A COMMUNITY RESILIENCE ASSESSMENT FRAMEWORK FOR UNIVERSITY TOWNS

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A Community Resilience Assessment Framework for University Towns

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CERTIFICATE OF ORIGINALITY

I hereby declare that this thesis is my own work and that, to the best of my knowledge and belief, it reproduces no material previously published or written, nor material that has been accepted for the award of any other degree or diploma, except where due acknowledgement has been made in the text.

(Signed)

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(Name of student)

DEDICATION

I dedicate this entire PhD journey to the superior power in heaven (The Almighty God) from whom I draw my strength and inspiration, to my biological parents (Mr. and Alhaja (Mrs) Abdul-Rahman) for their prayers and support all through my life, to Mr. and Mrs. Ademuyewo who picked me up from the street and sent me to school, to Mr. & Mrs. Sofowora and their family for supporting me all through my undergraduate studies, to my late mentor Mrs. Mariam Ladi Yunusa (whom I promised I would work very hard to get a PhD degree), to my beautiful wife (Mrs. Maryam Omowunmi Abdul-Rahman) and daughter (Miss Ayesha-Sauda Olufunmilola Abdul-Rahman) for practically doing this PhD with me (I call them my unofficial co-investigators), and finally, to my entire extended family and village for having their first PhD holder (this PhD belongs to the whole Shuwa Arab clan).

ABSTRACT

Due to the high global rate of urbanization in the 21st century and the global increase in the world's population in the last few decades, Higher Educational Institutions (HEIs) can no longer house their students within their campuses due to the increased number of enrolments and the unavailability of land for spatial expansion, especially in urban areas. Often, these HEIs' students have to live off-campus either in Purpose-Built Students Accommodations (PBSAs) or Housing with Multiple Occupancies (HMOs), preferably within the university town for ease of commuting to the HEIs. In most cases, the HEIs also act as pull factors for migration into the university towns as people who take up jobs in the HEIs often prefer to live closer to their places of work too. This increases the population and density of the university towns.

Over time, the HEIs take over the identities of their towns and almost everything in those towns become tailored, directly or indirectly, to cater to the university, its staff, and the students. This leads to "studentification", a term used to describe the contradictory social, economic, cultural, and spatial transformations of urbanism resulting from an influx of students into neighbourhoods around HEIs. Although studentification is not always a negative phenomenon as portrayed by the global media, extant literature shows that the negative impacts of studentification often outweigh its benefits. For example, in new and developing towns, HEIs become agents of development by fast-tracking governments supports to provide urban basic services in the area and attracting direct and indirect investments into the town in terms of service provision, real estate investments, etc, as well as providing a market for local businesses and a cheap and skilled workforce (fresh graduates and students who seek for part-time jobs and internships). On the other end, most studentification researchers posited that the negative impacts of studentification as the towns grow and the HEIs expand, are detrimental to the towns' sustainability. These include the gentrification of the old residents and the slumification

of the towns. According to literature, every university town has its unique studentification challenges. To develop sustainability in university towns, the towns need to be made resilient against the challenges of studentification. This involves the assessments of university towns to identify their unique challenges and developing resilience. However, there is no known Community Resilience Assessments (CRA) methodology specifically developed for this purpose.

In line with the United Nations Sustainable Development Goals (SDG 11) which aims to make human settlements inclusive, safe, resilient, and sustainable by 2030, this study aimed at filling the above gap by developing an Artificial Intelligence-based CRA framework for identifying and assessing community challenges and developing resilience in university towns. This was achieved through the following objectives: 1. reviewing the existing literature to understand the nature of community resilience challenges in university towns, understand concepts and theories related to studentification and community resilience nexus, as well as assessing the available CRA methodologies; 2. identifying the Critical Success Factors (CSFs) for CRA; 3. developing an Artificial Intelligence-based data pre-processing framework that identifies and assesses community resilience challenges in university towns using location-based User-Generated Contents (UGC), and; 4. developing a Composite Resilience Index (CRI) for university towns, using Akoka, Lagos – Nigeria, as a case study.

Contents and meta-analysis carried out in objective one showed that none of the existing CRA methodologies was designed to assess or develop the resilience of university towns. A few of the existing CRA methodologies use big data (mainly census, sensors and Geographic Information System-based data), measure cross-scale relationships or temporal dynamism. About half of the methodologies also only assess resilience but do not provide action plans. None of the existing CRA methodologies was designed to harness the potential of location-based textual big data generated from microblogs using Artificial Intelligence (AI) tools like Machine Learning (ML) or Natural Language Processing (NLP).

Every CRA is often seen as a multistakeholder and a complex project which needs efficient management of resources to achieve success. Objective two employed contents analysis to explore the community resilience literature for success factors for CRA and used an expert survey for measure the criticalities of the factors. 28 Critical Success Factors (CSFs) were found to be important for achieving success in carrying out CRA in university towns in both developed and developing countries.

Building on the outcomes of objectives 1 and 2 above, objective three was used to develop an AI-Based Data Pre-Processing Framework that simplifies pre-processing location-based user-generated big data using the Twitter Application Programming Interface (API). This framework combines three ML and NLP programmatic algorithms that help in mining and cleaning the big data, modelling the topics, and analysing the sentiment polarities. The framework helps communities to identify and analyse their studentification impacts (community challenges), and it was used to assess the community challenges of six university towns, one each from the six continents (Loughborough - UK, Akoka - Nigeria, Ann Arbor - USA, Hung Hom – Hong Kong, Sydney – Australia, and Aguita de la Perdiz – Chile).

Due to the complex nature of human communities, community resilience is best captured as a socio-ecological concept and therefore, apart from the Resilience Theory itself, the Socio-Ecological Systems Theory and Complex Adaptive Systems Theory were often used in the literature to deconstruct scenarios such as studentification. The above theories were used as meta and grand theories to drive this study. However, to better frame this study theoretically, Grounded Theory was used as a mid-range theory to drive the methodology. The AI-Based Data Pre-Processing Framework was designed to automate the steps and principles of

Grounded Theory for big data analysis. Action Theory was then used as a micro-theory to design the resilience action plans of the proposed CRA framework.

Building on the outcomes of objectives 1 – 3, and using Akoka as a case study, the last objective developed a Composite Resilience Index (CRI) using Delphi and Analytic Hierarchy Process (AHP) modelling. The CRI is the last part of the Community Resilience Assessment Framework for University Towns, and it helps university towns to assess the existing level of community resilience against studentification, develops localized solutions for the university towns and helps in reviewing, assessing, and rating the performance of initiatives (outcome indicators). In general, the proposed CRA framework would help professionals and decision-makers in developed and developing countries to harness UGC big data and use new technologies such as ML and NLP to assess community challenges in existing university towns and develop strategies to improve their resilience to the negative impacts of studentification, thereby making university towns inclusive, safe, and sustainable. This project also contributes immensely to the resilience, studentification and the artificial intelligence body of knowledge.

Keywords: Artificial Intelligence; Big Data; Critical Success Factors; Community Resilience Assessment; Complex Adaptive System; Composite Resilience Index; Grounded Theory; Higher Educational Institutions; Housing with Multiple Occupancies; Machine Learning; Natural Language Processing; Purpose-Built Students Accommodations; Socio-Ecological Concept; Sustainable Development Goals; and Studentification.

LIST OF RESEARCH PUBLICATIONS

The following provides a list of research publications that the author of this thesis made during his Ph.D. study, and as shown within the text, chapters of this thesis have been fully or partially published or under review.

A. Published Refereed Journal Papers from this Thesis

1. **Abdul-Rahman, M**., Chan, E. H. W., Wong, M. S., Irekponor, V. E., & Abdul-Rahman, M. O. (2020). A framework to simplify pre-processing location-based social media big data for sustainable urban planning and management. Cities, 102986. https://doi.org/10.1016/j.cities.2020.102986

B. Published Refereed Journal Partially Related to this Thesis

1. Soyinka, O., Adenle, Y. A., & **Abdul-Rahman, M.** (2021). Urban informality and sustainable design of public space facilities: a case study of Hong Kong SAR of China in 2018. Environment, Development and Sustainability, 1-28. https://doi.org/10.1007/s10668-021-01370-8

2. Adenle, Y. A., **Abdul-Rahman, M.**, & Soyinka, O. A. (2021). Exploring the usage of social media in extant campus sustainability assessment frameworks for sustainable campus development. International Journal of Sustainability in Higher Education, ahead-of-print(ahead-of-print). https://doi.org/10.1108/ijshe-03-2021-0091

C. Published Refereed Conference Papers or Book Chapters from This Thesis

1. **Abdul-Rahman M**., Chan E.H.W., Li X., Wong M.S., Xu P. (2021) Big Data for Community Resilience Assessment: A Critical Review of Selected Global Tools. In: Ye G., Yuan H., Zuo J. (eds) Proceedings of the 24th International Symposium on Advancement of Construction Management and Real Estate. CRIOCM 2019. Springer, Singapore. https://doi.org/10.1007/978-981-15-8892-1_94

D. Publications in relevant industry outlets

1. **Abdul-Rahman, M.**, Chan, E. H. W., & Wong, M. S. (2020). Developing A Community Resilience Assessment Framework for Sustainable University Towns. *The Hong Kong Report on the State of Sustainable Built Environment 2020.* Pg. 199. Construction Industry Council & The Hong Kong Green Building Council Limited, Hong Kong. Retrieved from: https://www.hkgbc.org.hk/tch/resources/publications/HKGBC-Publication/Reports/HK-Report-2020/index.jsp

E. Journal Papers Under Review from this Thesis

1. **Abdul-Rahman M.**, Soyinka, O., Adenle, Y. A. Comparative Study of the Critical Success Factors (CSFs) for Community Resilience Assessment (CRA) in Developed and Developing Countries. International Journal of Disaster Risk Reduction. Manuscript ID: IJDRR-D-21-01087.

2. **Abdul-Rahman, M.**, Chan, E. H. W., & Wong, M. S. Novel use of social media big data and artificial intelligence for Community Resilience Assessment (CRA) in university towns. Big Data & Society. Manuscript ID: BDS-21-0171.

F. Honours and Awards

1. **PhD Full Scholarship**, The Research Institute for Sustainable Urban Development (RISUD), Faculty of Construction and Environment, The Hong Kong Polytechnic University, Hong Kong.

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(Paper: **Abdul-Rahman M.**, Chan E.H.W., Li X., Wong M.S., Xu P. (2021) Big Data for Community Resilience Assessment: A Critical Review of Selected Global Tools. In: Ye G., Yuan H., Zuo J. (eds) Proceedings of the 24th International Symposium on Advancement of Construction Management and Real Estate. CRIOCM 2019. Springer, Singapore. https://doi.org/10.1007/978-981-15-8892-1_94)

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ABBREVIATIONS

AHP	-	Analytic Hierarchy Process
AI	-	Artificial Intelligence
API	-	Application Programming Interface
ARC-D	-	Analysis of Resilience in Communities to Disaster
AWRVI	-	Arctic Water Resources Vulnerability Index
BDA	-	Big Data Analytics
BCRD	-	Building Community Resilience to Disasters
BRACED	-	Building Resilience and Adaptation to Climate Extremes and Disasters
BRIC	-	Baseline Resilience Indicators for Communities
CARRI	-	Community and Regional Resilience Institute
CART	-	Communities Advancing Resilience Toolkit
CCRAM	-	Conjoint Community Resiliency Assessment Measure
CDR	-	Community Disaster Resilience
CDRI	-	Community Disaster Resilience Index
CDRI2	-	Climate Disaster Resilience Index
CDRS	-	Community Disaster Resilience Scorecard
CERD	-	Campus Evaluation of Resilience Dimensions
CERI	-	Community Economic Resilience index
CoBRA	-	Community Based Resilience Analysis
COPEWELL	-	Composite of Post-Event Well-being
CRA	-	Community Resilience Assessment
CRAFT	-	Community Resilience Assessment Framework and Tools
CRC	-	Cooperative Research Centre
CRDSA	-	Community Resilience to Disasters in Saudi Arabia
CRF	-	City Resilience Framework
CRI	-	Community Resilience Index/Composite Resilience Index
CRI2	-	Community Resilience Indicators
CRM	-	Community Resilience Manual
CRS	-	Community Resilience System
CRT	-	Community Resilience Toolkit
CSAR	-	Communities Self-Assessing Resilience
CSFs	-	Critical Success Factors

DFID	-	Department for International Development
DRI	-	Disaster Resilience Index
DRR	-	Disaster Risk Reduction
FCR	-	Framework for Community Resilience
HEIs	-	Higher Educational Institutions
HMOs	-	Housing with Multiple Occupancies
ICBRR	-	Integrated Community Based Risk Reduction
ICLEI	-	International Council for Local Environmental Initiatives
LACCDR	-	Los Angeles County Community Disaster Resilience
LDA	-	Latent Dirichlet Allocation
LDRI	-	Local Development Research Institute
MAPP	-	Mobilizing for Action through Planning and Partnerships
ML	-	Machine Learning
ND-GAIN	-	Notre Dame Global Adaptation Initiative
NIST	-	National Institute of Standards and Technology
NLP	-	Natural Language Processing
PBSAs	-	Purpose-Built Students Accommodations
PEOPLES	-	Population and Demographics, Environmental/ Ecosystem, Organized Governmental Services, Physical Infrastructure, Lifestyle and Community Competence, Economic Development, and Social-Cultural Capital.
RAPT	-	Resilience Analysis and Planning Tool
RELi	-	Resilient Living
ResilUS	-	Resilient United States
RITA	-	Resilience in the Americas Programme
SDGs	-	Sustainable Development Goals
SMBD	-	Social Media Big Data
SPSS	-	Statistical Package for Social Sciences
SPUR	-	San Francisco Planning and Urban Research
TCRI	-	Techno Cosmic Research Institute
THRIVE	-	Therapeutic interventions, Habit and routine, Relational-social factors, Individual differences, Values and beliefs, and Emotional factors.
UGC	-	User-Generated Contents
UCRA	-	Urban Community Resilience Assessment

UK	-	United Kingdom
UNISDR	-	International Strategy for Disaster Reduction
USA	-	United States of America
USAID	-	United States Agency for International Development
US-CRT	-	United States Climate Resilience Toolkit
USIOTWSP	-	United State Indian Ocean Tsunami Warning System Program
VADER	-	Valence Aware Dictionary and sEntiment Reasoner

CHAPTER 1: INTRODUCTION[1]

1.1 Introduction

This chapter sets the background, states the research problem, aim and objectives, defines the research scope, states the significance of the research and presents the structure of the thesis.

1.2 Research Background

1.2.1 Urbanization and the concept of resilience and community resilience assessments

Cities in the 21st-century house half of the world population. The urban population rose from 43 per cent in 1990 to about 56 per cent in 2016 and is expected to reach 70 per cent by the mid-21st century according to the United Nations (2016b). The fastest-growing cities are medium and small cities with less than one million inhabitants mostly dotted across Asia and Africa, two of the world's fastest-growing continents (UN-Habitat, 2016b). The pressure on ecosystem resources coupled with Climate change, unguided urbanization, an unprecedented level of migration, and forcibly displaced populations moving to cities among other factors have increased the pressure, intensity and impacts of urban crises (Munich, 2015; The Rockefeller Foundation & ARUP International Development, 2014). At the same time, cities have become the main drivers of sustainable development, equality, inclusivity, cultural diversity, and centres for learning and innovation (Dhar & Khirfan, 2017; Pickett et al., 2004).

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[1] This chapter was partly published in:

1. **Abdul-Rahman, M.**, Chan, E. H. W., Wong, M. S., Irekponor, V. E., & Abdul-Rahman, M. O. (2020). A framework to simplify pre-processing location-based social media big data for sustainable urban planning and management. Cities, 102986. https://doi.org/10.1016/j.cities.2020.102986

2. **Abdul-Rahman M.**, Chan E.H.W., Li X., Wong M.S., Xu P. (2021) Big Data for Community Resilience Assessment: A Critical Review of Selected Global Tools. In: Ye G., Yuan H., Zuo J. (eds) Proceedings of the 24th International Symposium on Advancement of Construction Management and Real Estate. CRIOCM 2019. Springer, Singapore. https://doi.org/10.1007/978-981-15-8892-1_94

The challenge is not just how to manage the current urban crises, but how to ensure that our cities can adapt to future risks related to physical and economic development, social polarization, and segregation by developing resilience (Desouza & Flanery, 2013; Spaans & Waterhout, 2017b).

The concept of resilience which is defined as the ability to prepare and plan for, absorb, recover from, and more successfully adapt to adverse events (National Research Council, 2012; Sorensen et al., 2018), has gained momentum in the last few decades due to the increasing challenges human settlements (communities) face from natural disasters and those induced by man (Meerow et al., 2016; Ribeiro & Pena Jardim Gonçalves, 2019). Resilience is an old concept with its roots in socio-ecological systems, psychology, and engineering (Syal, 2021; Wu et al., 2020). Both the theory and concept became a key part of the United Nations agenda at the beginning of the 21st century when the second United Nations World Conference on Disaster Reduction (UNISDR, 2014) recommended that the resilience of communities should be part of member states agenda to reduce risks and vulnerability.

As the transformative potential and interconnected challenges of urbanization in the 21st century became more apparent (Elmqvist et al., 2019; Pieterse, 2013), the United Nations Office for Disaster Risk Reduction (UNDRR) and the United Nations Human Settlements Programme (UN-Habitat) channelled more resources in 2015 to integrate sustainable urban development and urban risk reduction with resilience thinking (McGill, 2020), which led to the creation of the Sustainable Development Goal (SDGs) 11 (2016-2030) (Lee et al., 2016). This goal aims to make global cities integrated, safe, resilient, and sustainable (UN-Habitat, 2016a). Following this, a wide array of United Nations agencies have tailored their missions accordingly, using a multi-sectoral and multi-hazard understanding of the concept of resilience to promote resilience and sustainable development worldwide (Malalgoda et al., 2013). This global mandate has been passed since then to the 193 United Nations member nations who are signatories to the SDGs. At the national level, this mandate is also being localized globally by all habitat agenda partners (including local authorities, non-governmental organizations, and researchers in academia) (Oosterhof, 2018; Patole, 2018; Sietchiping & Omwamba, 2020).

According to UN-Habitat (2016a), for communities to become sustainable, they must first become resilient against the acute shocks and chronic stresses affecting them. Influenced by this philosophy and the United Nations accompanying global call to develop a sustainable world, resilience research and the concept of Community Resilience Assessment (CRA) have become more popular in both global policy and scientific research and discourse (Clark-Ginsberg et al., 2020; Marana et al., 2019; Sharifi, 2016). This has led to the creation of more CRA methodologies in the last decades, each with its purpose, aim, and objectives (Haase et al., 2018; Sharifi, 2016).

CRAs are defined as indexes, scorecards, tools, and frameworks that analyze the risks in complex geographies and socio-ecological entities occupied by a multi-layered heterogeneous group of people with common interests (human communities) (Alshehri et al., 2015; Sharifi, 2016; Sharifi & Yamagata, 2014). According to Sherrieb et al. (2010), some CRA methodologies are designed for assessing resilience against a single risk, while some are designed for multiple risk assessments, the same way some are developed for a particular place while others can be adapted regionally or globally.

Apart from the need to build a resilient world (Seeliger & Turok, 2013), the rise in CRA methodologies in the last two decades is also attributed to the increase in funding for resilience initiatives (Sharifi, 2016), the reliance of donors on such assessments for allocating resources (Cutter, 2016; Tyler & Moench, 2012), and the need for progress measurement on risk reduction as well as for benchmarking performance against global best practices (Schipper & Langston, 2015b). As Burton (2015) posited, assessing and measuring resilience is recognized as the first step towards reducing risks and being better prepared to withstand and adapt to natural or man-induced shocks and stresses in our communities.

Although the meaning of the term "community" itself is highly contested in the literature (Mulligan et al., 2016), this study defines it as a multi-layered heterogeneous group of people with a common geographical identity and common interests, who engage in collective actions and are linked by a dynamic web of socio-cultural, economic and political interactions (Alshehri et al., 2014; T. Frankenberger et al., 2013; MacQueen et al., 2001; Miles, 2015). Community boundaries are blurred when it comes to risks. This is due to the evolving ease of mobility and communication technologies as well as people having the power to be associated with more than one community across different scales ranging from the neighbourhood to the city or region (Mulligan et al., 2016; Sharifi, 2016). Some definitions also differentiate communities based on indicators such as urban, rural, imagined or virtual, or community composition such as a community of humans, animals, or things (Mulligan et al., 2016). This complexity also affects the definition of resilience and the confusion in corpus on community resilience, urban resilience, and other forms of spatial resiliencies, which contribute to the problems some of the CRA methodologies have with their usability and efficiency (Sharifi & Yamagata, 2014). Issues related to defining resilience or community resilience were extensively discussed in the literature (Meerow et al., 2016; Norris et al., 2008), hence it would not be repeated here. However, adopting a flexible definition for a community like the one above makes it easier to study communities as complex socio-ecological systems with multiple feedback loops (Evans, 2011).

1.2.2 *The global commercialization of higher education and its impacts on university towns*

As the world experiences geometric growth in population and youth bulge in the 21st century, radical changes had to be made to higher education funding in most countries to meet the increasing demand for higher education (Brooks et al., 2016; Kinton et al., 2018). In most countries like the United Kingdom and the United States, these changes have also led to a shift in the funding of most Higher Educational Institutions (HEIs) away from the state, which increased the marketization of higher education (Brooks, 2013; Brooks et al., 2016). According to Brooks et al. (2016), this commercialization of higher education has changed the narratives, and students now “see degrees as private investments rather than public good”. To get the best “investment”, students now travel far away from home in search of “quality” when making their higher education choices.

Related to this, Kinton et al. (2018) emphasized that global competitions among HEIs for student “customers” have made them more responsive, increased their quality of teachings and focus on providing more conducive learning environments. For students, the framing of “students-as-consumers” clearly extends beyond the selection of HEIs and courses, to other aspects of students’ life such as residential decision making and cost of living. As a result of the above, there has been a growing global debate on the changing trends of student geographies, with housing developments within university or college towns changing from traditional living pathways (on-campus accommodation) to off-campus shared Housing with Multiple Occupancies (HMOs) and Purpose Built Students Accommodation (PBSA) enclaves, which gradually changes the morphology of those towns and affect their sustainability (Holton & Riley, 2014; Kinton et al., 2018; Smith et al., 2014).

This gradual change taking place in our university towns globally is tagged “Studentification”, a term coined by British geographer Darren P. Smith in 2002 and used to describe the significant processes of urban change and the challenges university towns face as a result of the growing students' concentration off-campus due to the inability of HEIs to house all their students within their campuses (Hubbard, 2008; Sage et al., 2012; Smith & Hubbard, 2014; Smith et al., 2014).

1.2.3 Studentification: Structural issues, benefits, and practical challenges

Studentification leads to major urban changes over time. According to Smith (2002, 2006a) and Situmorang et al. (2020), these changes have five major dimensions: social, cultural, physical, economic, and institutions & governance. Socially, studentification leads to structural gentrification and segregation. Culturally, the social clusters or concentrations of youths with shared students' culture, lifestyle and consumption practices lead to the introduction of a new sub-culture in the area. Physically, the environment may either get upgraded to cater for the new teaming customers (especially in terms of housing, retail, and service infrastructure) or downgraded to a slum over time. And economically, changes in the housing stock to accommodate the students' population lead to higher densities, as well as inflation of property and rental prices. Local businesses also often change their business models over time to satisfy the needs of the students. With such rapid new complexities in the university towns, institutional and governance issues gradually start to manifest too.

Apart from urbanization and commercialization of higher education, studentification is often compounded, globally, in university towns due to several imperatives, which often include: the growth of the knowledge-based economy, society and the need for economic competitiveness (Foote, 2017; Smith, 2008), funding and expansion of HEIs and the need for a more skilled global workforce (Foote, 2017), an increase in mortgage finance, low-interest rates and economic capital coupled with a rise in investment cultures for "retirement pots" (Eshelby, 2015), deregulation in the real sector and the encouragement of the private sector to meet the housing deficit in some global economies (Hubbard, 2009), lack of adequate statutory enforcement of planning laws and the power to regulate free-market economies (Laidley, 2014), and finally, the shift in global ideologies in the transition from childhood to adulthood and the assumption of the right to attain a college or university degree (Smith & Holt, 2016). These structural issues have contributed globally to the rise in studentification.

Although studentification is often portrayed as a negative phenomenon both in the media and in research, the town-gown relationship is not all parasitic. Some of the benefits of studentification to the university towns and their residents include; the provision of a young and educated workforce, cheaper labour and increased volunteerism (Smith, 2006b), adding more diversity and vibrancy to local cultures and raising the aspirations of the local youths (Smith & Fox, 2019), enhancing the spending power, improving the local economy, creating more jobs and sustaining the local retail businesses (Holton, 2015), supporting the local real estate sector and its associated trades (agency, insurance, finance etc) and driving up demands for quality housing provision (Laidley, 2014), as well as making the town more attractive to tourists and investors (He, 2014). However, shreds of evidence from earlier studies on studentification show that the negative impacts of studentification outweigh the benefits and each university town has its unique challenges (Dewi & Ristianti, 2019; Hu et al., 2019; C. Sun et al., 2018).

Started in the United Kingdom as an urban planning and management issue in university towns, studentification and its impacts in university towns have been well documented in geography and real estate research globally for the last two decades. In the United States of America, Foote (2017) study on college towns as knowledge nodes showed that neighbourhood's socio-cultural changes take place rapidly in studentified areas resulting in cultural conflicts, social stratification and gentrification. Similarly, Gu (2015) and He (2014) studies in China both affirm the presence of studentification in Chinese university towns or villages and pointed out that the socio-economic, cultural and physical changes which are tied to seasonal population movements of university students vary in intensity (negativity) from country to country due to culture, however, they argued that international students behaviours in Chinese university towns are almost similar to those in the United Kingdom or the United States. In Canada, Moos et al. (2018), studied the linkages between the concepts of studentification, youthification and gentrification, they concluded that although studentification often leads to gentrification in the long run, not all gentrifiers are students or youths. They posited that the university staff and their families who migrate to live closer to their place of work (HEIs) also contribute to the negative impacts of studentification. Ackermann and Visser (2016); Donaldson et al. (2014) and Ndimande (2018) also studied studentification in different South African cities, their conclusions showed that studentification alters the housing structure and real estate market, leading to slumification and social disorder in the long run. In expanding the scope of studentification studies to Japan, Nakazawa (2017) also agrees that studentification affects Japanese university towns and has negative socio-cultural impacts. Further studies carried out in Hungary by Fabula et al. (2017), in Poland by Grabkowska and Frankowski (2016), in Australia by Fincher and Shaw (2009) and Ruming and Dowling (2017), and in Portugal by Malet Calvo (2017) among others also show that studentification of university towns have more negative impacts, and it affects not just the housing structure of neighbourhoods and causes gradual gentrification, but it also leads to slumification, social disorder and seasonal economic stresses in the university towns.

1.3 Research Problem

Over the years, few solutions have been proposed to solve the challenges of studentification in university towns from the research point of view. These solutions mainly proposed the development of PBSA and gated communities for HEIs students within the university towns (Hubbard, 2009; Kinton et al., 2016; Mulhearn & Franco, 2018; Revington et al., 2018; Sage et al., 2013) and urban renewal of run-down areas within the university towns to avoid “broken window” effects (Kinton, 2013).

Research on studentification across various databases such as the Clarivate Analytics Web of Science core citation database, Elsevier’s abstract and citation database (Scopus) and Google Scholar show no link between studentification and the theory and concept of community resilience. In the same light, none of the research on community resilience also identifies studentification as a resilience issue (The Rockefeller Foundation & ARUP International Development, 2014). This is because both concepts are birthed in different fields with different ideologies (Kinton, 2013; Kinton et al., 2018). Resilience is an old concept peculiar to the field of engineering, ecology, psychology and urban planning (S. L. Cutter et al., 2008; C.S. Holling, 1996; Meerow et al., 2016; Pendall et al., 2007) while studentification finds its roots in the field of human geography and real estate (housing studies) (Hubbard, 2009; Nakazawa, 2017; Smith, 2006a). In recent times, few researchers like Fabula et al. (2017) and Rhineberger (2003) have been studying studentification from the field of sociology, looking at the social disorder and the social impacts of studentification in university towns.

To easily manage the negative impacts of studentification, university towns need to be resilient to the stresses and possible shocks caused by studentification. The community stakeholders should be able to assess the situation, identify their challenges and know their community resilience status, prepare and plan for uncertainties related to studentification, absorb the stresses and shocks when they occur, recover from these events, and more successfully adapt and be able to provide their functions to all their residents as the intensity of studentification increases. This way, university towns can become sustainable.

The comprehensive review of literature conducted for this study (see chapter 2) shows that there are no CRA tools, indices, scorecards or frameworks specifically designed for assessing and building resilience in university towns worldwide, and generally, there is no CRA methodology designed for community resilience that utilizes the use of big data from microblogs, Natural Language Processes (NLP) and Machine Learning (ML) (Abdul-Rahman et al., 2021). As connected communities with a permanent online presence (Vorderer et al., 2016), methodologies for assessing and building resilience in university towns need to harness the use of User-Generated Contents (UGC) (big data) from microblogs in order to study the spatiotemporal dynamism of stresses related to studentification.

The research problem is not solely to design community resilience solutions for university towns or bridging the concepts of studentification and resilience planning but developing a CRA framework for university towns using innovative new methodologies that are compatible with university towns being smart and connected communities. The assumption that youthification equate to high use of Internet of Things (IoT) and microblogging sites has been proven by research studies related to the use of social media among university students and in university domains (Al-Rahmi & Othman, 2013; Hellon, 2019; Hussain, 2012; Jacobsen & Forste, 2011; Mese & Aydin, 2019; Shafique et al., 2010; Vorderer et al., 2016). This "connectedness" provides an opportunity to harness the use of big data from microblogs (User-Generated Contents) in developing a smart CRA framework for university towns to manage their studentification problems.

1.3.1 Justification for mainstreaming Artificial Intelligence processes and big data to address the identified research gap and raising research questions

Michael Batty et al. (2012) and the United Nations (2016a) posited that Information and Communication Technology (ICT) and big data are two key resources for assessing and building safe, resilient, and sustainable communities in the 21st-century. According to Bibri (2019a, 2019c, 2019d), modern human settlements have become constellations of devices across various scales and are fast-changing into hazes of software instructions, therefore, new planning tools need to take into consideration these new technological innovations and resources and mainstream them into their processes.

To provide solutions to the identified research problem, this study answered the four (4) sets of questions:

1. What are the characteristics of the existing CRA methodologies? Are any of the existing CRA methodologies adaptable for use in university towns against the negative impacts of studentification? What are the theories and concepts that can be used in framing a new CRA for university towns?
2. What are the Critical Success Factors (CSFs) for a CRA in university towns? Are they the same for university towns in developed and developing countries?
3. How can CRA be conducted in university towns and what methods can be used for this purpose? Do all the university towns have similar studentification challenges?
4. How can a Composite Resilience Index (CRI) for university towns be developed?

To answer the research questions above, the following research aim and objectives were set and fulfilled.

1.4 Research Aim and Objectives

This study aims to develop an artificial intelligence-based Community Resilience Assessment (CRA) framework for identifying and assessing community challenges and developing resilience in university towns.

To achieve the above aim, the following specific objectives were established and achieved. They include:

1. To review the existing literature to understand the nature of community resilience challenges in university towns, examine the characteristics of existing CRA methodologies, and identify the concepts and theories related to studentification and

community resilience that can be used to frame a new CRA Framework for university towns.

2. To identify Critical Success Factors (CSFs) for Community Resilience Assessment (CRA).
3. To develop an Artificial Intelligence-based data pre-processing framework that identifies and assesses community resilience challenges in university towns using location-based User-Generated Content (UGC).
4. To develop a Composite Resilience Index (CRI) for university towns, using Akoka, a case study in Lagos – Nigeria.

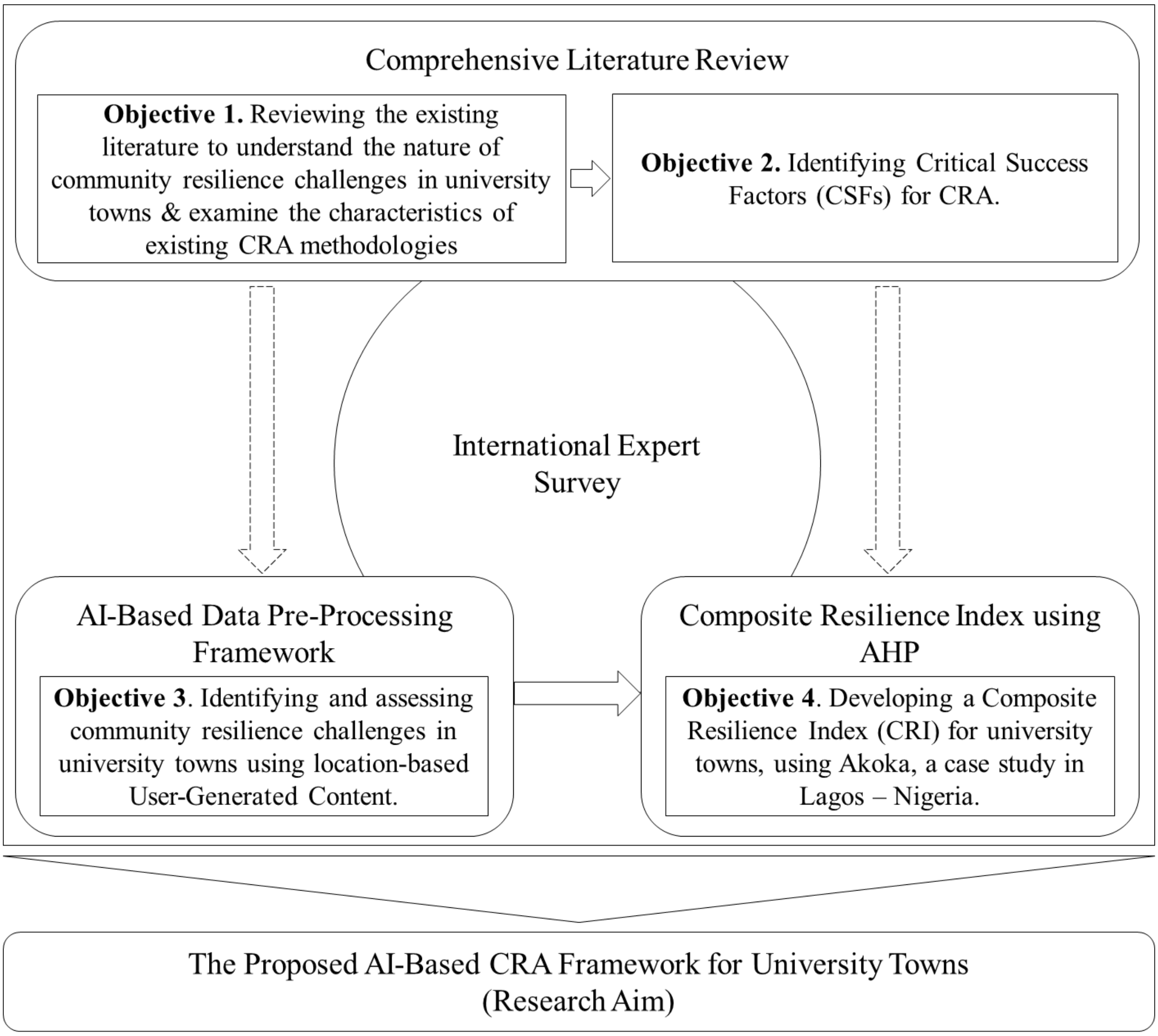

Figure 1.1 The relationships among the objectives and the research aim

As illustrated in Figure 1.1, achieving the research aim started with a comprehensive literature review to understand the nature of community resilience challenges in university towns, examining the characteristics of existing CRA methodologies, and identifying the concepts and theories related to studentification and community resilience that were used to frame the proposed AI-Based CRA framework. 20 years of community resilience and studentification literature were used for this content and meta-analysis. This makes up objective 1. From the comprehensive literature review, factors and considerations for a successful resilience assessment and developing resilience were identified. Through an international expert survey, the criticalities of these *success factors* were determined in Objective 2.

The research gaps identified in the comprehensive literature review of 51 existing CRA tools eg lack of the use of UGC (big data from microblogs) and the use of AI (ML and NLP) led to Objective 3 which aimed to develop an *AI-Based Data Pre-Processing Framework* that identifies and assesses community resilience challenges in university towns using location-based UGC. Now that studentification-based community resilience challenges could be easy identified and assessed in university towns using the proposed *AI-Based Data Pre-Processing Framework*, a *Composite Resilience Index* was developed in Objective 4 using one of the six case studies. This index helps university towns and communities/neighbourhoods to know their resilience status and provides localized output indicators (weighted) for the university towns to build resilience to the local challenges of studentification.

The *AI-Based Data Pre-Processing Framework* and the *Composite Resilience Index* make up the *AI-Based CRA Framework for University Towns* (the overall research aim).

1.5 Research Scope

This study focused on developing a CRA Framework for university towns to assess their studentification-induced challenges and building resilience. These stresses and shocks include those related to the five common themes of community resilience which include physical/environmental, social, cultural, economic and governance and institution.

The proposed CRA framework will not be adequate in assessing and building the resilience of engineering systems within the university towns and may not be effective in building community resilience in higher spatial scales beyond the city or town level. However, the proposed CRA framework would be able to assess and build resilience in lower spatial scales than the city or town, and it would also be able to study spatiotemporal dynamism between all horizontal scales (spatial hierarchies) and vertical scales (social hierarchies).

Although the use of the proposed framework has no geographical boundary, its development was conceptualized using 6 case studies, 1 each from the 6 continents (apart from Antarctica). The case studies were chosen based on them having the highest studentification sentiments on the Twitter database. Hung Hom, the home to The Hong Kong Polytechnic University in Hong Kong was used as a pilot to test the ML and NLP programmatic algorithms for data mining and pre-processing UGC from Twitter. Data from an international expert survey from 23 countries were used to validate the proposed framework. However, the CRI was developed using data from Akoka, the home of the University of Lagos, in Lagos, Nigeria. The CRI demonstrates how indices can be developed for each university town. The whole CRA framework can be adapted and modify to assess and build resilience in any university town worldwide (both in developed and developing countries).

1.6 Definition of Key Terms

1. *Resilience*: The ability to withstand shocks and stresses or the ability to prepare and plan for, absorb, recover from and more successfully adapt to adverse events (National Research Council, 2012).
2. *Community*: Defined as a multi-layered heterogeneous group of people with a common

geographical identity and common interests, who engage in collective actions and are linked by a dynamic web of socio-cultural, economic and political interactions (Alshehri et al., 2014; T. Frankenberger et al., 2013; MacQueen et al., 2001; Miles, 2015).

