which contaminate the purity of indexing targets and reduce the credibility of indexes. This means that the indicator validation issue of GPI and PPI should not be ascribed to the subjectiveness involved in indicator collection process. To get rid of invalid indicators, indicator validation function should be provided during indicator collection process to check the validity of indicators and deny those which are beyond the scope of indexing target.

2.3.3 Weight the indicators of GPI & PPI: Invalid PPI weighting

The weights of PPI indicators were set to be regression coefficients with internal GPI. IEP experts didn't tell why these coefficients are the relative importance of PPI indicators. As we have discussed in chapter 2.3.2, PPI contains an invalid indicator called "GDP per capita", which should not even be included in PPI according to the definition of positive peace, not to mention its weight.

A more reasonable way to weight indicators is to regress indexing target on indicators and set regression coefficients as indicators weights. This method requires knowledge of latent variable analysis since indexing target is unknown before being computed by indicators.

2.3.4 Deal with GPI & PPI missing values: Unrealistic assumption

Both GPI and PPI contain dozens of indicators which make them hard to compute, as long as one indicator's value is missing, the whole index will be incalculable. IEP experts decided to fill the missing values of the indicators of GPI and PPI with their nearest historical value, e.g., GPI includes an indicator called "Number and Duration of Internal Conflicts" which only has data between 2013-2017, data between 2018-2019 is missing. To compute GPI 2019, the data of "Number and Duration of Internal Conflicts" in 2017 was used to represent its value in 2019.

The missing value estimation method of GPI and PPI implies a strong assumption that the indicators will remain stable in the missing value period, regardless of the length of the period. This assumption increases the feasibility of GPI and PPI but decreases their accuracy since all the changes during the missing value period are ignored. To increase the credibility of the estimated values of GPI and PPI, the new missing value estimation method should rely on more realistic assumptions and consider the changes during the missing value period.

2.4 Criteria for Peace Indexing Method

To counter the four concrete limitations of GPI and PPI, we come up with the following four criteria that the peace indexing methods should have done:

1) Set up the indexing targets at the minimum scale, and after computing the levels of these minimum targets, check the empirical results of their correlations to determine whether they could be aggregated.

2) Have the indicator validation function to deny invalid indicators that are beyond the scope of the indexing target.

3) Compute correlations between the target and indicators as the indicator weights, which requires the framework of latent variable analysis.

4) Equip with a missing value estimation method which is based on more realistic assumptions and consider the changes during the missing value period.

2.5 Conclusions

In this chapter, we firstly review the methods of the GPI and PPI. Then, we propose four concrete limitations of GPI and PPI in terms of target aggregation, indicator validation, indicator weighting (PPI), and missing value estimation. To design the peace indexing method that can deal with these limitations, we come up with four criteria that the peace indexing method should meet.

Now the research gap has been identified and the first research problem has been answered. The low credibility of GPI and PPI are more possibly ascribed to their four concrete limitations, rather than Gottschalk's criticism towards the subjectiveness. The original research problems are now revised as follows:

1) How can we develop a peace indexing method to solve the target aggregation, indicator validation, indicator weighting (PPI), and missing value estimation limitations of the methods of the GPI and PPI?

The revised research aim is to create the peace indexes without the four concrete limitations of the GPI and PPI to measure the levels of negative and positive peace. As the first research objective in chapter 1.4 has been achieved, the rest research objectives are revised as follows:

1) To search for the existing indexing method that can meet the four criteria. If no such a method exists, we will propose our new peace indexing method.

2) To demonstrate the theoretical advantages of our peace indexing method by solving the target aggregation, indicator validation, indicator weighting (PPI), and missing value estimation limitations of the GPI and PPI methods.

3) To use the new peace indexing method to establish specific peace indexes to measure the levels of negative and positive peace as the evaluation to our peace indexing method, to check whether the peace indexes are free of the limitations of GPI and PPI.

The core contribution of this research will be the new peace indexing method, which we expect to overcome the concrete limitations of the GPI and PPI methods. In this thesis, some specific indexes will be created as the evaluation to our new peace indexing method, which can be seen as the side contribution of this research. In practice, any researchers who want to create peace index can apply our method to create their own.

Chapter 3 Research Methodology

3.1 Introduction

In this chapter, we will discuss the research methodology of this thesis. This research perfectly fits the philosophy of design science research (DSR) (Hevner & Chatterjee, 2010), which is a widely used paradigm in informatic system and computer science. Figure 3-1 shows the process of DSR (Peffers et al., 2020), including six steps, namely problem identification & motivation, objectives of a solution, design and development, demonstration, evaluation, and communication. We will illustrate these six steps to show how our research is conducted.

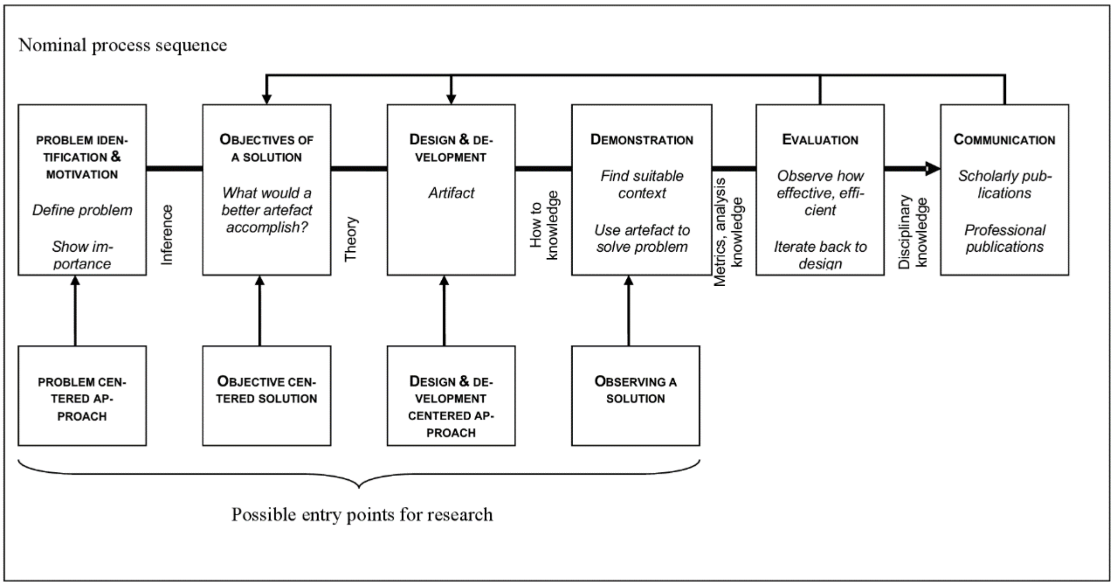


Figure 3-1. Design science process (Peffers et al., 2020)

3.2 Problem Identification & Motivation

In "problem identification & motivation" step, researchers should define their problems, understanding relevance, current solutions, and their weaknesses. Researchers will also need to demonstrate whether the envisioned design is crucial for practice (Sonnenberg

& Vom Brocke, 2012).

In chapter 1.2, we have illustrated the importance of the peace indexes, as they aim to measure the most important concepts in peace research, the negative and positive peace. The research problem is about establishing the peace indexes to measure the levels of negative and positive peace. Currently, the only solution to this problem is the GPI and PPI, yet both of which are hardly used in empirical peace research. The literature attributed the low credibility of GPI to the subjectiveness embedded in its method, which is not a persuasive explanation since it didn’t tell how the subjectiveness reduced the credibility of GPI.

In chapter 2.2 and 2.3, we review the methods of GPI and PPI and identify their four concrete limitations (weaknesses). The research problem has been fully identified in chapter 2.5: how can we develop a new peace indexing method to overcome the four concrete limitations of the methods of the GPI and PPI?

3.3 Objectives of a solution

The second step is to define the objectives of a solution. Researchers need to analyse how the problem should be solved by listing step-by-step objectives. By analysing the weaknesses of current solutions, specific criteria that the solution should meet need to be established, and knowledge of what is possible and what is feasible should be fully researched to set up the basis of the solution.

In chapter 2.4, we come up with four criteria that the peace indexing method should meet to avoid the limitations of the methods of the GPI and PPI. In chapter 2.5, after identifying the concrete research problem, we propose three research objectives to approach the research aim. At this point, this study is still undergoing this step since we haven’t reviewed the knowledge of the indexing methods. We will do this in chapter 4 to see if we can get some inspirations from other indexing literatures to build the peace indexing method that can deal with the limitations of the methods of the GPI and PPI.

3.4 Design and Development

The third step "design and development" is to create an artefact in which the research contribution is embedded that solves the research problem. This step relies on the knowledge and criteria in step two.

According to the four criteria in chapter 2.4, we will search for knowledge of indexing method to establish the peace indexing method which can overcome the four limitations of the GPI and PPI methods. If no existing indexing methods can meet these four criteria, we will propose our own. We will need to illustrate the theoretical advantages of our peace indexing method by solving the four concrete limitations of GPI and PPI methods.

3.5 Demonstration

In "demonstration" step, researchers need to demonstrate the usage of the new artefact in practice. Researchers should provide the knowledge of how to use the new artefact to create one or more specific instances.

In terms of our research, we will need to use the new peace indexing method to establish specific peace indexes to measure the level of negative and positive peace.

3.6 Evaluation

This "evaluation" step tries to answer how well the new artefact works in practice.

Researchers need to observe and measure how well the artefact supports a solution to the problem by comparing the objectives with the observed results.

In this research, we will need to use our peace indexing method to create specific peace indexes and see whether they are indeed free of the limitations of the GPI and PPI.

3.7 Communication

This step is trying to communicate the problem, its solution, and the utility, novelty, effectiveness, and limitations of the new solution to researchers and other relevant audiences.

We will need to clarify the contributions and limitations of our peace indexing method and give an outlook to the future works.

3.8 Conclusions

In chapter 3, we have illustrated the research methodology of this study, the design science research (DSR). In chapter 1 and 2, the "problem identification & motivation" step and "objectives of a solution" step have been fulfilled, that we have managed to identify the research problem, propose the weaknesses of current solutions, and set up some criteria for the better solutions. The next step will be searching for relevant indexing literatures and designing a new peace indexing method which can meet the criteria.

Chapter 4 Design and Development

4.1 Introduction

Chapter 4 corresponds to the design and development step of the DSR, in which we will review the existing indexing knowledge according to the four criteria proposed in chapter 2.4, and then create our new indexing method. We will illustrate this new indexing method step-by-step and demonstrate how it can deal with the four concrete limitations of GPI and PPI methods theoretically.

4.2 Reflective Indexing

There are two main types of indexing method, the formative indexing, and the reflective indexing. Many researchers have discussed the distinctions between formative indexing and reflective indexing (Coltman et al., 2008; Diamantopoulos & Siguaw, 2006; Freeze & Raschke, 2007).

The formative indexing is a model-free indexing method, which follows the philosophy of "constructing the target". The target of the formative index is the aggregation of indicators, which has nothing to do with causal analysis. The indicator weights of formative index are considerations of relative importance of indicators, analytic hierarchy process (AHP) is a classic weighting method of formative indexing. All the indexes mentioned in chapter 1 (HDI, CPI, DJIA, IF, and GPI & PPI) are the representatives of formative indexes.

The reflective indexing is a model-based (SEM-based) indexing method, which is derived from the philosophy of "reflecting the target". In reflective indexing, the target is a latent construct in SEM, the indicators are the outcome variables of the target, the weights are their factor loadings. The reflective indexing uses indicators to reflect the value of the target. Passenger Satisfaction Index (PSI) (Shen, Xiao & Wang, 2016; Zhang et al., 2019) and Customer Satisfaction Index (CSI) (Hsu, Chen & Hsieh, 2006) are the representatives of the reflective indexes.

We have found that the reflective indexing can naturally meet some of the criteria in chapter 2.4, due to its model-based characteristics. In chapter 4.2, we will illustrate why the reflective indexing could be a solid basis to develop our new peace indexing method. Since the reflective indexing is based on the structural equation modelling (SEM), we will firstly review the procedure of SEM analysis, then review the reflective indexing and compare it with the methods of GPI & PPI.

4.2.1 Structural Equation Modelling (SEM)

The structural equation modelling (SEM) can be seen as a combination of path analysis and factor analysis, which has been widely used in many research fields, such as sociology, psychology, biology, etc (Bollen, 1989)

In figure 4-1, we create an example to illustrate the procedure of the SEM analysis. In SEM, the circle nodes represent the latent constructs, the rectangular nodes represent the observed variables (a.k.a. outcome variables, measured indicators), and δ_{11}, δ_{21}, ζ_1, ζ_2, ε_{11}, ε_{21}, ε_{21}, ε_{22} represent residual variables. A directed edge from variable A to variable B means that variable A is a cause of variable B. If there is no edge pointing to a variable, the variable will be called an exogenous variable (e.g., ξ_1); otherwise, the variable will be called an endogenous variable (e.g., η_1 and η_2). All the latent constructs, the non-indicator covariates, and their causal relationships together form the conceptual model, which is created to describe the prior knowledge of reality. Every latent construct and its observed variables together form a measurement model.

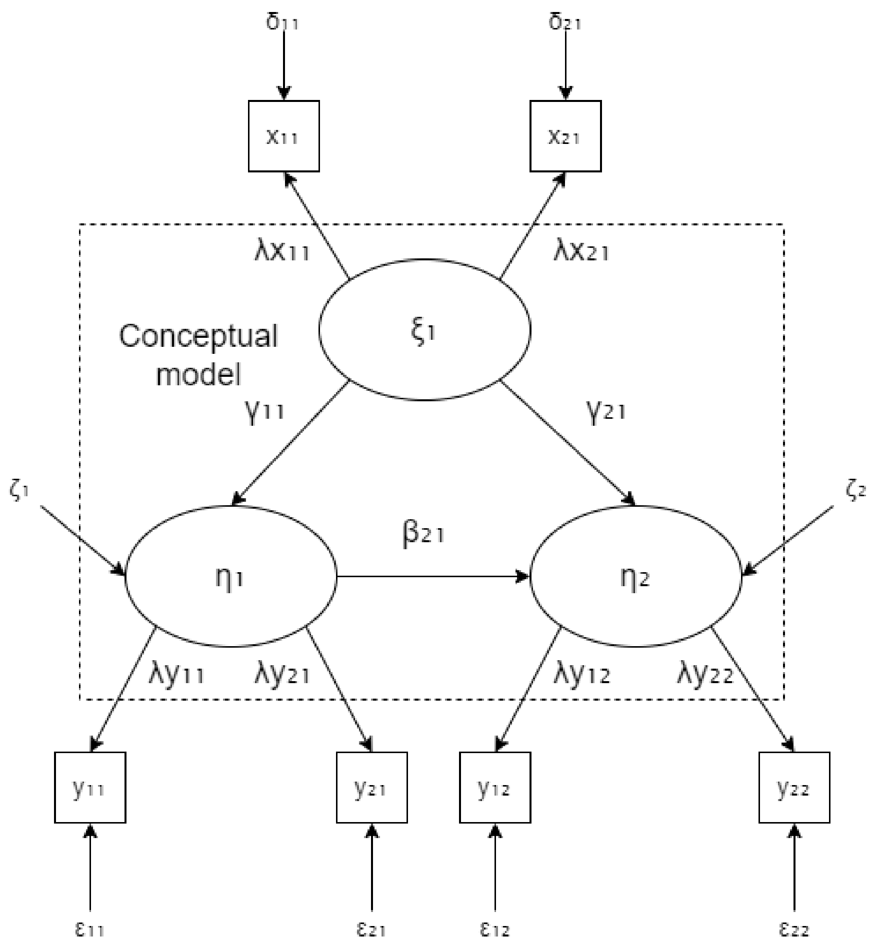


Figure 4-1. An example of SEM

If we put the linear assumption on the SEM, we will obtain a linear SEM (1) – (4), in which γ_{11}, γ_{21}, β_{21} are the structural coefficients, λx_{11}, λx_{21}, λy_{11}, λy_{21}, λy_{12}, λy_{22} are the factor loadings. The linear SEM is the most widely used SEM system, in which the variables are assumed to follow the normal distribution. If the normality assumption holds, the parameters of linear SEM can be estimated by reconstructing covariance structure using the maximum likelihood estimation (MLE). Otherwise, the parameters of linear SEM should be estimated using the partial least square (PLS) estimation (F. Hair Jr et al., 2014). In general, if the normality assumption holds, the MLE estimation will be better than PLS estimation, since the dimension reduction of PLS will lose the information of data.

$$\begin{pmatrix}\eta_1\\ \eta_2\end{pmatrix} = \begin{pmatrix}0 & 0\\ \beta_{21} & 0\end{pmatrix}\begin{pmatrix}\eta_1\\ \eta_2\end{pmatrix} + \begin{pmatrix}\gamma_{11}\\ \gamma_{21}\end{pmatrix}\xi_1 + \begin{pmatrix}\zeta_1\\ \zeta_2\end{pmatrix} \qquad (1)$$

$$\begin{pmatrix} x_{11} \\ x_{21} \end{pmatrix} = \begin{pmatrix} \lambda_{x11} \\ \lambda_{x21} \end{pmatrix} \xi_1 + \begin{pmatrix} \delta_{11} \\ \delta_{21} \end{pmatrix} \tag{2}$$

$$\begin{pmatrix} y_{11} \\ y_{21} \end{pmatrix} = \begin{pmatrix} \lambda_{y11} \\ \lambda_{y21} \end{pmatrix} \eta_1 + \begin{pmatrix} \varepsilon_{11} \\ \varepsilon_{21} \end{pmatrix} \tag{3}$$

$$\begin{pmatrix} y_{12} \\ y_{22} \end{pmatrix} = \begin{pmatrix} \lambda_{y12} \\ \lambda_{y22} \end{pmatrix} \eta_2 + \begin{pmatrix} \varepsilon_{12} \\ \varepsilon_{22} \end{pmatrix} \tag{4}$$

No matter which estimation method is used, in order to obtain a unique estimation of the parameters of the linear SEM, two conditions must be met (DeVellis & Thorpe, 2021): 1) The SEM must be identifiable, which means that every latent construct must have at least two observed variables. 2) The SEM must have a fixed measurement scale. In this research, the second condition is met by setting the variances of the latent constructs to be one. Therefore, the only condition left is to obtain at least two indicators for every latent construct. The four steps of the SEM analysis are shown in table 4-1:

Table 4-1. The procedure of the SEM analysis

1.	Establish a conceptual model to describe the prior knowledge of the reality.
2.	For every latent construct in the conceptual model, collect at least two indicators with content validity.
3.	Implement the confirmatory factor analysis (CFA) and find an indicator subset which can pass the reliability test, convergent validity test, and discriminant validity test on every measurement model (with decent CFA fitness). If such subset exists and every latent construct has at least two qualified indicators, then the indicator subset will be regarded as a reliable measurement and fed into the SEM (forward to step 4). Otherwise, for latent constructs that don't have enough qualified indicators, more indicators with content validity should be collected for them (back to step 2), or the conceptual model will need to be simplified by pruning off these latent constructs (back to step 1).
4.	Fit the SEM parameters with the qualified indicator subset returned by step 3.

There are some places that need to be further clarified in the above SEM procedure, such as the content validity test, the reliability test, the CFA, the convergent validity test, and the discriminant validity.

The content validity test is a subjective test of indicators, to pass which researchers need to demonstrate that, based on the domain knowledge or in common sense, the collected indicators are rational outcome variables of their corresponding latent construct.

The reliability test refers to the internal consistency test, which measures the extent of dependences across a set of indicators. The logic of internal consistency test is that if a group of indicators are significantly caused by the same latent construct, researchers should be able to observe strong correlations between these indicators. The Internal consistency of each measurement model is measured by Cronbach α (Brown, 2002), see Eq. (5), in which n is the number of indicators and y_i represents $i-th$

indicator. The more dependent the $y_i s$ are, the smaller $\sum_{i=1}^{n} Var(y_i)$ will be compared to $Var(\sum_{i=1}^{n} y_i)$, and the bigger Cronbach α will be. By convention, the acceptable value of Cronbach α should be greater than 0.7.

$$\alpha = \frac{n}{n-1}\left[1 - \frac{\sum_{i=1}^{n} Var(y_i)}{Var(\sum_{i=1}^{n} y_i)}\right] \tag{5}$$

The convergent validity test and the discriminant validity test check how likely a group of indicators are indeed caused by their corresponding latent construct, both of which are based on the result of the Confirmatory Factor Analysis (CFA). The CFA is constructed by extracting the latent constructs in the conceptual model and replacing the directed edges with bi-directional edges. The CFA for the SEM in figure 4-1 is shown in figure 4-2.

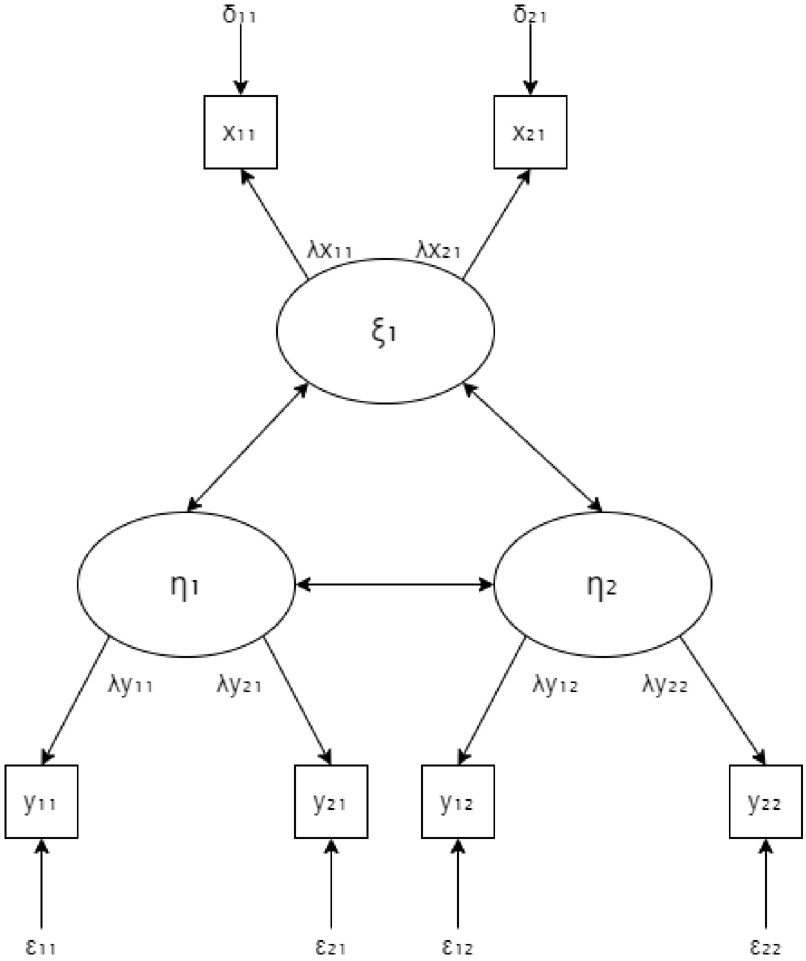


Figure 4-2. The CFA for the SEM in figure 4-1

The convergent validity test examines the average strength of factor loadings of the measurement model. If a group of indicators are caused by a latent construct, we will expect the average factor loading to be large. The convergent validity test on each measurement model j (with latent construct j) has three criteria (DeVellis & Thorpe, 2021): 1) All factor loadings λ_{ij} should be greater than 0.5. 2) Average Variance Extracted (AVE, see Eq. (6)) should be greater than 0.5. 3) Composite Reliability (CR, see Eq. (7)) should be greater than 0.7.

$$AVE_j = \frac{\sum_{i=1}^{n} \lambda_{ij}^2}{n} \tag{6}$$

$$CR_j = \frac{\left(\sum_{i=1}^{n} \lambda_{ij}\right)^2}{\left(\sum_{i=1}^{n} \lambda_{ij}\right)^2 + \sum_{i=1}^{n}\left(1 - \lambda_{ij}^2\right)} \tag{7}$$

The discriminant validity test examines to what extent the indicators of a latent construct are distinct from the indicators of other latent constructs. If the square root of AVE of a measurement model j is greater than correlations between the latent construct j and all other latent constructs, then the latent construct j and its indicators will be regarded to have discriminant validity.

The model fitness of CFA also needs to be checked, which measures how well the CFA model fits the practical data. If the CFA is poorly fitted, then the validity tests by this CFA should not be trusted. There are many criteria for measuring the fitness of CFA (or SEM), such as CFI, GFI, AGFI, NFI, TLI, and RMSEA. The most frequently used one is the root mean square error of approximation (RMSEA), see Eq. (8).

$$RMSEA = \sqrt{\frac{\frac{\chi^2 - df}{N}}{df}} \tag{8}$$

The minimum discrepancy function of covariance matrix follows χ^2 distribution, N is the sample size and df is the degree of freedom. The smaller χ^2 is, the better CFA (or SEM) fits the data. By convention, if the RMSEA is less than 0.05, then the CFA (SEM) will be seen as a well-fitted model, and researchers can demonstrate the credibility of the coefficients of their CFA (or SEM) model. The Modification Indice (MI) of an indicator is the reduction on χ^2 after removing this indicator from the CFA (SEM) (see Eq. (9)), which is often used to adjust the indicator set to get a better fitted CFA (SEM).

$$MI = \chi_{before}^2 - \chi_{after}^2 \tag{9}$$

The goal of step 3 is to find at least two qualified indicators for each latent construct. If a measurement model passes the reliability test and validity tests (with decent CFA fitness), then researchers can be confident that these indicators are indeed caused by the corresponding latent construct.

However, it is likely that some initial indicators will fail at either reliability test or validity tests (including CFA fitness test). To obtain a qualified indicator subset, researchers usually need to drop some indicators with small factor loadings to make the adjusted measurement models reliable and valid. If the CFA is poorly fitted, researchers need to drop some indicators with large MIs to make the adjusted CFA well-fitted. In the classic SEM studies, these adjustments were done manually and implicitly, researchers only displayed the final indicator set and demonstrated that they can pass the reliability and validity tests, without showing the indicator adjustment process.

4.2.2 Procedure of Reflective Indexing

The reflective indexing is an application of the SEM analysis. We will illustrate the reflective indexing procedure in table 4-2 according to the five indexing steps (Zhang et al., 2019):

Table 4-2. The procedure of the reflective indexing

1. Define the target of the reflective index. Researchers need to establish a conceptual model including the indexing target as a latent construct and describe the prior knowledge of the indexing target. If the target has multiple aspects, then these aspects should be set as individual latent constructs in the conceptual model, since the latent constructs as random variables, should have clear sample space.
2. Collect indicators for the target of the reflective index. For each latent construct in the conceptual model, at least two indicators with content validity should be collected. Then, the reliability and validity (including CFA fitness) of the indicator set should be tested. If the current indicator set can pass all the statistical tests, researchers can deliver it as a qualified indicator set to the SEM. Otherwise, researchers should drop some indicators with small factor loadings or large MIs and then rerun the statistical tests on the adjusted indicator set. This indicator selection process will be iterated until a qualified indicator set is returned, or some latent constructs don't have enough indicators (< 2). For the latter case, researchers will need to collect more indicators with content validity or prune off the invalid measurement model and then re-implement step 2.
3. Weight the indicators of the reflective index. Once a qualified indicator set is obtained, it can be used to fit the parameters of the SEM. The indicator weights of the reflective index are set to be the factor loadings between the indicators and their corresponding latent construct.
4. Deal with the missing values of the reflective index. The reflective indexing doesn't provide algorithms to estimate the missing values.
5. Compute the reflective index. The reflective index will be reflected by the weighted average of its indicators, the weights are the factor loadings between them.

4.2.3 Reflective Indexing vs. GPI & PPI methods

In chapter 2.3, we analysed four concrete limitations of GPI and PPI methods. Then in chapter 2.4, to solve these four limitations, we proposed four criteria that the peace indexing method should meet. In this section, we will discuss to what extent does the reflective indexing meet these four criteria.

When defining the indexing target, the reflective indexing requires the different aspects of the target to be individual latent constructs in the conceptual model, which can help to decompose the compounded concepts and reduce the possibility of debatable target aggregation.

The reflective indexing provides the reliability and validity tests to deny invalid indicators. The content validity test provides a framework based on the causal analysis to check whether the indicators make sense to be the observed indicators of the target, e.g., both the GPI indicator “Number of internal security officers and police per 100,000 people” and the PPI indicator “GDP per capita” will be denied since they are the causal variables of negative peace and positive peace respectively (Buonanno, Montolio & Vanin, 2009; Jonathan et al., 2021; Machin & Marie, 2005), rather than their outcome variables. The reflective indexing also provides the reliability test, convergent validity test, and discriminant validity test to check the statistical credibility of the collected indicators, which can ensure that the selected indicators are not only valid in terms of their content, but also in terms of their practical data.

The reflective indexing is based on the SEM, which is intrinsically related to the latent variable analysis. The indicator weights of reflective index are the factor loadings between indicators and corresponding latent construct, which are more reasonable than the indicator weights of PPI, since they directly measure the correlations between the target and the indicators.

Even though the reflective indexing doesn't equip any missing value estimation methods, the structure of the conceptual model can still be useful to estimate the missing values. For example, supposed that the current value of a latent construct is missing, but the values of its parent nodes can be obtained, then the current value of the latent construct can be deduced via the structural equation, this method is called the counterfactual analysis (Morgan & Winship, 2015). The conceptual model provides a basis for developing more specific and effective missing value estimation methods than GPI and PPI, since the structural equation can consider the changes of the indicators during the missing value period.

However, the reflective indexing method brings in its own limitation. Due to the lack of the standard indicator selection method, researchers need to manually drop the statistically invalid indicators. Given an initial indicator set, there might exist more than one set of indicators that can pass the reliability and validity tests, so researchers may end up with different qualified indicator set according to their different manipulations. Ideally, we want the qualified indicator subset to have the maximum indicators, therefore the reflective index can be the most comprehensive one among all the available qualified indicator subsets. This is however not easy if the indicator manipulation is done manually, especially when the indicator set is too large.

To different extents can the reflective indexing method help to solve the four limitations of GPI and PPI methods. The reflective indexing provides a solid basis for developing our new peace indexing method, which needs to go further by solving the limitations of GPI & PPI methods and dealing with the limitation of the reflective indexing method.

4.3 Automatic Reflective Indexing (ARI)

In chapter 4.2, we have reviewed the knowledge of the reflective indexing, which forms the basis for our new peace indexing methods. In this chapter, we will illustrate our new peace indexing method based on the reflective indexing, and then explain the theoretical advantages of this method compared to the reflective indexing and the GPI & PPI methods.

4.3.1 Procedure of Automatic Reflective Indexing (ARI)

The procedure of the automatic reflective indexing (ARI) is shown in table 4-3:

Table 4-3. The procedure of the automatic reflective indexing (ARI)

1. Define the ARI target (same to the reflective indexing). Researchers need to establish a conceptual model including the indexing target as a latent construct and describe the prior knowledge of the indexing target. If the target has multiple aspects, then these aspects should be set as individual latent constructs in the conceptual model.
2. Collect and select indicators for the ARI target. For each latent construct in the conceptual model, at least two initial indicators with content validity should be collected. Then, ARI provides an automatic indicator selection module to drop the invalid indicators according to the results of the reliability and validity tests. This process will be iterated until a qualified indicator set is returned, or some latent constructs don't have enough indicators (< 2). For the latter case, researchers will need to collect more indicators with content validity or prune off the invalid measurement models and then re-implement step 2.
3. Weight the ARI indicators (same to the reflective indexing) Once a qualified indicator set is obtained, it can be used to fit the parameters of the SEM. The indicator weights of the automatic reflective index are set to be the factor loadings between the indicators and their corresponding latent construct.
4. Compute the automatic reflective index (same to the reflective indexing). The automatic reflective index will be reflected by the weighted average of its indicators, the weights are the factor loadings between them.
5. Deal with the missing values in the index table. ARI provides a group of dynamic missing value estimation algorithms for fitting the missing values in the index table.

ARI has two major modifications to the reflective indexing, the automatic indicator selection module, and the dynamic missing value estimation algorithms. In ARI, the order of index computation and missing value estimation is switched, since the missing value estimation of ARI is conducted on the level of the index (the latent construct), rather than the level of indicators.

The first modification of ARI compared to reflective indexing is the automatic indicator selection module, see figure 4-3, which is created by using the greedy algorithm to formalise the indicator validity tests of reflective indexing. This module is trying to approach the maximum qualified indicator subset by pruning the minimum indicators in each iteration. Two small-scale iterations are implemented in the automatic indicator selection module, namely the reliability & validity tests, and the CFA model fitness test. Only valid indicators (in terms of both content and statistics) with transparent methods will be selected for use within the SEM model.

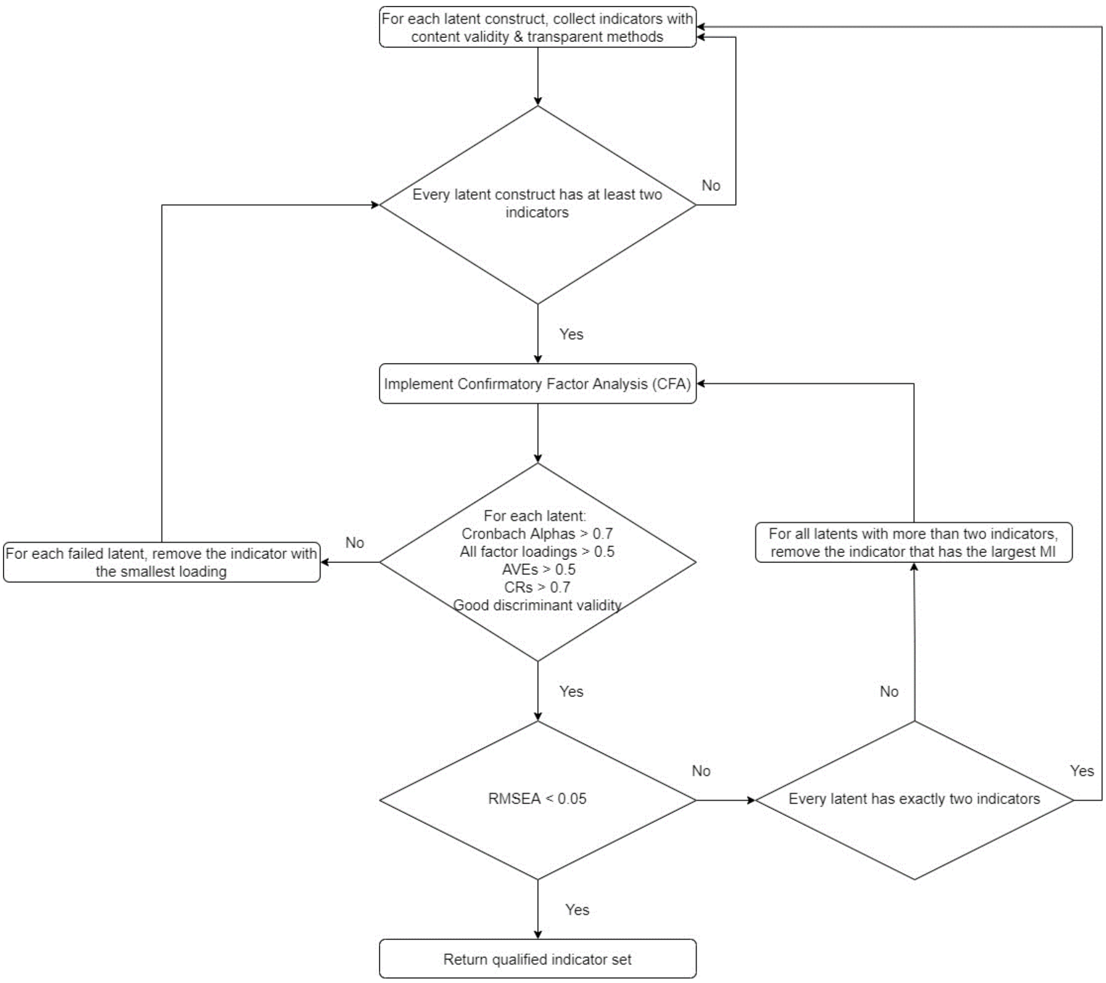


Figure 4-3. The automatic indicator selection module of ARI

Firstly, just like the reflective indexing, researchers will need to collect indicators with content validity to form the initial indicator set. For each latent construct, at least two initial indicators need to be collected. Since the ARI is also a model-based method, researchers can apply causal analysis to determine whether an indicator has content validity, or in other words, whether the indicator makes sense to be the observe variable of corresponding latent construct. Ideally, we want all the initial indicators to have transparent methods to ensure the transparency of the final ARI index.