3. *Community Resilience*: Refers to the capacity of a human community, whether a neighbourhood, city or a region, to sustain itself through crises that challenge its physical environment and social fabric (Dawes et al., 2004).
4. *Community Resilience Assessment (CRA):* Refers to the examination of human communities to identify shocks and stresses, measuring the community's ability to withstand them and plan to eliminate future occurrences. They are also defined as scorecards, indices, models and toolkits for diagnosing challenges in communities and measure the progress of resiliency (Sharifi, 2016).
5. *Studentification:* The process of change that takes place as a result of the growing residential concentrations of students living off-campus among non-students residents in neighbourhoods around the university (Smith, 2004). The impacts of studentification may be positive or negative (Smith & Fox, 2019).
6. *User-Generated Contents:* This refers to any form of content, such as text, images, videos, and audio, posted by users on microblogs such as Twitter, WeChat, Facebook, etc. They are online reviews, opinions or chats and conversations among users that contain vital information on wide varieties of discourse (Wyrwoll, 2014).
7. *Big Data:* Defined as a large volume of data – both structured and unstructured that can not fit into an excel sheet. Big data is characterized by high volume, variety, velocity, veracity, value and variability (Abdul-Rahman et al., 2021; Abdul-Rahman et al., 2020; Bibri, 2019c; Chen et al., 2014).
8. *Artificial Intelligence:* Refers to the simulation of human intelligence in machines that

are programmed to think like humans and mimic their actions (Nikitas et al., 2020; Pedro et al., 2019; Wu & Silva, 2010)

9. *Natural Language Processes*: This is a subfield of linguistics, computer science, information engineering, and artificial intelligence concerned with the interactions between computers and human languages (Daas, 1996). It converts textual data (human language) to machine language in order to process and make meaning of it (Abdul-Rahman et al., 2020).
10. *Machine Learning (ML):* This is a subsect of Artificial Intelligence that allows systems to study algorithms and statistical models in order to perform specific tasks without using explicit instructions, relying on patterns and inferences instead (Michie et al., 1994).
11. *Grounded theory:* The discovery of knowledge, constructs and theories after data collection and analysis. Grounded Theory provides a strong qualitative data analysis tool for building strong evidence within the analysis and for developing processes. It starts with finding repeated patterns in the data, assigning codes or phrases to the patterns, grouping the codes into themes or concepts hierarchically, and then analysing the relationships among the concepts or themes to discover knowledge or theories (Glaser et al., 2013; Strauss & Corbin, 1997).
12. *Analytical Hierarchy Process:* Analytical Hierarchy Process (AHP) is a methodology used to fix complex problems involving multiple scenarios, criteria and actors (Satty, 1980). AHP is a human cognitive tool used to determine the relative importance of alternatives using paired comparison and assigning weights to indicators (Cardona & Carreño, 2011).

1.7 Research Significance

1.7.1 Significance to Resilience Body of Knowledge and Research Methodology

This study contributes to the community resilience literature, body of knowledge and resilience research methodology by integrating new research tools and methods into resilience assessment and planning. Introducing Social Media Big Data Analytics (UGC from Microblogs) and Natural Language Processing and Machine Learning aspects of Artificial Intelligence into resilience studies creates new research frontiers and stimulate more multidisciplinary studies in that direction.

1.7.2 Theoretical Contribution

The theoretical framework adopted for this study uses a multi-level theoretical underpinning and adoption of theories outside the boundaries of the current resilience research and traditional planning theories, this will contribute to resilience research by introducing new theories and show examples of how these theories can be used to drive resilience studies.

1.7.3 Practical Significance

The research outcomes, the developed programmatic algorithms, the AI-Based Data Pre-Processing Framework, the Composite Resilience Index, as well as the overall AI-Based CRA Framework, would be useful to urban planners and city managers who wants to assess and manage the studentification crises and develop resilience in university towns globally.

1.8 The overall thesis structure and research framework

This thesis adopts a hybrid format that combines published research papers and traditional thesis writing. The thesis is comprised of 8 chapters. Chapters 2 and 4-7 each represent a research objective, while chapter 1 introduces the study, chapter 3 explains the methodology and chapter 8 gives the conclusions and recommendations. Below is a summary of the chapters. Figure 1.2 shows the sequence of the chapters in the thesis.

Chapter 1: Introduction – This chapter introduces the study, gives a background, states the research problem and research questions that needed answers, states the research aim and objectives, gives definitions of key terms, states the research significance and gives the overall thesis structure and research framework.

Chapter 2: Comprehensive Literature Review & Conceptual and Theoretical Framework – This study started with this chapter. Under this chapter, a comprehensive literature review was conducted to have a deeper understanding of the research gaps and examine the existing CRA methodologies to see if any existing CRA methodology had the capacity to solve the studentification problem or can be easily modified to assess the studentification-based crisis in university towns and propose action plans. Success factors for CRA as well as theories and concepts were also identified from this literature review. This chapter represents Objective 1.

Chapter 3: Research Methodology – This chapter gives an overview of the overall methodology, research methods used and the link between the methodology and conceptual and theoretical frameworks. Chapter 4-7 build on this overview and explain the methods in detail in each chapter.

Chapter 4: Comparative Study of the Critical Success Factors for Community Resilience Assessment in Developed and Developing Countries – Using the success factors identified in Chapter 2, this chapter used data from the international experts survey to measure the criticalities of the success factors, examine the difference in ranking between experts from developed and developing countries, and used factor analysis to put the critical success factors into components. 28 factors out of 31 were found to be critical. The 28 critical success factors were factorized into 7 components. The study also found out that there were no differences between the opinions of experts from developed and developing countries in the ranking of the success factors, therefore, the factors are applicable in both developed and developing countries. This chapter represents Objective 2.

Chapter 5: Developing an Artificial Intelligence-Based Data Pre-Processing Framework for Community Resilience Assessments for University Towns – This chapter demonstrates how Artificial Intelligence (ML and NLP) can be used to download location-based big data from microblogs and pre-processing the data to understand the community resilience challenges induced by studentification in university towns. This AI-Based Data Pre-Processing Framework can be used in any university town globally. All the open-source algorithms and codes are available on GitHub and published in Elsevier's Cities journal. This chapter represents Objective 3.

Chapter 6: Case Studies – The AI-Based Data Pre-Processing Framework developed in chapter 5 was piloted in Hung Hom, the home of the Hong Kong Polytechnic University, in Hong Kong, and 5 other case studies, which include Loughborough in Leicestershire, UK, Akoka in Lagos, Nigeria, Ann Arbor in Michigan, USA, Sydney in New South Wales, Australia and Aguita de la Perdiz in Concepcion, Chile. The data from these 6 case studies were validated by the data from the international experts' survey which started with experts from the 6 case studies and snowballed into 23 countries. This study gives a global overview of the challenges university towns experience due to studentification and shows that artificial intelligence can provide an easy, cheap and more accurate way of conducting community resilience assessments in urban communities, not just in university towns.

Chapter 7: A Composite Resilience Index for Developing Resilience and Sustainability in University Towns – This chapter shows the development of a Composite Resilience Index (CRI) using data from Akoka, Lagos – Nigeria, one of the 6 case studies. The composites of the index were determined by prioritizing online User-Generated Contents from Akoka on elements of resilience and risk reduction using the Delphi method and Analytic Hierarchy Process. The CRI can be easily replicated for any university town to check its resilience level and build resilience using localized and weighted output indicators.

Chapter 8: Conclusions and Recommendations – This chapter gives a summary of the research conclusions as well as the recommendations on the use of the overall AI-Based CRA Framework for University Towns and its components. It also states the research significance, limitations and gives directions for future research.

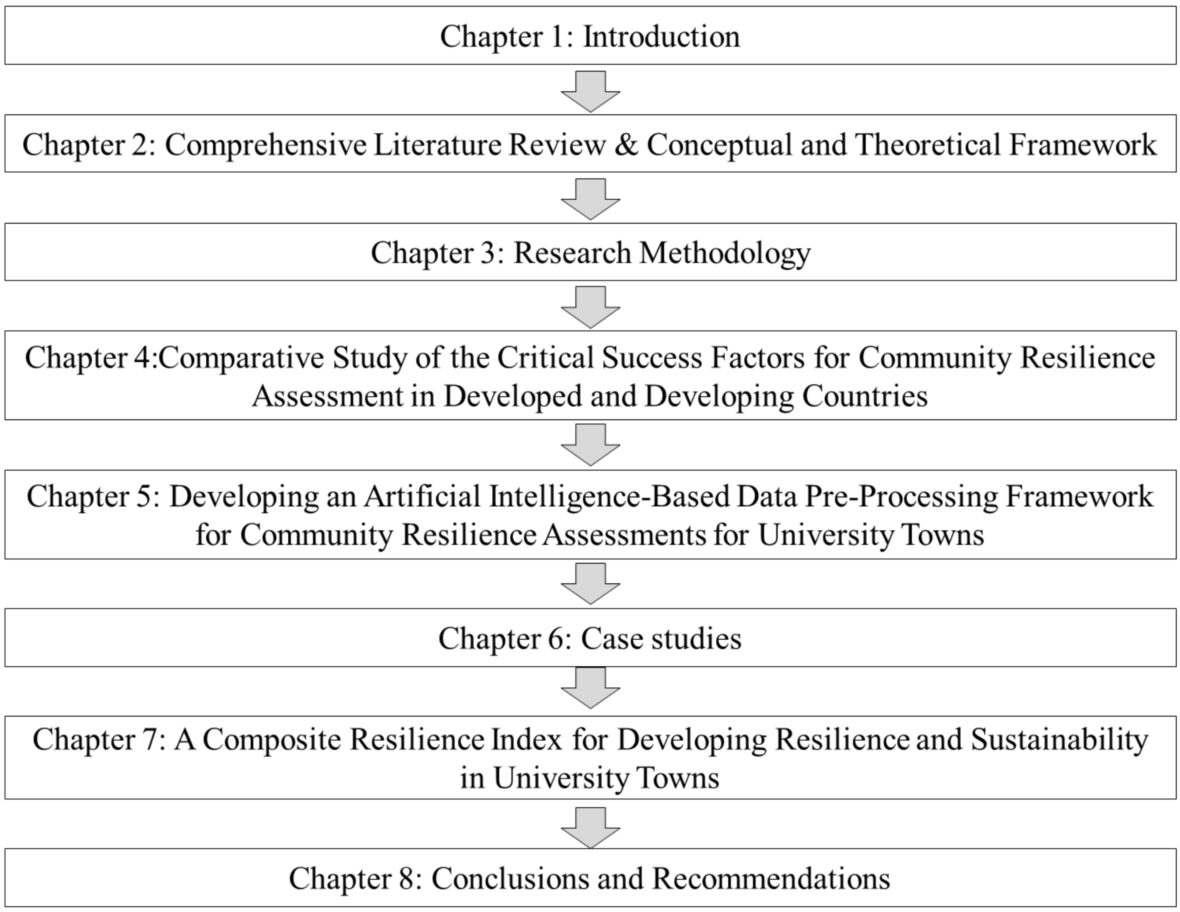

Figure 1.2 Sequence of chapters and thesis structure

1.9 Chapter Summary

This chapter presented a general overview of the full study starting with the background, research problem, questions, aim and objectives, scope, the definition of key terms, significance, and gave an overall structure of the thesis. Chapter 2 builds on this general overview to give deeper understanding of the characteristics, concepts, and theories of CRA.

CHAPTER 2: COMPREHENSIVE LITERATURE REVIEW & CONCEPTUAL AND THEORETICAL FRAMEWORK[2]

2.1 The literature review framework

To stand on the shoulders of giants, a comprehensive literature review was carried in this chapter on the exiting CRA methodologies, CRA success factors and studentification. The data was first downloaded in January 2019, it was updated in January 2020, and to keep the literature used in this study as current as possible, the latest version was updated in December 2020 using the algorithm below.

1. **Elsevier's Scopus**

(TITLE-ABS-KEY (community AND resilience AND assessment)) AND (success AND factors) AND (studentification) AND (LIMIT-TO (PUBYEAR , 2020) OR LIMIT-TO (PUBYEAR , 2019) OR LIMIT-TO (PUBYEAR , 2018) OR LIMIT-TO (PUBYEAR , 2017) OR LIMIT-TO (PUBYEAR , 2016) OR LIMIT-TO (PUBYEAR , 2015) OR LIMIT-TO (PUBYEAR , 2014) OR LIMIT-TO (PUBYEAR , 2013) OR LIMIT-TO (PUBYEAR , 2012) OR LIMIT-TO (PUBYEAR , 2011) OR LIMIT-TO (PUBYEAR , 2010) OR LIMIT-TO (PUBYEAR , 2009) OR LIMIT-TO (PUBYEAR , 2008) OR LIMIT-TO (PUBYEAR , 2007) OR LIMIT-TO (PUBYEAR , 2006) OR LIMIT-TO (PUBYEAR , 2005) OR LIMIT-TO (PUBYEAR , 2004) OR LIMIT-TO (PUBYEAR , 2003) OR LIMIT-TO (PUBYEAR , 2002) OR LIMIT-TO (PUBYEAR , 2001) OR

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[2] This chapter was presented at the 24th International Conference on Advancement of Construction Management and Real Estate organized by the Chinese Research Institute of Construction Management (CRIOCM). 29 November – 2 December 2019, Chongqing, China. It won the **Best Paper Award**.

1. **Abdul-Rahman M.**, Chan E.H.W., Li X., Wong M.S., Xu P. (2021) Big Data for Community Resilience Assessment: A Critical Review of Selected Global Tools. In: Ye G., Yuan H., Zuo J. (eds) Proceedings of the 24th International Symposium on Advancement of Construction Management and Real Estate. CRIOCM 2019. Springer, Singapore. https://doi.org/10.1007/978-981-15-8892-1_94

LIMIT-TO (PUBYEAR , 2000)) AND (LIMIT-TO (DOCTYPE , "ar") OR LIMIT-TO (DOCTYPE , "cp") OR LIMIT-TO (DOCTYPE , "re") OR LIMIT-TO (DOCTYPE , "ch")) AND (LIMIT-TO (PUBSTAGE , "final")) AND (LIMIT-TO (SUBJAREA , "ENVI") OR LIMIT-TO (SUBJAREA , "SOCI") OR LIMIT-TO (SUBJAREA , "EART") OR LIMIT-TO (SUBJAREA , "ENGI") OR LIMIT-TO (SUBJAREA , "ENER") OR LIMIT-TO (SUBJAREA , "ARTS") OR LIMIT-TO (SUBJAREA , "MULT") OR LIMIT-TO (SUBJAREA , "DECI"))

2. **Clarivate Analytics' Scopus**

You searched for TOPIC: (community resilience assessment)

Refined by: PUBLICATION YEARS: (2013 OR 2005 OR 2020 OR 2012 OR 2004 OR 2019 OR 2011 OR 2003 OR 2018 OR 2010 OR 2002 OR 2017 OR 2009 OR 2001 OR 2016 OR 2008 OR 2000 OR 2015 OR 2007 OR 2014 OR 2006) AND DOCUMENT TYPES: (ARTICLE OR REVIEW OR PROCEEDINGS PAPER) AND WEB OF SCIENCE CATEGORIES: (ENVIRONMENTAL SCIENCES OR ENVIRONMENTAL STUDIES OR WATER RESOURCES OR GEOSCIENCES MULTIDISCIPLINARY OR ECOLOGY OR ENGINEERING CIVIL OR TRANSPORTATION OR ARCHITECTURE OR GREEN SUSTAINABLE SCIENCE TECHNOLOGY OR BIODIVERSITY CONSERVATION OR ENGINEERING MULTIDISCIPLINARY OR GEOGRAPHY OR OCEANOGRAPHY OR MULTIDISCIPLINARY SCIENCES OR CONSTRUCTION BUILDING TECHNOLOGY OR AGRICULTURE MULTIDISCIPLINARY OR ENGINEERING ENVIRONMENTAL OR REGIONAL URBAN PLANNING OR MANAGEMENT OR ECONOMICS OR GEOGRAPHY PHYSICAL OR SOCIAL WORK OR ENGINEERING OCEAN OR SOCIAL SCIENCES INTERDISCIPLINARY OR DEVELOPMENT STUDIES OR URBAN STUDIES) AND TOPIC: (success factors AND studentification).

Timespan: All years. Indexes: SCI-EXPANDED, SSCI, A&HCI, CPCI-S, CPCI-SSH, ESCI.

The search phrases “Community Resilience Assessment”, “success factors” and “studentification” were used to query Scopus and Web of Science databases and the search was streamlined to download refereed articles, book chapters and conference papers published in the last 20 years (2000-2020). 2,239 papers matched the search algorithm on Scopus and 1,568 papers were found on the Web of Science. A total of 3,795 papers were left after removing all duplicates. To keep the review within a manageable scope and of relevance to this study, the 3,795 papers were further screened on the databases to downloaded only papers with “Community Resilience Assessment toolkit, index, scorecard, models or frameworks”, “Community Resilience Assessment success factors” and “studentification” in their titles, abstracts, and keywords and, papers that contain CRA methodologies that assess the community as a whole and not those that focus on single or selected components such as assessing the resilience of critical infrastructure or single systems. 602 papers were downloaded for content and meta-analysis. 51 CRA methodologies and 31 success factors for CRA were identified from the corpus, as well as concepts, theories, and research gaps. Figure 2.1 shows the literature review framework.

The 51 CRA methodologies and 31 success factors and their associated papers were identified for further analysis. The list of the 51 CRA methodologies and their basic characteristics can be found in Table 2.1 while the 31 success factors found in Table 2.2. Content analysis was used for evaluating the CRA methodologies and subsequent analysis in other sub-sections.

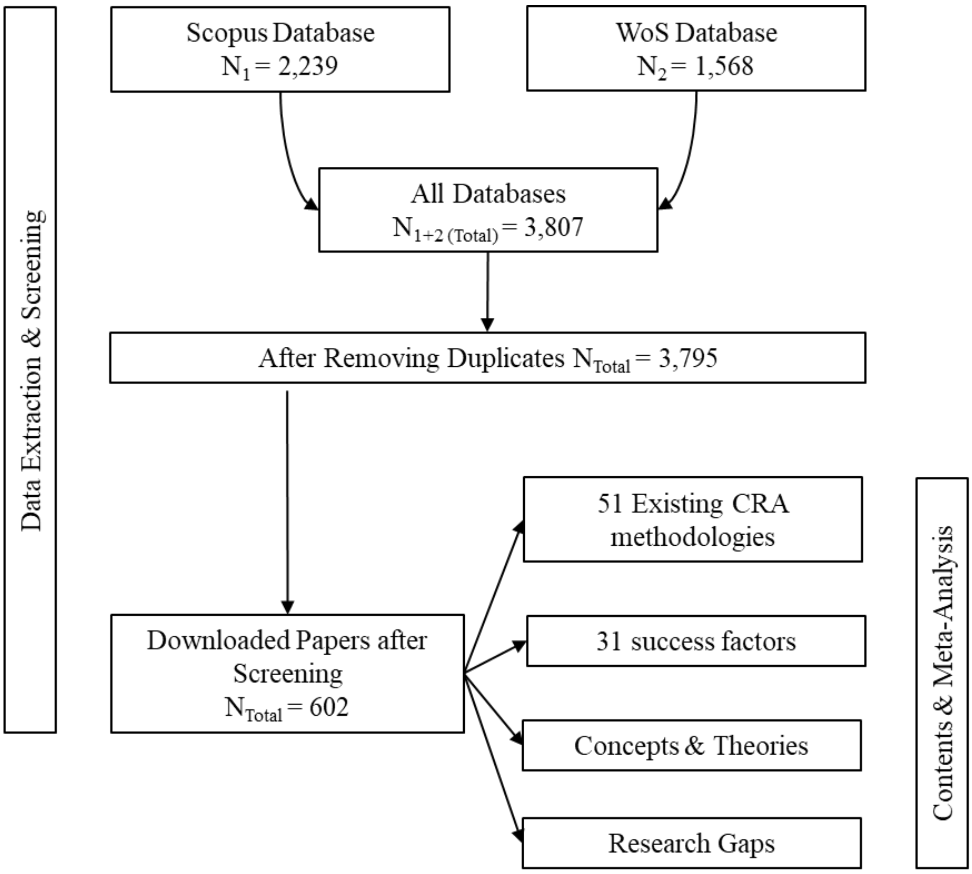

Figure 2.1 The literature review framework

Table 2.1 A brief overview of the identified 51 CRA methodologies

Tool	Year	Developer(s)	Region	Risks	End users	References
ARC-D	2015	GOAL	Global	Multiple	Local Authorities	GOAL (2015); Suryani and Soedarso (2019)
AWRVI	2008	Academia, Alesssa et al	Alaska, USA	Water	State and non-state actors	Alessa et al. (2008)
BCRD	2011	Rand Corporation	USA	Health	State and non-state actors	Chandra et al. (2011)
BRACED	2015	BRACED Myanmar Alliance and DFID	Myanmar	Natural	State and non-state actors	Bahadur et al. (2015)
BRIC	2010	Academia, Cutter et al	USA	Multiple	Local Authorities	Cutter et al. (2014); Cutter et al. (2010)
CARRI	2008	Community and Regional Resilience Institute	USA	Multiple	Community-based Organizations	S. L. Cutter et al. (2008)
CART	2011	Terrorism & Disaster Centre, University of Oklahoma	USA	Health	Community-based Organizations	Pfefferbaum et al. (2011)
CCRAM	2013	Academia, Cohen et al	Israel	Multiple	Community-based Organizations	Cohen et al. (2013)
CDR	2016	Academia, Yoon et al	Korea	Multiple	Local Authorities	Yoon et al. (2016)
CDRI	2010	Coastal Services Centre & the National Oceanic and	USA	Multiple	Community Leaders	Peacock et al. (2010)

		Atmospheric Administration				
CDRI2	2010	Academia, Shaw et al	South-East Asia	Multiple	Community Leaders/Local Authorities	Shaw et al. (2010)
CDRS	2012	Torrens Resilience Institute, Flinders University	Australia	Multiple	Planners, Local Authorities and Community members	Arbon et al. (2012); Arbon et al. (2016)
CERD	2018	Community Resilience Organizations (CROs), Second Nature and the Kresge Foundation	USA	Multiple	College Campus Managements and students	Blank (2018)
CERI	2010	Advantage West UK Midlands Strategy Team	UK	Recession	Local Authorities	Team (2010)
CoBRA	2014	UNDP/Dry Land Development Centre	Horn of Africa	Drought	State and non-state Actors	UNDP (2014)
COPEWEL L	2019	Academia, Schoch-Spana et al	Global	Multiple	Community-based Organizations & Local Authorities	Schoch-Spana et al. (2019)
CRAFT	2018	Institute for Building Technology and Safety	USA	Multiple	State and non-state Actors	IBTS (2018)
CRC	2015	Bushfire & Natural Hazards CRC	Australia	Multiple	Local Authorities & councils	Morley et al. (2015)
CRDSA	2015	Academia, Alshehri et al	Saudi Arabia	Multiple	Local Authorities	Alshehri et al. (2015)
CRF	2014	The Rockefeller Foundation and Arup International	Global	Multiple	Local authorities	The Rockefeller Foundation and ARUP International Development (2014)
CRI	2010	MS-AL Sea Grant/ National Oceanic and Atmospheric Administration	USA	Natural	Planners, Policy Makers and Emergency service providers	Sempier et al. (2010)
CRI2	2010	Academia, Sherrieb et al	USA	Multiple	Local Authorities	Sherrieb et al. (2010)
CRM	2000	Canadian Centre for Community Renewal	Canada	Recession	Local Authorities & Community members	Rowcliffe et al. (2000)
CRS	2013	Community & Regional Resilience Institute, Meridian Institute and Oak Ridge National Laboratory	USA	Multiple	Community Leaders	CARRI (2013); White et al. (2014)
CRT	2009	Bay Localize Project of the Earth Island Institute	USA	Recession	Planners, Community-based Organizations and individuals	Schwind (2009)
CSAR	2015	Swedbio, Oxfam Novib and the Agricultural Biodiversity Community	Global	Agro-Biodiversit y	Community members and Local Authorities	CSAR (2015)
DFID	2009	Department for International Development and other agencies	UK	Natural	State and non-state actors	Twigg (2009)
DRI	2015	Earthquakes & Megacities Initiative (EMI)	Global	Multiple	State actors (governments)	Khazai et al. (2015)

DRR	2014	United Nations Office for Disaster Risk Reduction.	Global	Multiple	State and non-state actors	UNISDR (2014)
FCR	2014	International Federation of Red Cross & Red Crescent Societies (IFRC)	Global	Multiple	IFRC programs and societies	IFRC (2014)
Grosvenor	2014	Grosvenor, Private sector	Global	Multiple	Local authorities & donor organizations	Barkham et al. (2014)
Hyogo	2008	UNOCHA& UNISDR	Global	Natural	State and non-state actors	UNISDR (2008)
ICBRR	2012	Palang Merah Indonesia and the Canadian Red Cross	Indonesia	Multiple	Local Authorities	S. K. Kafle (2010); Kafle (2012)
ICLEI	2014	ACCCRN, Rockefeller & ICLEI	Global	Natural	Local authorities	Gawler and Tiwari (2014)
LACCDR	2016	Los Angeles County Community Disaster Resilience Project	Los Angeles, USA	Multiple	Households and Community members	Eisenman et al. (2016)
LDRI	2013	Academia, Orencio & Fujii	The Philippines	Multiple	Local Authorities	Orencio and Fujii (2013)
MAPP	2012	National Association of County and City Health Officials.	USA	Health	Community-based Organizations	NACCHO (2012)
ND-GAIN	2015	Academia, University of Notre Dame Global Adaptation Initiative	Global	Climate	State and non-state actors	Chen et al. (2015)
NIST	2015	National Institute of Standards and Technology	USA	Multiple	Local Authorities	NIST (2015)
PEOPLES	2010	National Institute of Standards and Technology	USA	Multiple	Planners & Local Authorities	Renschler et al. (2010b)
RAPT	2019	The U.S Federal Emergency Management Agency (FEMA) and Argonne National Laboratory	USA	Natural	State and non-state actors	FEMA (2019)
RELi	2014	American National Standards Institute	USA	Multiple	Developers	C3LD (2014)
ResilUS	2011	Resilience Institute, Western Washington University	USA & Japan	Earthquake	Local Authorities	Miles and Chang (2011)
RITA	2013	American Red Cross and National Societies	Global	Multiple	State and non-state actors	American Red Cross (2013)
SPUR	2009	San Francisco Planning + Urban Research Association	USA	Earthquake	Local Authorities, Builders and Developers	Poland (2009)
TCRI	2015	Australia-Netherlands Water Challenge	Australia	Multiple	Local, State and National Governments & International Organizations	Perfrement and Lloyd (2015)
THRIVE	2016	Prevention Institute	USA	Health	Local Authorities and NGOs	L. Cohen et al. (2016)
UCRA	2017	World Resources Institute (WRI)	Global	Multiple	State and non-state actors	WRI (2017)

USAID	2013	USAID	Global	Poverty	State, non-state and donor organizations	T. Frankenberger et al. (2013)
US-CRT	2014	The U.S. National Oceanic & Atmospheric Administration	USA	Climate	State and non-state actors	Gardiner et al. (2019)
USIOTWSP	2007	U.S. Indian Ocean Tsunami Warning System Program	South-East Asia	Coastal	State & non-state organizations, aid agencies, banks, insurance companies and donor agencies	USIOTWSP (2017)

Table 2.2 Potential CSFs for community resilience assessment[3]

Code	Success factors	References
F1	Assessment of interlinkages	(Collier et al., 2013; Larkin et al., 2015; Schipper & Langston, 2015b)
F2	Assessment of cultural and social risk within the community	(Abdul-Rahman et al., 2020; Cimellaro et al., 2016; Cutter, 2016; L. Irajifar et al., 2013)
F3	Assessment of place attachment & sense of community and pride	(Cutter, 2016; S. L. Cutter et al., 2008; Katherine Pasteur, 2011; Renschler et al., 2010a)
F4	Simulation of alternate states	(Folke et al., 2010; E. McLeod et al., 2015; Ostadtaghizadeh et al., 2015; P Pringle, 2011)
F5	Inclusive & participatory CRA process	(Gibson, 2006; Pfefferbaum et al., 2015; Tyler et al., 2016)
F6	Evaluation of community social network	(Cutter, 2016; Renschler et al., 2010b)
F7	Co-creation & co-adoption of the CRA methodology	(Krishnan, 2019; Norris et al., 2008; Pfefferbaum, Pfefferbaum, Van-Horn, et al., 2013)
F8	Inclusive & participatory action planning process	(Hsiao, 2021; McEwen et al., 2018; Pfefferbaum et al., 2015; Spaans & Waterhout, 2017a)
F9	Repeated key assessment processes (iterative process)	(Larkin et al., 2015; Schipper & Langston, 2015b)
F10	Decentralized responsibilities & leadership during the CRA process	(Katherine Pasteur, 2011; Renschler et al., 2010b)
F11	Evaluation of the trust & reciprocity within the community	(Cutter et al., 2014; Jia et al., 2020; Renschler et al., 2010a)
F12	Evaluation of crime prevention & reduction mechanisms	(S. L. Cutter et al., 2008; Jia et al., 2020; K. Pasteur, 2011)
F13	Assessment of economic risks within the community	(Abdul-Rahman et al., 2020; L. Irajifar et al., 2013; Sharifi, 2016)
F14	Identification of present resilience challenges	(Sharifi, 2016; Walker & Salt, 2012a)
F15	Assessment of upper-scale relationships	(Chelleri, Waters, et al., 2015; P. Monaghan et al., 2014)
F16	Evaluation of available social safety-nets mechanisms	(Cutter, 2016; Cutter et al., 2010; Saja et al., 2018)
F17	Assessment of environmental risks	(Abdul-Rahman et al., 2020; L. Irajifar et al., 2013; Sharifi, 2016)
F18	Identification and assessment of shared assets within the community	(Cutter, 2016; S. L. Cutter et al., 2008; Saja et al., 2018)
F19	Prediction of future resilience challenges	(Sharifi, 2016; Walker & Salt, 2012b)
F20	Flexibility in action planning to accommodate	(Ostadtaghizadeh et al., 2015; Spaans & Waterhout, 2017a)

[3] Chapter 4 further builds on Table 2.2 to produce the critical success factors for CRA.

	evolving situations	
F21	Assessment of lower-scale relationships	(Chelleri, Schuetze, et al., 2015; P. Monaghan et al., 2014)
F22	Assessment of existing institutional and governance structures	(Pfefferbaum et al., 2015; Sharifi, 2016)
F23	Identification and evaluation of shared norms & value	(Copeland et al., 2020; Cutter, 2016; Cutter et al., 2014)
F24	Identification of past resilience challenges	(Sharifi, 2016; Walker & Salt, 2012a; Wang et al., 2018)
F25	Assessment of focal-scale relationships	(P. Monaghan et al., 2014; Quinlan et al., 2016)
F26	Integration of action plans with other existing community systems	(Sharifi, 2016; Spaans & Waterhout, 2017a)
F27	Assessment of community conflict resolution mechanisms	(Cutter, 2016; Cutter et al., 2010; Jia et al., 2020)
F28	Redundancies in the action plan to accommodate disruptions	(Spaans & Waterhout, 2017a)
F29	The resourcefulness of the action plan to respond to needs during crises	(Spaans & Waterhout, 2017a; Wang et al., 2018)
F30	Robustness of the action planning process	(Abdul-Rahman et al., 2021; Spaans & Waterhout, 2017a)
F31	Co-reflectiveness during plan-making	(Gladfelter, 2018; Hsiao, 2021; Spaans & Waterhout, 2017a)

2.2 A comprehensive overview of the 51 CRA methodologies selected for analysis

To examine the existing CRA methodologies, this study adopts and modifies Sharifi (2016) criteria for critically reviewing CRA methodologies using content and meta-analysis.

Data extracted from Table 2.1 and presented in Figures 2.2 to 2.6 show that there were no recorded CRA tools between 2001 and 2006. The Community Resilience Manual (CRM) was released in 2000 by the Canadian Centre for Community Renewal, and from 2007, at least one CRA methodology has been released yearly till 2019. The highest number of CRA methodologies were released from 2014-2015. This spike may be a result of the United Nations declarations for building resilient cities and the post-2015 sustainable development agenda.

The few CRA methodologies created in 2020 were related to the COVID-19 pandemic and were targeting single systems related to public health and sanitation, therefore, they were excluded from this analysis.

Most of the CRA methodologies were developed by government agencies, academia, the private sector and International NGOs, with government agencies and academia contributing to the creation of 64% of the CRA methodologies. The geographic focus of the tools spans across the world as most can be modified and used by people in different regions, however, the majority of the CRA methodologies created in the last two decades (from 2000 to 2020) were intended for use in the USA (about 41%), while about 27% are for global use by any country, region, city or community. The rest are intended for specific countries or regions.

The CRA methodologies released in the last two decades were mainly created to access different risks including climate change, water, agro-biodiversity, health, recession, poverty, drought, earthquakes, coastal erosions and other natural disasters, but about 57% of them were designed to access and provide resilience solutions for multiple risks. However, none was intended to assess the resilience of university towns and the risks associated with the interplay between the universities and the communities they are nested in.

The intended end-users of the CRA methodologies include academia, banks & insurance companies, developers, international non-governmental organizations, aid agencies & donor organizations, and urban planners. But, 82% of the CRA methodologies were developed for use by government agencies & local authorities as well as community-based organizations, community leaders & community members. The Campus Evaluation of Resilience Dimensions (CERD) was the only CRA tool designed for college campus managements by the Community Resilience Organizations (CROs), Second Nature and the Kresge Foundation. It is a summative scorecard for college students in the United States of America to assess and understand their resilience level.

The charts in Figures 2.2 to 2.6 below show an overview of the CRA methodologies released from 2000 to 2020.