Then, the automatic indicator selection module will check if the current indicator set can pass the reliability and validity tests. If not, for each failed measurement model, the indicator with the smallest factor loading will be dropped, and then the reliability and validity tests will be re-implemented on the adjusted indicator set. This process will iterate until either the current indicator set passes the reliability and validity tests, or any of the measurement models don't have enough indicators (< 2).

Once the current indicator set can pass the reliability and validity tests, then the fitness of the CFA model will be checked. If the CFA model is well-fitted (RMSEA < 0.05), then the indicator set will be returned. If the CFA model is poorly fitted (RMSEA > 0.05), then among all the measurement models that have more than two indicators, the one indicator that has the largest MI will be dropped, and then the CFA will be re-implemented on the adjusted indicator set. If the CFA is poorly fitted and every measurement model has exactly two indicators, which means that there are no extra indicators to drop, then researchers will need to collect more indicators with content validity to enlarge the initial indicator set.

The reason why we put the reliability and validity tests before the CFA model fitness test is that the implementation level of the former is lower than the implementation level of the latter. The reliability and validity tests check each component (measurement model) of the model, while the model fitness test examines the entire model. Therefore, dropping invalid indicators will also improve the model fitness. The design of the two small-scale iterations follows the philosophy of the greedy algorithm.

The second modification of ARI compared to reflective indexing is the missing value estimation algorithm. In chapter 4.2.3, we have illustrated that the conceptual model and the counterfactual analysis can help to estimate the changes during the missing value period. The ARI formalises this idea into specific computer algorithm. To better illustrate the missing value estimation algorithm of the ARI, we create a numerical example in table 4-4 for the SEM in figure 4-1, containing three latent constructs for two objects A and B from timestamp 1 to 3. Table 4-4 contains five missing values. If we want to establish specific index, e.g., the index of ξ_1 in timestamp 3, we can pick up corresponding rows (row three and row six) in table 4-4 to form the index.

Table 4-4. A numerical example of the missing values in the index table

Object	Timestamp	ξ_1	η_1	η_2
A	1	Known	I	Known
A	2	II	Known	Known
A	3	Known	Known	Known
B	1	Known	Known	Known
B	2	Known	III	IV
B	3	Known	V	Known

In chapter 4.2.1, we have reviewed the linear SEM, in which the value of endogenous latent construct is equal to a linear combination of its parent nodes plus its residual variable (e.g., Eq. (1)). Based on the structural equation, we propose a general algorithm of estimating a single missing value slot.

General Algorithm. Missing value estimation

Input: 1. Information of the slot (object, timestamp, latent construct).

2. Panel data of the index table.

Output: A fitted value for the slot.

```
1.  If the slot already has an observed value:
2.      Return the observed value.
3.  Else:
4.      If the slot is from an exogenous variable:
5.          Return NaN.
6.      Get the value of residual of the missing value slot.
7.      Get the values of parent nodes of the missing value slot.
8.      Fitted value = linear combination of parent nodes + residual
9.      Return the fitted value.
```

This general missing value estimation algorithm can be applied on any single data slot of the index table (e.g., table 4-4), regardless of being missing or observed, exogenous or endogenous. Since there is no need to estimate an observed value, the algorithm will directly return the observed value. If the missing value slot is from an exogenous variable, since the SEM doesn't have structural equation to compute the value of the exogenous variable, the algorithm will return NaN (Not a Number).

In line 8, the general missing value estimation algorithm only tells how to use the structural equation to compute the fitted value for the missing value slot, without detailing how to get the values of parent nodes and residual variable. By inserting different methods in line 6 and line 7 of the general missing value estimation algorithm, we will come up with different concrete missing value estimation algorithms.

To obtain the value of the residual of the missing value slot, we propose the n-stationary assumption, which assumes that for endogenous latent constructs, their residual variables ζs of a given object remain stable in the past n timestamps. The smaller n is, the weaker the n-stationary assumption will be. Given the information of a missing value slot, we can compute a historical value of its residual and then use the n-stationary assumption to obtain an estimation of the current residual.

To illustrate how the n-stationary assumption works, we apply this assumption on table 4-4 to show how it can help to obtain the value of the residual of a missing value slot. According to Eq. (1), we can try to compute the value of the residual for each missing value slot under the 1-stationary assumption. For slot I, the residual is unavailable, since it is the earliest record of object A, so no earlier residual ζ_1 can be calculated. For slot II, the residual is unavailable, since ξ_1 is an exogenous variable. For slot III, the residual is available, since the values of ξ_1 and η_1 of object B in timestamp 1 are both observed, we can use these values and Eq. (1) to compute the value of the residual ζ_1 of object B in timestamp 1, then according to the 1-stationary assumption, the residual of slot III will be equal to the residual ζ_1 of object B in timestamp 1. For slot IV, the residual is available, since the values of ξ_1, η_1, and η_2 of object B in timestamp 1 are all observed, we can compute the value of residual ζ_2 of object B in timestamp 1, which is equal to the residual of slot IV under the 1-stationary assumption. For slot V, if ζ_1 follows 1-stationary assumption, the residual of slot V will be unavailable, since the value of slot III is missing, we can't compute the value of ζ_1 of object B in timestamp 2. However, if we assume that the ζ_1 follows 2-stationary assumption, we will be able to compute the residual of slot V by looking at the record of object B in timestamp 1. As the values of ξ_1 and η_1 of object B in timestamp 1 are both observed, we can compute the value of residual ζ_1 of object B in timestamp 1 which is equal to the residual of slot V under 2-stationary assumption.

By inserting the n-stationary assumption into the general missing value estimation algorithm to compute the value of the residual of a missing value slot, and then directly reading the values of the parent nodes from the index table, we come up with a concrete algorithm for estimating a missing value slot which is called the n-stationary missing value estimation, see algorithm 1.

Algorithm 1. N-stationary missing value estimation

Input: 1. Information of the slot (object, timestamp, latent construct).

2. Panel data of the index table.

3. Stationary period n.

Output: A fitted value for the slot.

```
If the slot already has an observed value:
        Return the observed value.
Else:
        If the slot is from an exogenous variable:
                Return NaN.
        If the slot is the earliest record of an object:
                Return NaN.
        Compute historical ζs of the slot in the past n timestamps.
        If ζs contain at least one non-NaN value:
                Residual = average (non-NaN ζs)
        Else:
                Return NaN.
        For each parent node:
                Read its value from index table.
                If parent node is NaN:
                        Return NaN
        Fitted value = linear combination of parent nodes + residual
        Return the fitted value.
```

We apply the 1-stationary missing value estimation algorithm on table 4-4. The results are stored in table 4-5.

Table 4-5. The results of the 1-stationary missing value estimation

Object	Timestamp	ξ_1	η_1	η_2
A	1	Known	×	Known
A	2	×	Known	Known
A	3	Known	Known	Known
B	1	Known	Known	Known
B	2	Known	√	×
B	3	Known	×	Known

For slot I and II, their fitted values are both NaN since slot I is in the first record and slot II is of an exogenous variable. For slot III, a fitted value is returned under 1-stationary assumption. For slot IV, 1-stationary missing value estimation returns NaN since the value of its parent node η_1 is not observed. For slot V, 1-stationary missing value estimation returns NaN since the residual of the missing value slot is unavailable under the 1-stationary assumption. However, if we set n equals two, then 2-stationary missing value estimation will return a fitted value for slot V, since a historical value of the residual can be obtained by the residual ζ_1 of object B in timestamp 1.

There is a trade-off between index completeness and index accuracy for different missing value estimation algorithms to choose. 2-stationary missing value estimation can produce more fitted values than 1-stationary missing value estimation, but some of its fitted values can be not credible enough due to the strong assumption. In general, the bigger n is, the more complete but less credible the final index will be.

In algorithm 1, we read the values of the parent nodes from the index table to compute a fitted value for the missing value slot. We can revise this part to obtain another missing value estimation algorithm, called the N-stationary recursive missing value estimation (see algorithm 2).

Algorithm 2. N-stationary recursive missing value estimation

Input: 1. Information of the slot (object, timestamp, latent construct).

2. Panel data of the index table.

3. Stationary period N.

Output: A fitted value for the slot.

```
1.   If the slot already has an observed value:
2.       Return the observed value.
3.   Else:
4.       If the slot is from an exogenous variable:
5.           Return NaN.
6.       If the slot is in the earliest record of an object:
7.           Return NaN.
8.       Compute historical ζs of the slot in the past N timestamps.
9.       If ζs contain at least one non-NaN value:
10.          Residual = average(non-NaN ζs)
11.      Else:
12.          Return NaN.
13.      For each parent node:
14.          Parent node = N-stationary recursive estimation(parent node)
16.          If parent node is NaN:
17.              Return NaN
18.      Fitted value = linear combination of parent nodes + residual
19.      Return the fitted value.
```

In algorithm 2, line 14, we build a recursive structure to obtain the value of the parent nodes. Algorithm 2 no longer requires parent nodes to be fully observed. If parent nodes are fully observed, algorithm 2 will be equivalent to algorithm 1. Otherwise, if the value of any parent nodes is missing, we can use algorithm 2 to fit their values, and then feed these fitted values into the structural equation to compute a fitted value for the missing value slot.

We apply the 1-stationary recursive missing value estimation on table 4-4 and restore the estimations in table 4-6.

Table 4-6. The results of the 1-stationary recursive missing value estimation

Object	Timestamp	ξ_1	η_1	η_2
A	1	Known	×	Known
A	2	×	Known	Known
A	3	Known	Known	Known
B	1	Known	Known	Known
B	2	Known	√	√
B	3	Known	×	Known

The only difference between table 4-5 and table 4-6 is the estimation of slot IV. 1-stationary missing value estimation can't fit the value of slot IV since the value of its parent node slot III is not observed. In comparison, 1-stationary recursive missing value estimation firstly calls itself to estimate a fitted value for slot III, and then use this fitted slot III to estimate the value for slot IV. Under the same n-stationary assumption, algorithm 2 can produce indexes with higher completeness than algorithm 1, but some of the estimations of algorithm 2 might not be credible enough due to the recursive estimation.

4.3.2 Automatic Reflective Indexing (ARI) vs. Reflective Indexing

In chapter 4.2.3, we have discussed the limitation of the reflective indexing. The ARI formalises the ideas of the indicator selection process and the counterfactual analysis of the reflective indexing into concrete computer programmes. The automatic indicator selection module of the ARI can deal with the limitation of the reflective indexing, and the dynamic missing value estimation algorithms of the ARI can provide various options of trade-offs between index completeness and index accuracy for researchers to choose.

In the reflective indexing process, researchers need to manually drop invalid indicators, which makes it hard to approach the maximum qualified indicator subset especially when the indicator set is large. The indicator selection module of ARI uses the greedy algorithm to automatically drop the minimum invalid indicators in each iteration, which makes the final selected indicator set closer to the maximum qualified indicator subset than manual operation.

Besides, the ARI is more parameterised and automated compared to the reflective indexing. The high-level parameterisation makes the ARI more transparent than the reflective indexing. Given a conceptual model and a fixed initial indicator set, with the parameters determined, the ARI can produce unique qualified indicator subset and reproducible index. The benefit of being transparent is that the understanding and criticism towards the index will be facilitated, therefore researchers can be more aware of whether to use the index in their research. The high-level automation makes the ARI more efficient than the reflective indexing, the average complexity of the ARI is $O(n^3)$, which means that it can be scalable on medium-size dataset.

4.3.3 Automatic Reflective Indexing (ARI) vs. GPI & PPI methods

In chapter 2.3 and chapter 4.2.3, we have discussed the four concrete limitations of GPI and PPI method and why the characteristics of the reflective indexing can be helpful to deal with them, in this section, we will demonstrate the theoretical advantages of the ARI by solving the four concrete limitations of GPI and PPI methods.

When defining the indexing target, the ARI requires the different aspects of the target to be individual latent constructs in the conceptual model, which can help to decompose the compounded concepts and reduce the possibility of debatable target aggregation.

The ARI provides the automatic indicator selection module to deny invalid indicators in an efficient and effective manner. The content validity test provides a framework based on the causal analysis to check whether the indicators make sense to be the observed indicators of the target, e.g., both the GPI indicator “Number of internal security officers and police per 100,000 people” and the PPI indicator “GDP per capita” will be denied since they are the causal variables of negative peace and positive peace respectively (Buonanno, Montolio & Vanin, 2009; Jonathan et al., 2021; Machin & Marie, 2005), rather than their outcome variables. The reliability test, convergent validity test, and discriminant validity test are embedded in the ARI to check the statistical credibility of the collected indicators, which can ensure that the selected indicators are not only valid in terms of their content, but also in terms of their practical data. The ARI implements the greedy algorithm to approach the maximum qualified indicator subset, which can make the final index more comprehensive.

The ARI is based on the SEM, which is intrinsically related to the latent variable analysis. The indicator weights of ARI are the factor loadings between indicators and corresponding latent construct, which are more reasonable than the indicator weights of PPI, since they directly measure the correlations between the target and the indicators.

Based on the counterfactual analysis, the ARI provides a group of dynamic algorithms to estimate the missing values in the ARI index table, using the structural equation to compute the changes during the missing value period. The researchers can alter the “stationary period” parameter to obtain algorithms with different assumptions. If the stationary period is set to be small, then the algorithm can produce fitted values with realistic assumption, which can increase the credibility of the final peace index.

Except for the above advantages, the ARI is highly parameterised and automated, which makes the ARI more transparent, more efficient, and more scalable than the GPI and PPI indexing methods.

4.3.4 Manual of ARI software

A Python SEM package called Semopy (Igolkina & Meshcheryakov, 2020) has been used to code the ARI system. The automatic indicator selection module and the SEM indexing module are put in Appendix A and B respectively. The SEM indexing module encodes the functions of indicator weighting, index computation, and missing value estimation.

4.4 Conclusions

In this chapter, we propose the automatic reflective indexing (ARI) method, which is the core contribution of this research. Firstly, we review the knowledge of the SEM, the formative indexing, and the reflective indexing, illustrate why the reflective indexing can be a useful basis according to the four criteria in chapter 2.4. Then, we create our new peace indexing method, the ARI, by formalising the ideas of indicator validation and counterfactual analysis of the reflective indexing method. We demonstrate the theoretical advantages of the ARI by dealing with the limitations of both the reflective indexing and the GPI & PPI indexing methods.

Chapter 5 Demonstration and Evaluation

5.1 Introduction

Chapter 5 is the demonstration and evaluation steps of the DSR, in which we will use the ARI method to create specific ARI peace indexes to measure the level of negative and positive peace. The goal of this chapter is to demonstrate the usage of the ARI in practice and evaluate its performance. Researchers may use the ARI method to develop their own peace indexes.

5.2 Define the targets of ARI Peace Indexes

To line up with the aspects of the targets of GPI and PPI, we set the four aspects of peace, the internal negative peace (INP), internal positive peace (IPP), external negative peace (ENP), and external positive peace (EPP) as our targets (latent constructs). The goal of this indexing step is to create conceptual models to describe the prior knowledge of these latent constructs. The conceptual models are shown in figure 5-1 and 5-2, and their corresponding structural equations are Eq. (10) and Eq. (11).

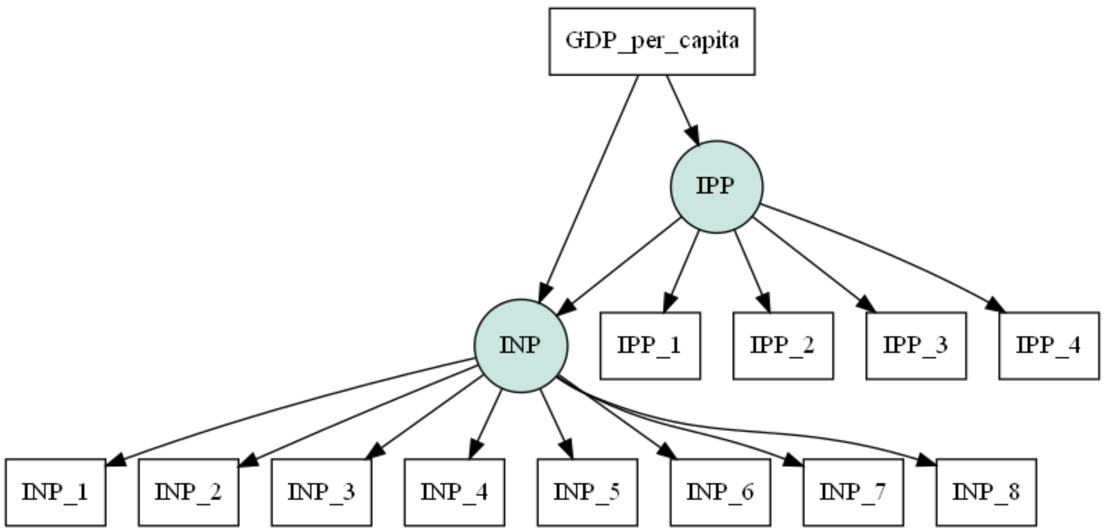


Figure 5-1. Conceptual model for IPP and INP

$$\begin{pmatrix} IPP \\ INP \end{pmatrix} = \begin{pmatrix} 0 & 0 \\ \beta_{21} & 0 \end{pmatrix} \begin{pmatrix} IPP \\ INP \end{pmatrix} + \begin{pmatrix} \gamma_{11} \\ \gamma_{21} \end{pmatrix} GDP\ per\ capita + \begin{pmatrix} \zeta_{IPP} \\ \zeta_{INP} \end{pmatrix} \tag{10}$$

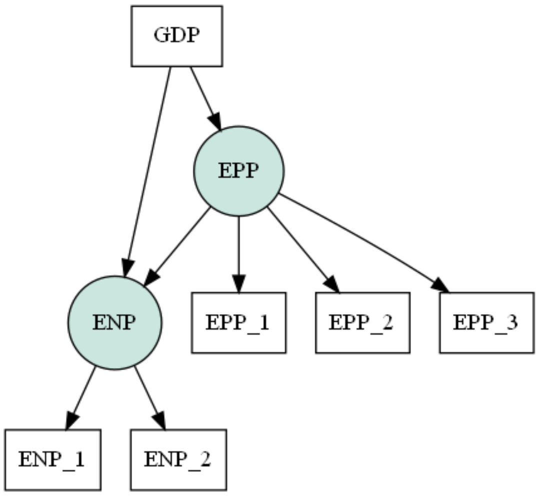


Figure 5-2. Conceptual model for EPP and ENP

$$\begin{pmatrix} EPP \\ ENP \end{pmatrix} = \begin{pmatrix} 0 & 0 \\ \beta_{21} & 0 \end{pmatrix} \begin{pmatrix} EPP \\ ENP \end{pmatrix} + \begin{pmatrix} \gamma_{11} \\ \gamma_{21} \end{pmatrix} GDP + \begin{pmatrix} \zeta_{EPP} \\ \zeta_{ENP} \end{pmatrix} \tag{11}$$

The prosperity can reduce internal violence by abundant security and educational resources (Buonanno, Montolio & Vanin, 2009; Jonathan et al., 2021), so in figure 5-1, we use the covariate “GDP per capita” to represent the level of prosperity and link the causal paths from “GDP per capita” to IPP and INP. Galtung (1975) claimed that the just structures and mechanisms can reduce the direct violence in a sustainable way, so we link causal paths from IPP to INP, and EPP to ENP. Besides, powerful countries will usually behave more aggressively than weaker countries (Clark, 2011), so we use covariate “GDP” to approximate the power of country and link the causal paths from “GDP” to EPP and ENP. Even though Kacowicz (1997) observed a negative correlation between internal and external peace across the west African countries, however to our best knowledge, there is no literatures that demonstrate the causal relationship between internal and external peace, so we decide to not link any causal paths between figure 5-1 and 5-2.

The structural equation Eq. (10) divides the causes of internal peace into two categories, the prosperity-dependent causes, and prosperity-independent causes (ζ_{IPP} and ζ_{INP}). Prosperity-dependent causes refer to the causal variables of internal peace embedded in any causal path between prosperity and internal peace, including prosperity itself and all mediators. The GPI indicator "Number of internal security officers and police per 100,000 people" is a prosperity-dependent cause, since it is a mediator which links a causal path from prosperity to internal negative peace. We don't need to capture all the causal paths between prosperity and internal peace explicitly in figure 5-1, since all the causal effects of mediators are stored in the structural coefficients β_{21}, γ_{11}, and γ_{21}. Prosperity-independent causes (ζ_{IPP} and ζ_{INP}) refer to the causal variables of internal peace which are not in any causal paths between prosperity and internal peace, such as the intrinsic culture.

Also, the structural equation Eq. (11) divides the causes of external peace into two categories, the power-dependent causes, and the power-independent causes (ζ_{EPP} and ζ_{ENP}). Power-dependent causes refer to the causal variables of external peace embedded in any causal path between national power and external peace, including national power itself and all mediators. Power-independent causes (ζ_{EPP} and ζ_{ENP}) refer to the causal variables of external peace which are not in any causal paths between national power and external peace.

Even though the models in figure 5-1 and figure 5-2 are trivial, they are still the credible prior knowledge according to the literatures, so we can use them to create the ARI peace indexes. By setting the different aspects of peace as the individual latent constructs in the conceptual model, we can keep in mind their distinctions. This operation can remind us to avoid the debatable target aggregation. Once we manage to compute the values of these latent constructs, we can compute the correlations between them to determine whether we can aggregate these aspects.

5.3 Collect indicators for ARI Peace Indexes

According to the indicator collection and selection step of the ARI, only valid indicators will be selected for use within the SEM. Firstly, for each latent construct in figure 5-1 and 5-2, at least two indicators with content validity as well as transparent methods should be collected to form the initial indicator set. In this research, we have searched open data series from many well-renowned entities, including the World Bank, the United Nations, and universities, etc., and collected four initial indicators for IPP and eight initial indicators for INP in table 5-1. All the indicators in table 5-1 are secondary indicators with detailed methods.

Table 5-1. Initial indicator set for IPP and INP

	Original indicator	Data source
	GDP per capita	World Bank
	Population	United Nations Population Division
IPP_1	Income Inequality	United Nations Development Programme
IPP_2	Education Inequality	United Nations Development Programme
IPP_3	Life expectancy Inequality	United Nations Development Programme
IPP_4	Gender Inequality Index	United Nations Development Programme
INP_1	Homicide deaths (per 100,000 people)	IHME, Global Burden of Disease
INP_2	Number of serious assaults	United Nations Office on Drugs and Crime
INP_3	Number of kidnappings	United Nations Office on Drugs and Crime
INP_4	Number of thefts	United Nations Office on Drugs and Crime
INP_5	Battle-related deaths	Uppsala Conflict Data Program
INP_6	Non-state conflict deaths	Uppsala Conflict Data Program
INP_7	One-sided violence deaths	Uppsala Conflict Data Program
INP_8	Number of conflict stock internal displacement	United Nations high Commissioner for Refugees

We collect four types of inequality from United Nations Development Programme (UNDP), namely income inequality (2010 - 2019), education inequality (2010 - 2019), life expectancy inequality (2010 - 2019), and gender inequality index (2010 - 2019), all of which are computed using the Atkinson Inequality (Atkinson, 1970). These four indicators can be seen as the observed outcome variables of the internal positive peace, which means that if the level of internal positive peace goes up, we should be able to observe more equalities on these indicators.

We collect eight direct violence indicator for INP, namely homicide death rate (2010 - 2019) from IHME, University of Washington, number of serious assaults (2010 - 2018), number of kidnappings (2010 - 2018), number of thefts (2010 - 2018) from United Nations Office on Drugs and Crime, number of battle-related deaths (2010 - 2019), number of non-state conflict deaths (2010 - 2019), number of one-sided violence deaths (2010 - 2019) from Uppsala Conflict Data Program, and number of conflict stock internal displacement (2010 - 2019) from United Nations high Commissioner for Refugees. If the level of internal negative peace raises, we should be able to observe smaller numbers on these indicators.

We have also searched the open data series for external peace from the well-renowned entities, including the World Bank and universities, etc., and collected three indicators for EPP and two indicators for ENP in table 5-2. All the indicators in table 5-2 are secondary data with detailed methods.

Table 5-2. Initial indicator set for EPP and ENP

	Original indicator	Data source
	GDP	World Bank
EPP_1	Military expense share	SIPRI Military Expenditure Database
EPP_2	Weapon export	SIPRI Arms Transfers Database
EPP_3	Personnel contribution to UN peacekeeping	International Peace Institute
ENP_1	External battle-related deaths	Uppsala Conflict Data Program
ENP_2	Number of supporting external conflicts	Uppsala Conflict Data Program

The three EPP indicators are EPP_1 military expense share (2010 - 2019) from SIPRI Military Expenditure Database, EPP_2 weapon export (2010 - 2019) from SIPRI Arms Transfers Database, and EPP_3 personnel contribution to UN peacekeeping (2010 - 2019) from International Peace Institute. These three indicators can reflect the attitude of a country towards its external affairs and therefore can be seen as observed variables of the external positive peace. EPP_1 refers to the ratio of military expense / GDP. If a country increases its military expense, then tensions in the international community will be aggravated. EPP_2 records the value of the export weapons. The more weapon a country exports, the more tensions will be caused by this country. EPP_3 counts the number of personnel serving in UN peacekeeping actions, which measures a kind of effort on sustaining peace for international community.

We collect two ENP indicators from Uppsala Conflict Data Program, ENP_1 external battle-related deaths (2010 - 2019) and ENP_2 number of supporting external conflicts (2010 - 2017), both of which are related to the external direct violence, so they can be seen as the observed variables of the external negative peace.

All the indicators in table 5-1 and table 5-2 need to be standardised to have zero mean and unit variance. Since the peace measures the absence of the violence, we feed the negative value of the violence indicators into the CFA to ensure the factor loadings to be positive.

Table 5-1 and 5-2 are the best we can do to set up the initial indicator set. Collecting more initial indicators with content validity from the wider data sources will cost more resources, which is beyond the scope of this research.

Now we can use the automatic indicator selection module to check the reliability and validity of the indicators in table 5-1 and 5-2 to deny those invalid ones. The selection results of IPP and INP are shown in figure 5-3. Two IPP indicators, IPP_3 and IPP_4, are qualified as the indicators of IPP. Three IEP indicators, IEP_5, IEP_6, and IEP_7 are qualified as the indicators of IEP.

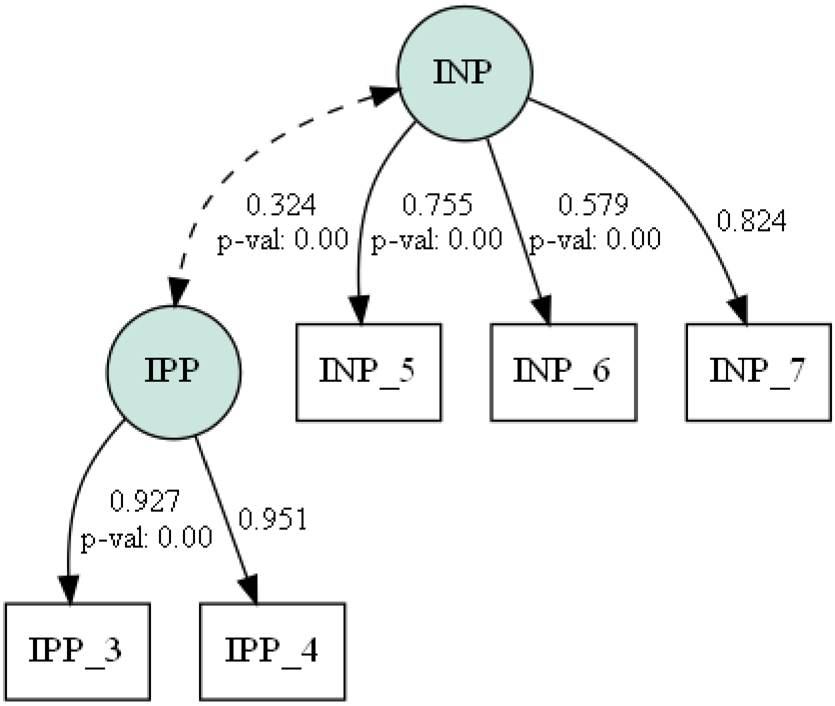


Figure 5-3. Indicator selection result for IPP and INP

Table 5-3 contains the results of the reliability and validity tests for the CFA model in figure 5-3. All factor loadings are greater than 0.5 with 1% significance. For both IPP and INP, their Cronbach αs, AVEs, CRs are greater than 0.7, 0.5, 0.7 respectively. These statistics confirm that the CFA in figure 5-3 has decent reliability and convergent validity. The square root of AVE for IPP is 0.939, for INP is 0.727, both are greater than the correlation coefficient between IPP and INP (0.324), which means that the IPP and INP and their indicators have strong discriminant validity. The RMSEA of the CFA in figure 5-3 is 0.044, which indicates that the model is well-fitted.

Table 5-3. Reliability test & Validity test for figure 5-3

Latent construct	Indicator	load	P value	Cronbach α	AVE	CR
IPP	IPP_3	0.927	***	0.927	0.882	0.937
	IPP_4	0.951	***			
INP	INP_5	0.755	***	0.809	0.528	0.767
	INP_6	0.579	***			
	INP_7	0.824	***			

The selection results of EPP and ENP are shown in figure 5-4. Two ENP indicators, ENP_1 and ENP_2, are qualified as the indicators of ENP. However, there are not enough qualified indicators to identify the EPP, as the EPP_1 and EPP_3 can't pass the statistical tests.

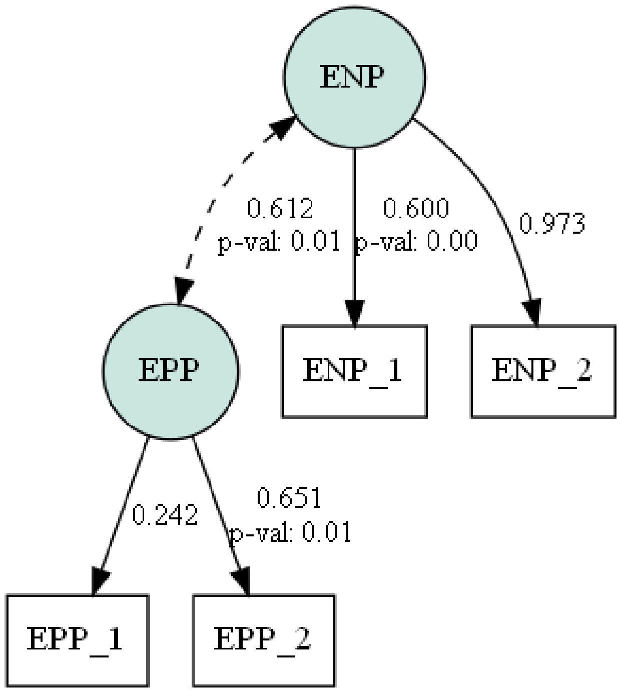


Figure 5-4. Indicator selection result for EPP and ENP

Table 5-4 contains the results of reliability and validity tests for the CFA model shown in figure 5-4. All factor loadings are 1% significant and the CFA model is well fitted (RMSEA = 0.01). For ENP, the factor loadings of ENP_1 and ENP_2 are both greater than 0.5, the Cronbach α, AVE, CR are greater than 0.7, 0.5, 0.7 respectively, all of which means that the ENP_1 and ENP_2 are qualified indicators for ENP. However, for EPP, the factor loading of EPP_1 is smaller than 0.5, the Cronbach α, AVE, CR are -0.151, 0.241, 0.344, which are smaller than 0.7, 0.5, 0.7 respectively. Thus, the EPP indicators in table 5-2 fails at the reliability test and convergent validity test, the level of EPP is not identifiable given this indicator set.

Table 5-4. Reliability test & Validity test for figure 5-4

Latent construct	Indicator	load	P value	Cronbach α	AVE	CR
EPP	EPP_1	0.242	***	-0.151	0.241	0.344
	EPP_2	0.651	***			
ENP	ENP_1	0.6	***	0.865	0.653	0.781
	ENP_2	0.973	***			

These are two solutions, either to collect more indicators with content validity for EPP, or to delete the latent construct EPP from figure 5-2. In this research, due to the limitation on resources, we adopt the second solution and only measure the level of the external negative peace.

To conclude the chapter 5.3, we manage to obtain two qualified indicators for IPP, three qualified indicators for INP, and two qualified indicators for ENP. These indicators are valid not only in terms of their content, but also in terms of their practical data series. Therefore, the indexes created by these indicators will not suffer from the invalid indicator limitation.

5.4 Weight indicators of ARI Peace Indexes

In last chapter, we have obtained two qualified indicators for IPP, three qualified indicators for INP, and two qualified indicators for ENP. Since many indicators in table 5-1 and 5-2 don’t follow the normal distribution, we use the PLS estimation to fit the parameters of the SEM. The SEM result of IPP and INP is shown in figure 5-5.