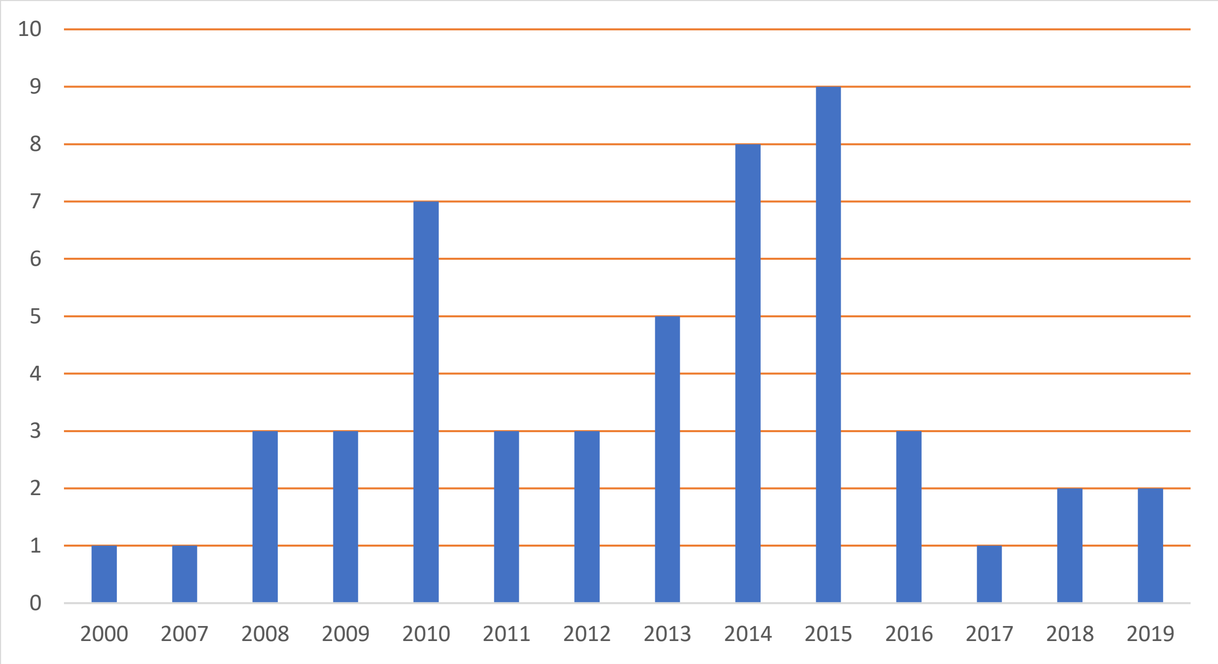

Figure 2.2 Frequency distribution of CRA methodologies by year of release

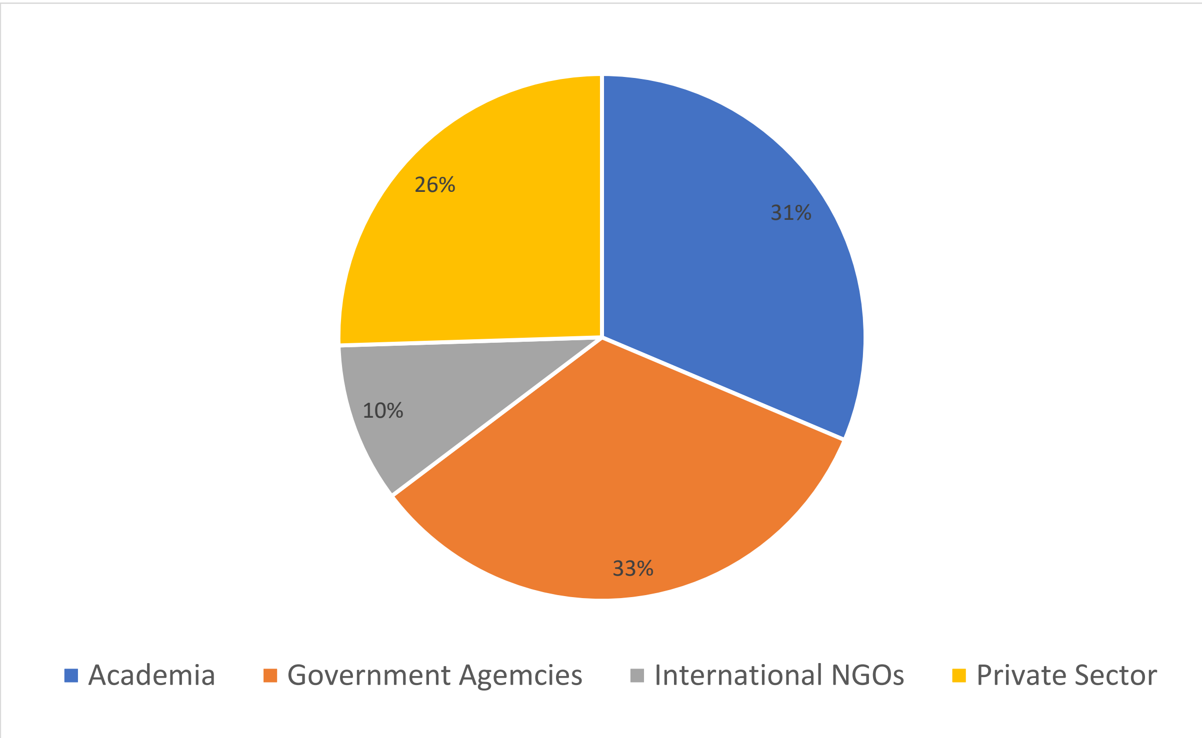

Figure 2.3 Chart showing the percentage of CRA methodologies and their developers

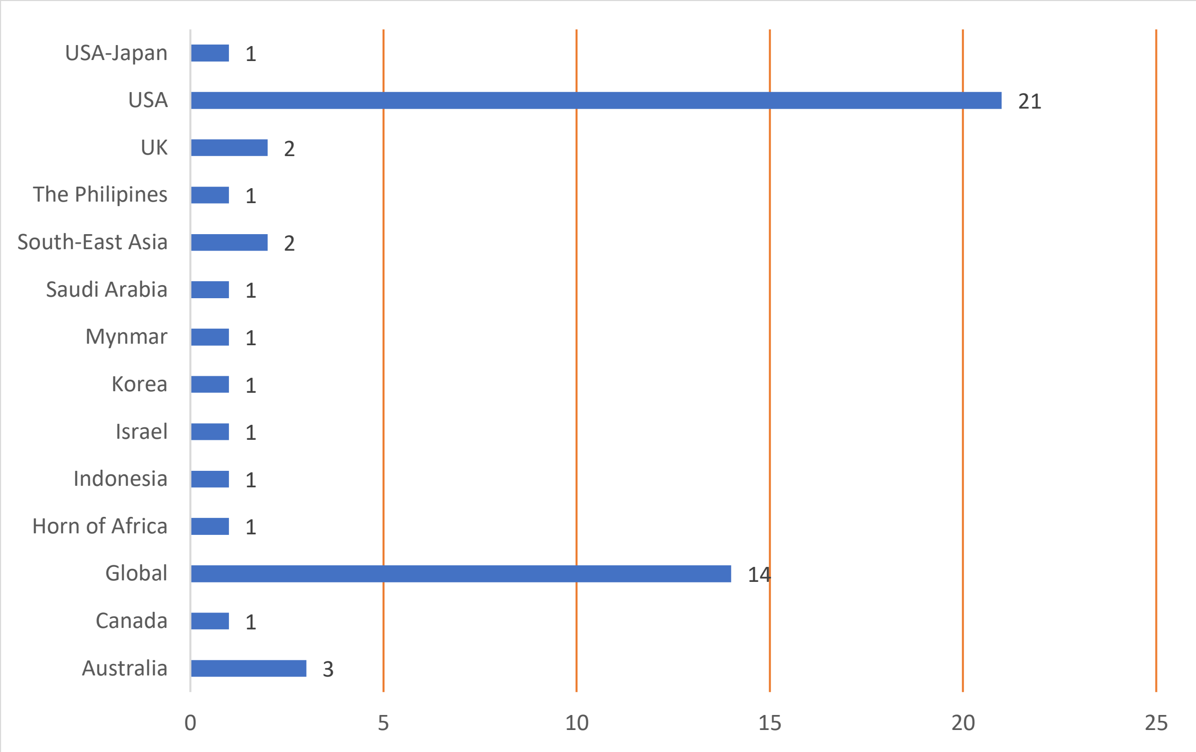

Figure 2.4 Frequency distribution of the CRA methodologies geographic focus

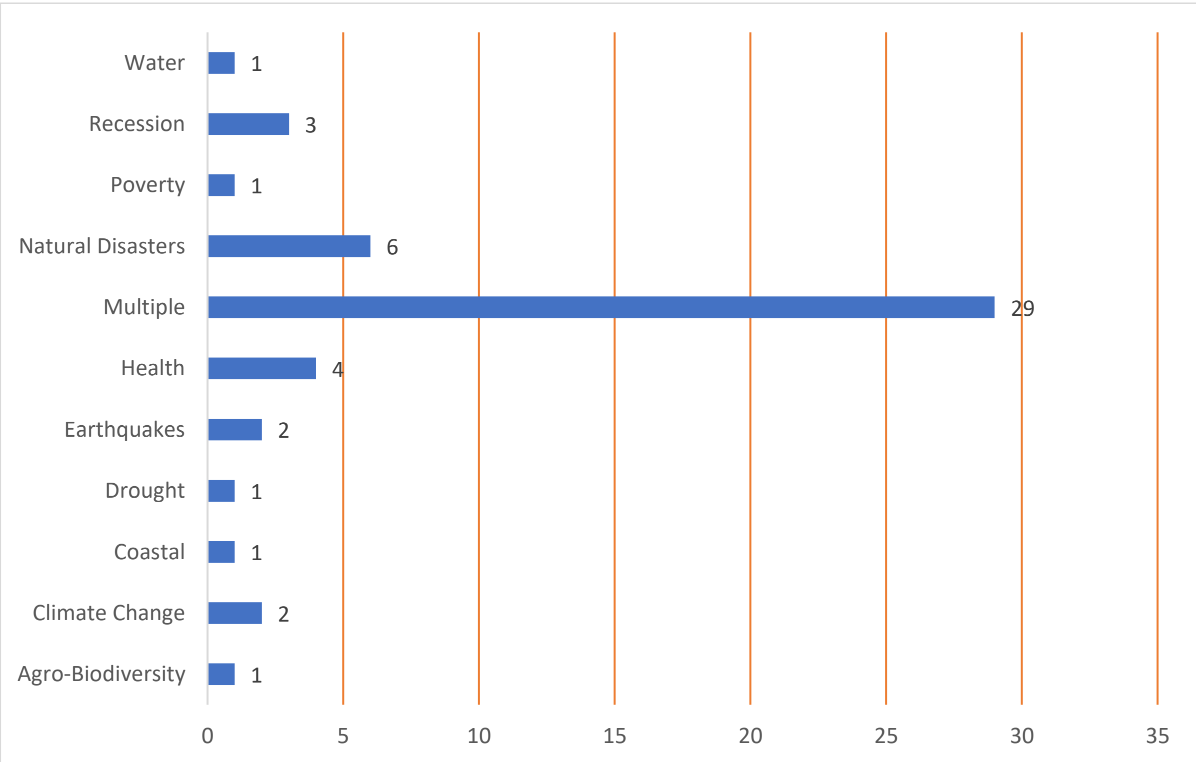

Figure 2.5 Frequency distribution of the risks addressed by the CRA methodologies

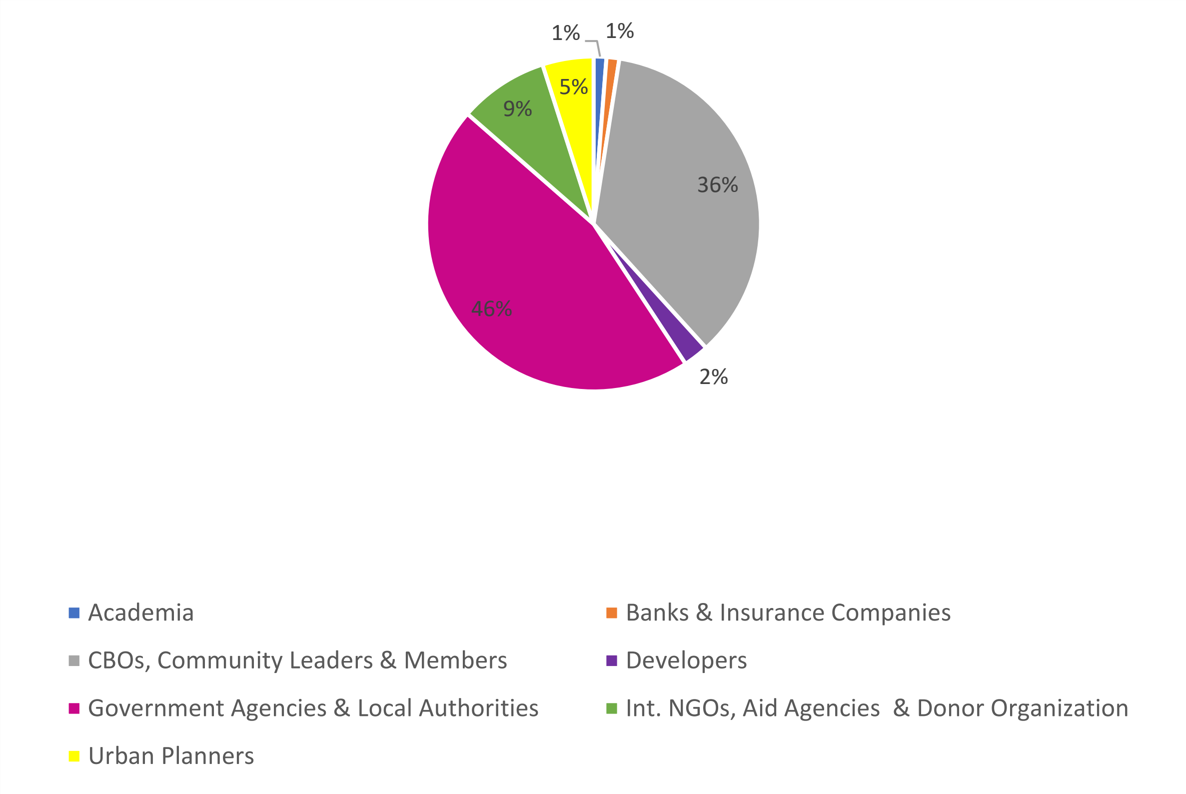

Figure 2.6 Chart showing the percentage of CRA methodologies intended end-users

2.2.1 Types of assessments and approaches and methods used

CRA methodologies are designed to be used at different spatial scales. In most cases, CRA methodologies only function at the focal scale they are created for and lower spatial scales. However, a good CRA methodology should be able to assess spatial relationships between all lower scale, focal scale and the immediate upper spatial scale (Constas et al., 2014). That is, a CRA methodology designed to function at the city level should be able to assess and build resilience at the city level (focal) and all other spatial lower scales under the city like districts, communities, neighbourhoods, etc. as well as assess the dynamism between the city and the upper scale it is nested in (region and other adjourning cities). From the analysis presented in Figure 2.7 below, 55% of the CRA methodologies released from 2000 to 2019 were designed for assessing and building resilience at the community level. 29% were designed for cities, 6% for districts, 4% for regions and neighbourhoods and only 2% were designed to function at the country level.

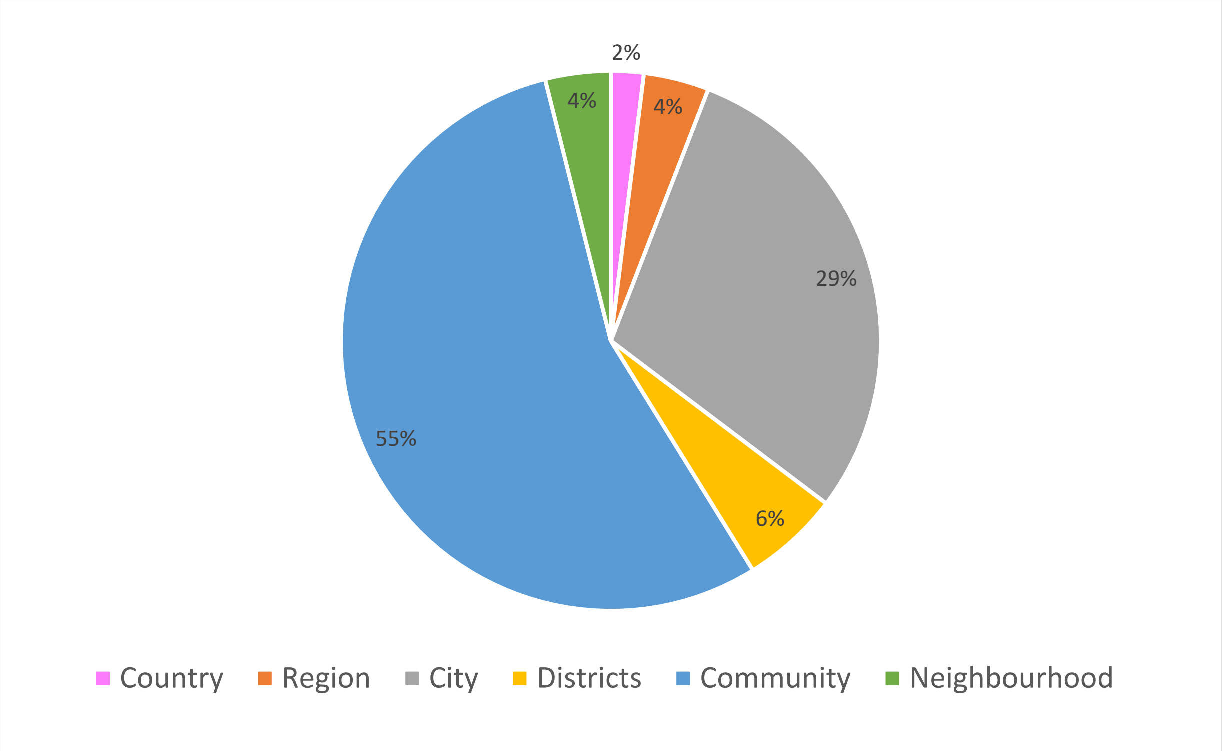

Figure 2.7 Chart showing the percentage of different CRA tools and the spatial scales they are created for.

Broadly speaking, CRA methodologies can be grouped into two types: formative and summative tools (P. Pringle, 2011; Sharifi, 2016). Formative assessment starts at the beginning of the resilience planning process and involves the continuous evaluation and monitoring of the community to increase adaptation. This provides room for learning, enhances local ownership of the process, and makes the process iterative which is good for addressing dynamism and capturing risks and uncertainties. Contrarily, summative assessments measure the effectiveness of resilience interventions and help communities to evaluate their strategies and modify or scale up if necessary (P. Pringle, 2011). As seen in Figure 2.8 below, 49% of the tools evaluated are summative while the remaining 51% are formative.

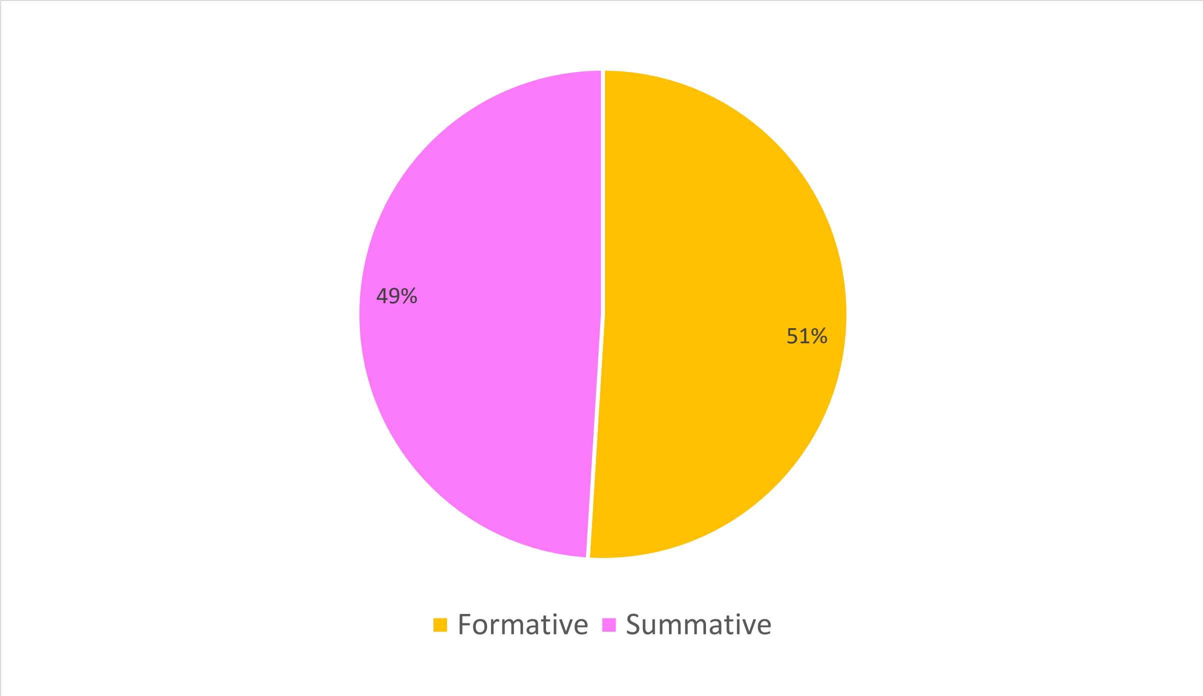

Figure 2.8 Chart showing the different types of CRA methodologies and their percentages

The systematic literature review also shows that all CRA methodologies adopted the use of the following formats: toolkits, indices, models and scorecards. Scorecards help in evaluating performance, while models are used for the estimation of future trajectories. Indices, on the other hand, help to show the resilience state of the community in a very simple form at any given time (Sharifi, 2016). Toolkits are the combination of the three above and provide a comprehensive mechanism to use scorecards, indices and models to assess and build resilience (Cutter, 2016). The analysis results in Figure 2.9 below show that most of the CRA methodologies are toolkits (57%), while 29% of the evaluated tools generate indices for community resilience, 10% are scorecards, and the remaining 4% are resilience models.

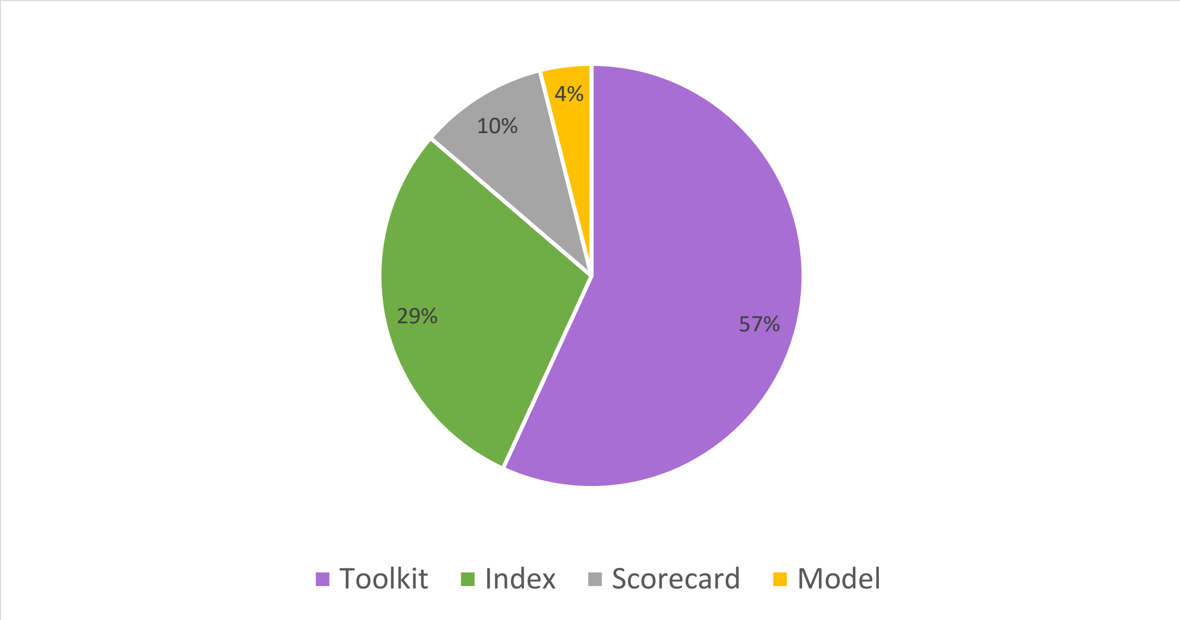

Figure 2.9 Chart showing the different CRA methodologies formats and their percentages

The review further shows that 61% of the CRA methodologies rely heavily on both primary and secondary sources of data for carrying out their resilience assessments. The secondary data used by many of the CRA methodologies include demographic data from census, historic records on events and data documented by local authorities, government agencies and non-profit organizations. The primary data include surveys and key informant interviews as well as data from fieldwork. 16% of the tools use only primary data, while 23% use only secondary data for their assessments. None of the methodologies generates or mine their own big data for assessments or resilience building, however, 10% of the CRA tools use Geographic Information System (GIS) or Census big data banks for their assessments. For data types, 63% of the CRA methodologies use both quantitative and qualitative data for their assessments, while only 10% use qualitative data and the remaining 27% use quantitative data. The frequency distributions of data usage by the CRA methodologies capture for this analysis are presented in Figure 2.10, Figure 2.11 and Figure 2.12.

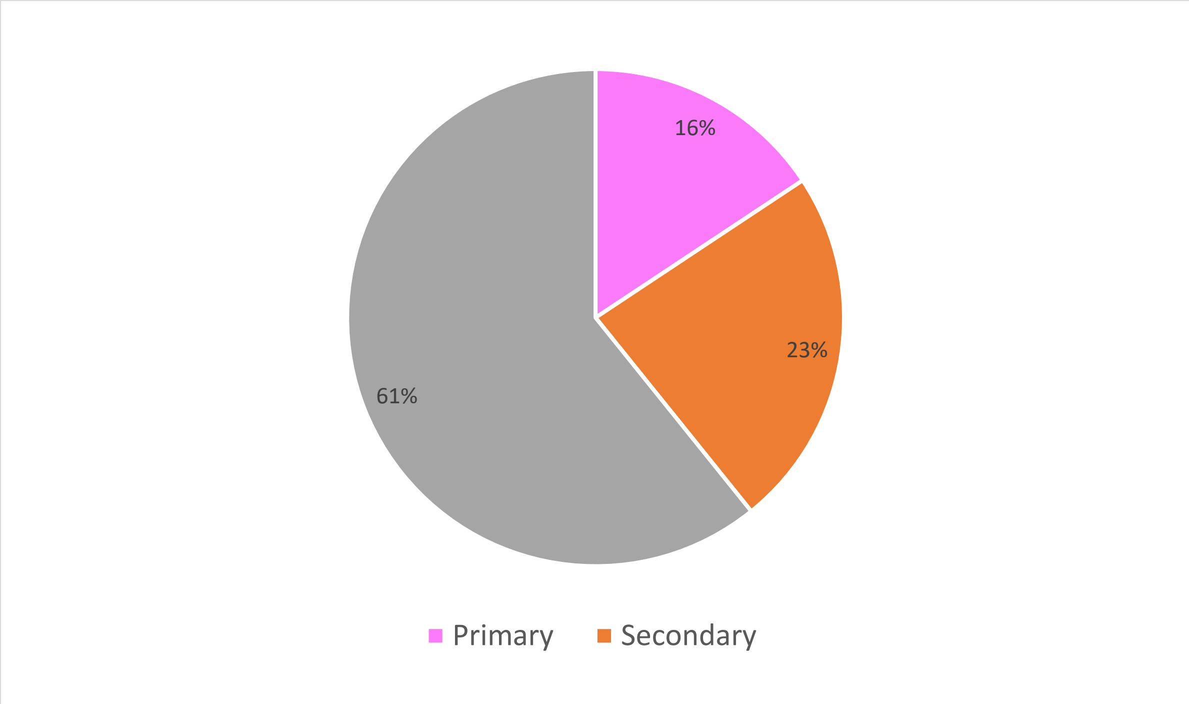

Figure 2.10 Chart showing the percentages data sources used by the CRA methodologies.

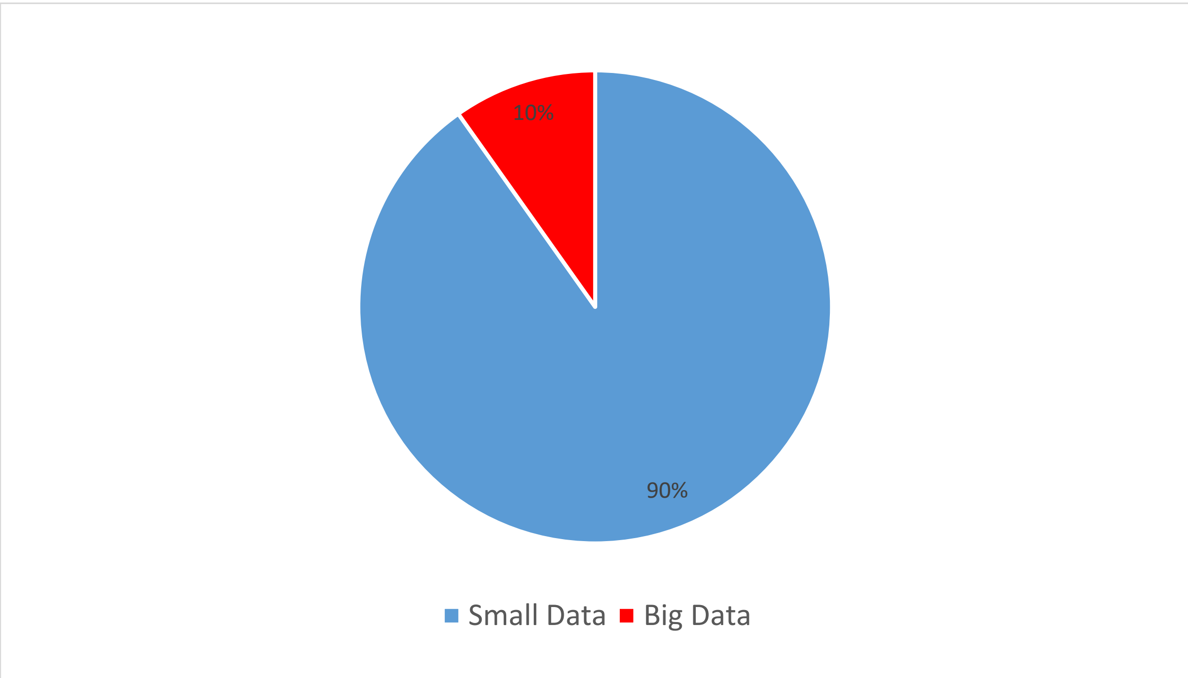

Figure 2.11 Chart showing the percentages of data sizes used by the CRA methodologies.

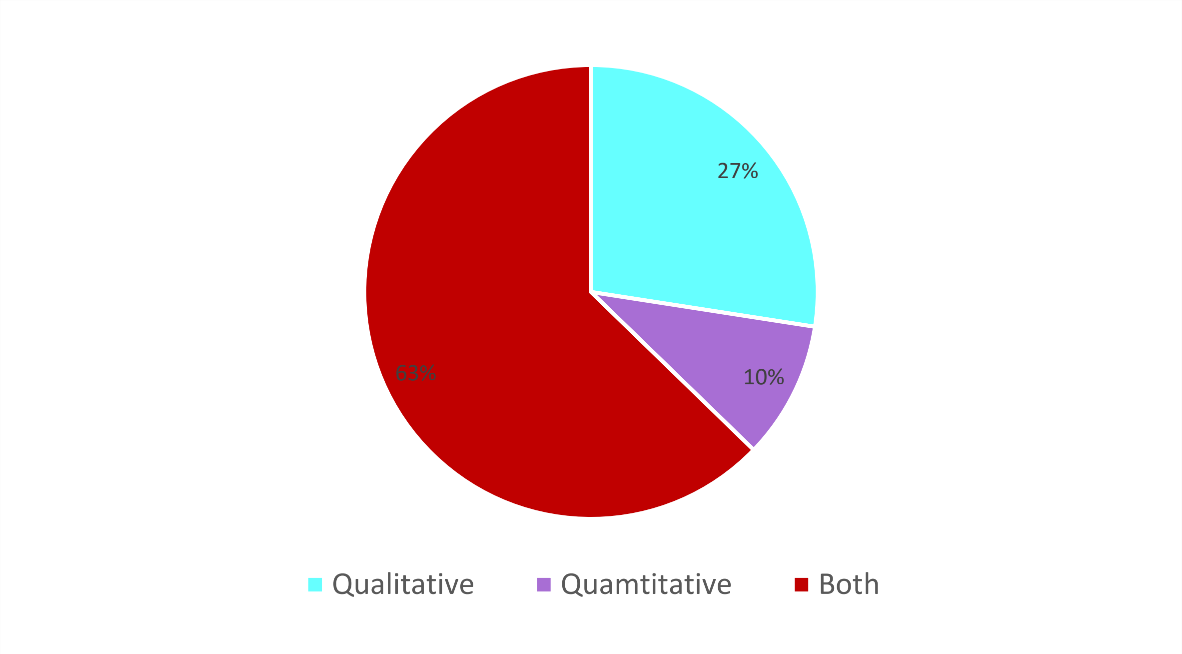

Figure 2.12 Chart showing the percentages of data types used by the CRA methodologies.

The captured CRA methodologies use different types of assessments ranging from measuring baseline conditions to setting thresholds, to assessment against the adopted resilience principles, benchmarking against peers and speed of recovery. Assessments against baseline conditions help communities to capture temporal dynamism or changes over time, while assessments against threshold values attached to each resilience criterion help the community to measure the progress of each program objective (Sharifi, 2016). It is also good practice to identify principles of good resilience and periodically update them based on the understanding of what constitutes resilience in a community (P. Pringle, 2011). Building resilience is all about learning from your peers and learning from past events, therefore, good CRA methodologies need to benchmark their resilience initiatives against both their peers and global best resilience practices. Post-disaster recovery speed is also important in understanding how community systems return to their former or a new equilibrium. This will help communities plan for the period the systems are recovering and work towards increasing the recovery time (Fox-Lent et al., 2015).

From the analysis carried out and presented in Figure 2.13, 56.9% of the CRA methodologies carry out their assessments against established baseline conditions, 47.1% carry out their assessments against agreed resilience principles, 35.3% benchmark their assessments against peers with similar resilience issues, 27.5% assess resilience against recovery time, while 13.7% assess resilience based on threshold values attached to each resilience criterion.

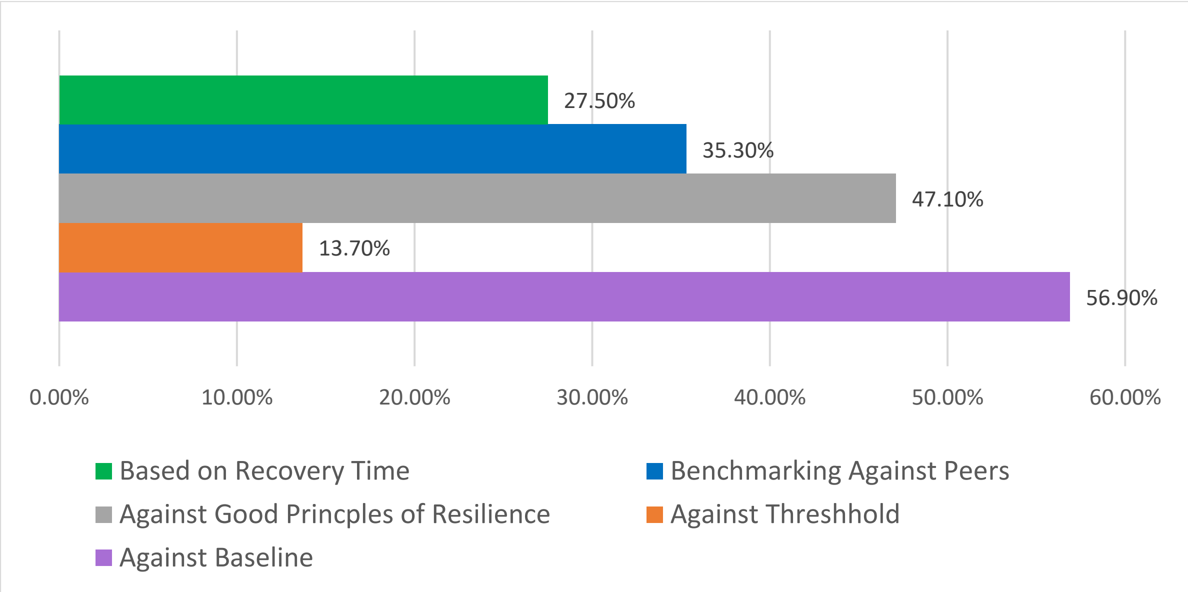

Figure 2.13 Percentage distribution of the major assessment types used by the CRA methodologies.

To carry out the above assessment types, CRA methodologies captured for this analysis use weighting, visual illustrations, measuring social and temporal dynamism, as well as identifying strengths and weaknesses. Equality in weighting community concerns is important (Larkin et al., 2015). This is not about the weights assigned to community resilience objectives alone but more of assigning equal weights to the different community groups (men and women, different age groups, etc). This brings fairness, and just like continuous communication, it increases local ownership of the resilience process. CRA methodologies need to have good illustrative techniques to enhance communication. This is done through visualization and translation into local languages, as the misunderstanding of negative results may lead to depression or panic in the community which might affect the development of resilience (preparation, planning, absorption, recovery and adaptation). Communication also needs to be continuous to allow stakeholders to see progress or areas lagging that need to be worked on.

It is also deduced that good CRA methodologies need to find features of the community that can help them achieve their set objectives (strengths) and those they need to strengthen to achieve their goal (Pfefferbaum, Neas, et al., 2013; Sharifi, 2016). Illustrative SWOT analysis was embedded in the assessment activities of some of the CRA methodologies.

Figure 2.14 below show that 66.7% of the CRA methodologies measure strengths and weaknesses, 56.9% assign weights to criteria, 51% both use illustrative approaches as well as to measure social capital, 31.4% identify changes in resilience over times (temporal dynamism), while only 21.6% carry out continuous communication and planning (periodic monitoring and evaluation processes).

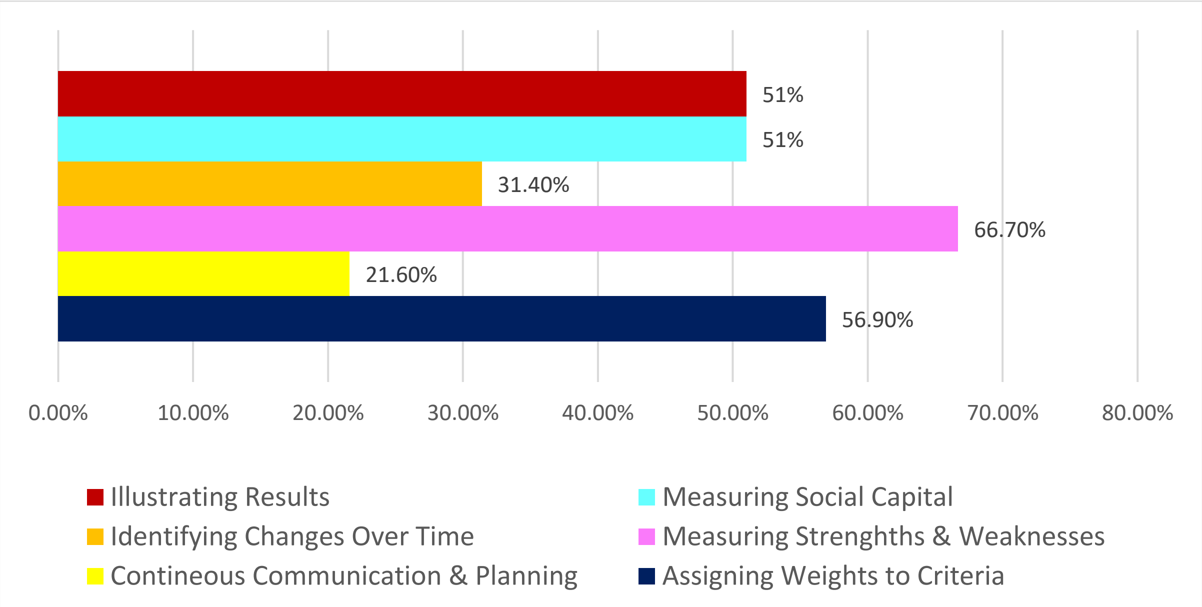

Figure 2.14 Frequency distribution of the key assessment methods used by the CRA methodologies.