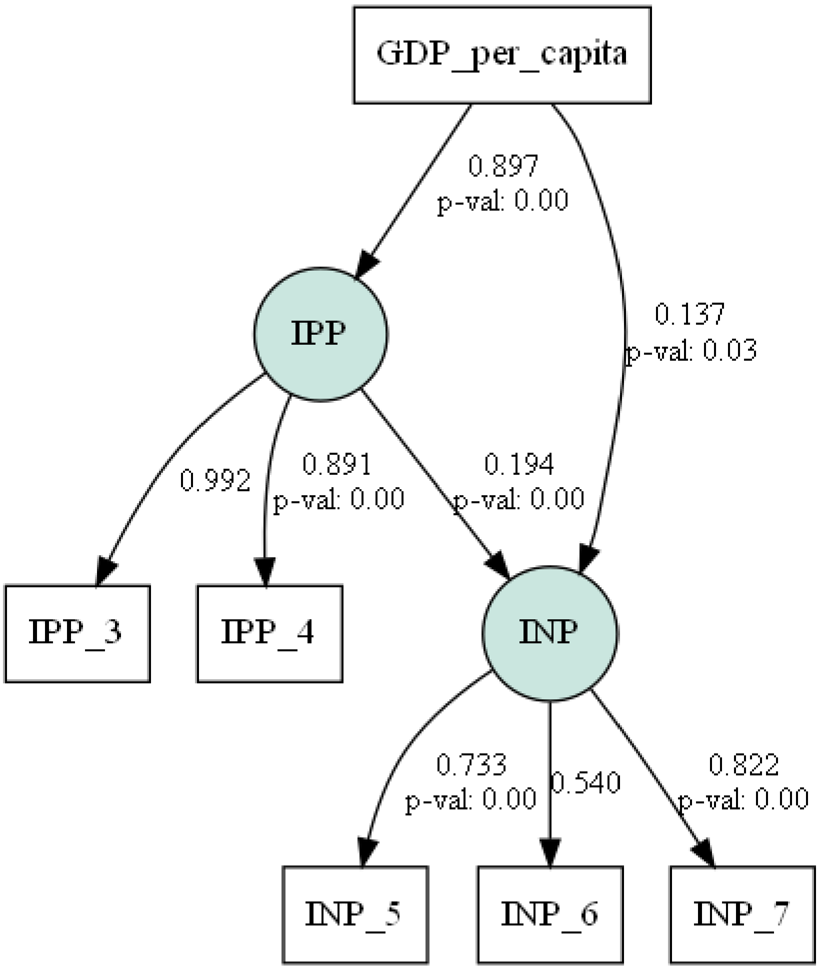


Figure 5-5. SEM for IPP and INP

Table 5-5 stores the fitted parameters of the SEM shown in figure 5-5. On average, one unit increase on GDP per capita will directly cause 0.897 unit increase on internal positive peace and 0.137 unit increase on internal negative peace, one unit increase on internal positive peace will directly cause 0.194 unit increase on internal negative peace, one unit increase on GDP per capita will cause 0.311 unit increase on internal negative peace. Now we have demonstrated that the internal positive peace indeed leads to the internal negative peace, since the causal effect β_{21} is positive and significant. The RMSEA of this SEM is 0.033, which means the SEM is well-fitted.

Table 5-5. SEM results of figure 5-5

SEM factor loadings

Latent construct	Indicator	load	P value
IPP	IPP_3	0.992	***
	IPP_4	0.891	***
INP	INP_5	0.733	***
	INP_6	0.54	***
	INP_7	0.822	***

Structural Coefficients

Path relation	Coefficient	P value
GDP per capita → IPP	0.897	***
GDP per capita → INP	0.137	***
IPP → INP	0.194	***

Now we can compute the weights of indicators of IPP and INP by standardising their factor loadings. Table 5-6 stores the weights of the indicators of IPP and INP.

Table 5-6. Weights of indicators of IPP and INP

Indicator	Weight	Latent construct
IPP_3	52.67%	IPP
IPP_4	47.33%	
INP_5	35.00%	INP
INP_6	25.79%	
INP_7	39.21%	

The SEM result of ENP is shown in figure 5-6.

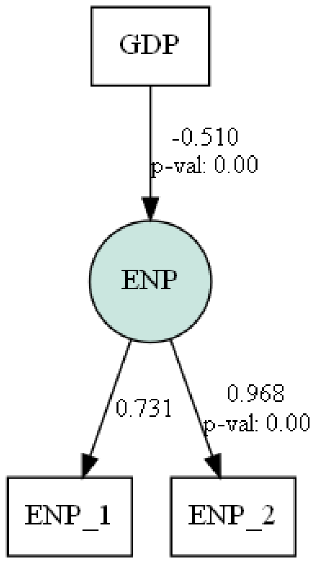


Figure 5-6. SEM for ENP

Table 5-7 stores the fitted parameters of the SEM in figure 5-6. All parameters of the SEM are 1% significant (P < 0.01). On average, one unit increase on GDP will reduce 0.51 unit external negative peace. Now we have demonstrated that the powerful countries tend to act more aggressively than the weaker countries. The RMSEA of the SEM is 0.001, which means the model is well-fitted.

Table 5-7. SEM results of figure 5-5

SEM factor loadings

Latent construct	Indicator	load	P value
ENP	ENP_1	0.731	***
	ENP_2	0.968	***

Structural Coefficients

Path relation	Coefficient	P value
GDP → ENP	-0.51	***

Now we can compute the weights of the indicators of ENP by standardising their factor loadings. Table 5-8 stores the weights of the indicators of ENP.

Table 5-8. Weights of indicators of ENP

Indicator	Weight	Latent construct
ENP_1	43.04%	ENPI
ENP_2	56.96%	

The weights in chapter 5.4 are more reasonable than the weights of PPI indicators, as they are the direct causal effects between the indicators and the target.

5.5 Compute ARI peace indexes

With the weights in table 5-6 and table 5-8, we can compute the rankings of the IPP index, the INP index, and the ENP index. Now we can compute the regressions between the internal and external peace, the positive and negative peace to solve the target aggregation limitation and determine whether we could aggregate these aspects of peace into a single overall peace index.

5.5.1 Internal Peace Index (IPI)

Figure 5-7 shows a regression between IPP and INP.

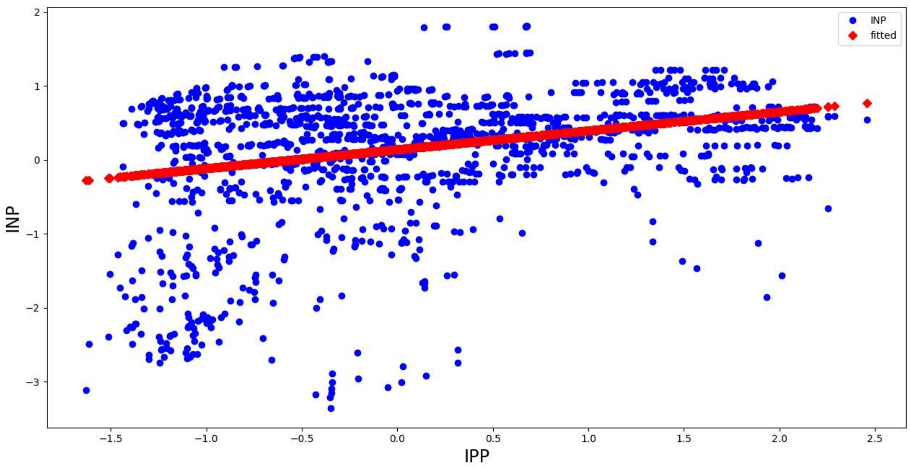


Figure 5-7. IPP vs. INP

The regression coefficient between IPP and INP is 0.2556, which is greater than zero with 1% significance. As we have discussed in chapter 2.3.1, if the correlation between IPP and INP is positive, then measuring the internal negative peace and the internal positive peace within an overall internal peace index could an option. Therefore, for the convenience of presentation, we only display the overall internal peace index (IPI) in this thesis, which is constructed by 50% IPP and 50% INP. The weights of IPP and INP can be arbitrary, as the rankings of IPP, INP, and IPI are close to each other.

Table 5-9 shows the information of the IPI 2019. Figure 5-8 shows the map of IPI 2019, whose full ranking is stored in appendix C. The higher the IPI ranking is, the more internally peaceful the country will be, the less internal violence the country will have.

In terms of the region, Europe, North America, and East Asia have the highest level of internal peace, while Africa and Middle East have the lowest level of internal peace, South America is in the middle. From figure 5-8, we can see that the internal peace index is positively correlated to the economic development, which corresponds to the positive structural coefficients of the SEM in figure 5-5.

Table 5-9. Information of IPI 2019

	Internal Peace Index
Target	Overall internal peace
Covering states/territories	162
Number of indicators	5
Indicator selection	ARI Indicator Selection Module
Indicator weighting	Factor loadings
Missing value	1-stationary recursive missing value estimation

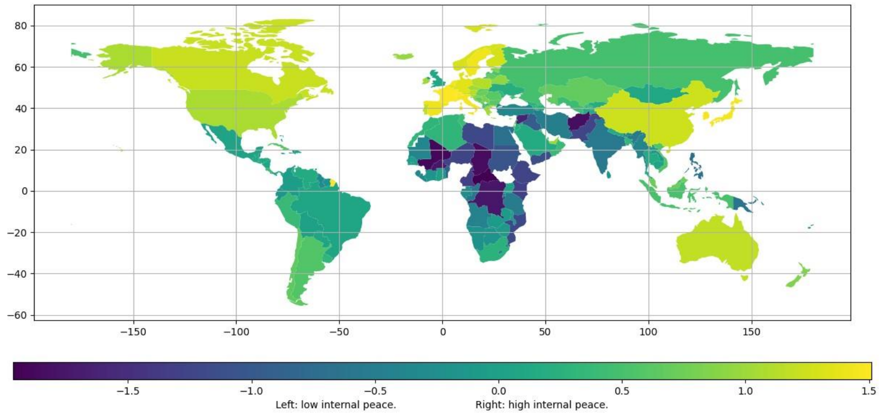


Figure 5-8. Internal Peace Index 2019

5.5.2 External Negative Peace Index (ENPI)

We compute the regression between the internal peace (IP) and external negative peace (ENP), the result is shown in figure 5-9, in which we observe a negative relationship. The regression coefficient is -0.225 with 1% significance. Thus, researchers should never aggregate the internal peace and external peace into single overall peace index since their rankings can be significantly different from each other. The rankings of GPI and PPI are not reliable as they both aggregate the internal and external aspects of peace simultaneously.

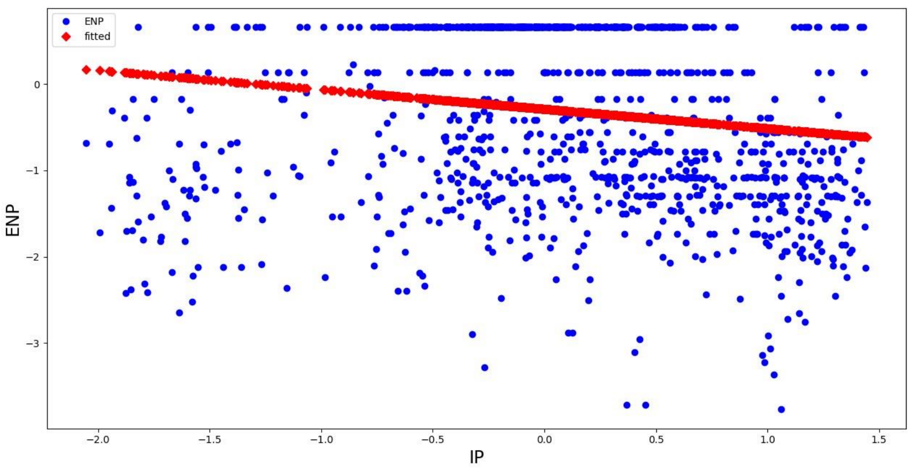


Figure 5-9. IP vs. ENP

As the ENP_2 only has the data between 2010 - 2017, we compute the ENPI 2017. Table 5-10 shows the information of the ENPI 2017. Figure 5-10 shows the map of ENPI 2017, whose full ranking is stored in appendix D. The higher the ENPI ranking is, the more externally peacefully the country will act, the less external direct violence the country will engage.

In terms of region, South America has the highest level of external negative peace, Africa, Europe, and Asia have the middle level of external negative peace, Russia and United States of America have the lowest level of external negative peace. From figure 5-10, we can see a negative correlation between the national power and the external negative peace, which corresponds to the negative structural coefficient of the SEM in figure 5-6.

Table 5-10. Information of ENPI 2017

	External Negative Peace Index
Target	External negative peace
Covering states/territories	206
Number of indicators	2
Indicator selection	ARI Indicator Selection Module
Indicator weighting	Factor loadings
Missing value	1-stationary recursive missing value estimation

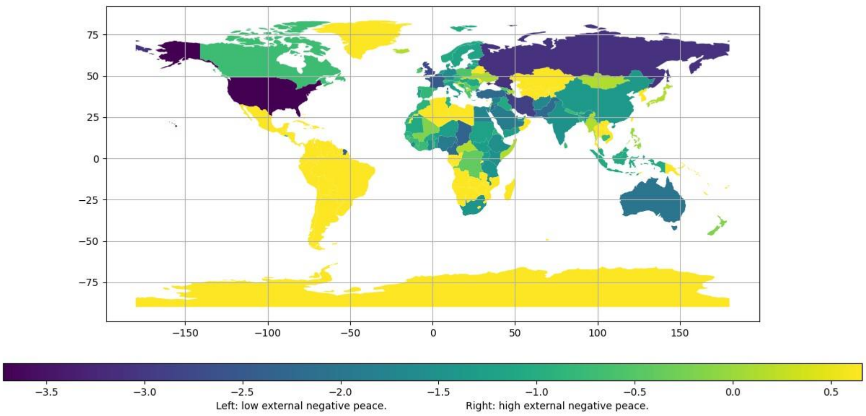


Figure 5-10. External Negative Peace Index 2017

In chapter 5.5, we compute two specific ARI peace indexes, Internal Peace Index (IPI) and External Negative Peace Index (ENPI). The IPI aggregates the rankings of internal positive peace (IPP) and internal negative peace (INP), which is supported by the positive correlation between IPP and INP. While the ENPI is reported independently since the correlation between internal peace (IPI) and external negative peace (ENP) is negative. Both IPI and ENPI will not suffer from the debatable target aggregation limitation of GPI and PPI, since their decisions of whether to aggregate peace aspects are made according to the empirical results of regressions.

5.6 Missing value estimation for ARI peace indexes

We implement the 1-stationary recursive missing value estimation algorithm to estimate the missing values of IPI 2019 and ENPI 2017, and the algorithm shows that none of the missing values of IPI 2019 can ENPI 2017 can be estimated. This is because the IPI 2019 and ENPI 2017 have used more realistic assumption (1-stationary assumption) than GPI and PPI to compute the estimations of the missing values.

If we want to obtain more non-NaN estimations, we could assume the stationary period to be longer (N > 1), which however will reduce the accuracy of the IPI 2019 and ENPI 2017, so we don't do this in our research. The trade of the index completeness for the index accuracy makes the rankings of IPI and ENPI to have less unreliable estimations than GPI and PPI, since the highly unreliable estimations will be denied in IPI and ENPI under the 1-stationary assumption.

5.7 Counterfactual analysis of ARI Peace Indexes

In chapter 5.2, we have explained the conceptual models of the internal peace and external peace, in which we bring in the concepts of prosperity-dependent causes and prosperity-independent causes (ζ_{IPP} and ζ_{INP}), power-dependent causes and power-independent causes (ζ_{EPP} and ζ_{ENP}). Two questions arise naturally:

1) How will the internal peace index change if all the countries have the same level of prosperity?

2) How will the external peace index change if all the countries have the same level of national power?

5.7.1 Prosperity adjusted Internal Peace Index

The first question can help to understand the reason behind the internal peace. To answer this question, we need to control the causal effect by setting all countries to have the same level of prosperity. We can implement counterfactual analysis to achieve this goal based on the SEM in figure 5-5. The prosperity adjusted IPI 2019 is shown in figure 5-11, whose ranking is stored in appendix E.

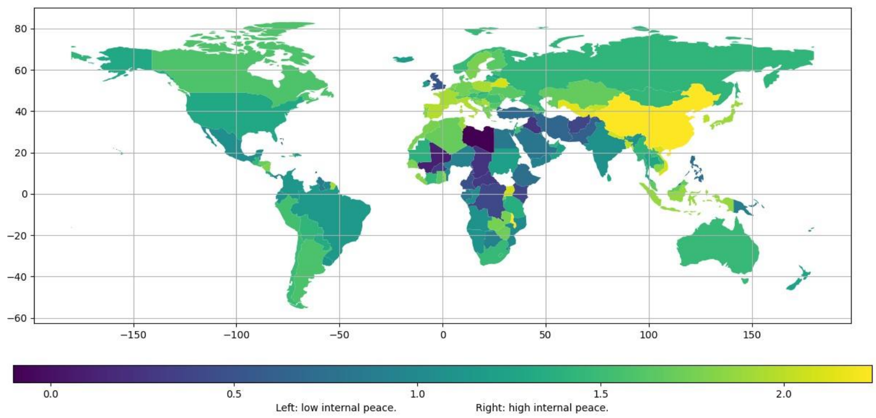


Figure 5-11. Prosperity adjusted IPI 2019

By comparing the IPI 2019 and prosperity adjusted IPI 2019, we propose two types of countries.

If a country has a high ranking in the IPI but a low ranking in the prosperity adjusted IPI, such as Switzerland (IPI: 2, prosperity adjusted IPI: 50) and Ireland (IPI: 25, prosperity adjusted IPI: 103), then its high-level internal peace should be mainly ascribed to its prosperity. It is hard to say this type of countries to be peaceful since they will perform terribly if the causal effect of prosperity is removed. For this type of countries, the more effective way to improve their internal peace is to improve the prosperity-independent causes, such as the violent culture.

If a country has a low ranking in IPI but a high ranking in prosperity adjusted IPI, such as Malawi (IPI: 106, prosperity adjusted IPI: 1) and Nepal (IPI: 77, prosperity adjusted IPI: 7), then its low-level internal peace should be mainly ascribed to its low-level development. We will regard this type of countries to have the peaceful attitude since they still perform decently even under the terrible economic status. For this type of countries, the more effective way to improve their internal peace is to develop the economy.

5.7.2 National power adjusted External Negative Peace Index

To answer the second question, we need to control the causal effects by setting all countries to have the same level of national power. With the fitted SEM in figure 5-6, we can use the counterfactual analysis to achieve this goal. The result of the national power adjusted ENPI 2017 is shown in figure 5-12 and appendix F.

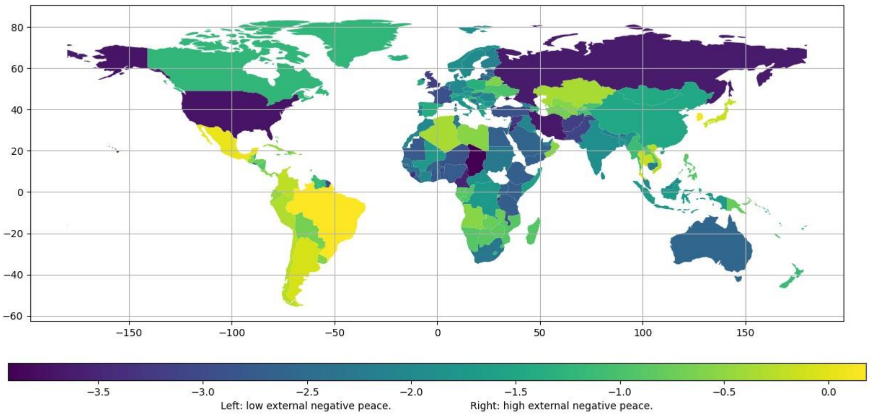


Figure 5-12. National power adjusted ENPI 2017

If a country has a high ranking in ENPI but a low ranking in national power adjusted ENPI, such as Dominica (ENPI: Tie for the first place, national power adjusted ENPI: 114), then this country's peaceful external behaviour should be ascribed to its weak power, in other words, the weak power doesn't support the country to do aggressive actions. However, if this country become stronger, then it will treat other countries more aggressively.

If a country has a low ranking in ENPI but a high ranking in national power adjusted ENPI, such as Philippines (ENPI: 115, national power adjusted ENPI: 45), then its low ENP should be mainly ascribed to its strong national power, or in other words, the aggressive actions of this country should be mainly ascribed to its powerful nature, but this country itself may have the willing to treat other countries peacefully.

5.8 Conclusions

In this chapter, we demonstrate the usage of the ARI by creating practical peace indexes to measure the level of negative and positive peace. We manage to create three peace indexes, the internal positive peace index (IPPI), the internal negative peace index

(INPI), and the external negative peace index (ENPI). We display the overall internal peace index (IPI) by aggregating the IPPI and the INPI according to their positive correlation and display the IPI and the ENPI separately according to their negative correlation. We evaluate the IPI and ENPI in each indexing step (from chapter 5.2 to chapter 5.6) and demonstrate that they have solved the four limitations of GPI and PPI. Furthermore, the conceptual model of ARI enables us to research the reasons behind peace and give different solutions to different types of countries. The process of using the method to create specific instance is called instantiation, researchers could establish their own peace indexes using the ARI with different prior knowledge (conceptual model) or different indicators.

Chapter 6 Contributions & Discussions

In final chapter, we will wrap up the whole research to highlight the contributions and limitations of this research. This chapter corresponds to the communication step of DSR.

We identify the research gap by noticing that the concrete limitations of GPI and PPI haven't been researched, so we review their methods in detail and come up with their four concrete limitations which can reduce their credibility, namely target aggregation limitation, indicator validation limitation, indicator weighting limitation (PPI), and missing value estimation limitation. Then according to the four criteria proposed for each limitation, we review an indexing method called the reflective indexing, which provide a solid basis for solving the four limitations of GPI and PPI.

Based on the reflective indexing, we develop a new indexing method called the automatic reflective indexing (ARI), which is the core contribution of this research. The ARI manages to solve the research problem by dealing with the target aggregation, indicator validation, indicator weighting (PPI), and missing value estimation limitations of the GPI and PPI methods. Also, the ARI can solve the limitation of the reflective indexing by using greedy algorithm to approach the maximum qualified indicator subset. Furthermore, ARI is more automatic, transparent, and efficient compared to other indexing methods, which means it can be used to create scalable index.

The research aim has been achieved, as we manage to create concrete ARI peace indexes to measure the levels of negative and positive peace. We show that the instances of ARI, the IPI and ENPI, are indeed free of the limitations of GPI and PPI.

However, even though the ARI has some theoretical advantages to the GPI and PPI methods, we still can't say that the IPI and ENPI are more credible than the GPI and PPI, since both the IPI and ENPI only contain few indicators, which make them less comprehensive than GPI and PPI. As individual researchers, table 5-1 and 5-2 are the best we could do so far to set up our initial indicator set, which are still not enough to identify the level of external positive peace, this evaluation result brings in a potential limitation of ARI, that since the ARI has a validity test module to deny invalid indicators, the final selected indicator set of ARI index will be smaller than GPI and PPI.

One solution to this limitation is to lower the threshold of the statistical tests to accept more indicators in the ARI index, but we don't recommend doing this as it will reduce the reliability and validity of the indicator set. Another solution is to collect more indicators with content validity to form a larger initial indicator set. Designing a scalable peace indicator database as the front system to ARI could be a promising research direction following this research.

Researchers who are interested in peace indexes can establish their own by applying the ARI on their prior knowledge and particular dataset. The conceptual models of IPI and ENPI are trivial, which certainly have not captured all the important causes of peace, therefore the counterfactual analysis of IPI and ENPI are also trivial. If researchers want to further analyse the causes of peace, they can develop more sophisticated conceptual model for negative and positive peace and implement more complex counterfactual analysis.

Furthermore, even though this research is about peace index, the ARI is an indexing method which can be applied on any indexing tasks, not only restricted to peace index. Researchers can apply ARI on their specific domain knowledge to create specific domain indexes.

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Appendix A: Automatic Indicator Selection Module of ARI

```
import numpy as np
import pandas as pd
import itertools
import copy
from semopy import Model
from semopy import calc_stats
from semopy import semplot


class CFA:
    '''
    This is CFA class, which is used to check reliability and validity
    of current indicator set, also can be used to select indicators.
    '''
    def __init__(self, cfa_dict, dataset):
        '''
        :param cfa_dict: {latent1: {latent1_indicators}, latent2: {latent2_indicators},...}
        :param dataset: Aggregated dataset.
        The header of dataset needs to contain all indicators of cfa_dict.
        '''
        for latent in cfa_dict:
            if len(cfa_dict[latent]) < 2:
                raise ValueError('Number of indicators of {} is less than two'.format(latent))
        self.cfa_dict = cfa_dict
        self.dataset = dataset
```

```
def cronbach_alpha(self, indicator_set):
    '''
    Compute cronbach alpha for a given indicator set.
    :param: Indicator set.
    :return: Cronbach Alpha.
    '''
    num_indicator = len(indicator_set)
    var_of_sum = np.var(self.dataset[indicator_set].dropna().copy().sum(1))
    sum_of_var = 0
    for indicator in indicator_set:
        sum_of_var += np.var(self.dataset[indicator].dropna().copy())
    return num_indicator / (num_indicator - 1) * (1 - sum_of_var / var_of_sum)

def reliability_test(self, alpha_threshold=0.7):
    '''
    Compute cronbach alpha for all latents and implement reliability test.
    :return: Bool, failed_cronbach_alpha_dict.
    '''
    cronbach_alpha_dict = dict()
    for latent in self.cfa_dict.keys():
        cronbach_alpha_dict[latent] = \
            self.cronbach_alpha(self.cfa_dict[latent])

    # Find latents with Cronbach Alpha < alpha_threshold.
    failed_cronbach_alpha_dict = dict()
    for latent, alpha in cronbach_alpha_dict.items():
        if alpha <= alpha_threshold:
            failed_cronbach_alpha_dict[latent] = alpha
```

```
        if not bool(failed_cronbach_alpha_dict):
            print('--> Pass the reliability test.')
            print('Cronbach alpha : {}'.format(cronbach_alpha_dict))
            return True, failed_cronbach_alpha_dict
        else:
            print('--> Fail the reliability test.')
            print('Cronbach alpha : {}'.format(cronbach_alpha_dict))
            print('Fail at : {}'.format(failed_cronbach_alpha_dict))
            return False, failed_cronbach_alpha_dict

    def run_cfa_model(self, cfa_dict, draw_graph=False):
        '''
        Run CFA model to compute loadings, aves, crs, correlations, rmsea and chi2.
        :param: cfa_dict.
        :return: loadings, aves, crs, correlations, rmsea, chi2.
        '''
        # Prepare data (slicing and normalising).
        total_indicator_set = set()
        for indicator_set in cfa_dict.values():
            total_indicator_set = total_indicator_set.union(indicator_set)
        data = self.dataset[total_indicator_set].dropna().copy()
        for column in data.columns:
            mean = np.mean(data[column])
            std = np.std(data[column])
            data[column] = (data[column] - mean) / std

        # Create formula string for cfa_dict.
        mod = ""
        for paired_latents in itertools.combinations(set(cfa_dict.keys()), 2):
```

```
        mod += paired_latents[0]
        mod += ' ~~ '
        mod += paired_latents[1]
        mod += '\n'
for latent in cfa_dict.keys():
    mod += latent
    mod += ' =~ '
    for num, indicator in enumerate(cfa_dict[latent]):
        if num < len(cfa_dict[latent]) - 1:
            mod += indicator
            mod += ' + '
        if num == len(cfa_dict[latent]) - 1:
            mod += indicator
    mod += '\n'

# Fit CFA model.
model = Model(mod)
model.fit(data)

if draw_graph == True:
    # draw graph for CFA result.
    semplot(model, 'CFA.png', plot_covs=True, std_ests=True)

# CFA results.
coefficients = model.inspect(std_est='lv')
coefficients.to_excel('CFA_coefficients.xlsx', index=0)
model_fit = calc_stats(model)
model_fit.to_excel('CFA_fit.xlsx', index=0)
rmsea = model_fit['RMSEA'][0]
```

```
chi2 = model_fit['chi2'][0]

# Create loadings, aves, crs, correlations dictionaries.
loadings = {}
aves = {}
crs = {}
correlations = {}
for latent in cfa_dict.keys():
    loadings_for_this_latent = {}
    for num_row in range(coefficients.shape[0]):
        if coefficients['lval'][num_row] in cfa_dict[latent] and \
            coefficients['op'][num_row] == '~' and \
            coefficients['rval'][num_row] == latent:
              loadings_for_this_latent[coefficients['lval'][num_row]] = \
                  coefficients['Est. Std'][num_row]
    loadings[latent] = loadings_for_this_latent
    aves[latent] = sum(map(lambda x: x ** 2,
loadings_for_this_latent.values())) \
                        / len(loadings_for_this_latent)
    crs[latent] = sum(loadings_for_this_latent.values()) ** 2 \
                        / (sum(loadings_for_this_latent.values()) ** 2 + \
                            len(loadings_for_this_latent) - \
                            sum(map(lambda x: x ** 2,
loadings_for_this_latent.values())))
for num_row in range(coefficients.shape[0]):
    if coefficients['lval'][num_row] in cfa_dict.keys() and \
        coefficients['op'][num_row] == '~~' and \
        coefficients['rval'][num_row] in cfa_dict.keys() and \
        coefficients['lval'][num_row] != coefficients['rval'][num_row]:
```

```
                    correlations[coefficients['lval'][num_row] +
                                 coefficients['op'][num_row] +
                                 coefficients['rval'][num_row]] = coefficients['Est.
Std'][num_row]

        return loadings, aves, crs, correlations, rmsea, chi2

    def validity_test(self,
                      loading_threshold=0.5,
                      ave_threshold=0.5,
                      cr_threshold=0.7,
                      rmsea_threshold=0.05):
        '''
        Implement convergent validity test and discriminant validity test.
        :return: Bool,
                 loadings,
                 failed_loading_dict,
                 failed_ave_dict,
                 failed_cr_dict,
                 failed_correlation_dict,
                 model_fit(Bool),
                 rmsea,
                 chi2.
        '''
        loadings, aves, crs, \
        correlations, rmsea, chi2 = self.run_cfa_model(self.cfa_dict)

        # For each latent, find indicators with loadings < loading_threshold.
        failed_loading_dict = {}
```

```
failed_loading_only_indicators = {}
for latent in loadings:
    failed_loading_dict[latent] = {}
    for indicator, loading in loadings[latent].items():
        if loading < loading_threshold:
            failed_loading_dict[latent][indicator] = loading
            failed_loading_only_indicators[indicator] = loading

# Find latents with aves < ave_threshold.
failed_ave_dict = {}
for latent, ave in aves.items():
    if ave < ave_threshold:
        failed_ave_dict[latent] = ave

# Find latents with crs < cr_threshold.
failed_cr_dict = {}
for latent, cr in crs.items():
    if cr < cr_threshold:
        failed_cr_dict[latent] = cr

# Check convergent validity.
if not bool(failed_loading_only_indicators) and \
   not bool(failed_ave_dict) and \
   not bool(failed_cr_dict):
    print('--> Pass the convergent validity test.')
    print('Loadings : {}'.format(loadings))
    print('AVEs : {}'.format(aves))
    print('Crs : {}'.format(crs))
    convergent_validity = True
```

```
else:
    print('--> Fail the convergent validity test.')
    print('Loadings : {}'.format(loadings))
    print('Fail at : {}'.format(failed_loading_dict))
    print('AVEs : {}'.format(aves))
    print('Fail at : {}'.format(failed_ave_dict))
    print('Crs : {}'.format(crs))
    print('Fail at : {}'.format(failed_cr_dict))
    convergent_validity = False

# Find latents whose square root of ave are smaller than some of their
# correlations.
failed_correlation_dict = {}
for latent in aves:
    for correlation in correlations:
        if latent in correlation:
            if np.sqrt(aves[latent]) < correlations[correlation]:
                failed_correlation_dict[latent] = correlation

# Check discriminant validity.
if not bool(failed_correlation_dict):
    print('--> Pass the discriminant validity test.')
    discriminant_validity = True
else:
    print('--> Fail the discriminant validity test.')
    print('Fail at : {}'.format(failed_correlation_dict))
    discriminant_validity = False

# Check model fit.
```

```
        if rmsea < rmsea_threshold:
            print('--> Pass the model fit test.')
            print('Rmsea: {}'.format(rmsea))
            model_fit = True
        else:
            print('--> Fail the model fit test.')
            print('Rmsea: {}'.format(rmsea))
            model_fit = False

        # Check overall validity for cfa_dict.
        if convergent_validity and discriminant_validity and model_fit:
            return True, loadings, failed_loading_dict, failed_ave_dict, \
                   failed_cr_dict, failed_correlation_dict, model_fit, \
                   rmsea, chi2
        else:
            return False, loadings, failed_loading_dict, failed_ave_dict, \
                   failed_cr_dict, failed_correlation_dict, model_fit, \
                   rmsea, chi2

    def indicator_selection(self):
        '''
        Find the maximum indicator set that passes reliability and validity test
        with good model fit.
        :return: Maximum credible indicator set.
        '''
        while True:
            print('------------------------------------------------------------')
            print('------------------------------------------------------------')
            print('Current cfa dict: {}'.format(self.cfa_dict))
```

```
# Run cfa model and reliability & validity tests.
reliability, failed_cronbach_alpha_dict = self.reliability_test()
validity, loadings, \
                failed_loading_dict, \
                failed_ave_dict, \
                failed_cr_dict, \
                failed_correlation_dict, \
                model_fit, \
                rmsea, \
                chi2 = self.validity_test()

# Find failed latents that have as least one issue in tests.
failed_latents = set()
failed_latents = failed_latents.\
      union(set(failed_cronbach_alpha_dict.keys()))
for latent in failed_loading_dict:
      if bool(failed_loading_dict[latent]):
            failed_latents.add(latent)
failed_latents = failed_latents.\
      union(set(failed_ave_dict.keys()))
failed_latents = failed_latents.\
      union(set(failed_cr_dict.keys()))
failed_latents = failed_latents.\
      union(set(failed_correlation_dict.keys()))

# Check if all latent pass reliability & validity tests.
if bool(failed_latents):
      for failed_latent in failed_latents:
```

```
                    indicator = min(loadings[failed_latent],
                                    key=loadings[failed_latent].get)
                    self.cfa_dict[failed_latent].discard(indicator)

                # Check number of indicators for each latent.
                latents_need_more_indicator = \
                    [latent for latent in self.cfa_dict
                     if len(self.cfa_dict[latent]) < 2]
                if bool(latents_need_more_indicator):
                    print('Need more indicators for statistical tests: {}'.\
                        format(latents_need_more_indicator))
                    return self.cfa_dict
                else:
                    continue

            else:
                # Use Modification Indice (MI) to remove indicators to improve
model fit.
                if not model_fit:
                    latents_num_indicators = \
                        {latent: len(indicators) for latent, indicators in
self.cfa_dict.items()}
                    if list(filter(lambda x: x == 2,
latents_num_indicators.values())) \
                        == list(latents_num_indicators.values()):
                        print('Need more indicators, the best we can get is {},
rmsea:{}'.\
                            format(self.cfa_dict, rmsea))
                        return self.cfa_dict
```

```
                else:
                    MI = {}
                    for latent in self.cfa_dict:
                        if len(self.cfa_dict[latent]) > 2:
                            for indicator in self.cfa_dict[latent]:
                                modified_cfa_dict                =
copy.deepcopy(self.cfa_dict)

modified_cfa_dict[latent].discard(indicator)
                                chi2_modified = \

self.run_cfa_model(modified_cfa_dict)[-1]
                                MI[indicator] = chi2 - chi2_modified
                    indicator = max(MI, key = MI.get)
                    for latent in self.cfa_dict:
                        if indicator in self.cfa_dict[latent]:
                            self.cfa_dict[latent].discard(indicator)
            # If pass the tests, return current cfa_dict.
            else:
                print('Success.')
                return self.cfa_dict
```