Table 2.3 shows the type of assessments as well as the methods and approaches used by the CRA methodologies captured in this comprehensive analysis

Table 2.3 Types of assessments and approaches and methods used

Methodology	Cross-scale (Highest)	Methodology Type	Format	Data Source	Data Size	Data Type	AI Tools	Base line	Threshold	Principles of Resilience	Bench-marking	Recovery time	Weighting	Continuous Commun-ication	Strengths/ Weaknesses	Temporal Dynamism	Social Dynamism	Results visualization
ARC-D	Community	Formative	Toolkit	Both	Small	Both	✗	✗	✓	✗	✓	✗	✓	✓	✓	✓	✓	✗
AWRVI	Community	Summative	Index	Both	Small	Both	✗	✗	✗	✓	✓	✗	✗	✗	✓	✗	✓	✗
BCRD	Community	Formative	Toolkit	Both	Small	Both	✗	✗	✗	✗	✗	✓	✗	✗	✗	✗	✓	✗
BRACED	Community	Formative	Toolkit	Both	Small	Both	✗	✗	✗	✓	✗	✓	✗	✗	✓	✓	✓	✓
BRIC	District	Summative	Index	Sec	Small	Quantitative	✗	✓	✗	✗	✓	✗	✓	✗	✓	✗	✓	✓
CARRI	Regional	Summative	Index	Sec	Small	Both	✗	✗	✗	✗	✓	✗	✓	✗	✗	✗	✓	✓
CART	City	Formative	Toolkit	Both	Small	Qualitative	✗	✓	✗	✗	✗	✗	✓	✓	✓	✗	✓	✗
CCRAM	Community	Summative	Scorecard	Both	Small	Both	✗	✓	✗	✓	✗	✗	✓	✓	✓	✓	✓	✓
CDR	City	Summative	Index	Sec	Small	Quantitative	✗	✓	✗	✗	✓	✗	✓	✗	✓	✗	✗	✓
CDRI	District	Summative	Index	Sec	Small	Both	✗	✓	✗	✗	✓	✗	✗	✗	✓	✗	✗	✓
CDRI2	City	Summative	Toolkit	Both	Small	Both	✗	✓	✓	✗	✓	✗	✗	✓	✓	✓	✗	✓
CDRS	Community	Summative	Toolkit	Both	Small	Both	✗	✓	✗	✓	✗	✓	✗	✗	✓	✗	✓	✗
CERD	Community	Summative	Scorecard	Pry	Small	Both	✗	✗	✗	✓	✗	✗	✓	✗	✓	✗	✗	✗
CERI	Regional	Summative	Index	Sec	Small	Quantitative	✗	✗	✗	✗	✓	✗	✗	✗	✓	✗	✗	✓
CoBRA	Community	Formative	Toolkit	Both	Small	Both	✗	✓	✓	✓	✓	✗	✓	✓	✓	✓	✓	✓
COPEWELL	Community	Summative	Toolkit	Both	Small	Both	✗	✗	✗	✓	✗	✗	✓	✗	✗	✓	✓	✓
CRAFT	Community	Summative	Toolkit	Both	Small	Both	✗	✗	✗	✗	✗	✓	✗	✗	✓	✗	✗	✓
CRC	Community	Summative	Index	Pry	Small	Both	✗	✗	✗	✗	✓	✗	✓	✗	✓	✗	✓	✓
CRDSA	Community	Summative	Index	Pry	Small	Both	✗	✓	✗	✗	✗	✗	✗	✗	✗	✗	✓	✓
CRF	City	Formative	Toolkit	Both	Small	Qualitative	✗	✓	✗	✗	✗	✓	✓	✗	✓	✗	✓	✗
CRI	Community	Summative	Index	Sec	Small	Qualitative	✗	✓	✗	✗	✗	✓	✓	✗	✓	✗	✗	✗
CRI2	District	Summative	Index	Sec	Small	Both	✗	✓	✗	✗	✓	✗	✓	✗	✓	✗	✓	✓
CRM	Community	Formative	Toolkit	Pry	Small	Both	✗	✓	✗	✗	✗	✗	✗	✗	✓	✗	✓	✗
CRS	Neighborhood	Formative	Toolkit	Both	Small	Qualitative	✗	✗	✗	✗	✗	✗	✗	✓	✓	✗	✗	✓
CRT	City	Formative	Toolkit	Both	Small	Qualitative	✗	✗	✗	✗	✗	✗	✓	✓	✓	✗	✓	✗
CSAR	Community	Formative	Toolkit	Pry	Small	Both	✗	✗	✗	✓	✗	✗	✓	✗	✓	✗	✓	✓
DFID	Community	Formative	Toolkit	Both	Small	Qualitative	✗	✓	✗	✓	✗	✓	✗	✓	✓	✗	✗	✗
DRI	City	Summative	Index	Pry	Small	Qualitative	✗	✗	✗	✓	✓	✗	✓	✗	✗	✓	✗	✓
DRR	City	Summative	Scorecard	Both	Small	Both	✗	✗	✗	✓	✗	✗	✓	✗	✗	✗	✗	✗
FCR	Community	Formative	Toolkit	Both	Small	Qualitative	✗	✗	✓	✗	✗	✗	✗	✗	✓	✓	✓	✗
Grosvenor	City	Summative	Index	Sec	Small	Qualitative	✗	✗	✗	✗	✓	✗	✓	✗	✗	✗	✗	✗
Hyogo	City	Formative	Toolkit	Both	Small	Both	✗	✓	✗	✓	✗	✓	✓	✗	✗	✓	✗	✗
ICBRR	Community	Formative	Index	Both	Small	Both	✗	✓	✗	✓	✗	✗	✗	✗	✗	✗	✓	✗
ICLEI	City	Formative	Toolkit	Both	Small	Qualitative	✗	✓	✗	✓	✓	✗	✗	✓	✓	✗	✗	✓
LACCDR	City	Formative	Toolkit	Both	Small	Both	✗	✗	✗	✓	✗	✗	✗	✓	✗	✗	✓	✗
LDRI	Community	Formative	Index	Both	Small	Both	✗	✗	✗	✓	✗	✗	✗	✗	✗	✗	✓	✗

MAPP	Community	Formative	Toolkit	Both	Small	Both	✕	✕	✕	✓	✕	✕	✓	✕	✓	✕	✓	✕
ND-GAIN	Country	Formative	Toolkit	Both	Big	Both	✓	✓	✕	✓	✓	✕	✓	✕	✕	✓	✕	✓
NIST	Community	Formative	Toolkit	Both	Big	Both	✓	✓	✓	✓	✕	✓	✓	✕	✓	✓	✕	✓
PEOPLES	Community	Summative	Toolkit	Both	Big	Both	✕	✓	✕	✕	✕	✓	✕	✕	✕	✓	✕	✓
RAPT	City	Summative	Scorecard	Sec	Big	Quantitative	✓	✓	✓	✕	✓	✕	✕	✕	✕	✓	✕	✓
RELi	Community	Summative	Index	Both	Small	Both	✕	✓	✓	✓	✕	✕	✓	✕	✓	✓	✕	✕
ResilUS	Community	Summative	Model	Sec	Small	Qualitative	✕	✓	✕	✕	✓	✓	✓	✕	✓	✓	✕	✓
RITA	Community	Formative	Toolkit	Pry	Small	Both	✕	✕	✕	✓	✕	✕	✓	✕	✓	✕	✕	✓
SPUR	City	Formative	Scorecard	Pry	Small	Qualitative	✕	✓	✕	✕	✕	✓	✓	✕	✕	✕	✕	✕
TCRI	Community	Summative	Model	Sec	Small	Quantitative	✕	✓	✕	✕	✓	✕	✕	✕	✓	✕	✓	✓
THRIVE	Neighborhood	Formative	Toolkit	Both	Small	Qualitative	✕	✕	✕	✓	✕	✕	✕	✕	✓	✕	✓	✕
UCRA	City	Formative	Toolkit	Both	Big	Both	✕	✓	✕	✕	✕	✓	✕	✓	✓	✓	✕	✕
USAID	Community	Summative	Toolkit	Both	Small	Both	✕	✓	✕	✕	✕	✕	✓	✕	✕	✓	✓	✕
US-CRT	City	Formative	Toolkit	Sec	Small	Both	✕	✓	✕	✓	✕	✕	✓	✕	✕	✓	✕	✓
USIOTWSP	Community	Formative	Toolkit	Both	Small	Qualitative	✕	✓	✕	✓	✕	✓	✓	✕	✓	✓	✕	✓

✓: Addressed
✕: Not addressed
Pry: Primary data
Sec: Secondary data
Both: Both primary or secondary data sources or both qualitative and qualitative data types
AI: Artificial Intelligence

2.3 Analysis based on the critical success factors of community resilience assessments

The 7 components from the outcome of the Principal Components Analysis (PCA) in chapter 4 of this thesis were used for further analysis of the captured CRA methodologies. They are:

1. *The comprehensiveness of Community Resilience Assessment:* Communities have complex multiple dimensions and such need to be addressed in the resilience assessment and the resilience-building process. Therefore, ideal CRA methodologies need to cover core themes including social, cultural, economic, physical/environmental, institutional, and others that make the socio-ecological fabric of communities (Cimellaro et al., 2016). To measure compliance with these criteria, Sharifi and Murayama (2015) methodology was adopted.
2. *Measuring temporal dynamism:* Capturing time horizons and knowing the conditions before events happen, the effectiveness of an intervention or natural coping mechanism at present and forecasting the future trends helps in building resilience better (Sharifi, 2016). Therefore, CRA methodologies need to capture past events, evaluate the present situation and develop solutions to prevent or manage future occurrences.
3. *Addressing uncertainties:* Adopting an iterative process will give room for periodic monitoring of performance against baseline conditions and this helps to reduce uncertainties (P. Pringle, 2011). To capture future risks, CRA methodologies need to periodically re-assess the communities and re-evaluate resilience-building strategies.
4. *Assessing spatial relationships:* The ability of CRA methodologies to take into consideration lower and upper spatial scales of the communities being assessed is a key step in building resilience. Since communities are nested in open spatial systems, they can be affected by other levels within the system, inter-relationships and dependencies (Constas et al., 2014).

5. *Assessing Social dynamics*: Ideal CRA methodologies need to pay attention to the social capital and measure interactions and the degree of connectedness among individuals and across groups within the community, especially the strength of social networks (bonds, bridges and linkages), trust and reciprocity, shared norms and values, conflict resolution mechanism, place attachment & sense of community and pride, shared assets, empowerment & social safety-nets mechanisms, as well as crime prevention & reduction, as these form the bedrock for building resilience in the community (Cutter, 2016).
6. *Adopting participatory approaches:* People make communities resilient. Adopting a multi-stakeholder approach goes a long way in involving as many people as possible in building resilience. Improving social networks is a key factor for building resilience (K. Pasteur, 2011). Ideal CRA methodologies should be able to involve the people in their design of assessment approaches and community goal-setting, carry them along during the assessment exercises and the continuous resilience process, as well as transfer local leadership and responsibilities to the people.
7. *Developing resilience action plans:* Ideally, every CRA should end up with strategies or a road map for building a more resilient community (Pfefferbaum, Pfefferbaum, Van-Horn, et al., 2013). Community resilience assessments should often end up providing solutions beyond just identifying the resiliency status of the communities. These resilience solutions or action plans should be flexible to accommodate evolving situations, be inclusive and integrated with other existing plans, redundant and able to reflect from past events, through the present and to future circumstances, be resourceful in managing the situation and be robust to encompass every major facet of the community.

2.3.1 Evaluation against the 7 components of the critical success factors

2.3.1.1 The comprehensiveness of Community Resilience Assessment

Reviewing the dimensions of the captured CRA methodologies, the meta-analysis carried out and presented in Figure 2.15 shows that most of the CRA methodologies address at least the four major themes of resilience: Social, cultural, physical/environmental, economic and institutional and governance. However, 82.4% of the tools measure and build social and cultural resilience, 58.8% take care of the economic dimension, 52.9% include physical/environmental dimension in their analysis and only 47.1% include institutional and governance resilience in their assessments and resilience building. On the mode of development, most of the tools are developed using literature review, stakeholders' input, expert opinions, and field testing. The mode of development of the methodologies is mainly top-down, it is during implementation that some of them incorporate bottom-up approaches.

Table 2.4 Thematic dimensions, development methods and places of deployment of the methodologies

Tools	Thematic dimensions	Development methods	Place(s) of deployment
ARC-D	Education, Health, Economic, Environmental, Infrastructure, Political / Governance, Social / Cultural, and Disaster Risk Management System	Literature review, Expert Opinions and fieldwork	11 countries in Africa, Asia, Central America and the Caribbean
AWRVI	Social and Environmental/Physical	Literature Review	Alaska, USA
BCRD	Physical and psychological health, social and economic well-being, Effective risk communication information, Integration and Social connectedness	Literature review, stakeholder input and expert opinions	Upland Areas of Vietnam
BRACED	Disasters, Climate Change, Infrastructure and Basic Services	Lit. review and expert opinions	Several Cities in Myanmar
BRIC	Social, Housing/infrastructure, Community capital, Economic, Institutional, Environmental	Literature Review	Few communities in the US
CARRI	Social vulnerability; built environment and infrastructure, natural systems and exposure, hazard mitigation and planning.	Expert Opinions	Several communities in the US
CART	Connection and Caring; Resources; Transformative Potential; Disaster Management; Information and Communication¨	Field Testing and Expert Opinions	Few communities in the US

CCRAM	Ecological, social, economic, institutional, infrastructure and community competence	Literature Review, Key Informant and Expert Opinions	15 communities in Israel
CDR	Human, social, economic, institutional, physical, environmental	Literature Review	229 municipalities in Korea
CDRI	Social capital, economic capital, and physical capital	Lit. review and expert opinions	Several communities along the U.S. Gulf coast
CDRI2	Social, environmental, economic and institutional	Expert survey	Southeast Asian cities
CDRS	Community connectedness; Risk and vulnerability levels; Planning, response, and recovery procedures; emergency planning, response and recovery resources	Lit. review and expert opinions	Several Australian communities
CERD	Infrastructure, Economics, Ecosystem Services, Social Equity & Governance, and Health & Wellness.	Expert Opinions	Green Mountain College, USA
CERI	Economic, Labor market, social	Expert Opinions	Applied to 30 districts in The West Midlands, UK
CoBRA	Social/human, environmental and economic	Literature review, stakeholders' input and fieldwork	Kenya, Uganda, Ethiopia etc.
COPEWELL	Healthcare and Public Health, Natural Systems, and Social Capital and Cohesion	Literature review, Instrument development, stakeholder engagement, and Field-testing	Chester County, USA
CRAFT	Social, economic and government	Expert Opinion	Few Communities in the USA
CRC	Emergency services, self-reliance, mitigation, economic capital, risk awareness and access to information, social cohesion/connectedness, recovery potential, natural capital	Literature Review	Implemented in several Australian Communities
CRDSA	Social, economic, physical and environmental, governance, health and well-being, and information and communication	Lit. review and expert opinions	Implemented in Saudi Arabia
CRF	Infrastructure and environment, leadership and strategy, health and wellbeing, economy and society.	Literature review, stakeholders' input and fieldwork	100 cities across all the continents
CRI	Critical infrastructure and facilities, Transportation, Community plans and arrangements, Mitigation measures Business plans, and Social systems	Expert Opinions	Widely deployed in Gulf Coast and Southeast coastal communities in the US
CRI2	Economic Development and Social Capital	Literature Review	Counties in the state of Mississippi, USA
CRM	People, organization, resources, community process		Revelstoke, Canada
CRS	Economic, Environmental, and Social	Stakeholder input	9 counties in the USA

CRT	Food, water, energy, transportation, housing, jobs and economy, and Social Services and Civic Preparedness (governance)	Expert Opinions	San Francisco Bay Area, USA
CSAR	Agricultural biodiversity and social-ecological landscapes	Expert Opinions	Ethiopia and India
DFID	Governance, Risk Assessment, Knowledge and Education, Risk Management and Vulnerability Reduction, Disaster Preparedness and Response	Lit. review, expert opinions, fieldwork	Communities in Bangladesh, Pakistan, Afghanistan, Malawi, the Philippines and Nepal
DRI	Institutional, capacity building, infrastructure, Developmental planning, regulation and risk mitigation	Stakeholders' input	India, Jordan and the Philippines
DRR	UNISDR's "Ten Essentials of disaster risk reduction and management" blueprint	Literature review	UNISDR member countries
FCR	Knowledge and health, social cohesion and connectedness, infrastructure, economy and natural assets	Literature review and Stakeholders' input	190 countries where the International Red Cross societies operate
Grosvenor	Climate, Environment, Resource Capacity, Infrastructure, Community, governance, institutions, technical and learning, planning systems and funding structure	Developed by experts	50 cities globally
Hyogo	Disaster risk reduction, Assessing & monitoring risk, knowledge, innovation, and education	Stakeholder input, Expert opinions	Costa Rica, Mozambique, Indonesia and other UNISDR member countries
ICBRR	Governance, risk assessment; knowledge and education, risk management and vulnerability reduction, disaster preparedness and response	Literature review	Coastal communities in Indonesia
ICLEI	Information and strategy, Budget Allocation and Financing Processes, Community Engagement	Developed based on the experiences from ACCCRN cities	India, Indonesia, Bangladesh and the Philippines
LACCDR	Public health, education and disasters and social wellbeing	Lit. review and stakeholder input	Los Angeles County, USA
LDRI	Environmental and Natural Resource Management, Human Health and Well Being, Sustainable Livelihoods, Social Protection, Financial Instruments, Physical Protection and Structural and Technical Measures, and Planning Regimes	Expert opinions and stakeholder input	Not enough information reported
MAPP	Public Health and Infrastructure	Lit. review and expert opinions	Several communities in the USA
ND-GAIN	Food, water, health, ecosystem service, human habitat, and infrastructure, economic, governance and social.	Lit. review and expert opinions	181 Countries
NIST	Social, financial, natural, infrastructure, political, cultural, human capital	Expert opinions	Riverbend, USA
PEOPLE	Population and Demographics, Environmental/Ecosystem, Organized Governmental Services, Physical Infrastructure, Lifestyle and Community	Literature review	A site in Western New York, USA

	Competence, Economic Development, and Social-Cultural Capital		
RAPT	Social, environmental and economic	Literature review	Counties in 8 regions in the USA
RELi	Planning, design, maintenance and operations, Hazard preparedness, Hazard adaptation and mitigation, Community cohesion, social and economic vitality, productivity, health and diversity, energy, water and food, materials and artefacts, Applied Creativity, Innovation and Exploration.	Stakeholder input	Several pilots, including the District of Columbia, USA
ResilUS	Social, economic and physical capital	Expert Opinions	Kobe earthquake, southwest Louisiana, Western Washington and Northridge earthquake, LA, USA
RITA	Community health, water and sanitation, risk reduction, organizational strengthening, rights and advocacy, mitigation micro project and risk reduction.	Lit. review and expert opinions	10 Communities in Colombia
SPUR	Safety during earthquakes, and usability during the response and recovery periods	Literature review	San Francisco, USA
TCRI	Social, Built, Natural, and economic environments	Literature review	10 communities in the Greater Brisbane Area, USA
THRIVE	The built environment, social capital, services and institutions.	Lit. review and expert opinions	Hidalgo County, New Mexico; Del Paso Heights, Sacramento, CA; and New York City District Public Health Offices, USA
UCRA	Climate change, energy, food, forests, water, oceans and sustainable development	Literature review, stakeholders' input and field testing	More than 50 countries including Brazil, China, Europe, India, Indonesia, Mexico and the United States.
USAID	Conflict resolution, social protection, natural resource management, risk reduction and public goods management	Literature review	267 communities and projects supported by USAID and the U. S. government.
US-CRT	Climate Change, Hazards/Disasters, Infrastructure, Social and economic	Developed by experts	5 Regions in the USA
USIOTWSP	Governance, Social, Economy, Coastal Resource Management, Land use and Structural Design, Risk Knowledge, Warning and Evacuation, Emergency response, and Disaster Recovery	Stakeholder input	Sri Lanka, Indonesia and Thailand and communities around the Indian ocean.

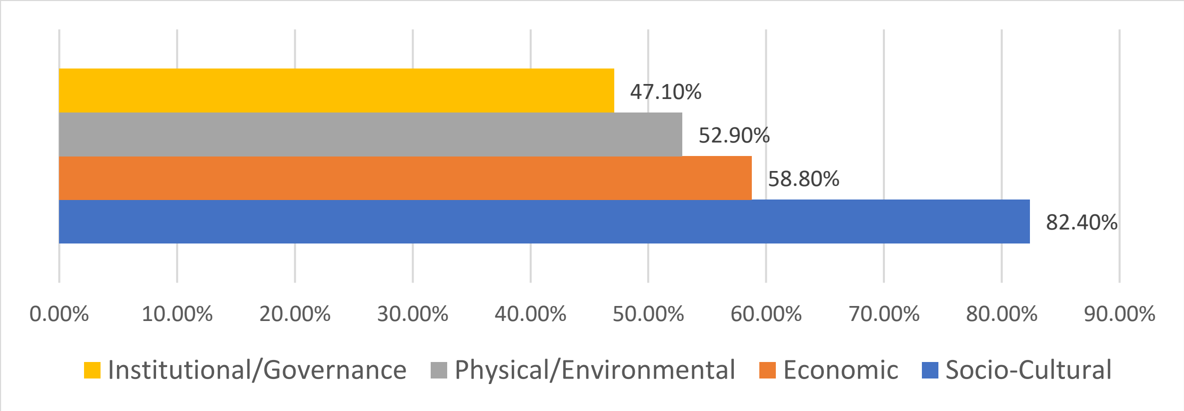

Figure 2.15 Percentage distribution of the major resilience dimensions used by CRA methodologies.

2.3.1.2 Measuring temporal dynamism

Assessing resilience within a temporal continuum where each step is connected to what is before it and what supersedes it, is important in building resilience (Norris et al., 2008). The difference between vulnerability assessment and resilience assessment is the ability to track changes within the temporal continuum (Schipper & Langston, 2015b). Analysis results presented in Figure 2.16 show that all CRA methodologies used for this analysis assess present risks, while 45.1% of the selected methodologies assess past events and only 23.5% model future scenarios and measure future risks.

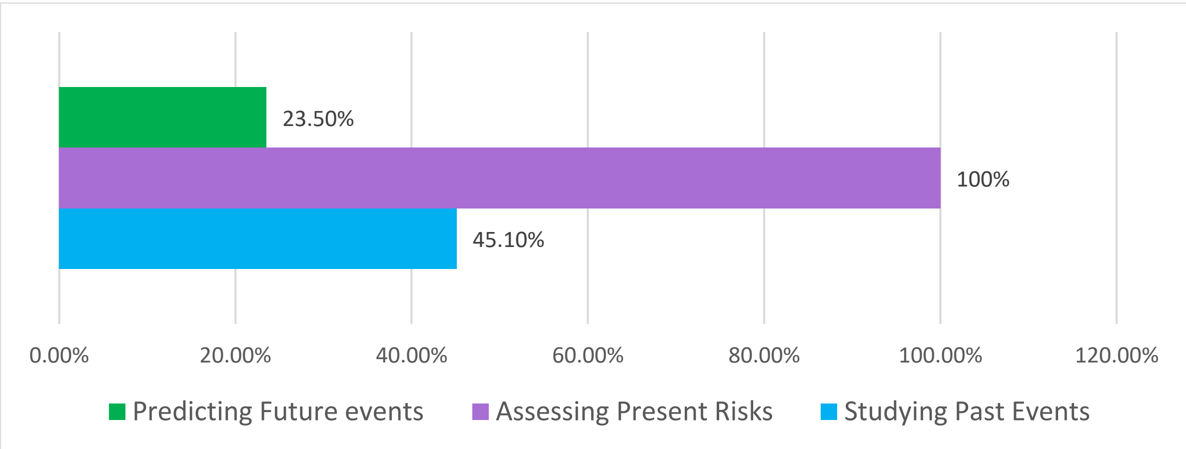

Figure 2.16 Percentage distribution of CRA methodologies that measure temporal dynamism

2.3.1.3 Addressing uncertainties

Continuous monitoring and assessment help to capture uncertainties (T. Frankenberger et al., 2013), therefore, adopting an iterative process will not just help to minimize risks, but also help the CRA tools to self-evaluate their performance and the overall decision-making process. In the absence of uncertainties, stimulating scenarios and assessing responses will help in preparing for future uncertainties and studying the alternate states of recovery. This will provide the community with information on their weaknesses and strengths. From the analysis presented in Figure 2.17 below, 37.3% of the CRA tools use iterative processes in their assessments and only 19.6% of the CRA tools measure alternate states and interlinkages of the complex community systems.

The speed of recovery, conducting surveys, as well as measuring changes in baseline conditions are the main methods these tools use for forecasting future trajectories and capturing uncertainties.

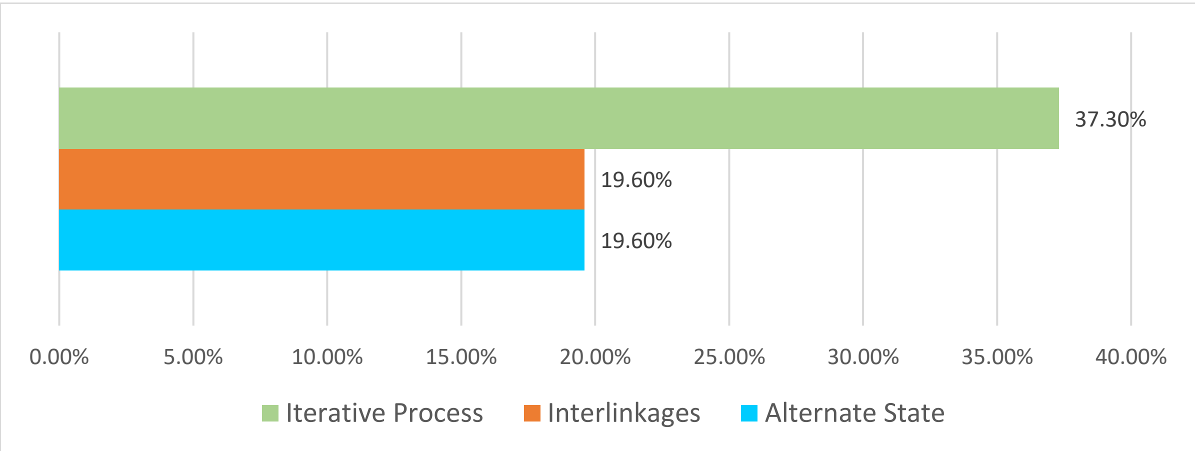

Figure 2.17 Percentage distribution of CRA methodologies that capture uncertainties

2.3.1.4 Assessing spatial relationships

Communities as the focus for assessments are nested within different hierarchies of scales. At the lower level, there are the blocks, households and individuals and at the higher scales, there is the city, region, country, etc. Cross scales are also not just horizontal, there are vertical hierarchies that CRA methodologies need to link within the community. These interlinkages will help communities to harness their collective resources towards achieving their set goals. As shown in Figure 2.18, all the CRA tools focus on their focal scale (the scale they are designed to operate on), but 19.6% of the methodologies focus on assessing both the focal and lower scales, while 13.7% assess both their focal and upper scales. 17.6% assess all three scales.

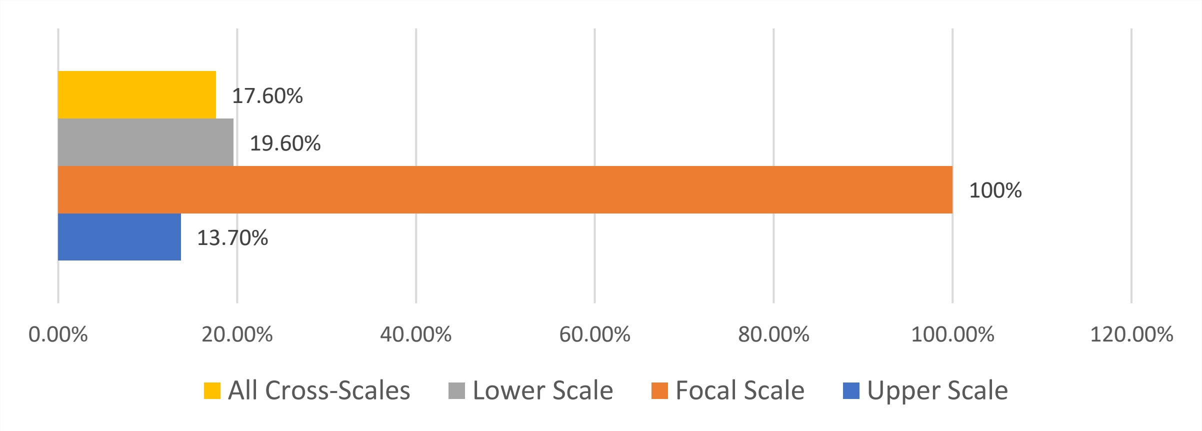

Figure 2.18 Percentage distribution of CRA methodologies that measure spatial cross-scales

2.3.1.5 Assessing Social dynamics

Studying the social capital base of the society and measuring interactions and the degree of connectedness among individuals and across groups within the community, trust and reciprocity among individuals, their shared norms and values, conflict resolution mechanism, place attachment & sense of community and pride, shared assets, empowerment & social safety-nets mechanisms, as well as crime prevention & reduction, form the bedrock for building resilience in the communities (Cutter, 2016). The analysis presented in Figure 2.19 shows the four key social capital indicators and the percentage distribution of the number of tools that measure them. From the analysis, social networks (bonds, bridges and linkages), as well as community social shared assets, are measured by 33.3% of the CRA methodologies. Only 7.8% measure community trust and reciprocity and only 3.9% consider shared norms and values in their community assessments and resilience-building exercises.

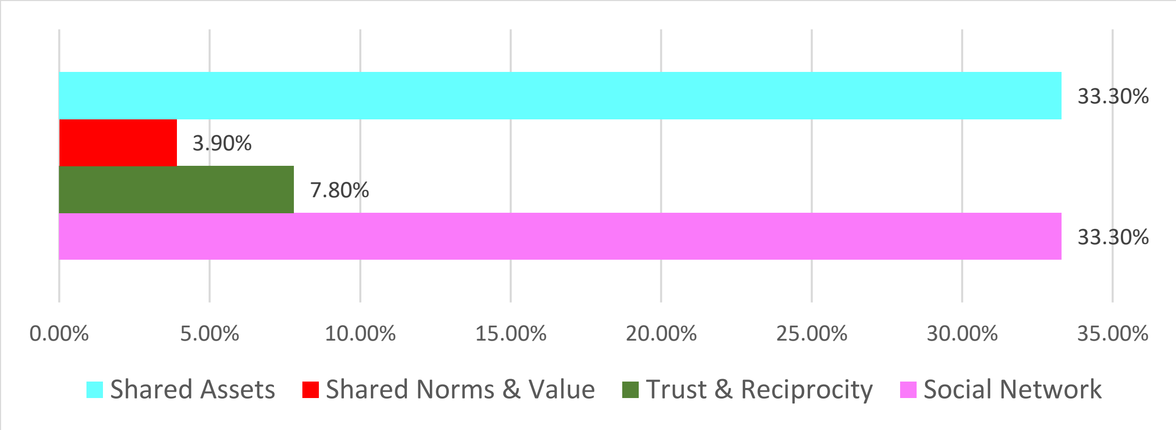

Figure 2.19 Percentage distribution of CRA methodologies that measure social dynamism

2.3.1.6 Adopting participatory approaches

Development of CRA methodologies including defining and deconstructing the community components, standardizing and weighting indicators, setting objectives, etc. are ideally, a collective community effort. As shown in Figure 2.20, only 27.5% of the tools got developed in partnership with the community stakeholders. The rest just use literature review and expert inputs. On the other hand, only 51.0% also involve the community stakeholders in the assessment and resilience-building exercise. The rest of the CRA methodologies are 100% top-down with zero community involvement. To design an iterative process that measures temporal and spatial dynamism as well as interlinkages, CRA methodologies need to incorporate bottom-up-top-down approaches from assessment development to implementation (Cutter, 2016).

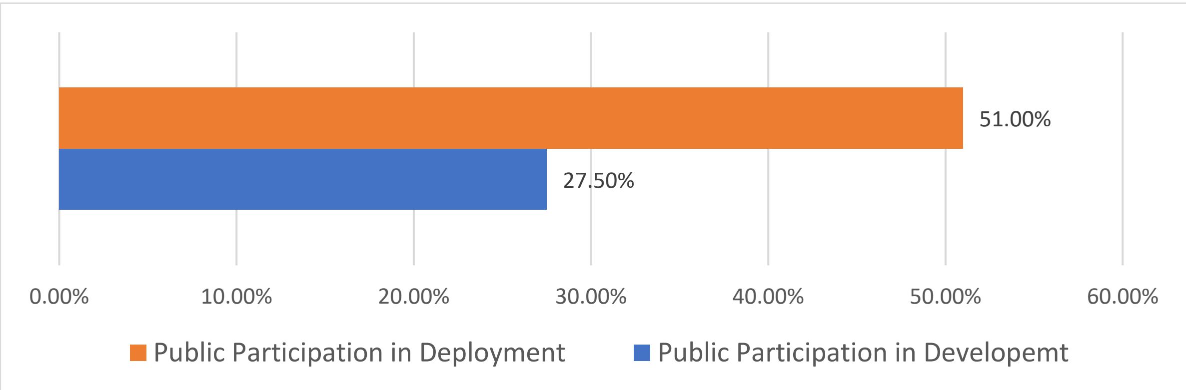

Figure 2.20 Percentage distribution of CRA methodologies that adopt participatory approaches

2.3.1.7 Developing resilience action plans

Good CRA methodologies should be able to find community resilience issues, prioritize the resilience challenges and identify leverage points for actions (Sharifi, 2016). Action planning helps the communities to channel their resources and efforts in the right direction towards building a sustainable and resilient future (Gawler & Tiwari, 2014). As shown in Figure 2.21, 52.9% of the CRA methodologies create action plans for the communities they are deployed in after assessments, while the remaining 47.1% only help communities to identify their challenges and know their resilience status.

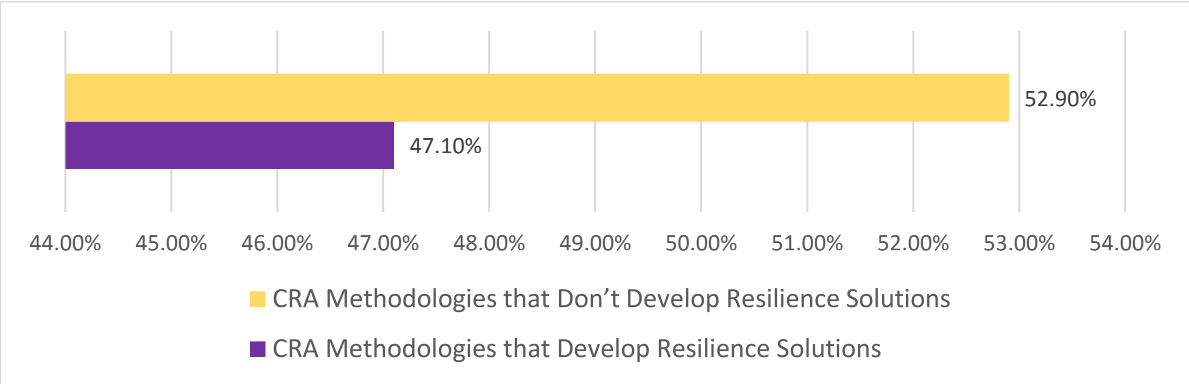

Figure 2.21 Percentage distribution of CRA methodologies that develop resilience actions plans

Table 2.5 shows the complete analysis of the compliance with the 7 components and the meta-analysis of the 51 identified CRA tools.

The next subsections show the conceptual and theoretical foundations that were used to drive the rest of this research and highlighted the gaps identified through the comprehensive literature review in regards to studentification and building resilience in university towns.

Table 2.5 Extent of compliance with the 7 components (critical success factors) for community resilience assessments

Tools	Temporal scale			Spatial scale			Social Capital				Alternate states	Inter-linkages	Iterative process	Participatory development	Participatory assessment	Action Plan
	Past	Present	Future	Upper	Focal	Lower	Network	Trust	Values	Assets						
ARC-D	✓	✓	✗	✗	✓	✗	✓	✗	✗	✓	✓	✗	✗	✗	✓	✓
AWRVI	✗	✓	✗	✗	✓	✗	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗
BCRD	✗	✓	✗	✗	✓	✗	✗	✗	✗	✓	✗	✗	✓	✗	✗	✗
BRACED	✓	✓	✗	✗	✓	✗	✓	✗	✗	✗	✗	✗	✗	✗	✓	✓
BRIC	✗	✓	✗	✗	✓	✗	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗
CARRI	✗	✓	✗	✗	✓	✓	✓	✓	✗	✗	✗	✗	✗	✗	✗	✗
CART	✗	✓	✗	✗	✓	✗	✗	✗	✗	✓	✗	✗	✓	✓	✓	✓
CCRAM	✓	✓	✗	✗	✓	✗	✓	✗	✗	✗	✗	✗	✗	✗	✓	✓
CDR	✗	✓	✗	✗	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗
CDRI	✗	✓	✗	✗	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗
CDRI2	✓	✓	✗	✗	✓	✗	✗	✗	✗	✗	✗	✗	✓	✗	✓	✓
CDRS	✗	✓	✗	✗	✓	✗	✗	✗	✗	✓	✗	✗	✓	✗	✓	✓
CERD	✗	✓	✗	✗	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗
CERI	✗	✓	✗	✗	✓	✗	✗	✗	✗	✗	✗	✗	✓	✗	✗	✗
CoBRA	✓	✓	✗	✗	✓	✗	✓	✓	✗	✗	✗	✗	✓	✓	✓	✓
COPEWELL	✓	✓	✓	✗	✓	✓	✗	✗	✓	✓	✗	✗	✗	✗	✓	✓
CRAFT	✗	✓	✗	✗	✓	✗	✗	✗	✗	✗	✓	✗	✗	✗	✗	✓
CRC	✗	✓	✗	✗	✓	✗	✗	✓	✗	✓	✗	✗	✓	✗	✗	✗
CRDSA	✗	✓	✗	✗	✓	✗	✗	✗	✗	✓	✗	✗	✗	✓	✗	✗
CRF	✗	✓	✗	✗	✓	✗	✗	✗	✗	✓	✗	✗	✗	✗	✓	✗
CRI	✗	✓	✓	✗	✓	✗	✗	✗	✗	✗	✓	✗	✓	✗	✓	✗
CRI2	✗	✓	✗	✗	✓	✗	✗	✗	✗	✓	✗	✓	✗	✗	✗	✗
CRM	✓	✓	✓	✗	✓	✗	✓	✗	✗	✗	✗	✓	✓	✗	✓	✓
CRS	✗	✓	✗	✗	✓	✗	✗	✗	✗	✗	✗	✗	✓	✓	✓	✓
CRT	✗	✓	✓	✓	✓	✗	✗	✗	✗	✓	✗	✗	✗	✓	✓	✓
CSAR	✗	✓	✗	✗	✓	✗	✓	✗	✗	✓	✗	✗	✗	✗	✓	✗
DFID	✓	✓	✗	✓	✓	✓	✗	✗	✗	✓	✗	✗	✓	✓	✓	✓
DRI	✓	✓	✗	✗	✓	✗	✗	✗	✗	✗	✗	✗	✓	✓	✓	✗
DRR	✗	✓	✓	✗	✓	✗	✗	✗	✗	✗	✓	✗	✗	✗	✓	✗
FCR	✗	✓	✗	✗	✓	✗	✓	✓	✗	✗	✗	✗	✗	✓	✗	✗
Grosvenor	✗	✓	✗	✗	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗
Hyogo	✓	✓	✓	✓	✓	✓	✗	✗	✗	✗	✗	✗	✓	✗	✗	✓
ICBRR	✗	✓	✗	✗	✓	✗	✓	✗	✓	✓	✗	✗	✗	✗	✗	✗

ICLEI	✓	✓	✓	✓	✓	✓	✗	✗	✗	✗	✓	✗	✗	✓	✓	✓
LACCDR	✗	✓	✗	✗	✓	✗	✓	✗	✗	✓	✗	✗	✗	✗	✓	✓
LDRI	✗	✓	✗	✗	✓	✗	✓	✗	✗	✗	✗	✗	✗	✓	✗	✗
MAPP	✗	✓	✗	✗	✓	✗	✓	✗	✗	✓	✗	✗	✗	✗	✓	✗
ND-GAIN	✓	✓	✗	✗	✓	✗	✗	✗	✗	✗	✓	✓	✗	✗	✓	✗
NIST	✓	✓	✗	✓	✓	✓	✗	✗	✗	✗	✗	✓	✓	✗	✗	✓
PEOPLES	✓	✓	✓	✓	✓	✓	✗	✗	✗	✗	✗	✓	✓	✓	✗	✓
RAPT	✓	✓	✗	✗	✓	✗	✗	✗	✗	✗	✓	✓	✗	✗	✗	✗
RELi	✓	✓	✗	✗	✓	✓	✗	✗	✗	✗	✓	✓	✗	✓	✗	✗
ResilUS	✓	✓	✓	✗	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗
RITA	✗	✓	✗	✗	✓	✗	✗	✗	✗	✗	✓	✓	✗	✗	✗	✓
SPUR	✓	✓	✓	✗	✓	✗	✗	✗	✗	✗	✓	✗	✗	✓	✗	✓
TCRI	✓	✓	✗	✗	✓	✗	✓	✗	✗	✗	✗	✗	✓	✗	✗	✗
THRIVE	✗	✓	✗	✗	✓	✗	✓	✗	✗	✓	✗	✗	✗	✗	✓	✓
UCRA	✓	✓	✗	✗	✓	✓	✗	✗	✗	✗	✗	✗	✗	✗	✓	✓
USAID	✓	✓	✓	✓	✓	✓	✓	✗	✗	✓	✗	✗	✓	✗	✓	✗
US-CRT	✓	✓	✗	✗	✓	✗	✗	✗	✗	✗	✗	✓	✗	✗	✓	✓
USIOTWSP	✓	✓	✓	✗	✓	✗	✗	✗	✗	✗	✗	✓	✓	✓	✓	✓

✓: Addressed

✗: Not addressed

2.4 Conceptual and Theoretical Frameworks

2.4.1 Introduction to the Concept and Theory of Resilience

Although resilience simply means "stability in the face of change", comprehending it through the "change" process necessitates a grasp of human processes and dynamics, as well as ways through which individuals impact their environment and vice versa (Walker et al., 2009; Walker et al., 2004). When we look at resilience in this light, additional questions arise. What impact does change have on people? And how do people have an impact on the social systems that surround them? We need to look at resilience holistically in a Complex Adaptive System (CAS) to comprehend the nature of the changes that individuals go through, or the dynamic interactions between individuals and their families, communities, and social structure (Anderies et al., 2002; Carpenter et al., 1999).