Appendix B: SEM Module of ARI

```
import numpy as np
import pandas as pd
from semopy import Model
from semopy import calc_stats
from semopy import semplot

class SEM:

    def __init__(self, sem_dict, covariate_set, structural_model_tree, dataset):
        '''
        :param sem_dict: {latent1: {latent1_indicators}, latent2:
{latent2_indicators},...}
        :param covariate_set: A set that contains all covariates in structural model.
        :param structural_model_tree: {structural node: {parent1, parent2, ...}, ...}
        :param dataset: Aggregated panel dataset.
        The header of dataset needs to contain 'Code', 'Year'.
        '''
        self.sem_dict = sem_dict
        self.covariate_set = covariate_set
        self.structural_model_tree = structural_model_tree
        self.dataset = dataset

        # Check if 'Code' and 'Year' in dataset columns.
        if 'Code' not in self.dataset.columns:
            raise KeyError("Code is not in the header of dataset.")
        if 'Year' not in self.dataset.columns:
            raise KeyError("Year is not in the header of dataset.")
```

```
        # Check if sem_dict and covariate_set together has the same structural node set as
        # structural_model_tree.
        if set(self.sem_dict.keys()).union(self.covariate_set) != \
                set(self.structural_model_tree.keys()):
            raise KeyError("Structural nodes don't add up.")

        # Create structural model from structural_model_tree.
        structural_model = ""
        for structural_node in self.structural_model_tree:
            if len(self.structural_model_tree[structural_node]) == 0:
                pass
            else:
                structural_model += structural_node
                structural_model += ' ~ '
                for num, parent_node in enumerate(self.structural_model_tree[structural_node]):
                    if num < len(self.structural_model_tree[structural_node]) - 1:
                        structural_model += parent_node
                        structural_model += ' + '
                    if num == len(self.structural_model_tree[structural_node]) - 1:
                        structural_model += parent_node
                structural_model += '\n'

        # Create SEM string.
        mod = ""
        for latent in self.sem_dict:
            mod += latent
```

```
            mod += ' =~ '
            for num, indicator in enumerate(self.sem_dict[latent]):
                if num < len(self.sem_dict[latent]) - 1:
                    mod += indicator
                    mod += ' + '
                if num == len(self.sem_dict[latent]) - 1:
                    mod += indicator
            mod += '\n'
        mod += structural_model
        self.mod = mod

        # Prepare data for SEM (data slicing and normalisation).
        header_set = set()
        header_set = header_set.union(self.covariate_set)
        for indicator_set in self.sem_dict.values():
            header_set = header_set.union(indicator_set)
        data = dataset[header_set].dropna().copy()
        for column in data.columns:
            mean = np.mean(data[column])
            std = np.std(data[column])
            data[column] = (data[column] - mean) / std
        self.data = data

    def run_sem_model(self):
        '''
        Run SEM.
        '''
        # Fit SEM
        model = Model(self.mod)
```

```
        model.fit(self.data)

        # Draw graph.
        semplot(model, 'SEM.png', plot_covs=True, std_ests=True)

        # Save coefficients.
        self.coefficients = model.inspect(std_est='lv')
        self.coefficients.to_excel('SEM_coefficients.xlsx', index=0)

        # Save model fitness.
        self.model_fit = calc_stats(model)
        self.model_fit.to_excel('SEM_fit.xlsx', index=0)

    def weighting(self):
        '''
        Compute weights for each indicators,
        self.run_sem_model must be run prior to this method.
        :return: weights.
        '''
        weights = {}

        for latent in self.sem_dict:

            weights[latent] = {}
            indicator_list = list(self.sem_dict[latent])
            # Read loadings.
            total_loadings = 0
            for indicator in indicator_list:
                loc_indicator = set(np.where(self.coefficients['lval'] ==
```

```
indicator)[0])
                loc_op = set(np.where(self.coefficients['op'] == '~')[0])
                loc_latent = set(np.where(self.coefficients['rval'] == latent)[0])
                loc                                                          =
list(loc_indicator.intersection(loc_op).intersection(loc_latent))[0]
                weights[latent][indicator] = self.coefficients.loc[loc, 'Est. Std']
                total_loadings += weights[latent][indicator]
            # Compute weights.
            for indicator in indicator_list:
                weights[latent][indicator] /= total_loadings

        return weights

    def compute_latent(self):
        '''
        Compute the value of latent, self.run_sem_model must be run prior to this
method.
        '''
        weights = self.weighting()

        # Compute value for each latent.
        for latent in self.sem_dict:
            # Order of indicators matters.
            ordered_indicator_list = []
            ordered_weight_list = []
            for indicator in weights[latent]:
                ordered_indicator_list.append(indicator)
                ordered_weight_list.append(weights[latent][indicator])
            ordered_weights = np.mat(ordered_weight_list)
```

```
        self.dataset[latent] = self.dataset[ordered_indicator_list] @ ordered_weights.T

        header_set = ['Code', 'Year'] + list(self.structural_model_tree.keys())

        self.index = self.dataset[header_set].copy()

    def estimate_missing_value_for_single_slot(self,
                                               code,
                                               year,
                                               structural_node,
                                               stationary_period=1,
                                               recursive=True):
        '''
        Compute estimation for single missing data slot, self.run_sem_model and
        self.compute_latent must be run prior to this method.
        :param code: Country code.
        :param year: Year of missing record.
        :param structural_node: Node to estimate.
        :param stationary_period: Assume that the distribution of residual zeta of
        structural_node remains stationary in the past stationary_period years.
        :param recursive: Use recursive method or not.
        :return: Estimation of missing value
        '''
        code_rows = list(np.where(self.index['Code'] == code)[0])
        year_rows = list(np.where(self.index['Year'] == year)[0])
        target_row = [row for row in code_rows if row in year_rows][0]
        target_row_index = code_rows.index(target_row)
```

```
# If the slot already has non nan value, return it.
if not np.isnan(self.index[structural_node].loc[target_row]):
    return self.index[structural_node].loc[target_row]

# The first row of each country returns itself.
if target_row_index == 0:
    return self.index[structural_node].loc[target_row]

# The exogenous variable returns itself.
if not bool(self.structural_model_tree[structural_node]):
    return self.index[structural_node].loc[target_row]

# For all other cases, we need to compute the residual zeta and its parent nodes.
# Compute the period that used to compute zeta.
if stationary_period <= target_row_index:
    zeta_period = code_rows[target_row_index - stationary_period:target_row_index]
else:
    zeta_period = code_rows[:target_row_index]
# Compute all zetas in the period.
parent_nodes = self.structural_model_tree[structural_node]
zeta_list = []
for timestamp in zeta_period:
    zeta = self.index[structural_node].loc[timestamp]
    for parent_node in parent_nodes:
        loc_child = set(np.where(self.coefficients['lval'] == structural_node)[0])
        loc_op = set(np.where(self.coefficients['op'] == '~')[0])
```

```
                loc_parent = set(np.where(self.coefficients['rval'] == parent_node)[0])
                loc = list(loc_child.intersection(loc_op).intersection(loc_parent))[0]
                zeta -= self.coefficients['Est. Std'][loc] * self.index[parent_node].loc[timestamp]
            zeta_list.append(zeta)

        # Compute the average zeta.
        zeta_list_drop_nan = list(filter(lambda x: not np.isnan(x), zeta_list))
        if not bool(zeta_list_drop_nan):
            average_zeta = np.nan
        else:
            average_zeta = np.average(zeta_list_drop_nan)

        # Use the structural model to compute estimation for missing data.
        # Recursive estimation can be used to solve this problem.
        if recursive == True:

            estimation = 0

            for parent_node in parent_nodes:
                loc_child = set(np.where(self.coefficients['lval'] == structural_node)[0])
                loc_op = set(np.where(self.coefficients['op'] == '~')[0])
                loc_parent = set(np.where(self.coefficients['rval'] == parent_node)[0])
                loc = list(loc_child.intersection(loc_op).intersection(loc_parent))[0]
```

```
                estimation += self.coefficients['Est. Std'][loc] * \

self.estimate_missing_value_for_single_slot(code, year, parent_node,
stationary_period)

        else:

            estimation = 0

            for parent_node in parent_nodes:

                loc_child = set(np.where(self.coefficients['lval'] ==
structural_node)[0])
                loc_op = set(np.where(self.coefficients['op'] == '~')[0])
                loc_parent = set(np.where(self.coefficients['rval'] ==
parent_node)[0])
                loc =
list(loc_child.intersection(loc_op).intersection(loc_parent))[0]
                estimation += self.coefficients['Est. Std'][loc] * \
                                      self.index.loc[target_row, parent_node]

        estimation += average_zeta

        return estimation

    def estimate_missing_values_for_entire_latent_table(self, stationary_period=1):
        '''
        Compute estimations for entire dataset, self.run_sem_model and
        self.compute_latent must be run prior to this method.
```

```
            :param stationary_period: Assume that the distribution of residual zeta of
            structural_node remains stationary in the past stationary_period years.
            '''
            header_set = ['Code', 'Year'] + list(self.structural_model_tree.keys())
            self.index_estimate = self.dataset[header_set].copy()      # same result as
self.index
                                                                        # in
line 211.

            code_set = set(self.index_estimate['Code'])
            year_set = set(self.index_estimate['Year'])
            structural_node_set = set(self.structural_model_tree.keys())

            # Iteratively look through entire dataset and fill missing values.
            for code in code_set:
                for year in year_set:
                    code_rows    =    list(np.where(self.index_estimate['Code']    ==
code)[0])
                    year_rows = list(np.where(self.index_estimate['Year'] == year)[0])
                    target_row = [row for row in code_rows if row in year_rows][0]
                    for structural_node in structural_node_set:
                        self.index_estimate.loc[target_row, structural_node] = \
                            self.estimate_missing_value_for_single_slot(code, year,
structural_node, stationary_period)
                            #self.estimate_missing_data_for_single_slot          use
self.index
                            #to compute the missing data in self.index_estimate
                            #we should never use the data from self.index_estimate
                            #to estimate the missing data of itself.
```

Appendix C: 2019 Internal Peace Index

States / territories	IPI	Ranking
France	1.510861359	1
Switzerland	1.504709928	2
Korea (the Republic of)	1.467334363	3
Japan	1.46209187	4
Netherlands	1.452653469	5
Italy	1.44972503	6
Sweden	1.441844044	7
Spain	1.426393161	8
Germany	1.359574697	9
Belgium	1.353169429	10
Denmark	1.30973565	11
Norway	1.303013954	12
Finland	1.292648595	13
Singapore	1.249188598	14
China	1.243060952	15
Canada	1.215564725	16
Australia	1.174314056	17
Portugal	1.165557339	18
Austria	1.156781189	19
Poland	1.119247351	20
Slovenia	1.087131277	21
United States of America	1.072902708	22
Greece	1.027127885	23
Czechia	1.024301741	24
Ireland	1.013435859	25
United Arab Emirates	1.01341525	26

Iceland	0.958902324	27
Belarus	0.931126931	28
Luxembourg	0.875134288	29
Estonia	0.858386047	30
New Zealand	0.84619274	31
Cyprus	0.845822631	32
Croatia	0.840428297	33
Serbia	0.821593545	34
Hungary	0.726823664	35
Malaysia	0.724745849	36
Lithuania	0.69215659	37
Montenegro	0.686793192	38
Kazakhstan	0.675893681	39
Slovakia	0.663557493	40
Bosnia and Herzegovina	0.658256057	41
Chile	0.657650866	42
Israel	0.634699135	43
Romania	0.623814489	44
Bulgaria	0.604429754	45
Cuba	0.594481018	46
Argentina	0.569778489	47
Viet Nam	0.566124063	48
Qatar	0.55052195	49
Latvia	0.536104089	50
Indonesia	0.510150401	51
Kuwait	0.499789046	52
Republic of North Macedonia	0.490871151	53
Russian Federation	0.48759179	54
Albania	0.482742096	55

Bahrain	0.449896851	56
Malta	0.425303121	57
Tunisia	0.422512844	58
Uzbekistan	0.420534542	59
Costa Rica	0.404824412	60
Oman	0.40192883	61
Peru	0.394567148	62
Moldova	0.341383267	63
Bangladesh	0.339499935	64
Armenia	0.325972572	65
Uruguay	0.323535723	66
Algeria	0.315413876	67
Lebanon	0.3121296	68
Morocco	0.302680702	69
Georgia	0.286623129	70
South Africa	0.27119176	71
Azerbaijan	0.233454635	72
Ukraine	0.226890589	73
Jordan	0.213354796	74
Kyrgyzstan	0.202596	75
Thailand	0.178767	76
Nepal	0.177518942	77
Tajikistan	0.174119237	78
Saudi Arabia	0.165611478	79
Venezuela	0.16553554	80
El Salvador	0.157481998	81
Honduras	0.155539052	82
Guatemala	0.150110099	83
Jamaica	0.122260134	84

Brunei Darussalam	0.119490268	85
United Kingdom	0.115776069	86
Mongolia	0.113667838	87
Nicaragua	0.107423853	88
Maldives	0.099797498	89
Panama	0.099045748	90
Brazil	0.096852887	91
Paraguay	0.086020205	92
Cambodia	0.082837358	93
Mauritius	0.081404624	94
Dominican Republic	0.063734493	95
Mexico	0.049884636	96
Bahamas	0.046816087	97
Uganda	0.032602852	98
Barbados	0.028573718	99
Ghana	0.022395519	100
Bolivia	0.009927732	101
Senegal	-0.008597987	102
Trinidad and Tobago	-0.032726252	103
Colombia	-0.041484179	104
Zimbabwe	-0.061085387	105
Malawi	-0.066156854	106
Zambia	-0.073490747	107
Lao	-0.08160776	108
Sri Lanka	-0.111608823	109
Ecuador	-0.117511409	110
Fiji	-0.13296046	111
Cabo Verde	-0.15061814	112
Côte d'Ivoire	-0.158215594	113

Botswana	-0.176489439	114
Belize	-0.176837243	115
Samoa	-0.180526582	116
Suriname	-0.190203658	117
Namibia	-0.190824386	118
Togo	-0.237265516	119
Bhutan	-0.239226245	120
Saint Lucia	-0.244271944	121
Haiti	-0.248242379	122
Tonga	-0.266118634	123
Gabon	-0.276166972	124
Guyana	-0.300918052	125
Rwanda	-0.315698483	126
Liberia	-0.332098686	127
Mauritania	-0.336822923	128
Turkey	-0.344036641	129
Sierra Leone	-0.359807748	130
Myanmar	-0.384728878	131
Gambia	-0.389596125	132
Eswatini	-0.41151771	133
Lesotho	-0.417158798	134
Angola	-0.426808338	135
Sao Tome and Principe	-0.473867872	136
Iran	-0.479973507	137
Tanzania	-0.515970832	138
India	-0.551586392	139
Congo	-0.556424202	140
Papua New Guinea	-0.613935602	141
Egypt	-0.651679347	142

Philippines	-0.703563689	143
Benin	-0.848807217	144
Iraq	-0.951438605	145
Sudan	-1.062821168	146
Burundi	-1.122356071	147
Yemen	-1.128950826	148
Mozambique	-1.192799398	149
Libya	-1.210923173	150
Pakistan	-1.23830591	151
Niger	-1.249942737	152
Ethiopia	-1.267692219	153
Cameroon	-1.309788204	154
Kenya	-1.313595019	155
Syrian Arab Republic	-1.616234327	156
Burkina Faso	-1.756107343	157
Congo (the Democratic Republic of the)	-1.759314265	158
Afghanistan	-1.836821891	159
Chad	-1.848255169	160
Mali	-1.896776136	161
Central African Republic	-1.965771889	162

Appendix D: 2017 External Negative Peace Index

States / territories	ENP	Ranking
Aruba	0.660663957	1
Angola	0.660663957	1
Andorra	0.660663957	1
Argentina	0.660663957	1
American Samoa	0.660663957	1
Antigua and Barbuda	0.660663957	1
Bahamas	0.660663957	1
Belarus	0.660663957	1
Belize	0.660663957	1
Bermuda	0.660663957	1
Bolivia	0.660663957	1
Brazil	0.660663957	1
Barbados	0.660663957	1
Botswana	0.660663957	1
Chile	0.660663957	1
Congo	0.660663957	1
Colombia	0.660663957	1
Comoros	0.660663957	1
Cabo Verde	0.660663957	1
Costa Rica	0.660663957	1
Cuba	0.660663957	1
CYM	0.660663957	1
Dominica	0.660663957	1
Dominican Republic	0.660663957	1
Algeria	0.660663957	1
Ecuador	0.660663957	1

Fiji	0.660663957	1
Faroe Islands (Pettersson et al.)	0.660663957	1
Micronesia	0.660663957	1
Gabon	0.660663957	1
Equatorial Guinea	0.660663957	1
Grenada	0.660663957	1
Greenland	0.660663957	1
Guatemala	0.660663957	1
Guam	0.660663957	1
Guyana	0.660663957	1
Hong Kong	0.660663957	1
Honduras	0.660663957	1
Haiti	0.660663957	1
Isle of Man	0.660663957	1
Jamaica	0.660663957	1
Kazakhstan	0.660663957	1
Kyrgyzstan	0.660663957	1
Kiribati	0.660663957	1
Saint Kitts and Nevis	0.660663957	1
Korea	0.660663957	1
Lao	0.660663957	1
Libya	0.660663957	1
Saint Lucia	0.660663957	1
Liechtenstein	0.660663957	1
Lesotho	0.660663957	1
Macao	0.660663957	1
Monaco	0.660663957	1
Moldova	0.660663957	1
Madagascar	0.660663957	1

Maldives	0.660663957	1
Mexico	0.660663957	1
Marshall Islands	0.660663957	1
Malta	0.660663957	1
Northern Mariana Islands	0.660663957	1
Mozambique	0.660663957	1
Mauritius	0.660663957	1
Namibia	0.660663957	1
New Caledonia	0.660663957	1
Nicaragua	0.660663957	1
Nauru	0.660663957	1
Oman	0.660663957	1
Panama	0.660663957	1
Peru	0.660663957	1
Palau	0.660663957	1
Papua New Guinea	0.660663957	1
Puerto Rico	0.660663957	1
Paraguay	0.660663957	1
Palestine	0.660663957	1
French Polynesia	0.660663957	1
Rwanda	0.660663957	1
Solomon Islands	0.660663957	1
San Marino	0.660663957	1
Sao Tome and Principe	0.660663957	1
Suriname	0.660663957	1
Eswatini	0.660663957	1
Seychelles	0.660663957	1
Turks and Caicos Islands	0.660663957	1
Thailand	0.660663957	1

Tajikistan	0.660663957	1
Turkmenistan	0.660663957	1
Timor-Leste	0.660663957	1
Tonga	0.660663957	1
Trinidad and Tobago	0.660663957	1
Tuvalu	0.660663957	1
Uruguay	0.660663957	1
Uzbekistan	0.660663957	1
Saint Vincent and the Grenadines	0.660663957	1
Virgin Islands	0.660663957	1
Viet Nam	0.660663957	1
Vanuatu	0.660663957	1
Samoa	0.660663957	1
Zambia	0.660663957	1
Zimbabwe	0.660663957	1
Azerbaijan	0.13746612	100
Brunei Darussalam	0.13746612	100
Central African Republic	0.13746612	100
Cyprus	0.13746612	100
Croatia	0.13746612	100
Iceland	0.13746612	100
Japan	0.13746612	100
Lebanon	0.13746612	100
North Macedonia	0.13746612	100
Myanmar	0.13746612	100
Mongolia	0.13746612	100
Singapore	0.13746612	100
Somalia	0.13746612	100
Slovakia	0.13746612	100

Ukraine	0.13746612	100
Philippines	0.023421412	115
Kuwait	0.168584995	116
Mali	0.168584995	116
New Zealand	0.168584995	116
Congo (the Democratic Republic)	0.385731717	119
Serbia	0.385731717	119
Albania	-0.5541638	121
Bulgaria	-0.5541638	121
Georgia	-0.5541638	121
Greece	-0.5541638	121
Ireland	-0.5541638	121
Luxembourg	-0.5541638	121
Montenegro	-0.5541638	121
Poland	-0.5541638	121
Slovenia	-0.5541638	121
Canada	0.691782832	130
BTN	0.758717819	131
Switzerland	0.758717819	131
Côte d'Ivoire	0.758717819	131
Guinea	0.758717819	131
Gambia	0.758717819	131
Guinea-Bissau	0.758717819	131
Cambodia	0.758717819	131
Liberia	0.758717819	131
Sri Lanka	0.758717819	131
Nepal	0.758717819	131
El Salvador	0.758717819	131
Togo	0.758717819	131

Spain	0.808138066	143
Israel	0.808138066	143
Djibouti	-0.83858957	145
Bahrain	-0.88975315	146
Morocco	-0.88975315	146
Austria	0.927149902	148
Bangladesh	0.927149902	148
Bosnia and Herzegovina	0.927149902	148
Czechia	0.927149902	148
Senegal	0.927149902	148
Tunisia	0.927149902	148
Iraq	1.058713452	154
Burkina Faso	1.064768935	155
Indonesia	1.064768935	155
Latvia	1.064768935	155
Mauritania	1.064768935	155
Norway	1.064768935	155
Romania	1.064768935	155
Malaysia	1.069817086	161
Finland	1.181124168	162
Hungary	1.181124168	162
Portugal	1.181124168	162
Sweden	1.181124168	162
Sudan	1.195804265	166
Uganda	1.280180703	167
Denmark	1.281915656	168
Estonia	1.281915656	168
Italy	1.281915656	168
Lithuania	1.281915656	168

Niger	1.281915656	168
Yemen	1.295977664	173
BEN	-1.37082005	174
China	-1.37082005	174
Netherlands	-1.37082005	174
Armenia	1.379111193	177
United Arab Emirates	1.412950987	178
Malawi	1.458071186	179
Tanzania	1.458071186	179
South Africa	1.458071186	179
India	1.480647303	182
Burundi	1.535884263	183
Ethiopia	1.535884263	183
Ghana	1.535884263	183
Kenya	1.535884263	183
Sierra Leone	1.535884263	183
Qatar	-1.58138307	188
Germany	1.648384202	189
Afghanistan	1.691311003	190
Egypt	1.723294103	191
Syrian Arab Republic	1.766976021	192
Nigeria	1.890650017	193
Saudi Arabia	1.893366285	194
Australia	2.013905035	195
Belgium	2.014761281	196
Cameroon	2.177576181	197
Pakistan	2.217656453	198
Turkey	2.220295563	199
Jordan	2.264460764	200

Chad	2.314801665	201
France	2.491492372	202
United Kingdom	2.755105839	203
Iran	2.877697666	204
Russia	3.102641018	205
United States of America	3.720653877	206

Appendix E: Prosperity adjusted IPI 2019

States / territories	Adjusted IPI	Ranking
Malawi	2.240865526	1
China	2.232198548	2
Tajikistan	2.174042098	3
Uzbekistan	2.140389638	4
Viet Nam	2.100046993	5
Belarus	2.097199869	6
Nepal	2.092622548	7
Uganda	2.07017657	8
Kyrgyzstan	2.035369194	9
Bangladesh	2.029381702	10
Korea (the Republic of)	1.992417846	11
Spain	1.981443009	12
Italy	1.957401342	13
Serbia	1.944041771	14
France	1.937506791	15
Poland	1.934332472	16
Japan	1.891244855	17
Tunisia	1.87435925	18
Indonesia	1.871674432	19
Togo	1.864421074	20
Bosnia and Herzegovina	1.859949907	21
Sierra Leone	1.845480879	22
Cambodia	1.822581071	23
Portugal	1.819520584	24
Liberia	1.805761735	25
Nicaragua	1.784873939	26

Senegal	1.783276256	27
Netherlands	1.774218838	28
Sweden	1.76905683	29
Morocco	1.768773571	30
Zambia	1.760639636	31
Greece	1.751469677	32
Albania	1.738516117	33
Montenegro	1.733855209	34
Germany	1.730032962	35
Zimbabwe	1.725958946	36
Belgium	1.723844654	37
Honduras	1.711211301	38
Rwanda	1.708835776	39
Republic of North Macedonia	1.698394931	40
Slovenia	1.696172198	41
Algeria	1.693271305	42
Kazakhstan	1.683376472	43
Croatia	1.675756465	44
Czechia	1.674012997	45
Malaysia	1.67026764	46
Moldova	1.667981953	47
Gambia	1.656594099	48
Finland	1.642986259	49
Switzerland	1.642273472	50
Ghana	1.642152972	51
Armenia	1.641865232	52
Ukraine	1.638580125	53
Bulgaria	1.611255022	54
Haiti	1.596244759	55

Georgia	1.595923649	56
Canada	1.588239202	57
Denmark	1.574104828	58
Argentina	1.573110959	59
Jordan	1.548971282	60
Peru	1.541748265	61
Azerbaijan	1.534475959	62
Romania	1.51857468	63
Hungary	1.515631265	64
El Salvador	1.513917132	65
Estonia	1.504127752	66
Austria	1.495893509	67
Chile	1.494068155	68
Lao	1.480482119	69
Singapore	1.480453173	70
Lesotho	1.4803175	71
South Africa	1.4801343	72
Australia	1.475049503	73
Norway	1.474823232	74
Guatemala	1.466246436	75
Mongolia	1.455436007	76
Côte d'Ivoire	1.447959372	77
Bolivia	1.433774136	78
Russian Federation	1.427027844	79
Cyprus	1.425725918	80
Lebanon	1.425185179	81
Myanmar	1.418347419	82
Lithuania	1.416093585	83
United Arab Emirates	1.41447197	84

Slovakia	1.394570982	85
Mauritania	1.393961147	86
Tanzania	1.380045667	87
Burundi	1.370889162	88
Jamaica	1.360868695	89
Paraguay	1.337109483	90
Costa Rica	1.321596696	91
United States of America	1.303763992	92
Latvia	1.298888629	93
Thailand	1.279944768	94
Sri Lanka	1.278906223	95
Cabo Verde	1.267305752	96
New Zealand	1.25705259	97
Oman	1.226241728	98
Sudan	1.215413723	99
Bhutan	1.212778031	100
Sao Tome and Principe	1.19641785	101
Iceland	1.179554488	102
Ireland	1.168002731	103
Samoa	1.162738889	104
Brazil	1.152830532	105
Dominican Republic	1.140691023	106
Colombia	1.139276816	107
Uruguay	1.125828844	108
Belize	1.122343825	109
Bahrain	1.09944453	110
Namibia	1.096423196	111
Angola	1.095883734	112
India	1.087705191	113

Ecuador	1.079161313	114
Maldives	1.074619862	115
Fiji	1.064238405	116
Mexico	1.051824215	117
Congo	1.049096801	118
Mauritius	1.038392379	119
Mozambique	1.031538301	120
Israel	1.031135619	121
Tonga	1.025642334	122
Kuwait	1.022892864	123
Benin	1.013131851	124
Suriname	0.994968987	125
Malta	0.977315664	126
Eswatini	0.974597463	127
Niger	0.935364924	128
Yemen	0.919075461	129
Botswana	0.916653869	130
Panama	0.91312656	131
Papua New Guinea	0.90315034	132
Luxembourg	0.875134288	133
Guyana	0.868471101	134
Egypt	0.838767959	135
Gabon	0.827101404	136
Saudi Arabia	0.821557816	137
Qatar	0.802035258	138
Barbados	0.784083616	139
Trinidad and Tobago	0.74008357	140
Ethiopia	0.739363378	141
Philippines	0.728083715	142

Saint Lucia	0.6942307	143
Turkey	0.6931361	144
Iran	0.667049425	145
Brunei Darussalam	0.654464096	146
Pakistan	0.602267824	147
Bahamas	0.534804509	148
United Kingdom	0.524249964	149
Cameroon	0.46526785	150
Congo (the Democratic Republic of the)	0.406616627	151
Kenya	0.385033503	152
Afghanistan	0.384651288	153
Central African Republic	0.288664227	154
Burkina Faso	0.285325214	155
Iraq	0.260676872	156
Chad	0.235578665	157
Mali	0.099296647	158
Libya	-0.103355666	159

Appendix F: National power adjusted ENPI 2017

States / territories	**Adjusted ENPI**	Ranking
Brazil	0.180840804	1
Korea	0.129634682	2
Mexico	0.057531827	3
Argentina	-0.068168338	4
Thailand	-0.141659944	5
Japan	-0.156174024	6
Hong Kong	-0.203769182	7
Colombia	-0.223016569	8
Viet Nam	-0.245035182	9
Chile	-0.248858733	10
Peru	-0.306530475	11
Algeria	-0.352595071	12
Kazakhstan	-0.356771146	13
Ecuador	-0.457140177	14
Puerto Rico	-0.458889915	15
Cuba	-0.47296886	16
Oman	-0.511546784	17
Dominican Republic	-0.513828837	18
Guatemala	-0.537371703	19
Angola	-0.545523325	20
Libya	-0.551220921	21
Uruguay	-0.560736792	22
Panama	-0.567604768	23
Uzbekistan	-0.568022323	24
Costa Rica	-0.573480371	25
Belarus	-0.594973156	26

Macao	-0.612402412	27
Paraguay	-0.667399325	28
Turkmenistan	-0.673350443	29
Bolivia	-0.675717129	30
Singapore	-0.725767886	31
Zambia	-0.75508674	32
Trinidad and Tobago	-0.778582206	33
Honduras	-0.778987147	34
Papua New Guinea	-0.782654703	35
Zimbabwe	-0.83762708	36
Lao	-0.843964166	37
Palestine	-0.856111446	38
Botswana	-0.856636384	39
Haiti	-0.871102471	40
Gabon	-0.872615645	41
Jamaica	-0.87434773	42
Nicaragua	-0.889648364	43
Malta	-0.894047619	44
Philippines	-0.896020246	45
Mauritius	-0.897972004	46
Mozambique	-0.898622154	47
Madagascar	-0.899314738	48
Namibia	-0.903924819	49
Bahamas	-0.913025654	50
Equatorial Guinea	-0.915753	51
Congo	-0.936064562	52
Ukraine	-0.964933124	53
Moldova	-0.96544804	54
Rwanda	-0.974867648	55

New Caledonia	-0.976704192	56
Slovakia	-0.999407565	57
Kyrgyzstan	-1.014051121	58
Tajikistan	-1.018721522	59
Bermuda	-1.030201758	60
Isle of Man	-1.035127914	61
Liechtenstein	-1.051191128	62
Monaco	-1.05261346	63
Guam	-1.066988167	64
French Polynesia	-1.073471156	65
Fiji	-1.091822117	66
Myanmar	-1.093406922	67
CYM	-1.099418972	68
Barbados	-1.10720748	69
Croatia	-1.112437876	70
Maldives	-1.1171943	71
Guyana	-1.117464282	72
Lebanon	-1.124911242	73
Eswatini	-1.133597126	74
New Zealand	-1.140266283	75
Virgin Islands	-1.16541315	76
Suriname	-1.177129286	77
Azerbaijan	-1.180594514	78
Aruba	-1.209131289	79
Andorra	-1.215588105	80
Faroe Islands (Pettersson et al.)	-1.217756608	81
Canada	-1.219499548	82
Greenland	-1.226442001	83
Kuwait	-1.255154508	84

Lesotho	-1.271815347	85
Iceland	-1.287961466	86
Saint Lucia	-1.302606506	87
Cyprus	-1.304650919	88
Belize	-1.319513458	89
Poland	-1.325925307	90
Cabo Verde	-1.328398235	91
Timor-Leste	-1.3478794	92
Seychelles	-1.353533842	93
Northern Mariana Islands	-1.355365761	94
San Marino	-1.35970743	95
Solomon Islands	-1.366070368	96
Antigua and Barbuda	-1.368360775	97
Spain	-1.38466439	98
Ireland	-1.422287655	99
Grenada	-1.42510576	100
Comoros	-1.434468227	101
Saint Kitts and Nevis	-1.437827397	102
Brunei Darussalam	-1.440230096	103
Turks and Caicos Islands	-1.445682614	104
Mongolia	-1.451952371	105
North Macedonia	-1.455212466	106
Switzerland	-1.468242293	107
China	-1.468907478	108
Vanuatu	-1.477717311	109
Saint Vincent and the Grenadines	-1.485745105	110
Samoa	-1.489714037	111
Greece	-1.53297534	112
American Samoa	-1.555358248	113

Dominica	-1.589539304	114
Somalia	-1.605051468	115
Tonga	-1.616204358	116
Sao Tome and Principe	-1.659696602	117
Israel	-1.663975947	118
Micronesia	-1.664849469	119
Serbia	-1.687128992	120
Mali	-1.695709017	121
Indonesia	-1.696110597	122
Palau	-1.718477872	123
Congo (the Democratic Republic of the)	-1.719222769	124
Austria	-1.748616438	125
Luxembourg	-1.770701648	126
Italy	-1.77254309	127
Marshall Islands	-1.780736641	128
Bulgaria	-1.793009479	129
Kiribati	-1.807407801	130
Central African Republic	-1.81786379	131
Bangladesh	-1.823629993	132
Slovenia	-1.835224655	133
Czechia	-1.886760279	134
Norway	-1.896125128	135
India	-1.906886433	136
Sri Lanka	-1.9142277	137
Nauru	-1.92342688	138
Sweden	-1.947075167	139
Malaysia	-1.948600523	140
Morocco	-1.996793609	141

Germany	-2.003932791	142
Côte d'Ivoire	-2.026977536	143
Romania	-2.031267393	144
Netherlands	-2.044304911	145
Iraq	-2.05147479	146
Georgia	-2.069421686	147
Finland	-2.107301156	148
Tuvalu	-2.11218676	149
Albania	-2.116698326	150
Portugal	-2.138083227	151
Nepal	-2.150296845	152
Denmark	-2.15215894	153
El Salvador	-2.181987691	154
Cambodia	-2.207417365	155
Hungary	-2.231267646	156
Bahrain	-2.238055794	157
Tunisia	-2.23852509	158
United Arab Emirates	-2.251280564	159
Sudan	-2.266986742	160
South Africa	-2.298717245	161
Montenegro	-2.327466176	162
Guinea	-2.370822906	163
Senegal	-2.387541945	164
Bosnia and Herzegovina	-2.419517266	165
Latvia	-2.445473207	166
Togo	-2.473189728	167
Lithuania	-2.566660682	168
Australia	-2.588108321	169
Qatar	-2.606258333	170

Saudi Arabia	-2.607767623	171
Liberia	-2.608815061	172
Burkina Faso	-2.610160888	173
Uganda	-2.659065102	174
Egypt	-2.666804606	175
BTN	-2.678235851	176
Estonia	-2.689157787	177
Yemen	-2.703872953	178
Kenya	-2.70500071	179
Ethiopia	-2.705692274	180
Tanzania	-2.719271051	181
Djibouti	-2.732474833	182
Nigeria	-2.734515341	183
Mauritania	-2.766127795	184
Ghana	-2.770416247	185
Gambia	-2.78243188	186
Belgium	-2.796385717	187
Guinea-Bissau	-2.805621374	188
Niger	-2.876912059	189
Turkey	-2.887435208	190
France	-2.922320491	191
BEN	-2.938640315	192
Armenia	-2.967663708	193
Pakistan	-3.08338848	194
Malawi	-3.100869308	195
Afghanistan	-3.175850689	196
United Kingdom	-3.17754645	197
Syrian Arab Republic	-3.280951529	198
Sierra Leone	-3.366207576	199

Burundi	-3.433693599	200
Cameroon	-3.522147255	201
Jordan	-3.579698045	202
Russia	-3.640314155	203
Iran	-3.666293652	204
United States of America	-3.720653877	205
Chad	-3.933727291	206