According to Walker et al. (2006), resilience is both a concept and a theory. This has been deconstructed, at least in practice, by resilience researchers in ecosystem management. For example, in 2006, a special issue concentrating on the application of resilience concept and theory to 15 real-life case studies was published, and the researchers used these case studies to inform us about resilience theory and practice. The following are key principles from the resilience concept and theory that have been summarized:

- In CAS, resilience theory is defined as a system's ability to continue to perform its tasks even after being impacted by a natural or man-made disaster. The resilience concept is embedded in developing this “ability”.
- Many misunderstandings in the interpretation of the theory are caused by issues of spatial scale. More precisely, the absence of a clear definition of the system to which the resilience idea is applied, which can range from a block, neighbourhood, community, urban, rural, city, region, state, nation, and so on, creates uncertainty.
- Vulnerability, adaptability, adaptive capacity, transformability, and robustness are all

words that are frequently employed in connection with the resilience concept. These concepts are connected and have to do with spatial scale too. Individuals or households (unit of decision-making) have traditionally been referred to as vulnerable (which is the opposite of resilience) and adapting. In this example, the system refers to a single decision-making unit and its surroundings.

- Vulnerability is frequently employed as an antithesis to resilience. The apparent contradiction in this use emphasizes the fact that "resilience" is extremely contextual. Ascriptions (and analogies) make sense only after the "resilience to what" has been defined. Let us examine the commonly held belief that people living in poverty are both more resilient and more susceptible than those in other socioeconomic categories. Poverty is linked to a considerably increased risk of some economic difficulties that are not experienced by people in other income categories. These other groups, who have not been as exposed to difficulty, may do poorly if they are subjected to the same adversity. As a result, poverty is linked to a higher level of resilience to the challenges they experience. However, if we consider resilience to adversity to one's surroundings, individuals in poverty are more susceptible; their environment exposes them to greater hazards and lacks many of the resources provided to those with better incomes.
- The term "sustainability" encompasses a larger idea than "resilience." Sustainability refers to the conservation of something or a function and is generally used to indicate that what is conserved is desirable. Risk aversion, restoration, and enhanced efficiency are examples of non-resilient approaches to achieve sustainability. If, on the other hand, one accepts the additional premise that large-scale disruptive occurrences cannot be averted, then long-term sustainability necessitates resilience at each point. As a result, the link between these two words is theoretical rather than semantic.
- The question of temporal scale is also crucial. Robustness, like resilience, refers to a

system's ability to function in the face of external shocks. Robustness concepts, on the other hand, are usually applied to a fixed system with a fixed set of external disturbances. This means that the system is investigated during a brief (short time scale) period under which the system's essential characteristics and external shocks remain constant. Resilience, on the other hand, places a premium on long-term learning and development (on a large time scale). This means on short periods, robustness and resilience are approximately similar notions, but resilience is a more general term that encompasses a wider range of periods.

- Adaptive capacity and transformability are two concepts that describe resilience. The ability of a system to effectively cope with shocks is referred to as adaptive capacity. Because the phrase refers to a system, it implies that it is concerned with shorter time scales (robustness). Transformability, on the other hand, refers to a system's ability to reorganize into a new system when its current form is no longer adequate. When we talk about a system's identity, we are talking about the collection of actors and interactions that make up its structure. Transformability refers to a system's ability to modify its identity. Transformability is a feature of resilience that is significant over longer periods since such changes occur implicitly over time.
- The resilience concept is based on two properties of systems. The first is the concept that systems do not tend to have a singular, fixed identity, but instead, can display several identities and switch between them quickly. The second concept is that systems go through change cycles. That is, system identities are not fixed; biological communities, for example, do not trend toward a fixed distribution of species but rather change cyclically. Adaptive cycles are what we call them. Finally, these adaptive cycles may be linked to build a Panarchy by connecting them across geographical and temporal dimensions and organizational levels.

- Returning a system to its pristine state after a change is almost impossible, so more scholars have tilted towards Social-Ecological Systems (SESs). Under the SESs sub-theory of resilience, resilience is seen either to have *multiple identities* (multiple stable attractors*)* that the system shifts to, or the system goes through an *adaptive cycle.* While single systems within the community may develop multiple stable attractors, the community as a whole goes through adaptive cycles due to human's adaptive capacity.

2.4.2 The Resilience Theory, Social-Ecological Systems and Complex Adaptive Systems

Deductions from the literature show that resilience as a theory operates at the meta-level. The resilience theory needs to be further broken down for it to be operational. Since communities are seen as multi-layered heterogeneous groups of people with common geographical identities and common interests, who engage in collective actions and are linked by dynamic webs of socio-cultural, economic and political interactions (Alshehri et al., 2014; T. Frankenberger et al., 2013; MacQueen et al., 2001; Miles, 2015), then effects of change such as studentification can only be effectively studied using grand theories such as SESs and CAS under the resilience meta-theory (Berkes et al., 2008).

Literature from SESs resilience studies on community resilience from 2000 to 2020 has two major:

- Institutions and governance systems within communities are inextricably linked to the setting in which they operate including physical/environmental, economic and socio-cultural systems (Berkes et al., 2008).
- Building resilience requires creativity and novelty, and encouraging innovation requires the integration of institutions and governance systems (Lebel et al., 2006)

To re-organize institutions and governance systems after a major "change" or any disruption, Lebel et al. (2006) stated that:

a. Public engagement fosters trust and mutual understanding, which are necessary for mobilization and self-organization.
b. Polycentric and multilayered institutions enhance the connection across knowledge, behaviour, and socio-ecological settings, allowing communities to self - adaptive at suitable levels.; and
c. Accountable authorities also promote "fair" allocations of benefits and unavoidable risks to improve disadvantaged groups' and society's adaptive ability.

The deductions made by Lebel et al. (2006) are based on Ostrom's Nobel Prize-winning work on SESs, from which she established principles for driving community resilience through institutions and governance. They are according to Ostrom (1990):

- Principle 1: Well-defined boundaries in communities make building resilience easier through self-governance.
- Principle 2: Existing or new institutional rules must “fit” the biophysical context to solve community challenges.
- Principle 3: Individuals affected by the change must participate in modifying the operational rules set to bring resilience to their communities.
- Principle 4: Monitoring and evaluations are key. This is best done with members of the community, who are affected by the change, being part of the team.
- Principle 5: A graduated sanctioning system builds community cohesiveness through trust and punishing serious instances and preserving proportionality between the severity of breaches and punishments.
- Principle 6: Conflict management systems in communities help them to recover better or stay stronger together in a time of crisis.

- Principle 7: Local institutions outside the official state institutions should be recognized because in times of change or crises they have better cohesion and self-organizing spirits.
- Principle 8: Communities are nested in different scales, both spatially and socially. Governance and institutions from all hierarchies should be involved using a holistic approach to build resilience.

According to Anderies et al. (2003, 2004), Janssen and Anderies (2007) and Janssen et al. (2007), Ostrom has extended these ideas beyond SESs to CAS, especially in urbanization studies, property rights, and robustness of resilience strategies. In CAS, Ostrom's principles were used to study the socio-cultural interactions in communities (Ernstson et al., 2010).

One of the principles of managing CAS (community) is novelty (Ernstson et al., 2010). Communities or towns self-organize in response to studentification challenges that disrupt normal function (Gunderson et al., 2008). This involves self-assessment, learning from past events (temporal dynamism), and designing innovative and participatory smart solutions; these, according to Gunderson et al. (2008) are the major characteristics of novelty that allow self-organizing behaviour in response to varying challenges of studentification.

Studentified communities undergo both adaptability and transformability as adaptive cycle systems. Adaptability simply means the capacity to influence resilience (Berkes et al., 2008) by preserving some key functions in the face of internal or external shocks or stresses. But transformation occurs when the whole community system or a part of it is total broken by the change, and such community system or its part can no longer self-organize, so it breaks down and then totally transforms into another one that cannot serve its former (original) functions, but new functions that may benefit a sub-class or none (Walker et al., 2009).

Scale is a major difference between adaptability and transformability as sub-concepts of CAS (Biggs et al., 2009; Folke et al., 2004; Kinzig et al., 2006; Scheffer & Carpenter, 2003; Scheffer et al., 2001). Transformability on a particular time scale, for example, is just an adaptive capacity on a wider period. This is why the notion of "Panarchy" has been included in the adaptive cycle to address the issue of scale (Holling & Gunderson, 2002). As shown in Figures 2.22 and 2.23, Panarchy is a set of adaptive cycles linked together across spatiotemporal scales.

Fast levels produce novelty (revolt), whereas slower levels stabilize the entire system and give records of previous novelty attempts (Holling & Gunderson, 2002). As a result, the Panarchy as a whole both produces and conserves information when the many levels are combined. In a nutshell, the Panarchy represents multi-solutions that address different problems in all spatial and social scales, big or small.

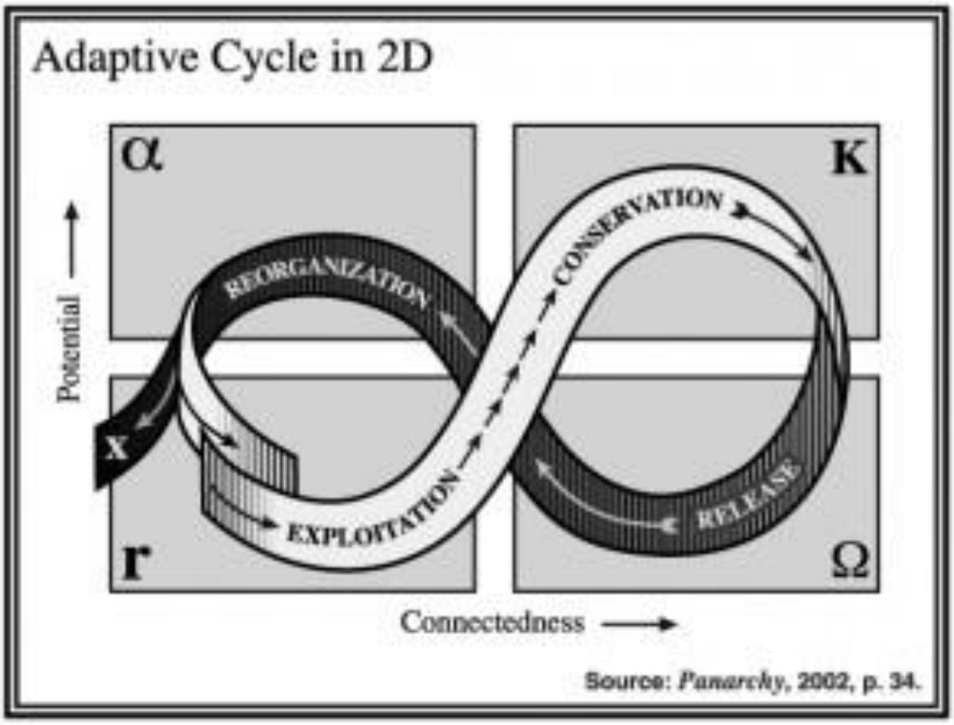

Figure 2.22 Adaptive cycle diagram with network descriptions. The arrow labelled "X" indicates the potential for systems to jump between adaptive cycles at different scales. Adapted from (Holling & Gunderson, 2002).

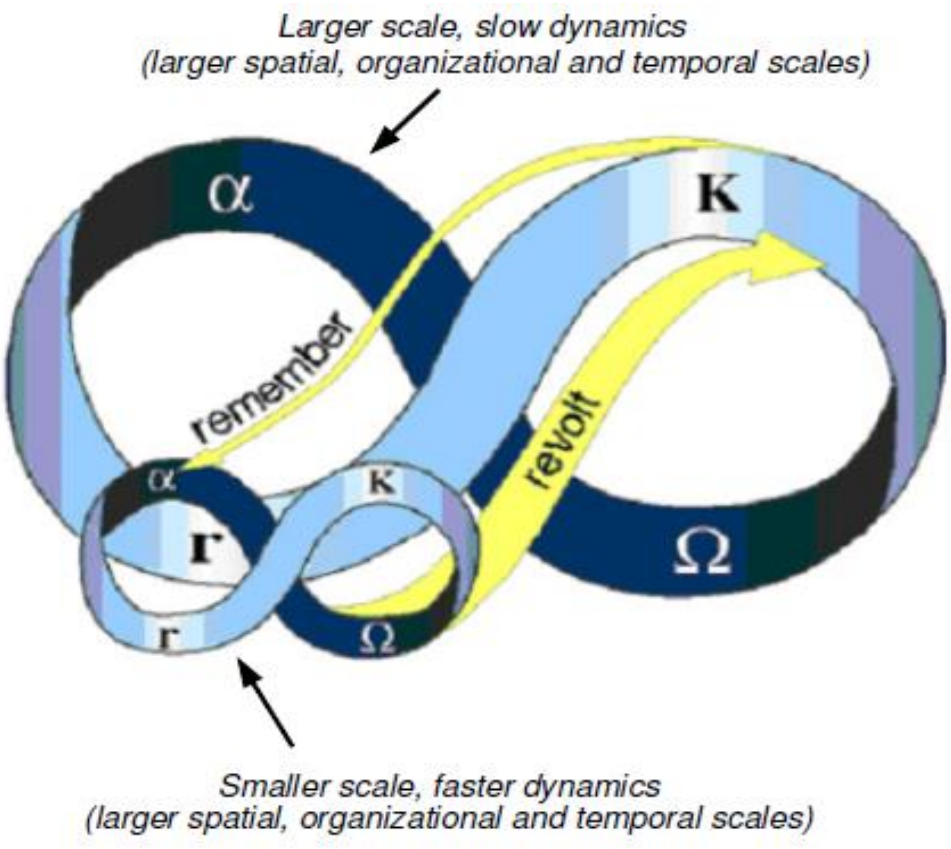

Figure 2.23 Panarchy illustrating adaptive cycles coupled across scales. Adapted from www.resalliance.org/index.php/panarchy.

2.4.3 Developing a Theoretical Framework for Community Resilience Assessment in University Towns

2.4.3.1 Meta and Grand Theories

Deconstructing the resilience theory and concepts in the sections above shows that resilience theory and the other theories under it (especially SESs and CAS) are best used as meta and grand theories, instead of mid-range theories. Meta-theories are theories that stem from others before them (Zhao, 1991), in this case, resilience came from ecology, psychology and engineering. To date, the resilience theories and concepts borrow ideas from these fields and theories under them (Delaware et al., 2013). A major advantage of such theories is their ability to explain the complex phenomenon that combines multiple study fields and methods (Wallis, 2010). Meta theories are "general philosophical thinking" best for meta-studies and meta-analysis (Zhao, 1991). SESs and CAS are sub-theories under the resilience theory. From the ecological dimension of resilience came the SESs theory to explain the human-environment relationship concept, and under the SESs theory came CAS to explain the concept of human behaviour to change within the environment (Wallis, 2008).

Grand theories are abstract theories that pay more attention to formal organization and arrangements of concepts rather than understanding the social realities (Skinner, 1990). In Summary, grand theories help to reduce the ambiguity of meta-theories into related concepts for further understanding and deeper analysis (Siegler, 1996; Spencer et al., 2006; Turner & Boyns, 2001). The difference between meta and grand theories lies in problem specification, the number of variables, and assumptions. Meta theories have a limited number of assumptions and variables and high problem specifications, while grand theories are all-encompassing with more variables and low precise specifications and falsifiability (Siegler, 1996; Turner & Boyns, 2001; Wallis, 2010; Wallis, 2008).

However, Weick (1974) posits that for effective problem solving, science needs to move to Mid-Range theories.

2.4.3.2 Mid-Range Theory

Mid-Range theories are methodological (Pinder & Moore, 2012). Mid-Range theories integrate Meta theories (abstract philosophies) and Grand theories (concepts) into empirical research (Morrow & Muchinsky, 1980; Spencer et al., 2006). Results from Mid-Range theories can be easily replicated and verified using qualitative and quantitative data (Bluedorn & Evered, 1980; Moore et al., 1980; Pinder & Moore, 2012).

Grounded Theory was used in this study as a Mid-Range theory to drive the methodology. Grounded Theory in simple terms is the identification of patterns in data and the generation of theories from such patterns (Walsh et al., 2015). Simply put, a Grounded theory is the creation of theories or getting findings from data (Glaser & Strauss, 1967). It is one of the most widely used qualitative methodologies in social sciences and related fields because it allows converting qualitative data to quantitative data and back to qualitative data (Charmaz, 2014). Grounded Theory users start the research with nothing in mind, the data leads them to the main research problem and its nature (Dey, 2004; Glaser et al., 2013; Payne, 2007; Pidgeon & Henwood, 2004). The theory allows you to develop theories that answer what, why, when, how and whom, and offer data-backed explanations to changes in the society and main concerns of the population of your substantive area and how the concerns were resolved, being processed or how they can be fixed (Oktay, 2012; Suddaby, 2006). This means Grounded Theory can be divided into two parts (Birks & Mills, 2015):

- The Grounded Theory (a research methodology), that will produce.
- A theory grounded-in-data ie. a *grounded theory*.

Both the research methodology and the output of the research process have the same name, which can be confusing (Dey, 2004).

Researchers systematically gather qualitative data from various sources and analyse them by using comparative analysis to construct new theories from the data (Shaw & McKay, 1942). Three major steps are often adopted to achieve this: data coding, memo writing, and theoretical sampling (Oktay, 2012). The coding process has three phases: open coding where researchers describe the data line by line to encourage theoretical sensitivity; axial coding, where similar data is clustered together; and selective coding where the researcher analyses the clusters to systematically identify relationships between the clusters and the core category (Walsh et al., 2015). The core category lies at the heart of the emerging theory and is central to its integration (Glaser et al., 2013). New theories are findings or discoveries (Payne, 2007).

In this research, Artificial Intelligence was used to automate the Grounded Theory methodology. Machines Learning and Natural Language Processing programmatic algorithms were used to download millions of textual big data (qualitative data), code and group the data into related clusters and the relationships among the clusters, to the core category were then determined. The discovered grounded theories were then validated using surveys and used with the concepts from the Grand theories (SESs and CAS) to develop a Micro Theory.

The Artificial Intelligence-Based Data Pre-Processing Framework for Community Resilience Assessments (Chapter 5) was developed based on the principles of Grounded Theory.

2.4.3.3 Micro-Level Theory

Mid-Range theories lead to Micro-Level Theories (Collins, 1988). Micro-Level Theories focus on a single construct and deconstruct it or provide specific solutions or guidelines (Knorr-Cetina, 1981). They are best for answering the question “How” (Dietz et al., 1990).

Action Theory was adopted for this study. Action Theory is a psychology and sociology that generally refer to people collectively coming together to solve the problems of their communities (Goldthorpe, 1998). It is a task-orientated view of human behaviour that describes how residents can carry out certain tasks to bring about resilience based on the identified Grounded Theories. Tasks may include community action, simple neighbourhood acts or regulations that coordinate self-organization or re-organization (Joas & Beckert, 2001; Wikström, 2015).

The Composite Resilience Index for Developing Resilience and Sustainability in University Towns (Action Plan) (Chapter 7) was developed based on the principles of Action Theory.

Figure 2.24 shows the theoretical framework used for this study and the relationships between the theories and research objectives. Grounded theory drives the proposed AI-Based Data Pre-

Processing Framework presented in Chapter 5 of this thesis.

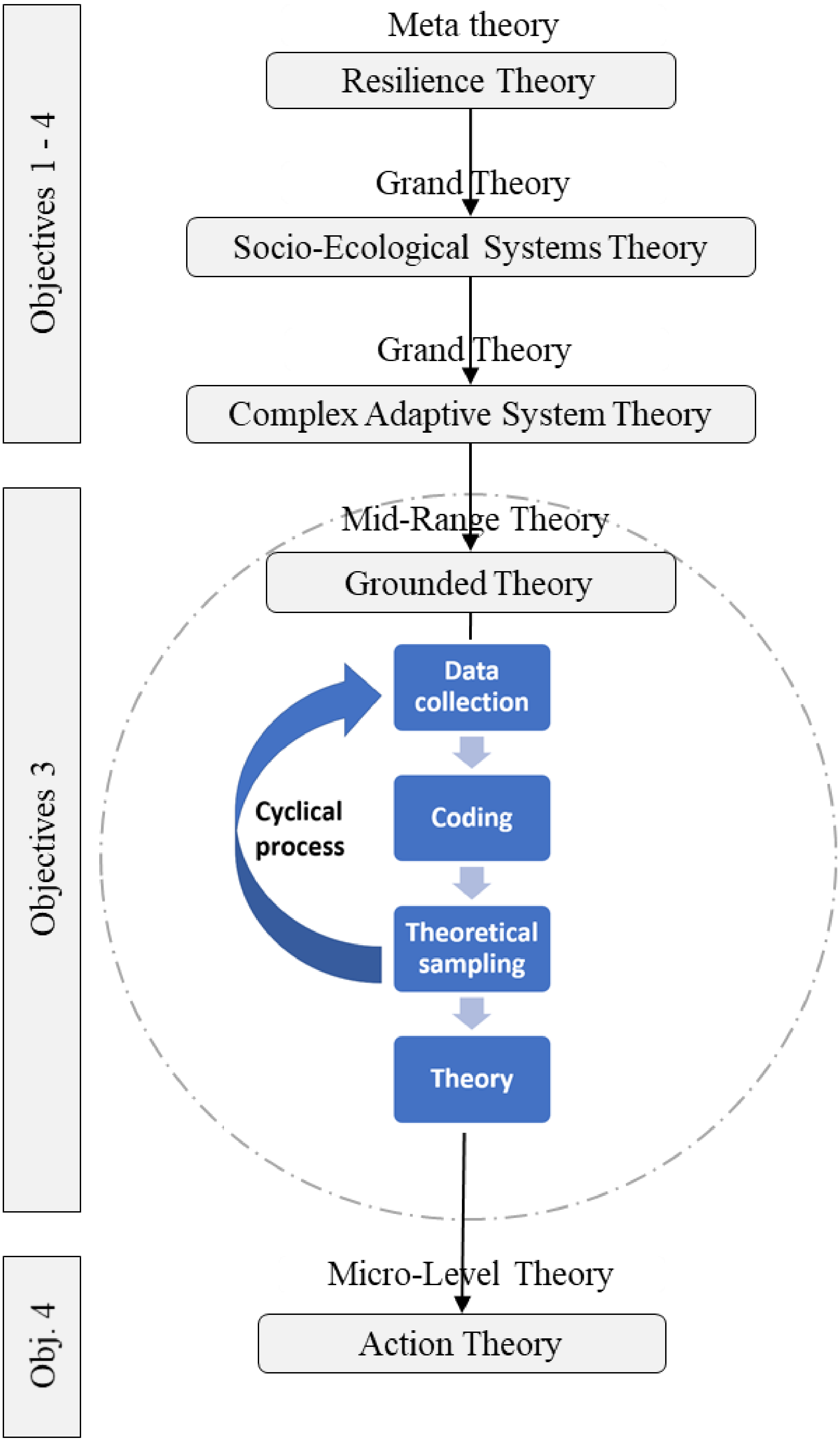

Figure 2.24 Theoretical Framework

2.5 Research Gaps

From the comprehensive literature review conducted, the following were major research gaps identified.

a. Gaps Related to Developing Countries and Case Studies

There are very few CRA methodologies developed by local experts, local authorities, and organizations to appropriately reflect local needs and conditions in developing countries (Sherifi, 2016). For example, there is currently no CRA methodology developed in Nigeria or specifically for Nigeria (one of the case studies). The only CRA methodology ever to be used in Nigeria is the City Resilience Framework (CRF) by The Rockefeller Foundation and ARUP International Development (2014) which is used to build the Resilient Lagos Initiative. It is city-wide and focal in scale (does not take into cognizance lower scales), therefore, it cannot be adapted for use in university towns in Lagos).

b. Gaps Related to Research Area

There are no known CRA methodologies online that assess and build the resilience of university towns despite the existence of several studies that justify the existence of studentification challenges in university towns globally. The only CRA methodology that has to do with HEIs is Campus Evaluation of Resilience Dimensions (CERD) which is a summative scorecard developed by Community Resilience Organizations (CROs), Second Nature and the Kresge Foundation (Blank, 2018). The tool helps college members in the USA to assess and understand their individual resilience levels.

c. Gaps Related to the Nature of Existing CRA Methodologies

1. Only a few CRA methodologies take into consideration cross-scale relationships (Alliance, 2010; Davis et al., 2013; Tim Frankenberger et al., 2013; Sharifi, 2016)
2. There are very few CRA methodologies that take into consideration temporal dynamism

(Schipper & Langston, 2015a; Sharifi, 2016)

3. Very few CRA methodologies also consider Spatio-Temporal Interlinkages in their assessment (Sharifi, 2016)
4. Very few methodologies also study the socio-cultural dynamism in the community apart from the environmental and economic (Cutter, 2016)
5. Very few methodologies adopt Iterative approaches to assess possible changes in shocks and stresses over time (Schipper & Langston, 2015b; Sempier et al., 2010; UNDP, 2014)
6. Very few methodologies also consider scenario making to model alternative states that the community may shift to during uncertainties (Gawler & Tiwari, 2014; Poland, 2009; Schwind, 2009; Sharifi, 2016).
7. Most of the CRA methodologies are based on top-down approaches, therefore lack adequate citizens participation in their development, in risks assessment and resilience building (Cutter, 2016; Sharifi, 2016)
8. Only a few CRA methodologies end up developing community resilience action plans (Fox-Lent et al., 2015; Sharifi, 2016)
9. There are no CRA methodologies that use User-Generated Content (big data) from Microblogs (social media) and Artificial Intelligence systems like Natural Language Processing and Machine Learning for risks assessments and developing resilience in university towns.
10. Finally, there are no CRA methodologies that are developed using theoretical frameworks that combine the four levels of theorization (Meta, Grand, Mid-Range and Micro-Level).

2.6 Chapter Summary

Chapter two shows the comprehensive literature review, the conceptual and theoretical framework that drives the research and states the identified research gaps from the empirical study of community resilience and the studentification landscape.

The next chapter shows the summaries of all the methodologies used to fulfill objectives 1-4, the types of data and the types of methods used to analyse the data in each chapter. It shows how the expert questionnaire survey was administered and the biodata of the respondents from the 24 countries the questionnaire snowballed to.

The next chapter sets the foundation for the rest of the research objectives and chapters.

CHAPTER 3: GENERAL RESEARCH METHODOLOGY[4]

This chapter builds on the comprehensive literature review in chapter 2. Methods and methodologies were identified from the literature and vetted. Those selected for analysing the hypothesis of this thesis were presented and explained in this chapter. The methods in this chapter were explained in detail in the subsequent chapters with data.

3.3 Introduction

The influence of methodology on the outcomes and contributions of any research study cannot be undermined. To ensure the attainment of the research objectives, it is crucial to choose the right research methodology (Fellows & Liu, 2015). Applying proper research methods allows a researcher to achieve meaningful results and contribute significantly to theory and practice (Walker, 1997). Abowitz and Toole (2010) stated that drawing on the knowledge and experience of past related research studies and the experience of industry professionals is imperative to enrich the outcomes of a research study. Hence, this study drew primarily on the knowledge, understanding, experience, and perceptions of earlier research studies and involve industry professionals in examining and validating some of the issues under study. The study also uses Resilience Theory, Socio-Ecological Systems Theory, Complex Adaptive System Theory and Grounded Theory to drive the methodological approach, findings and conclusions.

Given that the selection of research methods is influenced by the types of research objectives, questions, and settings (Fellows & Liu, 2015), there are no hard and fast rules for selecting research methods, neither is there anything called "best research methods" (Yin, 1994). Thus, the kind of data needed to achieve the research objectives should be given careful consideration

[4] This Chapter is partly published in:

1. **Abdul-Rahman, M.**, Chan, E. H. W., Wong, M. S., Irekponor, V. E., & Abdul-Rahman, M. O. (2020). A framework to simplify pre-processing location-based social media big data for sustainable urban planning and management. Cities, 102986. https://doi.org/10.1016/j.cities.2020.102986

Table 3.1 Research Methodology and Methods

Research Objectives	Research Methodology												
	Data Collection Methods			**Data Analysis Methods (Tools = SPSS, Python Programming Language and Microsoft Suite)**									
	Literature Review	**Quest. Survey**	**Text Mining**	**Topic Modelling using LDA**	**Sentiment Analysis VADAR**	**Content & Mata-Analysis**	**Cronbach's Alpha**	**Mean Score Rank**	**Chi-Square**	**Mann-Whitney U test**	**Wilcoxon's signed rank test**	**Principal Component Analysis**	**Analytical Hierarchy Process**
1													
2													
3													
4													

Objectives:

1. To review the existing literature to understand the nature of community resilience challenges in university towns, examine the characteristics of existing CRA methodologies, and identify the concepts and theories related to studentification and community resilience that can be used to frame a new CRA Framework for university towns.
2. To identify Critical Success Factors (CSFs) for Community Resilience Assessment (CRA).
3. To develop an Artificial Intelligence-based data pre-processing framework that identifies and assesses community resilience challenges in university towns using location-based User-Generated Content (UGC).
4. To develop a Composite Resilience Index (CRI) for university towns, using Akoka, a case study in Lagos – Nigeria.

in the selection of research methods (Akadiri, 2011). It should also be noted that the adoption of well-known and widely used methods not only help to ensure meaningful results that could be easily compared with the results of other studies that used similar methods, but it also hones the reproducibility of the research results (Alwaer & Clements-Croome, 2010).

3.4 Data Collection Methods

3.4.1 Comprehensive Literature Review

A comprehensive literature review provides a solid foundation for developing the knowledge base in a research area (Webster & Watson, 2002) and it is done by consolidating and analysing previous related studies (Chow, 2005). According to Koebel et al. (2015) standing on the shoulders of giants help in identifying concepts, theories and variables to include in a study, and it presents an array of the methods and tools to adapt or use.

This study commenced with a comprehensive literature review in Chapter 2. 602 referenced journals articles, reviews, conference papers and book chapters published from 2000 to 2020 within the Community Resilience and studentification domain was used for the analysis (See Figure 2.1 for the literature review framework). 51 existing CRA methodologies, 31 success factors, as well as concepts and theories and research gaps, were identified. This comprehensive literature review makes up research **objective 1** and part of **objective 2**.

3.4.2 International Questionnaire Survey

A questionnaire survey was deployed for data collection. As Darko, Chan, et al. (2017) posited questionnaire survey is a systematic method of primary data collection widely used to gather information from local and international experts in the built environment. An international survey was conducted in this study to:

1. Get the opinions of community resilience experts to determine the criticalities of the

identified success factors, measure the level of agreements between the opinions of experts in developed and developing countries in ranking the identified success factors, and finally, group the factors into components in objective 2 (Chapter 4).

2. Validate the research outcomes in objective 3 (Chapter 5 and 6)
3. Seek participants for the Analytical Hierarchy Process in Objective 4 (Chapter 7). 22 experts from Lagos, Nigeria, indicated interest to participate in the AHP.

In section A of the questionnaire, respondents were asked to provide their background information, including the country they are answering the questionnaire from and if the questionnaire was sent directly to them by the authors or it got forwarded to them by someone else, if it was forwarded, which country was it forwarded from. The respondents were instructed to answer for just the country specified by them (their location) and not give generic answers based on their multinational experiences. This information was used to ascertain the reliability of the responses and track the snowballing of the questionnaire. Snowballing was selected as a nonprobability sampling method because it helps in locating hidden populations (Johnson, 2014). Since the sample frame is unknown, the sample size was calculated using the following parameters: margin of error (+/- 5%), confidence level (95%), Z Score (1.96) & standard of deviation (0.5%) as proposed by Smith (2019). The formula is as follows:

$$\text{Sample Size} = (\text{Z-score})^2 \times \text{StdDev} \times (1-\text{StdDev}) / (\text{margin of error})^2$$

$$= ((1.96)^2 \times 0.5(0.5)) / (0.05)^2$$

$$= (3.8416 \times .25) / 0.0025$$

$$= 0.9604 / 0.0025$$

$$= 384.16 \text{ (approximately 385 questionnaires)}$$

A minimum of 385 questionnaires was expected to be sufficient for the global survey using the above formula. To get such a number of experts with a wide global spread, Emerson (2015) and Goodman (1961) recommended leveraging on the networks of experts by using the snowballing sampling technique.

Section B of the questionnaire was used to collect data on community resilience challenges in university towns due to studentification and to get an overview of the respondents' understanding of CRA (this section applies mainly to the respondents in the 6 case studies). The questions were scaled using a 5-point Likert scale (1 = strongly disagree, 2 = disagree, 3 = Neutral, 4 = agree, and 5 = strongly agree). Section C contained the CSFs on a 5-point Likert scale (1 = not important, 2 = less important, 3 = Neutral, 4 = important, and 5 = very important). A Likert scale was used because it gives the respondents brevity and conciseness (Abdul-Rahman et al., 2020; Adabre & Chan, 2019; Ji & Chan, 2019). The questionnaire is attached in Appendix A. For Section C, respondents were allowed to list and rate any CSFs not captured in the questionnaire.

The primary experts in this study were identified through their work on community resilience and Studentification in top journals and professional networking sites like LinkedIn and ResearchGate. The Survey took 7 months (from June 2020 to February 2021) and about 250 emails were sent to experts from the 6 case studies. The experts were asked to forward the questionnaire to others they feel are eligible to answer the questionnaire within their network including experts outside of their countries. A total of 392 valid questionnaires were retrieved from experts in 23 countries, comprising of 14 developed countries (The United Kingdom, The United States of America, Australia, Canada, Portugal, Germany, Poland, Spain, France, Hungary, Ireland, Japan, New Zealand, and the Netherlands,) and 9 developing countries (Nigeria, Hong Kong (China), South Africa, Indonesia, Chile, Israel, Ghana, Saudi Arabia, and Brazil). These classifications were made based on the United Nations World Economic Situation and Prospects Report (United Nations, 2019) which uses both the World Bank's Human Development Index (HDI) (World Bank, 2018) and the United Nation's Human

Development Data (HDD) (United Nations Development Programme, 2018) to classify countries into developed and developing (Paprotny, 2021). Although Hong Kong is a developed city, it is a special administrative region of China (Soyinka et al., 2021a), and China is a developing country according to the World Bank and United Nations classification, hence data from Hong Kong (China) was analyzed under "developing countries". The received total valid questionnaires were more than most surveys were done in the built environment (Adabre & Chan, 2019; Samuel et al., 2020).

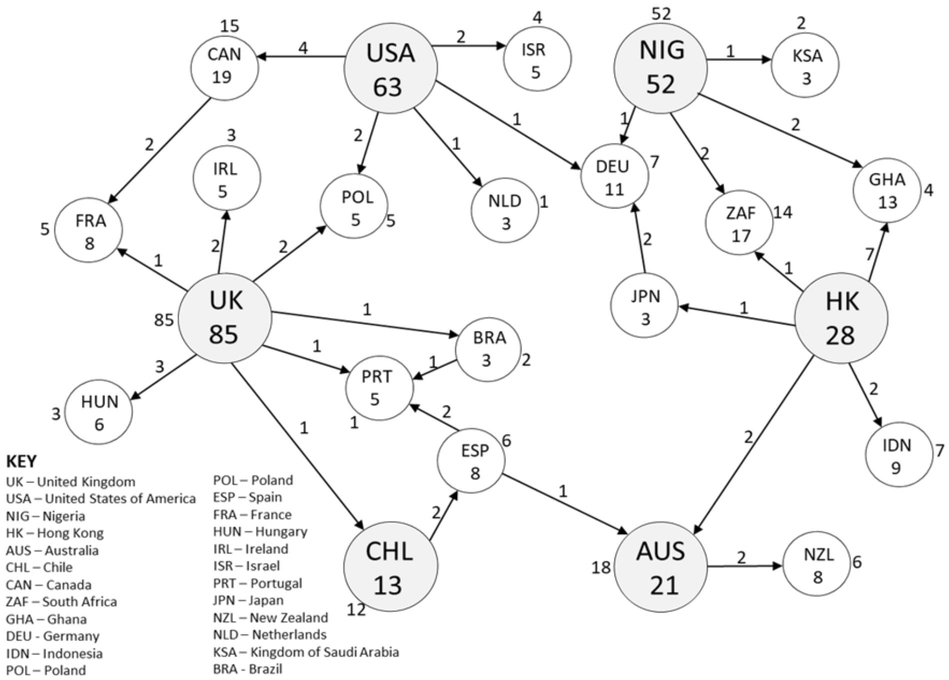

Figure 3.1 Network showing how the questionnaire survey snowballed from the 6 case study countries into countries 23

Table 3.2 summarizes the respondents' profiles. Data from the survey show that almost half of the respondents work in academia or research institutes (48.2%). The rest work in intergovernmental/international NGOs like the United Nations, the World Bank, Rockefeller Foundation, etc (24.8%), private sector/consulting (10.7%), and the public sector/civil service (9.2%). With regards to professions, most were researchers/academics (32.7%), followed by urban planners (28.6%), and resilience project managers and officers (13%). More than half of the respondents (67.6%) had more than ten years of experience in community resilience. Furthermore, all the respondents indicated that they had been involved in either the development or use of a CRA methodology or other aspects of community resilience.

Table 3.2 Respondents' profile

Countries	Responses	Data on survey respondents	Responses	Percentage
The United Kingdom	85	**Category**		
United States	63	Academia/research institute	189	48.2
Nigeria	52	Consulting/private sector	42	10.7
Hong Kong (China)	28	Public sector/government agency or department	36	9.2
Australia	21	Intergovernmental organization/international NGO	97	24.8
Canada	19	Others	28	7.1
South Africa	17	**Profession**		
Chile	13	Academic/researcher	128	32.7
Ghana	13	Urban planner	112	28.6
Germany	11	Resilience project manager/officer	51	13.0
Indonesia	9	Architect	29	7.4
Poland	9	Economist/development economist	12	3.0
Spain	8	Sociologist	22	5.6
France	8	Engineer (civil, construction, etc)	27	6.9
Hungary	6	Others	11	2.8
Ireland	5	**Years of experience**		
Israel	5	1-5 years	36	9.2
Portugal	5	6-10 years	91	23.2
Japan	3	11-15 years	102	26.0
New Zealand	3	16-20 years	55	14.0
The Netherlands	3	Above 20 years	108	27.6
Saudi Arabia	3	**Type of involvement in community resilience & Sustainability**		
Brazil	3	Development of as assessment methodology	191	48.7
Total	**392**	Use of an assessment method	138	35.2
		All of the above	51	13.0
		Others	12	3.1

3.4.3 Text Mining using Artificial Intelligence

This study incorporates the use of User-Generated Contents from microblogs (Twitter) to identify studentification-induced community resilience challenges in university towns. A Python-based open-source programmatic algorithm was specially developed for this study to query the Twitter search engine and download Tweet messages generated within the spatial boundaries of the case study areas for the last 10 years. These sentiment laden messages are public and do not have personal identifying metadata apart from the usernames which are also public. These qualitative data are coded, clustered, analysed and converted to qualitative data using Natural Language Processing (NLP) and Machine Learning (ML) tools following the principles of Grounded Theory (adopted Mid-Range Theory for this study). This location-based big data shows the community resilience challenges over the last ten years and their sentiment polarity across spatial scales (spatiotemporal dynamics). The international survey was used to validate the research outcomes. This textual big data was used for objectives 3 and 4 (Chapters 5, 6 and 7).

3.5 Data Analysis Methods

3.5.1 Topic Modelling using Latent Dirichlet Allocation

Latent Dirichlet Allocation (LDA) is a flexible and easily interpretable Bayesian theorem-based machine learning algorithm, first proposed by Pritchard et al. (2000) and later developed into a graphical model by Blei et al. (2003). The model splits the downloaded textual data into major topics using python-based machine learning algorithms (Charlin et al., 2015), and also shows the relationship between topics (McAuley et al., 2015). Blei et al. (2010), Chuang et al. (2012), Sievert and Shirley (2014) and Moody et al. (2016), have good and easy to understand papers on how to use this model in domains such as computer vision, genetic markers, survey data, big data from microblogs (social media).

LDA was used as part of the machine learning mining algorithms and it was also used for topic modelling in objective 3 (Chapter 5).

3.5.2 Sentiment Analysis Valence Aware Dictionary for sEntiment Reasoning

Sentiment Analysis is a sub-field of Natural Language Processing (NLP) that identifies and extracts opinions within a given text (Neethu & Rajasree, 2013). This step is used to gauge sentiments and evaluate attitudes and emotions of people or residents within the case study based on the computational treatment of subjectivity in their tweets (Alharbi et al., 2018a;

Asghar et al., 2019). Sentiment analysis can be done manually but it is extremely challenging when the data is big, unstructured, and filled with short forms, memes, and emoticons (Agarwal et al., 2011; Uma Maheswari & Dhenakaran, 2019). There are many sentiment analysis open-source tools, but due to the huge bias and the nature of social media data, this study used Valence Aware Dictionary for sEntiment Reasoning (VADER), a parsimonious rule-based model for sentiment analysis of social media text developed by Hutto and Gilbert (2014) to understand people's complaints or views about their university town. VADER is an open-source script that classifies lexical futures not just according to their semantic orientation (positive, negative, and neutral) but also tests their sentiment intensity (Hutto & Gilbert, 2014).

3.5.3 Conducting a comprehensive literature review using Content & Mata-Analysis

Content analysis is a research method for determining the existence of specific words, topics, or concepts in qualitative data (Stemler, 2015). Researchers can also measure and evaluate the existence, meanings, and correlations of the words, topics or concepts (Drisko & Maschi, 2016). While Meta-analysis is a quantitative method performed on more than one study addressing the same research questions to draw conclusions on the body of research based on shreds of evidence from the sampled studies (Field & Gillett, 2010). Meta-analysis is also used to assess, appraise, compare and critique empirical studies addressing similar research questions using (Borenstein et al., 2021).

Content and Meta-Analysis were used for the comprehensive literature review in objective 1 (Chapter 2) and objective 2 (Chapter 4).

3.5.4 Testing reliability of scales using Cronbach's Alpha

Cronbach's alpha is a common method of evaluating scale accuracy. To determine the questionnaire's reliability, it determines the average correlation or internal consistency among components in the survey questionnaire. Cronbach's alpha coefficient runs from 0 to 1, and it may be used to describe the consistency of variables derived from multipoint and/or binary structured scales (Santos, 1999). The greater the Cronbach's alpha coefficient, the more reliable the chosen measuring scale is, however, a figure smaller than 0.70 is seen as unreliable (Nunnally & Bernstein, 1978). The Cronbach's alpha coefficient value could be computed using SPSS (Li et al., 2005):

$$\alpha = \frac{k\,\overline{cov}/\overline{var}}{1 + (k-1)\overline{cov}/\overline{var}}$$

where α = Cronbach's alpha coefficient value; k = the number of scale items; var = the average variance of the scale items; and cov = the average covariance among the scale items. When the factors are standardized and have a common variance, the formula above can be simplified as:

$$\alpha = \frac{k\overline{r}}{1 + (k-1)\overline{r}}$$

where r = the average correlation among the scale items.

Cronbach's alpha coefficient test was used to evaluate the reliabilities of the five-point rating scales used to capture the international survey responses for objectives 2 and 3.

3.5.5 Ranking the importance of factors using Mean Scores

As a typical quantitative analysis technique for ranking the relative agreement and criticality, the mean score ranking technique has been widely used in research within the built environment (Huo et al., 2018; Nguyen et al., 2017; Shi et al., 2013; Zhao et al., 2018). In this research, the mean score ranking technique was used to determine the relative rankings of the CRA success factors in objective 2 (Chapter 4) in descending order of criticality, as perceived by the respondents (international experts). Mean score ranking was also used for objectives 3 and 4 (Chapters 5, 6 and 7). In the case of two or more factors having the same mean, Mao et al. (2015) recommended that the factor with the smallest Standard Deviation (SD) would be given the highest rank. A smaller SD suggests that the differences in responses are not statistically large and thus the average is more likely to be valid for the majority (Staplehurst & Ragsdell, 2010). The one-sample t-test was used to test the significance of the mean scores. The null hypothesis of the one-sample t-test is that "the mean score is not statistically significant", while the alternative hypothesis is that "the mean score is statistically significant". The one-sample t-test would be conducted at a 95% confidence level with a 0.05 p-value. Hence, the null hypothesis for a factor would be rejected if its p-value is lower than 0.05.

$$B_i = \frac{\sum_{j=1}^{n} \alpha_{ij}}{n}$$

where n = the total number of respondents; α_{ij} = the importance/criticality of the factor i rated by the respondent j; and B_i = the mean score of the importance/criticality of the factor i.

3.5.6 Testing the degree of association using Chi-Square

To test for the degree of association or if experts' rankings are in agreement with that of others within their group, Chi-square (X^2) was used in objective 2 (Chapter 4). Chi-square is a nonparametric analysis that gives accurate results for variable size > 20, with a degree of freedom (df) = N - 1 (approximate distribution) for the observed coefficient of concordance (Siegel, 1957). The scientific assumption for conducting this test is the null hypothesis (H0) = *no agreements among expert rankings within the total sample*. This is rejected if the value of X^2 has a low significance ($p \leq 0.001$). This means some degree of consensus exists amongst the scaled answers to the questions.

3.5.7 Test of inter-group agreements using Mann-Whitney U test

To test if the agreements of experts from developed countries differ from those in developing countries (object 2, Chapter 4) in ranking the individual success factors, the Mann-Whitney U test was used. This test is ideal for statistically identifying the differences in opinions amongst two or more independent groups answering the same questions on continuous variables, without prior assumption on data distribution (Chan et al., 2009). According to Lam et al. (2015), the sample sizes in the two independent groups do not matter in conducting the U test since it converts individual scores on each continuous measure to ranks within each group and then compares the ranks in the two groups to see if they are significantly different or not. The null hypothesis (H0) for this test says, "*there is no significant difference between the rankings in the two groups*". The H0 would be rejected if, at p-value ≥ 0.05, the U value is more than the critical value.

3.5.8 Variable comparison using Wilcoxon's Signed Rank test

Wilcoxon's signed-rank test is a non-parametric test that was performed to identify key variables, that is variables with the highest level of priority (Pallant, 2013). This test was chosen because it does not assume a normal distribution of data (Lam et al., 2009). Wilcoxon's signed-rank test is an appropriate test to compare matched variables (Wu et al., 2015) without assuming any specific nature of data distribution or requiring an equal variance of data (Field, 2013).

This test was used in objective 2 (Chapter 4).

3.5.9 Linear combinations of variables using Principal Component Analysis

Principal Components Analysis (PCA), a factor analysis technique used for data reduction and generation of linear combinations of variables was adopted to investigate the underlying relationship among the identified critical success factors for CRA in objective 2 (Chapter 4).

Without the need for causal models, the PCA method combines the many critical success factors into “components” (Xu et al., 2011).

To test for data adequacy and appropriateness, both the Kaiser-Mayer-Olkin (KMO) test and Bartlett’s Test of Sphericity were carried out. A zero KMO value means the data are unsuitable, while a value greater than 0.5 means the data are suitable for PCA and will give closely related components (Chan & Adabre, 2019).

3.5.10 Index formation using Analytical Hierarchy Process

Analytical Hierarchy Process (AHP) is a methodology used to fix complex problems involving multiple scenarios, criteria and actors (Satty, 1980). AHP is a human cognitive tool used to determine the relative importance of alternatives using paired comparison and assigning weights to indicators (Cardona & Carreño, 2011). AHP was used in objective 4 (Chapter 7) to prioritize the criteria and elements that best describe a resilient Akoka community from the user-generated contents (Twitter location-based historic big data) containing potential criteria and elements of a resilient community and elements of risk reduction.

3.6 Chapter Summary

Chapter 3 shows the research methodological framework and explains the data collection and data analysis methods used to achieve the four research objectives. The methods are further elaborated in each chapter. The next chapters 4 to 7 are organized in article formats, each providing answers to research questions and fulfilling an objective. For example, chapter 4 (objective 2) shows the development of the CSFs for CRA, Chapter 5 (objective 3) shows the development of an AI-Based Data Pre-Processing Framework, Chapter 6 shows the deployment of the AI-Based Data Pre-Processing Framework in 6 case studies, while Chapter 7 (objective 4) shows the development of a Composite Resilience Index for one of the case studies (Akoka, Lagos – Nigeria).

CHAPTER 4: COMPARATIVE STUDY OF THE CRITICAL SUCCESS FACTORS FOR COMMUNITY RESILIENCE ASSESSMENT IN DEVELOPED AND DEVELOPING COUNTRIES[5]

The criticalities of the success factors for CRA identified from the literature in chapter 2 were analyzed in this chapter using data from the internal survey.

4.1 The concept of Resilience and the need for CSFs for CRA

The concept of resilience which is defined as the ability to prepare and plan for, absorb, recover from, and more successfully adapt to adverse events (National Research Council, 2012; Sorensen et al., 2018), has gained momentum in the last few decades due to the increasing challenges human settlements (communities) face from natural disasters and those induced by man (Meerow et al., 2016; Ribeiro & Pena Jardim Gonçalves, 2019). Resilience is an old concept with its roots in socio-ecological systems, psychology, and engineering (Syal, 2021; Wu et al., 2020). Both the theory and concept became a key part of the United Nations agenda at the beginning of the 21st century when the second United Nations World Conference on Disaster Reduction (UNISDR, 2014) recommended that the resilience of communities should be part of member states agenda to reduce risks and vulnerability. As the transformative potential and interconnected challenges of urbanization in the 21st century became more apparent (Elmqvist et al., 2019; Pieterse, 2013), the United Nations Office for Disaster Risk Reduction (UNDRR) and the United Nations Human Settlements Programme (UN-Habitat) channelled more resources in 2015 to integrate sustainable urban development and urban risk reduction with resilience thinking (McGill, 2020), which led to the creation of the Sustainable

[5] This chapter is currently under review as journal article in a Q1 journal:

1. **Abdul-Rahman M**., Soyinka, O., Adenle, Y. A. Comparative Study of the Critical Success Factors (CSFs) for Community Resilience Assessment (CRA) in Developed and Developing Countries. International Journal of Disaster Risk Reduction. Manuscript ID: IJDRR-D-21-01087.

Development Goal (SDGs) 11 (2016-2030) (Lee et al., 2016). This goal aims to make global cities integrated, safe, resilient, and sustainable (UN-Habitat, 2016a). Following this, a wide array of United Nations agencies have tailored their missions accordingly, using a multi-sectoral and multi-hazard understanding of the concept of resilience to promote resilience and sustainable development worldwide (Malalgoda et al., 2013). This global mandate has been passed since then to the 193 United Nations member nations who are signatories to the SDGs. At the national levels, it is being also localized globally by all habitat agenda partners (including local authorities, non-governmental organizations, and researchers in academia) (Oosterhof, 2018; Patole, 2018; Sietchiping & Omwamba, 2020).

According to UN-Habitat (2016a), for communities to become sustainable, they must first become resilient against the acute shocks and chronic stresses affecting them. Influenced by this philosophy and the United Nations accompanying global call to develop a sustainable world, resilience research and the concept of community resilience assessment (CRA) have become popular in both global policy and scientific research and discourse (Clark-Ginsberg et al., 2020; Marana et al., 2019; Sharifi, 2016). This has led to the creation of more than 100 CRA methodologies in the last two decades, each with its purpose, aim, and objectives (Haase et al., 2018; Sharifi, 2016).

CRAs are defined as indexes, scorecards, tools, and frameworks that analyze the risks in complex geographies and socio-ecological entities occupied by a multi-layered heterogeneous group of people with common interests (human communities) (Alshehri et al., 2015; Sharifi, 2016; Sharifi & Yamagata, 2014). According to Sherrieb et al. (2010), some CRAs are designed for assessing resilience against a single risk, while some are designed for multiple risk assessments, the same way some are developed for a particular place while others can be adapted regionally or globally.

Apart from the need to build a resilient world (Seeliger & Turok, 2013), the rise in CRA methodologies in the last two decades is also attributed to the increase in funding for resilience initiatives (Sharifi, 2016), the reliance of donors on such assessments for allocating resources (Cutter, 2016; Tyler & Moench, 2012), and the need for progress measurement on risk reduction as well as for benchmarking performance against global best practices (Schipper & Langston, 2015b). As Burton (2015) posited, assessing and measuring resilience is recognized as the first step towards reducing risks and being better prepared to withstand and adapt to natural or man-induced shocks and stresses in our communities.

The concept of CRA is still evolving (Davoudi et al., 2012; Kirmayer et al., 2009). Most of the indexes, scorecards, tools, and frameworks were developed to analyze climate change-related risks, with the exception of a few that measure other socio-economic challenges across the world (O. Cohen et al., 2016; Cutter, 2016). The majority of the CRA methodologies are developed through research (Abdul-Rahman et al., 2021) but very few studies have been carried out to understand the "critical success factors" of carrying out CRA (Jordan & Javernick-Will, 2012; Zautra et al., 2008).

The concept of "success factors" was first coined by D. Ronald Daniel of the McKinsey and Company in 1961 was later refined as critical success factors (CSFs) by Rockart (1979), who defined CSFs as "key areas of an activity where favourable results are necessary for a manager to reach his or her goals". Adabre and Chan (2019) and Yu et al. (2018) posit that CSFs can also be seen as variables that need to be considered while carrying out a project to attain high performance and reach the necessary goals.

Previous researchers have investigated CSFs for PPP projects (Amović et al., 2020; Deng et al., 2021; Li et al., 2019), sustainable construction management and green buildings (Gunduz & Almuajebh, 2020; Vrchota et al., 2021), infrastructure sustainability (Xue et al., 2018), sustainable transport management (Yang et al., 2021), sustainable e-learning (Ahmad et al., 2018), designing business start-up (Kim et al., 2018), as well as affordable housing (Adabre & Chan, 2019). However, limited empirical studies exist on the CSFs for CRA (Jordan & Javernick-Will, 2012). This is mainly because the concept of CRA is new and the resilience area of research is very wide (Meerow et al., 2016). For example, most studies focus on the CSFs of "individuals" instead of "communities" (Christiansen et al., 1997; McMillan & Reed, 1994; Morales & Trotman, 2004; Tait, 2008). Few studies also focus on business resilience and knowledge management for disaster resilience (Ayala & Manzano, 2014; Seneviratne et al., 2010). The only studies that looked at the CSFs of resilience at the community level were that of Chou and Wu (2014) and Bahmani and Zhang (2021) which investigated the CSFs for post-disaster recovery.

Given the above background and limitations in scholarship on the CSFs for CRA, this chapter aimed to complement the global efforts to build more resilient communities and answer key research questions that would help community resilience experts to carry out better CRA with high success rates both in developed and developing countries. This is done by answering the following questions:

1. What are the considerations and factors that guarantee a successful assessment of risks and challenges in our communities? And,
2. Are these factors the same in both developed and developing countries?

Globally, the results are expected to help community resilience experts and developers of CRA methodologies (both in developed and developing countries) to embed CSFs and guide CRA managers and policymakers to improve performance and achieve success in CRA (Zargun & Al-Ashaab, 2014). It will also help policymakers to be more informed and giving them suggestive policy options regarding CRA and in developing resilience (Adabre & Chan, 2019).

The study also adds to the CRA body of knowledge and the concept and theory of resilience in general. In developing countries where resources are more limited for assessing and developing resilience (Hosseini et al., 2016), findings from this study will help practitioners and government agencies to focus more on indicators that will help them to achieve success in their CRA projects and reduce redundancies (Chou & Wu, 2014; Sina et al., 2019).

Following a systematic approach, a comprehensive literature review was conducted in chapter 2 (objective 1) to theoretically analyze the research problem and justify the motivation for this chapter and identify potential CSFs from community resilience literature (see Figure 4.1 and Table 4.1). Secondly, a pilot survey was carried out with senior resilience researchers and practitioners to vet the identified factors from the literature and correct the technical language and construct of the questionnaire. A global survey was then carried out to get the opinions of resilience experts on the criticalities of each of the nominated factors. Mean ranking and t-tests were used to rank the factors and eliminate those not found to be critical enough. After which, principal components analysis was used to investigate the underlying relationship among the identified CSFs and clusters them into components. The rationale for the adopted methodology (methods, the questionnaire design and sampling technique) forms section two. The results are presented and discussed in section 4.3, while section 4.4 contains the summary of the chapter, research implications, limitations, future studies, and recommendations.

4.1.1 Theoretical and conceptual background and the need for CSFs for CRA

Based on the iron triangle theory, any project (including CRA) is deemed successful if it is delivered within the agreed timeframe and budget and at the desired quality (Ashley et al., 1987; Pinto & Slevin, 1987). However, Xu et al. (2011) and Adabre and Chan (2019) argued that the determinants of success are distinctive to the different types of projects and are beyond the iron triangle criteria due to unforeseen risks and project typology. Yan et al. (2019) explained this school of thought using the River Themes flood resilience project. The project delivery exceeded the agreed timeframe and budget due to unforeseen factors like prolonged stakeholder consultations, delay in approval times, etc, but the project was still successful. Over the years, researchers have continued to study project-specific CSFs for each project type (Adabre & Chan, 2019). For instance, Chan et al. (2004) identified 41 CSFs for partnering in construction projects using literature review, questionnaire surveys, and face-to-face interviews with experts. Using a similar methodology, Chan and Lee (2008) also identified 6 critical factors for improving the social sustainability of urban renewal projects. For sustainable energy performance contracting in hotel buildings in China, Xu et al. (2011) also identified 21 CSFs using literature review, survey, and expert interviews. Most recently, Adabre and Chan (2019) identified 13 CSFs for sustainable affordable housing using a literature review and questionnaire survey administered to housing experts worldwide.

Although studies on the CSFs in the community resilience domain are limited, success factors for CRA have been indirectly highlighted in a couple of studies on CRA (Rus et al., 2018). For instance, Leila Irajifar et al. (2013), while presenting their paper on "disaster resiliency measurement frameworks" at the 2013 World Building Congress, Brisbane, Australia, highlighted that CRA methodologies need to take care of all aspects of the community including sociocultural, economic, and environmental (since a community challenge in one may affect the other), as well as show redundancy in accommodating all disruptions within the community for the assessment process to be comprehensive.

Paul Monaghan et al. (2014), while explaining the features of six online toolkits for assessing community resilience expatiated that most of the available methodologies were not designed to measure community resilience within the three major spatial scales (focal, upper or lower scale), which is critical to achieving success in CRA. Pfefferbaum et al. (2015) also identified community participation in developing and deploying CRA tools as one of the key factors for a successful resilience assessment exercise. Furthermore, they also explained that leadership and decentralized responsibilities among the various community groups also help in developing an inclusive and participatory action plan for resilience. In another study, Larkin et al. (2015) while studying the characteristics and functionalities of seven CRA frameworks used in the United States highlighted that to adequately address uncertainties, CRA processes need to be iterative and assess interlinkages among the many facets of the society.

Apart from the above studies, few systematic literature review papers were also published on CRA methodologies. For example, Ostadtaghizadeh et al. (2015) reviewed selected resilience assessment models and tools and concluded that most of them lacked the ability to simulate the alternate states to which complex adaptive systems shift during and after a shock in the community. They argued that this factor is critical for successfully assessing future risks in a community. In another comprehensive review, Cutter (2016), while studying the landscapes of disaster resilience indicators, also highlighted the need to co-create resilience assessment methodologies and assess social dynamism in the community as key success factors. She further explained that social networks, trust, norms and values, and shared assets are very important in assessing the social dimension of community resilience. Sharifi (2016), while carrying out a critical review of 36 selected CRA tools and building on earlier reviews explained that the CRA process is not successful or complete if the process does not lead to resilience action plans and the development of solutions.

Although most of the above polemics point to what success in CRA entails, the criticality of such factors was not well conceptualized and accepted by a wide range of experts (Wang et al., 2018). Most of the studies were also country-specific (Koliou et al., 2017). Therefore, this justifies the need to develop CSFs for CRA on a global level, sampling the opinions of both experts from developed and developing countries (Chou & Wu, 2014). Such CSFs for CRA can be easily adapted and used in any developed or developing country.

4.2 Materials and Methods

The framework in Figure 4.1 shows the research stages, processes, and methodology employed in this chapter.

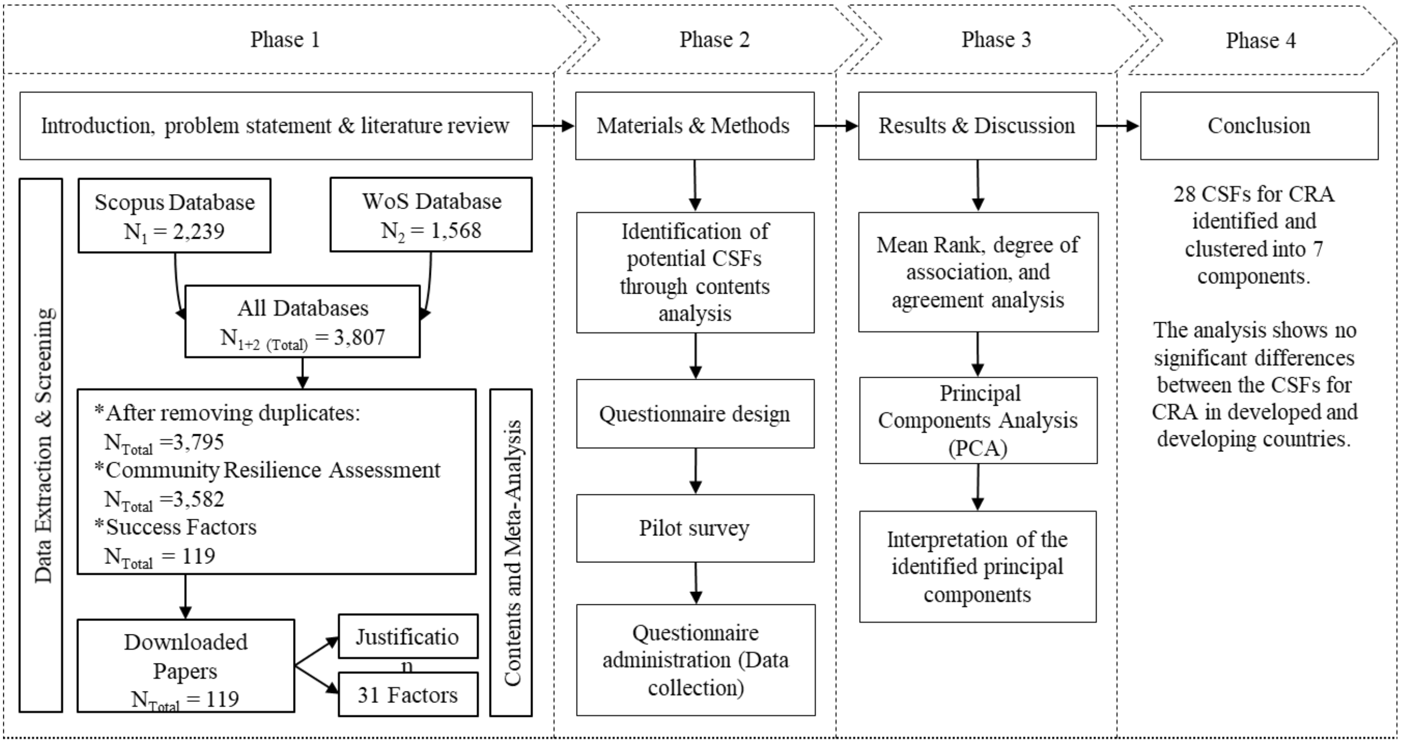

Figure 4.1 Research Framework for chapter 4

4.2.1 Identifying the potential CSFs for CRA

To identify the potential CSFs for CRA, a comprehensive literature review was conducted (see Chapter 2). From the 3,795 discovered after extraction, screening and removing duplicates, only 119 papers were downloaded for extracting success factors for CRA. 31 success factors were identified from the corpus, as well as justifications for the study. Figure 4.1 shows the framework for the data extraction and screening and the overall research for this chapter. The search algorithms are contained in Chapter 2 of this thesis.

A pilot survey was carried out before the main questionnaire design. The purpose of the pilot survey was to test the survey procedures, verify the comprehensiveness of the critical factors and the use of technical language (Soyinka et al., 2021b). The pilot survey was administered to five participants: two professors, one chief resilience officer, one post-doctoral researcher, and a PhD student. These participants are all well knowledgeable in the field of CRA. This process saw some factors merged, others eliminated, and some added. The completeness was confirmed and presented in Table 4.1.

Table 4.1 Potential CSFs for community resilience assessment

Code	Success factors	References
F1	Assessment of interlinkages	(Collier et al., 2013; Larkin et al., 2015; Schipper & Langston, 2015b)
F2	Assessment of cultural and social risk within the community	(Abdul-Rahman et al., 2020; Cimellaro et al., 2016; Cutter, 2016; L. Irajifar et al., 2013)
F3	Assessment of place attachment & sense of community and pride	(Cutter, 2016; S. L. Cutter et al., 2008; Katherine Pasteur, 2011; Renschler et al., 2010a)
F4	Simulation of alternate states	(Folke et al., 2010; E. McLeod et al., 2015; Ostadtaghizadeh et al., 2015; P Pringle, 2011)
F5	Inclusive & participatory CRA process	(Gibson, 2006; Pfefferbaum et al., 2015; Tyler et al., 2016)
F6	Evaluation of community social network	(Cutter, 2016; Renschler et al., 2010b)
F7	Co-creation & co-adoption of the CRA methodology	(Krishnan, 2019; Norris et al., 2008; Pfefferbaum, Pfefferbaum, Van-Horn, et al., 2013)
F8	Inclusive & participatory action planning process	(Hsiao, 2021; McEwen et al., 2018; Pfefferbaum et al., 2015; Spaans & Waterhout, 2017a)
F9	Repeated key assessment processes (iterative process)	(Larkin et al., 2015; Schipper & Langston, 2015b)
F10	Decentralized responsibilities & leadership during the CRA process	(Katherine Pasteur, 2011; Renschler et al., 2010b)
F11	Evaluation of the trust & reciprocity within the community	(Cutter et al., 2014; Jia et al., 2020; Renschler et al., 2010a)
F12	Evaluation of crime prevention & reduction mechanisms	(S. L. Cutter et al., 2008; Jia et al., 2020; K. Pasteur, 2011)
F13	Assessment of economic risks within the community	(Abdul-Rahman et al., 2020; L. Irajifar et al., 2013; Sharifi, 2016)
F14	Identification of present resilience challenges	(Sharifi, 2016; Walker & Salt, 2012a)
F15	Assessment of upper-scale relationships	(Chelleri, Waters, et al., 2015; P. Monaghan et al., 2014)

F16	Evaluation of available social safety-nets mechanisms	(Cutter, 2016; Cutter et al., 2010; Saja et al., 2018)
F17	Assessment of environmental risks	(Abdul-Rahman et al., 2020; L. Irajifar et al., 2013; Sharifi, 2016)
F18	Identification and assessment of shared assets within the community	(Cutter, 2016; S. L. Cutter et al., 2008; Saja et al., 2018)
F19	Prediction of future resilience challenges	(Sharifi, 2016; Walker & Salt, 2012b)
F20	Flexibility in action planning to accommodate evolving situations	(Ostadtaghizadeh et al., 2015; Spaans & Waterhout, 2017a)
F21	Assessment of lower-scale relationships	(Chelleri, Schuetze, et al., 2015; P. Monaghan et al., 2014)
F22	Assessment of existing institutional and governance structures	(Pfefferbaum et al., 2015; Sharifi, 2016)
F23	Identification and evaluation of shared norms & value	(Copeland et al., 2020; Cutter, 2016; Cutter et al., 2014)
F24	Identification of past resilience challenges	(Sharifi, 2016; Walker & Salt, 2012a; Wang et al., 2018)
F25	Assessment of focal-scale relationships	(P. Monaghan et al., 2014; Quinlan et al., 2016)
F26	Integration of action plans with other existing community systems	(Sharifi, 2016; Spaans & Waterhout, 2017a)
F27	Assessment of community conflict resolution mechanisms	(Cutter, 2016; Cutter et al., 2010; Jia et al., 2020)
F28	Redundancies in the action plan to accommodate disruptions	(Spaans & Waterhout, 2017a)
F29	The resourcefulness of the action plan to respond to needs during crises	(Spaans & Waterhout, 2017a; Wang et al., 2018)
F30	Robustness of the action planning process	(Abdul-Rahman et al., 2021; Spaans & Waterhout, 2017a)
F31	Co-reflectiveness during plan-making	(Gladfelter, 2018; Hsiao, 2021; Spaans & Waterhout, 2017a)

4.2.2 Data Collection

Data was collected through an international expert survey. See chapter 3, section 3.2.2 for the survey procedure, respondents' profile and other details. Section C of 392 valid questionnaires received from 23 countries was analysed and used for this chapter. The questionnaire is attached as Appendix A.

4.3 Results and Discussions

IBM SPSS Statistics (v26) was used to analyze the data collected. Cronbach's alpha coefficient (α) was first performed to test the reliability of the collected data. The general rule of thumb is that a Cronbach's alpha of 0.70 and above is good, 0.80 and above is better, and 0.90 and above is the best for measuring the consistency and accuracy of the data (George & Mallery, 2016). The section of survey used for this chapter had a Cronbach's alpha score of 0.906, which shows the high consistency and accuracy of the data. The garnered data were then grouped into responses from developed countries and those from developing countries. Next, statistical mean and t-tests were calculated to measure the significance of the CSFs and rank them using the opinions of experts from both developed and developing countries. Only success factors with p-value < 0.05 (significant level), and a mean value > 3.5 (Mean Item Score (MIS) of the 5-points Likert scale) were considered to be critical/significantly important (Chan et al., 2009; Darko, Chan, et al., 2017; Darko, Zhang, et al., 2017). Chi-square was used to examine the internal agreement within the two individual expert groups on their rankings of the CSFs. To check if there are differences in opinions among the two groups in the ranking of the selected factors, the Mann-Whitney U test was computed (Adabre & Chan, 2019; Chan et al., 2009; Pratt, 1964). Finally, principal components analysis was carried out to group the factors into their underlying components.

4.3.1 *Mean ranking, identification of CSFs, and tests of hypothesis*

The statistical mean values and t-tests for data from all countries were calculated (as shown in Table 3). The analysis shows that only 28 out of the 31 potential CSFs were significantly important (critical). The three factors with one-sample t-test $p > 0.05$ were 'Evaluation of crime prevention and reduction mechanisms' (F12) with mean value 3.55 and $p = 0.732$, 'Evaluation of available social safety-nets mechanism' (F16) with mean value 3.53 and $p = 0.954$, and 'Flexibility in action planning to accommodate evolving situations' (F20) with a mean value of 3.56 and $p = 0.246$.

To test for the degree of association or if experts' rankings are in agreement with that of others within their group, Chi-square (X^2) was used. Chi-square is a nonparametric analysis that gives accurate results for variable size > 20, with a degree of freedom (df) = N - 1 (approximate distribution) for the observed coefficient of concordance (Siegel, 1957). The scientific assumption for conducting this test is the null hypothesis (H0) = *no agreements among expert rankings within the total sample*. This is rejected if the value of X^2 has a low significance ($p \leq 0.001$). This means some degree of consensus exists amongst the scaled answers to the questions. The Chi-square critical value for the total sample is 365.199. Df = 30 and the probability of occurrence was under $p < 0.001$ (Asymp. Sig. = 0.000), which means H0 was rejected. Therefore, the result shows there are internal agreements among the expert ranking.

To test if the agreements of experts from developed countries differ from those in developing countries in ranking the individual CSFs, the Mann-Whitney U test was used. This test is ideal for statistically identifying the differences in opinions amongst two or more independent groups answering the same questions on continuous variables, without prior assumption on data distribution (Chan et al., 2009). According to Lam et al. (2015), the sample sizes in the two independent groups do not matter in conducting the U test since it converts individual scores on each continuous measure to ranks within each group and then compares the ranks in the two groups to see if they are significantly different or not. The null hypothesis (H0) for this test says, "*there is no significant difference between the rankings in the two groups*". The H0 would be rejected if, at p-value ≥ 0.05, the U value is more than the critical value. Table 1 in Appendix C shows the test results for each of the 28 CSFs, and their corresponding level of significance (p values). Only 'co-creation & co-adoption of the CRA methodology' (F7) with $p = 0.039$ falls below the above benchmark. This means experts from developed and developing countries have no statistically differing views concerning the rankings of the remaining 27 CSFs apart from F7.

Table 4.2 Ranking of the 31 potential CSFs for community resilience assessment

Code	Developed Countries		All Countries			Developing Countries	
	Mean	Rank	Mean	Rank	Sig.	Mean	Rank
F1	4.52	10	4.53	9	0.000	4.50	9
F2	4.76	1	4.72	1	0.000	4.69	1
F3	4.27	17	4.26	17	0.000	4.22	17[b]
F4	4.51	11	4.50	10	0.000	4.47	10[b]
F5	4.16	20	4.15	20	0.000	4.13	21
F6	3.87	22	3.86	22	0.000	4.01	22
F7	4.54	8[b]	4.38	14	0.000	4.37	14
F8	3.77	24	3.74	24	0.002	3.69	24
F9	4.54	8[b]	4.54	8	0.000	4.51	8
F10	3.98	21	3.97	21	0.000	4.22	17[b]
F11	4.32	16	4.33	16	0.000	4.29	16
F12	3.58	29[b]	3.55	30	0.732[a]	3.51	30
F13	4.66	3	4.65	3	0.000	4.65	3[b]
F14	4.60	5	4.59	5	0.000	4.58	5
F15	4.39	14	4.39	13	0.000	4.38	13
F16	3.57	31	3.53	31	0.954[a]	3.50	31
F17	4.73	2	4.70	2	0.000	4.67	2
F18	4.18	18[b]	4.24	18	0.000	4.22	17[b]
F19	4.59	6	4.58	6	0.000	4.55	6
F20	3.58	29[b]	3.56	29	0.246[a]	3.54	29
F21	4.46	13	4.45	12	0.000	4.44	12
F22	4.64	4	4.63	4	0.000	4.65	3[b]
F23	4.37	15	4.36	15	0.000	4.32	15
F24	4.56	7	4.55	7	0.000	4.53	7
F25	4.49	12	4.48	11	0.000	4.47	10[b]
F26	3.61	28	3.60	28	0.043	3.58	28
F27	4.18	18[b]	4.20	19	0.000	4.17	20
F28	3.67	26	3.66	26	0.013	3.65	25[b]
F29	3.71	25	3.70	25	0.001	3.65	25[b]
F30	3.84	23	3.80	23	0.000	3.74	23
F31	3.66	27	3.65	27	0.011	3.61	27
Chi-square	365.199						
df	30						
Asymp. Sig.	0.000						

Note: a Success factors with insignificant results of one-sample t-test ($p > 0.05$) = not critical

b Equal ranks meaning the next rank is skipped.

Table 4.3 U test to determine the agreements between the opinions of experts in developed countries and those from developing countries in rating the criticality of the selected 28 CSFs for CRA

Codes	**Test Statistics**[a]			
CSFs	Mann-Whitney U	Wilcoxon W	Z	Asymp. Sig. (2-tailed)
F1	1305.000	2241.000	-0.013	0.985
F2	1099.500	2045.500	-1.352	0.136
F3	1231.000	2177.000	-0.651	0.513
F4	1134.000	2080.000	-0.953	0.318
F5	1167.000	2113.000	-0.986	0.323
F6	1245.500	2191.500	-0.426	0.667
F7	1010.000	1956.000	-2.219	0.039[b]
F8	1158.000	2104.000	-1.077	0.283
F9	1244.000	2190.000	-0.506	0.611
F10	1202.000	2148.000	-1.017	0.321
F11	1168.000	2114.000	-0.987	0.324
F13	1286.000	2232.000	-0.531	0.751
F14	1223.500	2169.500	-1.023	0.536
F15	1102.000	2048.000	-1.476	0.140
F17	1254.000	2200.000	-0.445	0.701
F18	1258.500	2204.500	-0.376	0.707
F19	1102.500	2.048.500	-0.665	0.471
F21	1198.000	2144.000	-0.251	0.501
F22	1253.000	2199.000	-0.524	0.434
F23	1066.000	2012.000	-1.640	0.101
F24	1169.500	2115.500	-0.564	0.541
F25	1157.500	2103.500	-1.076	0.282
F26	1102.500	2048.500	-1.476	0.140
F27	1174.000	2120.000	-1.324	0.238
F28	1228.000	2174.000	-0.564	0.571
F29	1177.000	2123.000	-0.825	0.444
F30	1240.000	2186.000	-0.488	0.624
F31	1247.000	2193.000	-0.511	0.610

4.3.2 Principal Components Analysis

Principal Components Analysis (PCA), a factor analysis technique used for data reduction and generation of linear combinations of variables was adopted to investigate the underlying relationship among the 28 identified CSFs for CRA (Xu et al., 2011). Without the need for causal models, this method combines the many CSFs into "components".

To test for data adequacy and appropriateness, both the Kaiser-Mayer-Olkin (KMO) test and Bartlett's Test of Sphericity were carried out. A zero KMO value means the data are unsuitable, while a value greater than 0.5 means the data are suitable for factor analysis and will give closely related components (Chan & Adabre, 2019). The KMO value for this study was 0.784. The Bartlett's Test of Sphericity score was 372.004 with a 0.000 significance level. This suggests that the correlation matrix is not an identity matrix and the data is appropriate for PCA (Adabre & Chan, 2019).

The eigenvalues of the 28 CSFs were used as a criterion to measure the contribution of the variables to the principal components. Since all the 28 CSFs have more than 1.0 eigenvalues, they are all retained (Adabre & Chan, 2019). PCA was carried out using Varimax Rotation with Kaiser Normalization. 7 components were extracted which explained 79.11% of the total variance (see Table 3 in Appendix C). The components are named as follows: component 1: Comprehensiveness of Community Resilience Assessment; component 2: Measuring temporal dynamism; component 3: Addressing uncertainties; component 4: Assessing spatial relationships; component 5: Assessing social dynamics; component 6: Adopting participatory approaches, and component 7: Developing resilience action plans. These components were named manually based on the collective aim the underlying success factors under each component wants to achieve or represent (Chan et al., 2004; Chan et al., 2010; Chan & Adabre, 2019; Chan & Lee, 2008; Chan & Hou, 2015). Discussion on the components above in the order of importance is contained in the next sub-section.

4.3.2.1 Results and interpretation of the identified principal components

The results discussed in this section are presented in Tables 4.4 and 4.5.

Table 4.4 Correlation matrix of the CSFs for community resilience assessment

Code	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F13	F14	F15	F17	F18	F19	F21	F22	F23	F24	F25	F26	F27	F28	F29	F30	F31
F1	1.000																											
F2	.112	1.000																										
F3	.184	.165	1.000																									
F4	.315[a]	.072	-.203	1.000																								
F5	.098	.209	.051	-.202	1.000																							
F6	-.155	.067	.563[b]	.082	-.132	1.000																						
F7	.167	.177	.119	.242	.311[a]	.115	1.000																					
F8	.170	.150	.200	.121	.041	.026	.125	1.000																				
F9	.441[b]	-.078	.028	.372[a]	.119	-.228	.022	-.200	1.000																			
F10	.082	.170	.220	.009	.506[b]	.214	.399[a]	-.050	.160	1.000																		
F11	.123	.222	296[a]	.011	.144	.297[a]	.124	-.033	.099	.103	1.000																	
F13	-.151	.523[b]	.110	.215	.091	.004	.032	.137	.121	-.118	.098	1.000																
F14	.199	.092	.081	.076	-.201	.223	.109	.167	.091	.056	.103	.206	1.000															
F15	.155	-.029	.059	.029	.072	.252	.198	.150	.023	-.110	.054	.199	-.077	1.000														
F17	.099	.447[b]	.162	.047	.075	.207	.089	.011	-.106	.003	.072	.081	.021	.050	1.000													
F18	.045	.090	.333[a]	.092	.104	.141	.181	-.031	.234	.044	-.145	.092	.006	.219	.012	1.000												
F19	.081	.103	-.152	.172	-.136	-.067	.066	-.090	.003	.051	.110	-.025	.280[a]	.107	.098	.126	1.000											
F21	-.201	.156	-.106	-.241	.022	.081	-.033	.115	.061	-.205	.013	.051	.067	.313[a]	-.172	-.169	.081	1.000										
F22	.101	.583[b]	-.070	.046	.009	.251	.128	.008	.091	.085	.087	.495[b]	.035	.241	.445[b]	.002	-.108	.080	1.000									
F23	.118	.108	.355[a]	.123	.033	.204	.002	.056	.005	.059	.265[a]	.049	.006	.186	.209	.420[b]	-.233	.061	.061	1.000								
F24	.102	.078	.213	-.186	.169	.071	-.118	.166	-.145	.083	-.006	.132	.601[b]	-.175	.154	.065	.317[a]	.099	.106	.189	1.000							
F25	-.049	.088	.171	.007	.149	.022	.193	.208	.077	.077	.108	.048	-.231	.289[a]	.006	.054	.261	.339[a]	.119	.139	-.033	1.000						
F26	.045	-.060	.154	.192	.152	-.107	.117	.377[a]	.147	.167	.029	.021	.177	.251	.206	.134	.159	.128	.171	.156	.178	.144	1.000					
F27	.106	.122	.301[a]	.058	.071	.052	.076	-.066	.208	.191	.341[a]	.134	.152	.072	-.161	.272[a]	.099	-.142	-.241	.507[b]	.206	.116	.215	1.000				
F28	.204	.134	.120	.068	-.200	.056	-.111	.409[b]	.133	.211	.135	.092	.017	.150	.056	.072	.056	.095	.057	-.066	.024	.048	.483[b]	-.040	1.000			
F29	-.111	.196	.065	.027	.013	-.151	.204	.279[a]	.009	.160	.073	.031	.026	.034	.106	-.066	.075	.092	.245	.008	.057	-.022	.611[b]	.174	.384[a]	1.000		
F30	.214	.071	.080	.207	-.102	.069	-.034	.381[a]	.122	.087	.099	-.122	.173	.038	.175	.122	-.089	-.166	.194	.120	.124	-.160	.444[b]	.122	.297[a]	.310[a]	1.000	
F31	.150	.030	-.038	.109	-.205	.070	.135	.508[b]	.156	.033	.182	.035	.184	.207	.235	.149	.123	-.003	.171	.070	.023	.194	.257[a]	-.054	.401[b]	.276[a]	.628[b]	1.000

(F1 = Assessment of interlinkages; F2 = Assessment of cultural and social risk within the community; F3 = Assessment of place attachment & sense of community and pride; F4 = Simulation of alternate states; F5 = Inclusive & participatory CRA process; F6 = Evaluation of community social network; F7 = Co-creation & co-adoption of the CRA methodology; F8 = Inclusive & participatory action planning process; F9 = Repeated key assessment processes (iterative process); F10 = Decentralized responsibilities & leadership during the CRA process; F11 = Evaluation of the trust & reciprocity within the community; F13 = Assessment of economic risks within the community; F14 = Identification of present resilience challenges; F15 = Assessment of upper-scale relationships; F17 = Assessment of environmental risks; F18 = Identification and assessment of shared assets within the community; F19 = Prediction of future resilience challenges; F21 = Assessment of lower-scale relationships; F22 = Assessment of existing institutional and governance structures; F23 = Identification and evaluation of shared norms & value; F24 = Identification of past resilience challenges; F25 = Assessment of focal-scale relationships; F26 = Integration of action plans with other existing community systems; F27 = Assessment of community conflict resolution mechanisms; F28 = Redundancies in the action plan to accommodate disruptions; F29 = The resourcefulness of the action plan to respond to needs during crises; and F30 = Robustness of the action planning process; F31 = Co-reflectiveness during plan-making).

a Correlation is significant at the 0.01 level (2-tailed)

b Correlation is significant at the 0.05 level (2-tailed

Table 4.5 Rotation component matrix

Code	CSFs for community resilience assessment	Components						
		1	**2**	**3**	**4**	**5**	**6**	**7**
Component 1: Comprehensiveness of Community Resilience Assessment								
F2	Assessment of cultural and social risk within the community	0.895	-	-	-	-	-	-
F17	Assessment of environmental risks	0.811	-	-	-	-	-	-
F13	Assessment of economic risks within the community	0.797	-	-	-	-	-	-
F22	Assessment of existing institutional and governance structures	0.684	-	-	-	-	-	-
Component 2: Measuring Temporal Dynamism								
F24	Identification of past resilience challenges	-	0.801	-	-	-	-	-
F14	Identification of present resilience challenges	-	0.788	-	-	-	-	-
F19	Prediction of future resilience challenges	-	0.699	-	-	-	-	-
Component 3: Addressing Uncertainties								
F4	Simulation of alternate states	-	-	0.703	-	-	-	-
F1	Assessment of interlinkages	-	-	0.675	-	-	-	-
F9	Repeated key assessment processes (iterative process)	-	-	0.658	-	-	-	-
Component 4: Assessing Spatial Relationships								
F15	Assessment of upper-scale relationships	-	-	-	0.821	-	-	-
F25	Assessment of focal-scale relationships	-	-	-	0.709	-	-	-
F21	Assessment of lower-scale relationships	-	-	-	0.645	-	-	-
Component 5: Assessing Social Dynamics								
F6	Evaluation of community social network	-	-	-	-	0.809	-	-
F11	Evaluation of the trust & reciprocity within the community	-	-	-	-	0.795	-	-
F23	Identification and evaluation of shared norms & value	-	-	-	-	0.777	-	-
F27	Assessment of community conflict resolution mechanisms	-	-	-	-	0.723	-	-

F3	Assessment of place attachment & sense of community and pride	-	-	-	-	0.696	-	-
F18	Identification and assessment of shared assets within the community	-	-	-	-	0.689	-	-
Component 6: Adopting Participatory Approaches								
F7	Co-creation & co-adoption of the CRA methodology	-	-	-	-	-	0.725	-
F5	Inclusive & participatory CRA process	-	-	-	-	-	0.685	-
F10	Decentralized responsibilities & leadership during the CRA process	-	-	-	-	-	0.622	-
Component 7: Developing Resilience Action Plans								
F26	Integration of action plans with other existing community systems	-	-	-	-	-	-	0.799
F28	Redundancies in the action plan to accommodate disruptions	-	-	-	-	-	-	0.759
F30	Robustness of the action planning process	-	-	-	-	-	-	0.734
F8	Inclusive & participatory action planning process	-	-	-	-	-	-	0.643
F31	Co-reflectiveness during plan-making	-	-	-	-	-	-	0.602
F29	The resourcefulness of the action plan to respond to needs during crises	-	-	-	-	-	-	0.598
	Eigenvalue	**5.869**	**3.541**	**3.011**	**2.602**	**1.992**	**1.489**	**1.208**
	Variance (%)	**22.254**	**14.872**	**11.002**	**9.231**	**7.542**	**7.211**	**6.998**
	Cumulative Variance (%)	**22.254**	**37.126**	**48.128**	**57.359**	**64.901**	**72.112**	**79.110**

a. Component 1: Comprehensiveness of Community Resilience Assessment

This component consists of four underlying CSFs: ‘assessment of cultural and social risk within the community’ (89.5%), ‘assessment of environmental risks’ (81.1%), ‘assessment of economic risks within the community’ (79.7%), and ‘assessment of existing institutional and governance structures’ (68.4%). The total variance explained by this component is 22.25%. The factors are closely related and point to the need for the CRA process to assess resilience in the four key dimensions of resilience which include: Social, environmental, economic, and governance (Meerow et al., 2016), hence the component is named comprehensiveness of community resilience assessment. “Comprehensiveness” means looking at the community holistically (Cimellaro et al., 2016).

Communities are complex adaptive socio-ecological systems (Gunderson et al., 2008), therefore, a community challenge or risk in one dimension may affect other parts of the system. In the past two decades, a lot of CRA methodologies have been designed to assess only one or two dimensions, mostly the physical environment (including resilience in engineering systems) and society (Sharifi, 2016). However, such assessments may not be complete as environmental or social community challenges are likely going to affect the economy or have impacts on economic activities within the community (Cutter et al., 2014). Hence, the need to assess the risks and their impacts on all the dimensions, including the existing institutional and governance structures within the community. Resilience in communities depends largely on the soundness of the available local institutions that manage the community (Pfefferbaum et al., 2015). Sometimes, those institutions may be affected by risks or community challenges, therefore, it is important to also assess the availability and adequacy of such institutions while assessing the resiliency of the community (Spaans & Waterhout, 2017a).

b. Component 2: Measuring temporal dynamism

This is the second-largest component. It emphasized the need for spatiotemporal assessment and capturing time horizons, hence the name given to the component. The total variance accounted for by this component is 14.872%. The three CSFs that make up the component are: 'identification of past resilience challenges' (80.1%), 'identification of present resilience challenges' (78.8%), and 'prediction of future resilience challenges' (69.9%).

Comparing the baseline conditions with those recorded before a disruption took place helps in understanding the extent to which existing resilience action plans have been effective in absorbing shocks and community challenges (Walker & Salt, 2012a). It also helps to understand the extent of recoveries after past disruptive events in the community (Sharifi, 2016). According to Sharifi (2016), assessing past and present resilience challenges, and understanding system dynamics within the community will help predict uncertainties and strategies to absorb them. Therefore, for CRA projects to be successful, the methodology adopted must be able to identify and assess, holistically, the past and present resilience challenges and be able to forecast future trends. Although there would be some inaccuracies in predicting risks due to shifting thresholds of climate-related models, the use of smart technologies and artificial intelligence would improve the prediction accuracies of future resilience challenges if incorporated in the CRA methodologies (Abdul-Rahman et al., 2020).

c. Component 3: Addressing uncertainties

Component 3 has three CSFs: 'simulation of alternate states' (70.3%), 'assessment of interlinkages' (67.5%), and 'repeated key assessment processes (iterative process)' (65.8%). This component accounts for 11% of the total variance. Hence, the three significantly correlated factors focus on addressing uncertainties within communities, hence the chosen name for this component.

To capture future risks, CRA methodologies need to periodically re-assess the community and re-evaluate the resilience-building strategies, as well as ‘simulate alternate states’ that the community systems may shift to during and after crisis (T. Frankenberger et al., 2013; Elizabeth Mcleod et al., 2015). Understanding the alternate states would enable resilience managers to prepare better for crises and loss of systems functionalities (Watson et al., 2014). Since communities are said to be complex adaptive socio-ecological systems (Gunderson et al., 2008), CRA should be set through revolutionary processes that assess all the interlinkages among the many facets of the communities (Collier et al., 2013; Folke et al., 2010; Schipper & Langston, 2015a). On the other hand, adopting an iterative process will give room for periodic monitoring of performance against baseline conditions which will also help in reducing uncertainties (P. Pringle, 2011).

d. Component 4: Assessing spatial relationships

Component 4 consists of three CSFs with a total variance of 9.23% (as shown in Table 4.5). The three factors are: ‘assessment of upper-scale relationships’ (82.1%), ‘assessment of focal-scale relationships’ (70.9%), and ‘assessment of lower-scale relationships’ (64.5%). The factors in this component all focus on the need to assess spatial relationships between the community and the higher spatial hierarchy and lower spatial hierarchy, hence the name given to this component.

Communities are nested in open spatial systems; therefore, they can be affected by other levels within the system, inter-relationships, and dependencies (Constas et al., 2014; Samuel et al., 2020). The focal scale refers to the spatial scale at which resilience is being assessed e.g. Neighbourhood. The neighbourhood is made up of blocks or wards that represent lower spatial scales. On the other hand, neighbourhoods are nested within higher spatial hierarchies like districts or cities which represent upper spatial scales. A resilience challenge (shock or stress) in one spatial scale is likely going to affect another spatial scale due to the inter-relationships these spatial scales share (Chelleri, Schuetze, et al., 2015; Chelleri, Waters, et al., 2015). For instance, traffic congestion in a neighbourhood may be caused by a business district outside of the neighbourhood. Communities also depend on each other for a lot of systems supports such as shopping, recreation, education, etc. a breakdown in service provision due to a shock in one spatial hierarchy may likely affect the other hierarchies (Constas et al., 2014).

e. Component 5: Assessing social dynamics

Component 5 has six CSFs which account for 7.54% of the total variance. They are: 'evaluation of community social network' (80.9%), 'evaluation of the trust & reciprocity within the community' (79.5%), 'identification and evaluation of shared norms & value' (77.7%), 'assessment of community conflict resolution mechanisms' (72.3%), 'assessment of place attachment & sense of community and pride' (69.6%), and 'identification and assessment of shared assets within the community' (68.9%). The six factors centre around assessing the social dynamics in the community, hence the component name.

People make communities resilient (Renschler et al., 2010b), therefore, their unity and cooperation are key to assessing and building community resilience (Cutter, 2016; S. L. Cutter et al., 2008). 'Evaluation of community social network' means assessing the bonds, bridges, and linkages among people who live in the community. Socially, there are communities within communities, and physically, there are also communities within communities (Renschler et al., 2010b). While the physical communities are spatial and horizontal in configuration, the social communities are vertical, and they include age groups, gender, social and economic status groups, associations, people with disabilities, etc. Most of the time, they are naturally organized in these vertical hierarchies within the community. 'Evaluation of the trust & reciprocity within the community' during assessment also helps in knowing if people will stand together and help one another during crises.

Conflicts and lack of harmony often lead to or sustain crisis (Cutter et al., 2014), therefore 'assessment of community conflict resolution mechanisms' help to identify local systems for conflict resolution that can be strengthened to maintain peace during the crisis, adaptation, or recovery period. There is also a need for 'place attachment and sense of community and pride'. When people are psychologically attached to a community, they go the extra mile to protect it and uphold its vision and values. Lack of such attachment, therefore, leads to a lack of concern about the community and oftentimes, breakdown of law, and order (Katherine Pasteur, 2011). Lastly, having shared assets within the community help to create bonds, bridges, linkages, build trust among residents and promote a sense of community (S. L. Cutter et al., 2008). These shared assets may be physical assets such as open spaces and parks that bring people together or socio-cultural values and religions that bind people together (Renschler et al., 2010b). CSFs in this component mainly point to the need to pay attention to social capital and measure interactions and the degree of connectedness among individuals, and across social groups, within the community, for the CRA process to be successful.

f. Component 6: Adopting participatory approaches

The three underlying factors that make up this component point to the need for top-bottom–bottom-up approaches in CRA projects, hence the component is named 'adopting participatory approaches'. They are: 'co-creation & co-adoption of the CRA methodology'(72.5%), 'inclusive & participatory CRA process' (68.5%), and 'decentralized responsibilities & leadership during the CRA process' (62.2%). The component accounts for 7.21% of the total variance (as shown in Table 4.5).

CRA methodologies are generally created to assess certain community challenges or specific types of risks (Sharifi, 2016). Often, the methodologies are modified and localized for use in specific communities. Experts believe for success in CRA, there should be 'co-creation & co-adoption of the CRA methodology'. According to Renschler et al. (2010b), CRA projects aiming to be successful should involve the community members in the methodology design or adoption and community goal-setting. They further buttressed that taking along the community members from the inception will enable experts to capture the needs and aspirations of the people for their community from the beginning. Beyond co-creation of the CRA methodology, adopting a multi-stakeholder approach in CRA goes a long way in involving as many people as possible in building resilience (Katherine Pasteur, 2011). 'Inclusive & participatory CRA process' means no social group within the community is left behind from start to finish, and their capacity is developed to build resilience in their community (Douglas et al., 2018). Lastly, 'decentralized responsibilities & leadership during the CRA process' will make the community members own the CRA process, and allow the experts to identify local champions that will drive the implementation of the action plans and sustain the resilience of the community (Pfefferbaum et al., 2015; Pfefferbaum, Pfefferbaum, Van-Horn, et al., 2013).

g. ***Component 7: Developing resilience action plans***.

The last component has the lowest total variance in the correlation matrix (approximately 7%) as shown in Table 4.5. The component comprises of six CSFs: 'integration of action plans with other existing community systems' (79.9%), 'redundancies in the action plan to accommodate disruptions' (75.9%), 'robustness of the action planning process' (73.4%), 'inclusive & participatory action planning process' (64.3%), 'co-reflectiveness during plan-making (60.2%), and 'the resourcefulness of the action plan to respond to needs during crises' (59.8%). The CSFs all discuss action plans; hence the component was re-named in line with that.

According to Pfefferbaum, Pfefferbaum, Van Horn, et al. (2013), every CRA should end up with strategies or road maps for building a more resilient community. Sharifi (2016) also argued that CRA projects should often end up providing solutions beyond just identifying the resilience status of the communities. He further explained that the success of any CRA project is measured by the quality of its action plans. Communities are made up of many interconnected systems and plans, therefore, the 'integration of action plans with other existing community systems' makes implementation easier and more effective (Sharifi, 2016). To ensure quality action plans, there should be 'redundancies in the action plan to accommodate disruptions'. This includes diversity; multiple ways to achieve a particular function. Redundancies should be intentionally created as alternatives within the planning process (Spaans & Waterhout, 2017a). 'Robustness of the action planning process' means it is all-encompassing and well-conceived to address all community concerns. To be robust, action plans need to be 'inclusive & participatory in their action planning process' (Pfefferbaum et al., 2015) and also give room for 'co-reflectiveness during plan-making (Spaans & Waterhout, 2017a). Reflective action plans are easily modifiable to capture future risks because they systematically learn from the past to inform future decisions. And lastly, 'the resourcefulness of an action plan to respond to needs during crises' shows how great the action plan is (Schwind, 2009; Spaans & Waterhout, 2017a). Resourcefulness is instrumental to a community's ability to restore the functionality of critical systems during a crisis and 'build back better'.

4.4 Chapter Summary and Conclusion

The absence of CSFs for CRA leads to failure or low performance. Likewise, determining whether a CRA is a success or failure is difficult at the moment because there are no studies that provide a comprehensive list of CSFs for CRA. In bridging this gap and other gaps identified in this study, a comprehensive literature review was conducted, through which 31 success factors were identified. An international questionnaire survey was conducted, in which

392 questionnaires were received from experts in twenty-three countries. After data analysis, 28 of the success factors were found to be critical in defining the success of CRA. The three not found to be significant include: ‘evaluation of crime prevention & reduction mechanisms’ (F12), ‘evaluation of available social safety-nets mechanisms’ (F16), and ‘flexibility in action planning to accommodate evolving situations’ (F20). The top five CSFs include: ‘assessment of cultural and social risk within the community’ (F2), ‘Assessment of environmental risks’ (F17), ‘assessment of economic risks within the community’ (F13), ‘assessment of existing institutional and governance structures’ (F22), and ‘identification of present resilience challenges’ (F14). The opinions of experts from developed countries were compared with those from developing countries to know if they will have different opinions regarding the rankings and criticalities of the success factors. The results indicated that, generally, there were no statistically significant differences in the opinions of experts from developed and developing countries except in one factor; ‘co-creation & co-adoption of the CRA methodology’ (F7). (as shown in Table 4.3). Experts from developed countries rated F7 higher than experts in developing countries. Furthermore, the principal components analysis grouped the 28 CSFs into seven components: ‘comprehensiveness of community resilience assessment’, ‘measuring temporal dynamism’, ‘addressing uncertainties’, ‘assessing spatial relationships’, ‘assessing social dynamics’, ‘adopting participatory approaches’, and ‘developing resilience action plans’.

Although the study aim was achieved, it is noteworthy to mention that this study only identified CSFs for CRA and not CSFs for other forms of resilience such as system/engineering resilience and individual resilience. This limitation can be covered by future research using the same research approach and analytical framework. Albeit the above limitation, the research findings have several theoretical and practical/managerial implications. This includes the CSFs for CRA and the classifications of CSFs in components that can be implemented concurrently. For example, comprehensiveness in CRA could be attained by implementing factors in component

1. Component 2 and 4 help in achieving success at the spatiotemporal scale. Component 3 helps in addressing uncertainties. Component 5 helps in achieving success in understanding cultural and social dynamics within the community. Component 5 helps in achieving success in adopting an inclusive and participatory assessment. Lastly, component 6 helps in successfully developing resilience action plans and making communities more sustainable. Overall, these CSFs for CRA would help CRA managers to carry out successful CRA projects and build community resilience.

The next chapter shows the development of the programmatic algorithms and the development of the AI-Based Data Pre-Processing Framework. This chapter tests the hypothesis for objective 3.

CHAPTER 5: DEVELOPING AN ARTIFICIAL INTELLIGENCE-BASED DATA PRE-PROCESSING FRAMEWORK FOR COMMUNITY RESILIENCE ASSESSMENTS FOR UNIVERSITY TOWNS[6]

Based on the characteristics of the existing CRAs and the identified concepts and theories in chapter 2, this chapter develop new algorithms and a framework to pre-process location-based data to automatically identify community challenges.

5.1 Introduction

The world is undergoing a lot of changes and challenges in the 21st century, so is humanity. According to the United Nations (2016b), the urban population of the world rose from 43 per cent in 1990 to about 56 per cent in 2016 and is expected to reach 70 per cent by the mid-21st century. This growth is mostly taking place in the urban areas of medium and small cities (UN-Habitat, 2016b). The pressure on ecosystem resources coupled with Climate change, unguided urbanization, an unprecedented level of migration, and forcibly displaced populations moving to cities among other factors have increased the pressure, intensity, and impacts of urban crises (The Rockefeller Foundation & ARUP International Development, 2014). At the same time, cities have become the main drivers of sustainable development, equality, inclusivity, cultural diversity, and centres for innovation (Dhar & Khirfan, 2017; Pickett et al., 2004). The aforementioned challenges, among others, have resulted in the global drive for building sustainable and smart cities in the 21st century (United Nations, 2015). Urban planners among other professionals in the built environment are challenged more than ever to address this

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[6] This chapter was published in Elsevier's **Cities** journal (Special Issues on Big Data and Urban Planning).

1. **Abdul-Rahman, M.**, Chan, E. H. W., Wong, M. S., Irekponor, V. E., & Abdul-Rahman, M. O. (2020). A framework to simplify pre-processing location-based social media big data for sustainable urban planning and management. Cities, 102986. https://doi.org/10.1016/j.cities.2020.102986

hyperreality by re-planning and managing old cities or building smart sustainable ones that will adequately cater for the needs of the fast urbanizing world without compromising the opportunities of future generations (UN-Habitat, 2016b).

As the field of urban planning is evolving to adequately capture the planning needs of the 21st century, other aspects of human knowledge are also evolving. The current fourth industrial revolution has led to great scientific and technological breakthroughs, disruptions of many industries, and the increase in the use of everyday smart gadgets called the "Internet of Things" (IoT). IoT is a collection of heterogeneous electronic devices that are uniquely addressable and capable of collecting and sharing information with nominal human interactions, generating billions of data globally every day (Silva et al., 2018). This makes modern cities constellations of devices across various scales, and fast-changing into a haze of software instructions that need to be harnessed by urban planners (Bibri, 2019b).

With the rising complexities of global cities in this information age, traditional urban planning and management methods are fast reaching their limits (Future Cities Laboratory, 2019), therefore, urban planning can no longer rely on static and sectoral approaches involving a very limited number of citizens and stakeholders for relevant decision making. Hence, urban planners need to utilize the potentials of new tools like big data for evidence-based high-quality decision making across spatiotemporal scales. However, the main challenges of this are; the ease of understanding the technicalities of mining, processing, and using such huge data sets by urban planners. Therefore, this paper aims to provide urban planners and other allied professionals in the built environment with limited programming skills, a framework to harness the potentials of big data, natural language processing, and machine learning in planning and managing sustainable towns and cities. The objectives of this chapter include 1. to propose an AI-based Data Pre-Processing Framework for harnessing user-generated textual big data from microblogs (social media) to identify community challenges, and 2. to demonstrate the use of the proposed framework using a case study.

5.1.1 Textual Big Data from Microblogs (Social Media) and User Sentiments

Big Data has become a buzzword since 2011 and has been evolving rapidly through the years (Gandomi & Haider, 2015). Various definitions have been proposed over the years by different authors; but according to one of the most cited definitions by Batty (2013), big data is any "*data that cannot fit into an Excel spreadsheet*". Since an Excel spreadsheet contains about a million rows and less than a million columns, this suggests that big data is a type of dataset that runs into millions. The above definition also suggests that big data must be defined in relation to the tools that enable it to be processed for use (Reades, 2013). According to Batty (2013), big data is an old concept that exists in every era where the tools for data processing are always stretched to their limits by the increasing sizes of the datasets. These datasets have always driven innovations in mathematics and computing over the centuries. Therefore, the current hype in big data is mainly attributed to the rise in the production of big data in the current century due to the increased digital miniaturization and usage of IoT that generate an unprecedented quantity of data every second (Batty, 2013; Ma et al., 2018). Big Data is not expressed in petabytes or zettabytes, but in the fact that it has outgrown today's conventional databases and common data warehousing solutions, therefore, today's Big Data is tomorrow's small data (M. Batty et al., 2012).

Among the many types of IoT, smart devices like mobile phones and personal computers in possession of about 3 billion people generate billions of data per second in form of text, images, voice, and video (Batty, 2013). This is done mostly through social media microblogging (social networking) sites like WeChat, Twitter, Facebook, and Instagram which are part of the everyday lives of millions of people who constantly share their opinions about life, information, knowledge, interests, and so on every second (Carlos et al., 2017). Mining this textual social media big data is called *text mining*, a sub-sect of data mining (Gupta & Lehal, 2009). According to Mishra and Rastogi (2016) and Uma Maheswari and Dhenakaran (2019), these large unstructured datasets remain the biggest source of knowledge discovery in many areas of big data analytics.

Al-Garadi et al. (2016) stated that microblogs portray a multi-layer of interactions through which users become friends, information is propagated, ideas are shared, and interactions are constructed within an online social network. In the field of mass communication and marketing, microblogs are seen as platforms where people or "customers" come online to connect and talk to other fellow customers, share their sentiments and reviews about products and services as well as places (Foux, 2006; Larsson et al., 2012). These reviews and sentiments allow products and service providers to know how their customers feel about their products and services and the best ways to satisfy them (Fang & Zhan, 2015). Just like products and services, social media users also write sentiments about the places they visit for leisure and tourism, shopping, and where they work and live, including their commuting experiences and the challenges they experience in those places. Hence, it is imperative for urban planners to also harness the potential of these datasets for sustainable planning and management of cities.

5.2 The Proposed AI-based Data Pre-Processing Framework

Chang (2017, 2018) and Chen et al. (2014) pointed out that social media data is relevant to big data development and society because of its volume, velocity, variety, veracity, and value. The challenge, however, is that social media data is generated in millions every second through different sites (microblogs) which makes it highly unstructured and full of noise. Each microblog has its Application Program Interfaces (APIs) and a unique data structure or format. This study uses Twitter which is a goldmine for sentiment analysis and is the most used platform in marketing and social research (Alharbi et al., 2018b). Twitter has two APIs that can be accessed by users with developers' accounts; the Representative State Transfer (ReST) API and the Streaming API (Karhan et al., 2018; Pak & Paroubek, 2010). The ReST API allows users to access Twitter messages, often called Tweets, for the past seven days, while the Streaming API allows users to continuously stream tweets as they come. Tweets are a maximum of 280 characters (text) that come with metadata such as Username/Nickname, a picture avatar, User Identity (Tweeter Handle), Date of Tweet, Hashtags, and voluntary attachments such as other Twitter handles, pictures or videos. Under each Tweet are four buttons: Reply, Re-Tweet, Favourite/Like, and Forward (to send to others as a private message, copy the link or bookmark the message) as shown in Figure 5.1 below:

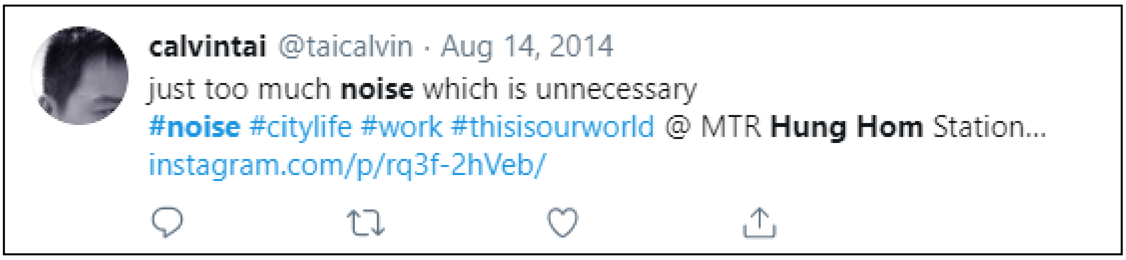

Figure 5.1 Structure of a typical Tweet

Due to the restrictions of the official Twitter APIs and the need to measure temporal dynamism in urban planning issues, this study proposed a framework to intelligently query the Twitter search engine and ethically download back-dated textual big data (tweets) for sentiment analysis and information retrieval. The framework is composed of the following five functionalities:

1. *Text Mining*: This refers to data extraction from Twitter using python-based open-source libraries to query the Twitter search engine and downloaded back-dated tweets. The proposed framework will mine and save the big data on a local host for further analysis.

2. *Topic Modelling:* This refers to the process of splitting the downloaded big data into major topics using python-based machine learning tools. This process will also help in saving the big data into smaller and manageable sizes per topic of discussion for easy analysis.
3. *Sentiment Analysis*: To understand people's complaints or views about their human settlements and the community's basic services and conditions, the data would be cleaned and analyzed using a trained python-based machine learning tool to measure the people's sentiments polarity on each modeled topic.
4. *Data Validation:* To reduce bias, the proposed framework would validate the big data using a questionnaire survey (small data).
5. *Data and Visualization:* Data visualization is an important step to reduce data complexity and making it easily understandable. The proposed framework would model and visualizes the data in 3D.

The advantages of the proposed framework lie in its simplicity and use of open-source Python-based algorithms to provide community resilience and urban planners with millions of data at a fraction of the time and cost it will take to get such data through a traditional questionnaire survey.

5.2.1 Related Work

A lot of studies were carried out in the last few decades on the use of social media big data. For instance, Suh et al. (2010) demonstrated how millions of tweets can be utilized as a part of big data analytics. Their work perfectly demonstrated that researchers and developers can develop algorithms to mine millions of data from Twitter in whatever format they need, for different purposes. For example, if a research study aims to know how customers feel about certain products, twitter data can be queried using the product hashtags, all textual data (tweets) about the products would be downloaded, the sentiments polarized and the data is then visualized. In another example, if the research aims to know people's reactions to new public safety measures concerning a disease epidemic in a city, the researchers may download twitter data generated from that city, analyze the sentiments and visualize people's views about the new measures. That way, the government can easily understand people's views and use the information for informed decision making. According to Chang (2017), the major challenges in effectively utilizing social media big data is the complexity, implication, and interpretation of data science. A lot of frameworks, methods and tools have been developed especially in the era of web 2.0 that has changed the landscape of social networks and user behaviours (Farkas, 2007; Gross & Acquisti, 2005).

Among these frameworks were those who use other microblogs like Facebook. For instance, Chang (2017) used the Facebook Graph API to design a social cloud to analyze work relations and provide approaches for social media big data processing on the cloud with no cost and high efficiency. The study fully demonstrated the use of cybernetics for social cloud and big data processing, and it can efficiently visualize relationships between Facebook users using APIs. But since the system is fully built using Facebook API, it cannot be used for mapping user relationships on Twitter or other microblogs. Building on the concept of the Internet of People (IoP) and studies carried out by Mislove et al. (2007), Ronen and Shmueli (2009), Neville and Jensen (2007), and He and Singh (2008) based on Web 1.0, Chang (2018) proposed a Facebook-based social network analysis platform using social media real data analytics. The proposed framework could be used to map and visualize links and their activities within a defined network on Facebook.

Although few other studies use other microblogs, like Y. Sun et al. (2018) who used WeChat data to quantitatively measure the market trends and tourist opinions towards scenic spots in China, it is wise to streamline this section to those that use Twitter big data for sentiment analysis since this study is based on Twitter. For example, Alharbi et al. (2018b) demonstrated how Tweet messages from Twitter can be used to study customer perception about the iPhone using sentiment analysis. The study shows how happy or sad people are with their phones and the percentages of happy to sad customers. In another study conducted by Asghar et al. (2019), big data from twitter was used to know what automobile brands people prefer or don't. Generally, companies use social media big data to understand how customers feel about their products, understand customers' expectations, and how customers compare their products with similar products from other manufactures (Jansen et al., 2009; Khan et al., 2018).

Carlos et al. (2017) while studying the temporal dynamism and spatial distribution of dengue outbreaks in Brazil used machine learning tools like K-Means and Support Vector Machine (SVM) algorithm to analyze twitter big data. The study showed high accuracy when the outcome was validated using data from the Ministry of Health of Brazil. The authors suggested that similar machine learning frameworks could be developed to study different challenges cities have beyond medical issues or disease outbreaks. Also, while reviewing the use of social media in the tourism planning and hospitality sector, Leung et al. (2013) pointed out that several studies have confirmed the impacts social media has on travel-related decisions, travel behaviour, and the consumption of cities' public facilities as well as places. They explained that the reviews of global cities' spaces and places are now readily available online (especially on google services) and on microblogs. Although this particular study is more related to tourism and more useful to tourism planners, the same concepts apply to cities and urban planning and management since there are no studies or frameworks available online to demonstrate directly the use of social media textual big data in community resilience assessment.

5.2.2 The Framework

To harness the potentials of social media textual big data for community resilience assessment, a framework is proposed for data mining and analysis. The framework is a combination of a few open-source Python-based algorithms and word processing tools shown in the architecture in Figure 2 below.

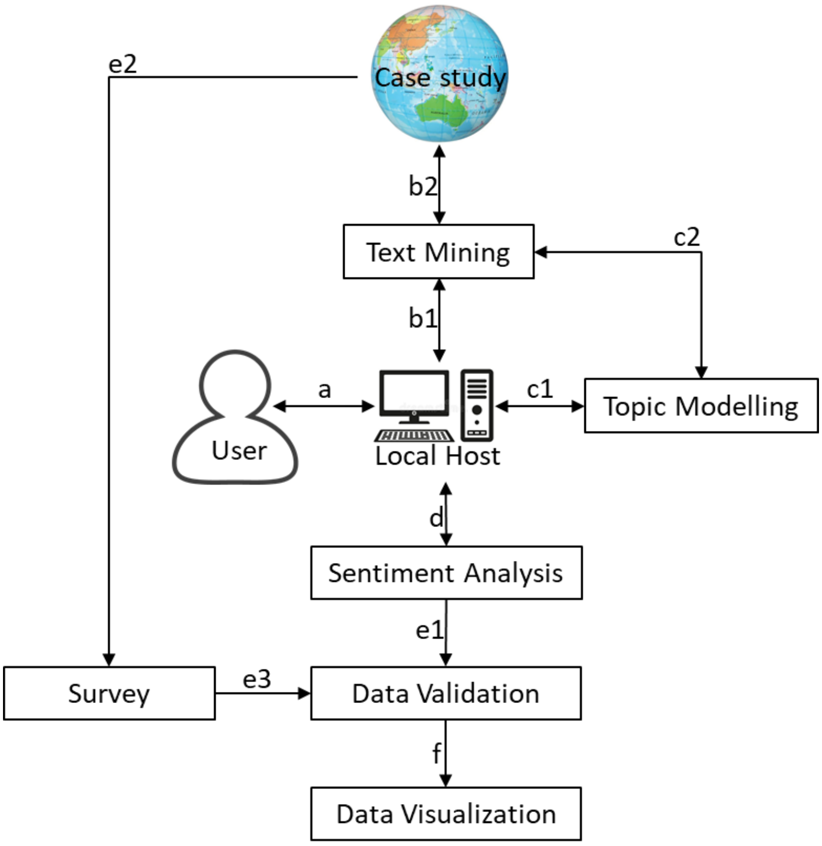

Figure 5.2 The architecture of deploying the framework

The proposed framework has six steps numbered a – f in Figure 5.2 above.

a. The *User* connects to a computer with internet and Python 3.x, PyQuery and Lxml installed.

b. Then downloads or clones the *Optimized-Modified-GetOldTweets3-OMGOT*[7] tool from GitHub and follows the instructions in the *ReadMe file* to mine textual data from Twitter

[7] https://github.com/marquisvictor/Optimized-Modified-GetOldTweets3-OMGOT

from any case study in the world using spatial coordinates. The downloaded big data is saved on the *Local Host* in *.csv* files. This Python tool is specifically modified for this project from the original script written by Henrique (2016). All system specifications and use cases are available on the GitHub page.

c. The *User* then calls a *Topic Modelling* tool within the Python environment using the command prompt on the *Local Host* to know the topics of discussion within the case study from the corpus. The topics are first modeled using the mined data (c1) and split into topics, and then re-mined based on each topic (c2) to re-check for data that were not captured around those topics in the initial mining. This last step also helps the user to have the big data broken into smaller files for easy cleaning and analysis. There are several open-source algorithms and models for Topic Modelling, but we recommend using *Latent Dirichlet Allocation (LDA)*[8]; a flexible & easily interpretable Bayesian theorem-based machine learning algorithm, first proposed by Pritchard et al. (2000) and later developed into a graphical model by Blei et al. (2003). The model output shows topic trends (Charlin et al., 2015), and also the relationship between topics (McAuley et al., 2015). Blei et al. (2010), Chuang et al. (2012), Sievert and Shirley (2014) and Moody et al. (2016), have good and easy to understand papers on how to use this model in domains such as computer vision, genetic markers, survey data, and social media big data.

d. The *User* also calls a sentiment analysis tool while on the python environment to analyze the sentiment polarity within the textual big data around each topic. Sentiment Analysis is a sub-field of Natural Language Processing (NLP) that identifies and extracts opinions within a given text (Neethu & Rajasree, 2013). This step is used to gauge sentiments and evaluate attitudes and emotions of people or residents within the

[8] https://github.com/lda-project/lda

case study based on the computational treatment of subjectivity in their tweets (Alharbi et al., 2018a; Asghar et al., 2019). Sentiment analysis can be done manually but it is extremely challenging when the data is big, unstructured, and filled with short forms, memes, and emoticons (Agarwal et al., 2011; Uma Maheswari & Dhenakaran, 2019). There are many sentiment analysis open-source tools, but due to the huge bias and the nature of social media big data, this study proposes the use of VADER[9] (Valence Aware Dictionary for sEntiment Reasoning), a parsimonious rule-based model for sentiment analysis of social media text developed by Hutto and Gilbert (2014). VADER is an open-source script that classifies lexical futures not just according to their semantic orientation (positive, negative, and neutral) but also tests their sentiment intensity (Hutto & Gilbert, 2014).

e. Although the output from VADER has high accuracy, since the model has been trained and validated with F1 Classification Accuracy = 0.96 and 0.84 respectively (Kumar et al., 2018), it is still good to add another step to revalidate the final output using small data from questionnaire survey from the case study (e2 and e3) to further reduce bias.
f. The final output from this big data analytics can be modelled and visualized for better understanding either within the python environment or using other word processing tools like Microsoft Power BI or Microsoft Excel. This final output can be used by urban planners for making informed decisions on planning issues within the case studies.

The next section practicalized the proposed framework using a pilot case study in Hong Kong and discussed the findings.

[9] https://github.com/cjhutto/vaderSentiment

5.3 Results and Discussions from Case Study

The Hung Hom District in Hong Kong was used as a case study to demonstrate the use and functionalities of the proposed framework. The district is divided into five neighbourhoods namely, Old Hung Hom; which houses the Hung Hum metro station and The Hung Kong Polytechnic University (PolyU), Hung Hom Bay, Lo Lung Hang, Hok Yuen, and Whampoa Gardens. It is bordered in the North by To Kwa Wan, on the West by Ho Man Tin, Yau Ma Tei, and parts of Tsim Sha Shui East, and on the South and East, it shares a boundary with the Kowloon Bay. As of June 2016 national census, Hung Hom has a population of 14,235 with about 49% males and 51% females, and a high concentration of foreigners. It has an Area of 0.149 km² and a Density of 95,422/km² (City Population, 2016).

As an old district currently undergoing some urban renewal, the district suffers from a lot of urban challenges and studentification, which makes it an ideal pilot case study for this study. 10 years of Twitter data (July 2009 to June 2019) was downloaded from the study area.

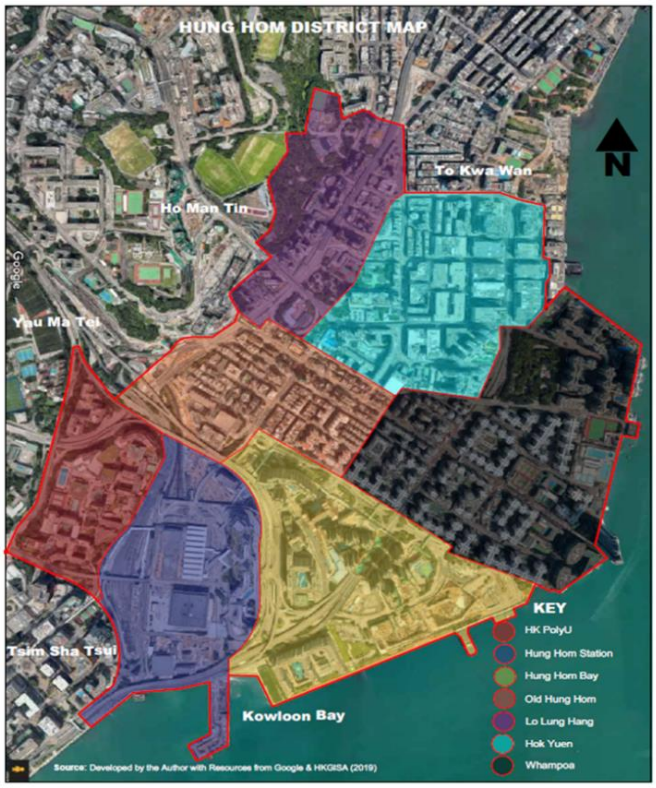

Figure 5.3 Map of Hung Hom District Source: Developed by authors with resources from Google and HKGISA (http://www.hkgisa.org.hk/hong-kong-gis-resources)

5.3.1 Text Mining using Optimized-Modified-GetOldTweets3-OMGOT

The text mining for this study took about 24hours; this may vary due to internet speed and system specifications. A total of 605,121 tweets were downloaded with metadata such as username, permalink, replies, favourites, retweets hashtags, and dates. Pictures and videos were not downloaded since they were not needed. Although this unstructured dataset could fit into an Excel sheet, it contains more than 5 million words, slang, emojis, punctuations and emoticons, and a lot of noise. It does not fit the definition of big data adopted for this study, but it is good enough for demonstrating the use of the proposed framework for sustainable urban planning. The components, command-line arguments, and use cases for mining are attached in Appendix B of this thesis.

5.3.1.1 Procedures for Text Mining

The following steps are used in this study for Text Mining:

1. Install Python 3.x[10] if not pre-installed.
2. Set the environment variable path on python through the command or terminal without getting any error. The easiest way to do so on Windows is to run the Python installer again and tick the box asking to "*Add Python to environment variables*" under the advanced option. For Ubuntu distribution on Linux OS, run `sudo apt-get install python3.6` on the terminal, and start python3 after installation by typing "`python`".
3. Install pyQuery and Lxml for handling requests and xml/html document types. This can be done by running `pip install pyquery` and `pip install lxml` on the terminal or command prompt.

[10] https://www.python.org/

4. Download the *Optimized-Modified-GetOldTweets3-OMGOT* library on the computer from the repository on GitHub (https://github.com/marquisvictor/Optimized-Modified-GetOldTweets3-OMGOT) or clone it without downloading.
5. Read the script/instructions to understand the algorithm by going through the README file and run the cmd command directly from the folder.
6. Start mining old tweets using any of the command line arguments and one of, or combination of the six *"use cases"* from the README file (see Appendix 1)
7. The tweets would be saved on the computer as an output.csv file. Specify a name to save the downloaded dataset by passing a "name".csv to the "--output argument". If the output cannot fit into a single Excel sheet, multiple .csv files would be generated and saved automatically on the host computer or designated cloud storage.

The command-line arguments used for text mining in this study are shown below.

```
#First Mining for LDA
python GetOldTweets3.py --near "22.3029, 114.1816" --within 4km --lang
es --since 2009-07-01 --until 2019-06-30
```

```
#Second Mining using Keywords for Sentiment Analysis
python GetOldTweets3.py --near "22.3029, 114.1816" --within 4km --lang
es --since 2009-07-01 --until 2019-06-30 --querysearch "keywords"
```

A 3-step Gensim line of command to clean up the big data and eliminate noise.

1. Launch Python and load a copy of the dataset to a panda's data frame

```
df = pd.read_csv('hunghom_v2.csv')
```

2. Carry out basic cleaning to reduce noise like hashtags, stop words and punctuations

```
from nltk.corpus import stopwords
from nltk.stem.wordnet import WordNetLemmatizer
import string

stop = set(stopwords.words('english'))
exclude = set(string.punctuation)
lemma = WordNetLemmatizer()

def clean(doc):
          """this is a basic function that takes
      a document as input and cleans it for further use"""

    stop_free = " ".join([i for i in doc.lower().split() if i not in
stop])
    punc_free = ''.join(ch for ch in stop_free if ch not in exclude)
    normalized = " ".join(lemma.lemmatize(word) for word in
punc_free.split())
    return normalized
```

3. Convert the corpus into a document-term matrix.

```
#Import gensim library
import gensim
from gensim import corpora
#Create the term dictionary for the corpus, where every unique term is
assigned an index.
dictionary = corpora.Dictionary(doc_clean)
#Then, convert the list of documents (corpus) into Document Term Matrix
using dictionary prepared above.
doc_term_matrix = [dictionary.doc2bow(doc) for doc in doc_clean]
```

5.3.2 Topic Modelling using Latent Dirichlet Allocation

Using Latent Dirichlet Allocation (LDA), the top twenty topics were identified from the downloaded corpus. These topics were then used as keywords to re-mine and re-download the data into 20 smaller files for ease of analysis (see *use case 3* in Appendix B). The output is shown in Table 1 below, while the coding scripts are attached in Appendix C. In total, 593,059 tweets were mined and clustered around the top 20 topics (98.01% of the initial mining). The remaining 12,062 tweets were outside of these topics.

Table 5.1 The top 20 topics and their Tweet sizes

Topics	No of Tweets
Lack of social interactions	49,023
Conversion of apartments to Homes with Multiple Occupancy (HMO) & studios	46,576
High rental prices	44,165
Noise pollution	43,982
Segregation and social stratification	37,912
Defacing the neighbourhood with graffiti, posters, and writings	36,734
High cost of living (goods and services)	34,605
Congestion and overcrowding	33,699
The influence of social and cultural diversity	32,275
Community youthification	28,901
High rate of commercialization	26,840
Crime and lawlessness	26,067
Structural gentrification	25,004
Waste pollution	23,192
Parking challenges	22,241
Youthification of goods and services	17,949
Air pollution	17,481
Drugs and alcoholism	16,362
Slumification	15,333
Cultural and religious practices and norms	14,718
Total Tweets	**593,059**

5.3.3 Sentiments Analysis using Valence Aware Dictionary for sEntiment Reasoning

Knowing the topics of discussion within the case study is not useful until the sentiments behind the topics are polarized. Sentiment analysis helps the urban planners to know if the discussions are positive, neutral, or negative. Table 5.2 shows the sentiment metrics and the corresponding scores used by VADER and adopted for this study.

Table 5.2 Sentiment Index

Sentiment Metric	**Score**
Positive	0.674
Neutral	0.326
Negative	0.0
Compound	0.735

From the above, Positive, Negative, and Neutral represent polarity scores of the sentences in each tweet. It means that the sentence is 67% positive, 33% neutral, and 0.0% negative. The three polarity scores add up to 1.0. On the other hand, the Compound score is a metric that calculates the sum of all the lexicon ratings which have been normalized between -1 and +1. For better accuracy, the compound score metric is set as follows:

Positive sentiment polarity: compound score > = 0.05

Neutral sentiment polarity: compound score > - 0.05 and < 0.05

Negative sentiment polarity compound score < = - 0.05

The sentiments analysis procedure, parameters, and codes are attached in Appendix 3, while the normalized weighted composite scores (sentiment polarity) for the 20 topics are presented in Table 5.3.

Table 5.3 Normalized weighted composite scores (sentiment polarity) for 593,059 Tweets.

S/N	**Topics**	**negTweets**	**neuTweets**	**posTweets**	**∑Tweets**
1	Lack of social interactions	42,241	5,221	1,561	49,023
2	Conversion of apartments to HMO & studios	25,753	15,002	5,821	46,576
3	High rental prices	33,351	9,752	1,062	44,165
4	Noise pollution	20,541	14,756	8,685	43,982
5	Segregation and social stratification	13,651	17,525	6,736	37,912
6	Defacing the neighbourhood with graffiti, posters, and writings	24,130	8,253	4,351	36,734
7	High cost of living (goods and services)	27,146	6,625	834	34,605

8	Congestion and overcrowding	31,165	1,892	642	33,699
9	The influence of social and cultural diversity	1,241	16,013	15,021	32,275
10	Community youthification	2,534	10,113	16,254	28,901
11	High rate of commercialization	4,257	9,652	12,931	26,840
12	Crime and lawlessness	1,172	15,026	9,869	26,067
13	Structural gentrification	17,211	5,267	2,526	25,004
14	Waste pollution	11,415	4,536	7,241	23,192
15	Parking challenges	1,164	18,921	2,156	22,241
16	Youthification of goods and services	12,524	4,514	911	17,949
17	Air pollution	13,528	3,152	801	17,481
18	Drugs and alcoholism	5,721	9,982	659	16,362
19	Slumification	10,526	3,851	956	15,333
20	Cultural and religious practices and norms	7,956	3,527	3,235	14,718
	Total	**307,227**	**183,580**	**102,252**	**593,059**

The data in Table 5.3 shows the sentiment analysis of each topic and the summation of all the negative, positive, and neutral tweets. This data summarizes Hung Hom residents' views towards issues shown in the top 20 topics for the last ten years. The negative tweets show their displeasures, positive tweets show they are okay or happy with the situation, and neutral tweets represent the views of those who are indifferent about the situation (Alharbi et al., 2018b; Mishra & Rastogi, 2016; Pålsson & Szerszen, 2016). Since urban planners are mainly concerned with challenges communities or cities face, the topics and their negative polarities are clustered around environmental, social, and economic themes. See Table 5.4.

Table 5.4 Thematic clusters with negative polarity scores

Theme	Negative Polarity Scores
Environmental-Related Issues (35%)	
Conversion of apartments to HMO & studios	25,753
Defacing the neighbourhood with graffiti, posters, and writings	24,130
Noise pollution	20,541
Air pollution	13,528
Waste pollution	11,415
Slumification	10,526
Parking challenges	1,164
Social-Related Issues (40%)	
Lack of social interactions	42,241
Congestion and overcrowding	31,165
Structural gentrification	17,211
Segregation and social stratification	13,651
Cultural and religious practices and norms	7,956
Drugs and alcoholism	5,721
Community youthification	2,534
The influence of social and cultural diversity	1,241
Crime and lawlessness	1,172
Economic-Related Issues (25%)	
High rental prices	33,351
High cost of living (goods and services)	27,146
Youthification of goods & services	12,524
High rate of commercialization	4,257

To this point, the whole evidence is based on social media data and machine learning procedures, therefore, there is a need to further validate the claims to reduce bias and error before using the data for informed decision making. The next subsection shows the validation of the data using a survey questionnaire.

5.3.4 Data Validation using Survey Questionnaire

A simple survey questionnaire was used to validate the resident's complaints (topics with negative polarities). The questionnaire was made up of four parts. The first was for collecting the correspondents' biodata, and the last three represent each cluster (environmental, social, and economic). Residents were asked to validate the above claims and rank them using a five-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). A 4-step data analysis framework was used. (1) Cronbach's alpha coefficient test was used to measure the reliability of the scales; (2) the mean value/score ranking technique was used to rank the mean values; (3) standard deviation scores were calculated; and lastly, the mean values were normalized (Normalized value = (mean – minimum mean) / (maximum mean – minimum mean)). According to Darko (2019), topics with normalized mean values ≥ 0.5 should be considered accurate. Statistical Package for Social Sciences (SPSS) v25 was used for the data analysis.

50 questionnaires were administered through a snowballing sampling technique and 42 were retrieved. According to Norusis (2010) and Ott and Longnecker (2015), this number is representative enough. The Cronbach's alpha coefficient was 0.904, which is above the threshold of 0.7 (Norusis, 2010). Table 5 shows the analyzed results of the survey.

Table 5.5: Validation Table

Community Challenges in Hung Hom District, Hong Kong.	Mean Score	Standard Deviation	Normalized Value	Validated Rank	Twitter Rank
High rental prices	4.12	1.005	1.00	1	2
High cost of goods and services	4.07	1.078	0.92	2	4
Congestion and overcrowding	4.02	0.938	0.85	3	3
Lack of social interactions	4.00	0.926	0.82	4	1
Waste Pollution	4.00	0.951	0.82	5	12
Noise Pollution	3.95	0.999	0.74	6	6
Defacing the neighbourhood with graffiti, posters, and writings	3.93	0.856	0.71	7	7
Structural gentrification	3.93	0.910	0.71	8	8

Segregation and social stratification	3.93	0.986	0.71	9	9
Air Pollution	3.88	1.074	0.63	10	10
Parking challenges	3.86	1.014	0.60	11	20
Youthification of goods & services	3.84	0.974	0.57	12	11
Conversion of apartments to HMO & studios	3.83	1.006	0.55	13	5
Slumification	3.83	1.118	0.55	14	13
Cultural and religious practices and norms	3.81	1.226	0.52	15	14
Drugs and Alcoholism	3.81	1.041	0.52	16	15
High rate of commercialization	3.80	1.049	0.51	17	16
Community youthification	3.69	1.094	0.34	18	17
The influence of social and cultural diversity	3.58	1.220	0.17	19	18
Crime and lawlessness	3.47	1.386	0.00	20	19

The mean scores for all the identified topics were above 3.0, however, two of the topics fell below the accepted normalized mean value of ≥ 0.5, which means they were not perceived by the respondents as accurate or critical. The calculated mean ranks also justified the above since the two community challenges also have the lowest mean scores. Overall, there were slight differences between the validated ranking and the sentiment analysis ranking, but the changes were not significant enough, this proves that the social media sentiments were valid, and the proposed framework can be used to identified community challenges remotely.

The top 3 ranked community challenges in Hung Hom were modelled and visualization in the next sub-section for spatiotemporal understanding.

5.3.5 Data Visualization

3D Columns under *Chart Design* on Microsoft Excel (Office 365) were used to generate the sentiment polarity-based models in this subsection. The 3D Columns algorithms give room for visualizing data parsed over months and years. This makes it useful to study community challenges over time and analyze temporal dynamism. The top 3 community challenges in Hung Home were visualized in Figure 5.4 – 5.6.

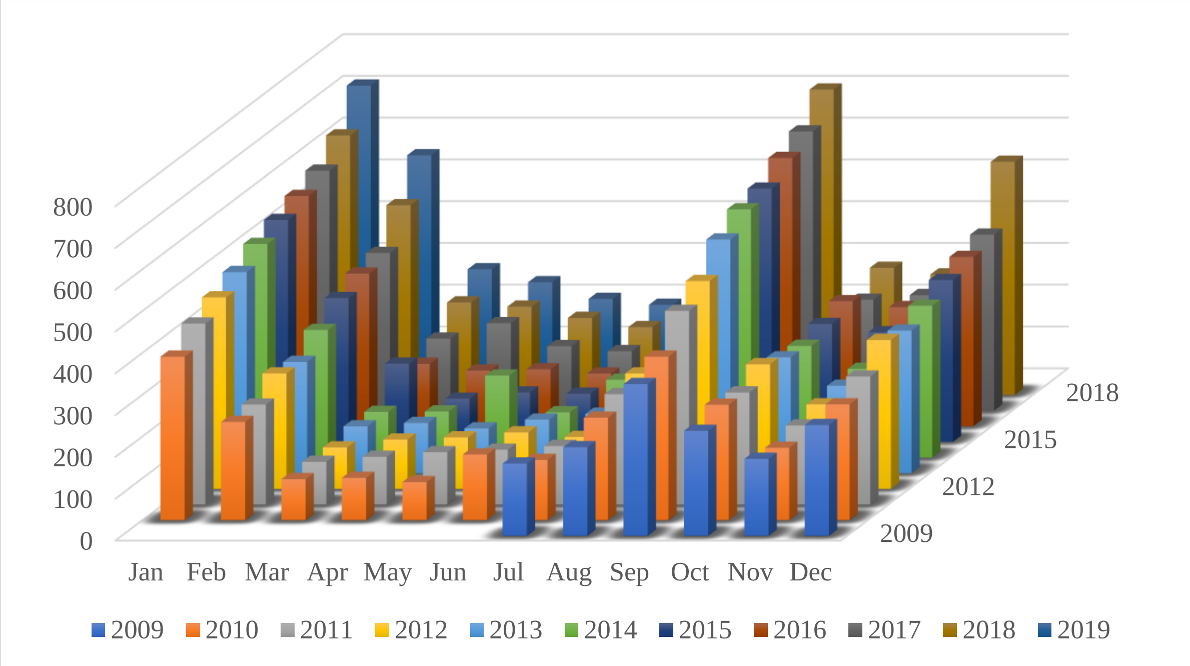

Figure 5.4 Polarity-Based Model for High rental prices

The polarity-based model for high rental prices (Figure 5.4) shows that the complaints on high rental prices have been increasing over the last 10 years, with spikes around September and January every year for the last 10 years. This may be due to the resumption periods of The Hong Kong Polytechnic University (PolyU) when students staying off-campus seek accommodation and increase the demand for housing around the university.

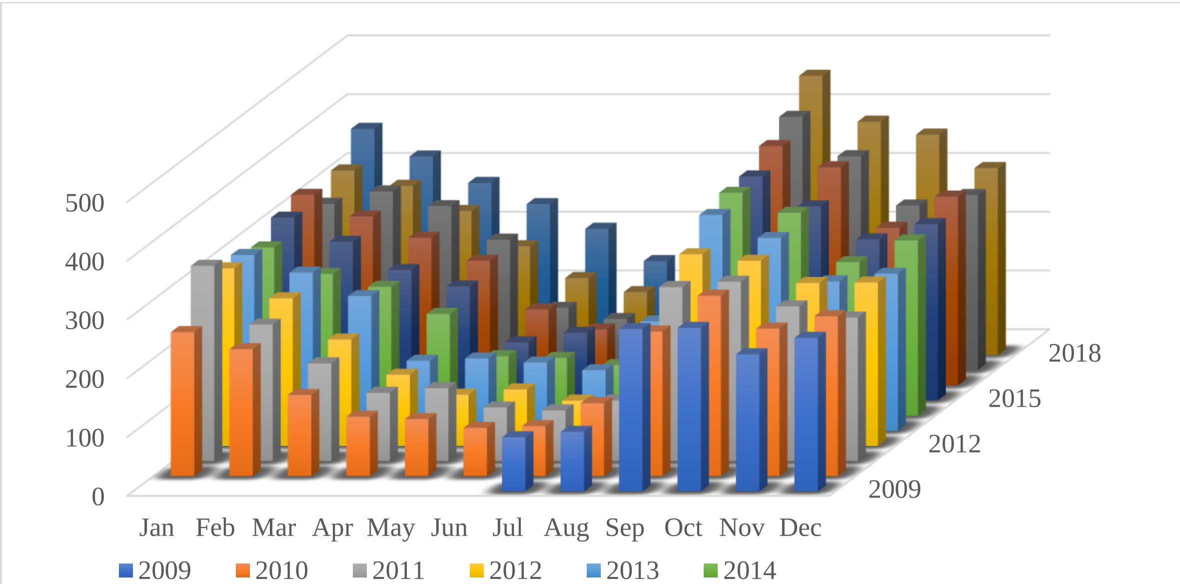

Figure 5.5 Polarity-Based Model for High cost of goods and services

Figure 5.5 represents the model for the high cost of living (goods and services). It also follows the same pattern of gradual increase in frequency over the years and a decrease in complaints during the summer periods when PolyU students are on break. This may be due to the complainers mainly being students or some other variables that require further investigation.

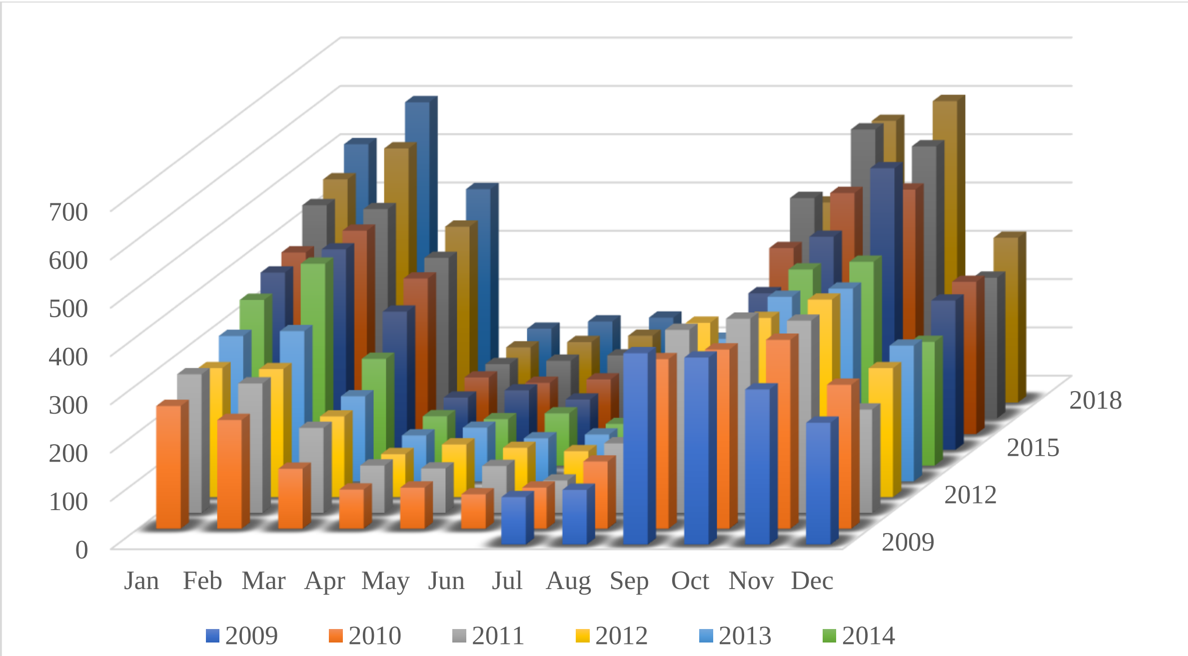

Figure 5.6 Polarity-Based Model for Congestion and overcrowding

The model for congestion and overcrowding in Hung Hom (Figure 5.6) also shows that congestion has been gradually increasing over the years but there is a reduction in complaints usually around April to August each year. This may be attributed to the summer periods when PolyU students are on holiday.

The three models show that the identified problems in Hung Hom district have been increasing over the years and the situation needs to be addressed to create a better community that is socially equitable, environmentally bearable, and economically viable; one that is resilient and sustainable.

5.4 Chapter Summary and Conclusion

This study fulfils its aim of proposing an easy-to-adopt AI-Based Data Pre-Processing Framework for the use of social media textual big data for community resilience assessments. The study demonstrated how textual data can be downloaded from Twitter by bypassing the Twitter API restrictions legally. Using the concept and principles of Grounded Theory, the programmatic algorithms function by web-scraping the Twitter search engine and downloading all messages from a specified case study. LDA was then used to clean the big data and cluster the data around relevant topics. VADER was then used to analyze the polarity of the sentiments around the top 20 topics (Grounded theories). Small data from a questionnaire survey was used to validate the outcomes, and Microsoft Excel was used to visualize three of the final results.

This study contributes to knowledge by demonstrating the processes involved in data mining and processing using Natural Language Processing and Machine Learning. All codes used are Python-based open-source scripts hosted on GitHub for other researchers and professionals to modify and use for free under the GNU General Public License v3.0. The proposed novel framework allows urban planners and community managers to sample millions of opinions easily through the use of social media big data remotely and with fewer resources over a short period. This is exceedingly difficult through traditional methods like surveys. Future works may include the use of Twitter Streaming API and artificial intelligence to make the framework stream twitter data and automatically model and analyze the sentiments in real-time. Another area for future research may include creating a channel through which urban planners can identify influential spreaders within the mined corpus and connect with them to extract more information. This proposed framework is designed to work with Twitter, therefore, there is a need to modify the framework to work on other microblogs like WeChat and Facebook.

The next chapter deploys this framework in 6 case studies to further test its novelty.

CHAPTER 6: CASE STUDIES[11]

This chapter used the *AI-Based Data Pre-Processing Framework* developed in Chapter 5 to assess the studentification challenges in 6 university towns and validates the outcome using data from the international expert survey used in chapter 2.

6.1 Introduction

As the world experiences geometric growth in population and youth bulge in the 21st century, radical changes had to be made to higher education funding in most countries to meet the increasing demand for university education (Brooks et al., 2016; Kinton et al., 2018). In most countries like the United Kingdom and the United States, these changes have also led to a shift in the funding of most Higher Educational Institutions (HEIs) away from the state, which increased the marketization of higher education (Brooks, 2013; Brooks et al., 2016). According to Brooks et al. (2016), this commercialization of higher education starting from the United Kingdom has changed the narratives, and students now "see degrees as private investments rather than public good". To get the best "investment", students now travel far away from home in search of "quality" when making their higher education choices. Related to this, Kinton et al. (2018) emphasized that global competitions among HEIs for student "customers" have made universities more responsive, increased their quality of teachings and increased their focus on providing more conducive learning environments. For students, the framing of "students-as-consumers" clearly extends beyond the selection of universities and courses, to other aspects of university life such as residential decision making, cost of living and students' lifestyle. As a result of the above, there has been a growing global debate on the changing trends of student

[11] This Chapter is under review in Big Data and Society (Sage) as:

1. **Abdul-Rahman, M.**, Chan, E. H. W., & Wong, M. S. Novel use of social media big data and artificial intelligence for Community Resilience Assessment (CRA) in university towns. Big Data & Society. Manuscript ID: BDS-21-0171.

geographies, with housing developments changing from traditional living pathways (on-campus accommodation) to off-campus shared Housing with Multiple Occupancies (HMOs) and Purpose Built Students Accommodation (PBSA) enclaves, which gradually change the morphology of university towns and affect their sustainability (Holton & Riley, 2014; Kinton et al., 2018; Smith et al., 2014).

"Studentification", a term coined by British geographer Darren P. Smith in 2002 which entered the English Macmillan Dictionary as a buzzword in 2004, has been globally used to describe the significant processes of urban change and the challenges university towns face as a result of the growing students' concentration off-campus due to the inability of universities to house all their students within their campuses (Hubbard, 2008; Sage et al., 2012; Smith & Hubbard, 2014; Smith et al., 2014). Some of the impacts of studentification have been well documented in the research corpus for the last two decades, but they were mainly weaved around housing studies. This chapter deploys the AI-Based Data Pre-Processing Framework developed and tested in Chapter 5 to six case studies, to further test the viability and reliability of the programmatic algorithms. The six university towns chosen as case studies include Loughborough in Leicestershire, UK, Akoka in Lagos, Nigeria, Ann Arbor in Michigan, USA, Hung Hom in Kowloon, Hong Kong, Sydney in New South Wales, Australia and Aguita de la Perdiz in Concepcion, Chile. These towns were selected because they have the highest studentification user-generated content in each continent based on Twitter big data.

This chapter gives a global overview of the challenges university towns face due to studentification beyond the housing issues often discussed in studentification studies and shows that AI and social media big data can provide an easy, cheap, and more accurate way of conducting community resilience assessments.

Figure 6.1 Map showing the location of the six case studies. **Source**: Authors' fieldwork

6.2 Material and Methods

This chapter uses the framework developed in Chapter 5, however, apart from adapting the framework to identify and assess the negative impacts of studentification in six case studies, the validation step was also modified to online expert validation. This makes the validation step easier and faster.

For validation, this chapter uses data from section B of the international questionnaire survey.

6.3 Results

6.3.1 Data mining using the Optimized-Modified-GetOldTweets3-OMGOT library

10 years of Twitter historic UGC within the six case study areas was downloaded (from 01 January 2010 to 31 December 2020). A total of 4,577,107 tweets containing slags and emojis and their metadata (usernames, permalinks, replies, favourites, dates, etc) were mined from all case studies. See Table 1 in Supplementary Data for the breakdown of the tweets per case study and Appendix A for the codes used for text mining and data cleaning.

Table 6.1 Case studies and the number of tweets downloaded

S/N	Case study	Number of Tweets (UGC) mined	
		First mining	**Based on topics**
1	Loughborough, UK	1,297,112	1,292,011
2	Ann Arbor, USA	1,052,425	1,049,385
3	Akoka, Nigeria	936,575	935,822
4	Hung Hom, Hong Kong	724,055	721,776
5	Sydney, Australia	502,615	498,473
6	Aguita de la Perdiz, Chile	64,325	63,844
	Total	4,577,107	4,561,311

45 topics were identified from the first mining datasets combined (total) using LDA. The topic modelling was also done per case study. 31 of the 45 topics match those from Loughborough's data, 28 from Ann Arbor, 35 from Akoka, 18 from Hung Hom, 22 from Sydney and 17 from Aguita de la Perdiz. The data mining was then repeated in the case studies based on each topic found in the case studies using case 3 of the *Optimized-Modified-GetOldTweets3-OMGOT* library (see Chapter 3 and Abdul-Rahman et al. (2020)). In total, 4,561,311 tweets were mined under the 45 topics (99.65% of the first mining). 15,796 tweets were automatically excluded because they did not fit into any of the major 45 topic clusters and the topics they were under didn't have significant data under them.

Table 6.2 45 topics generated from the big data mined from the 6 case study areas

Theme	Code	Generated Topics	Number of mined tweets per case study					
			Lough-borough	Ann Arbor	Akoka	Hung Hom	Sydney	Aguita de la Perdiz
Cultural	C01	Demographic changes leading to more youths	30,178	21,553	8,173	29,324	21,003	-
	C02	Declining moral and community values	18,526	-	-	-	-	2,520
	C03	Lack of community cohesion and integration due to the transient nature of the student population	16,124	-	8,062	-	8,352	-
	C04	Aversion of crime and barriers to community policing caused by a transient population	-	22,652	18,251	-	-	-
	C05	Differing standards of acceptable behaviours by different social groups	-	-	12,335	-	-	2,992
	C06	Cultural diversity and lifestyle conflicts	15,251	25,872	-	48,764	-	-
	C07	Divergent perceptions on what makes up communal obligations	-	-	10,072	-	7,983	-
	C08	Inconsideration and lack of place attachment	21,261	17,008	8,586	-	-	-
	C09	Increased racism, tribalism and religious challenges	-	-	10,611	-	-	-
Social	S01	Increased anti-social behaviour and social disorder.	116,352	72,555	70,055	-	40,021	-
	S02	High level of crime due to the vulnerability & carelessness of the youthful population	-	26,881	9,356	27,013	-	4,144
	S03	Increased level of alcoholism, drugs peddling and abuse.	65,444	57,637	47,014	17,271	25,551	4,252
	S04	Increased level of prostitution and sexually transmitted diseases	-	-	42,625	-	-	-
	S05	Loss of social services like reduction in catchment areas for public schools & elderly care	15,009	27,321	-	-	-	-
	S06	Marginalization of permanent residents	-	30,764	-	-	18,562	-
	S07	Displacement/replacement of established residents (gentrification)	18,111	50,002	18,152	26,962	39,623	4,592
	S08	Increased competition for privately rented apartments	14,889	31,666	9,176	-	7,063	-
	S09	Lack of year-round goods & services due to the resort-economy nature of the community	-	14,414	8,003	-	-	-
	S10	Establishments of night-time entertainment ventures at the detrimental impacts of residential amenities	14,752	33,111	17,787	-	6,994	-
	S11	Segregation and social stratification	-	17,526	11,773	39,563	-	-
	S12	Lack of social interactions among groups	-	-	-	51,033	-	-
Physical	P01	Illegal subdivision of family homes & apartments into housing with multiple occupancies	142,858	100,369	88,426	51,723	50,522	6,771
	P02	Changes in community land use	21,016	16,336	34,795	-	-	-
	P03	Community slumification due to the decline in housing renovations and environmental maintenance.	71,003	42,732	25,892	16,046	5,627	5,251
	P04	Defacing neighbourhoods with graffiti, posters, writings and rental boards and advertisements	91,251	86,375	16,251	41,324	29,351	5,931
	P05	Congestion and overcrowding on the streets and in public places including shops.	-	-	13,998	34,883	12,413	2,221

	P06	Increased population density	66,521	46,788	9,005	-	32,102	-
	P07	High environmental pollution – Noise, air pollution and indiscriminate waste/garbage disposal	100,526	74,576	58,524	89,261	52,061	7,220
	P08	Increased incidents of protests leading to vandalism of the physical environment.	-	-	9,222	91,222	-	-
	P09	Increased pressure on urban basic services due to higher population than planned for	17,653	10,169	-	-	5,165	-
	P10	On-street parking and traffic congestion	74,251	34,001	-	25,421	14,006	-
	P11	Pressure on public transport	-	-	51,196	-	-	1,942
	P12	Ghost community during off-term periods	11,993	-	20,014	-	-	2,014
Economic	E01	High rental prices	95,267	99,761	81,153	45,999	47,002	5,032
	E02	Lucrative student housing business deters access to affordable housing for non-student residents.	11,782	-	15,551	-	-	-
	E03	Change in consumer behaviour and taste leading to changes in business models & structures.	44,031	16,094	23,623	23,061	5,026	-
	E04	High cost of living (goods and services)	57,220	39,691	76,011	35,752	43,873	4,803
	E05	High influx of commercial activities	40,308	11,452	29,112	27,154	16,021	1,701
	E06	Seasonal demand for students' accommodation	11,506	-	-	-	10,152	-
	E07	Seasonal scarcity of manpower in shops, restaurants, bars, etc	13,991	-	-	-	-	1,441
	E08	Seasonal customer base (on and off term periods)	12,016	-	9,937	-	-	-
	E09	Low tax generation from the community since students are exempted from taxation.	35,478	-	-	-	-	1,017
Institution And Governance	I01	Weak and disjointed community leadership	-	12,007	38,927	-	-	-
	I02	Neglect by politicians due to low voting power.	14,666	-	15,261	-	-	-
	I03	Challenges to existing urban plans and policies	12,777	10,072	8,893	-	-	-
		Total Tweets	**1,292,011**	**1,049,385**	**935,822**	**721,776**	**498,473**	**63,844**
		No of Topics	**31**	**28**	**35**	**18**	**22**	**17**

6.3.2 Sentiments Analysis using VADER

Each tweet within each topic was analysed and classified using the sentiment index in Table 3. Generally, tweets with sentiment matric scores of 0.674 (67%) are regarded as positive. This means the authors (residents or visitors) are satisfied with the situation in the community. Tweets with scores of 0.0326 (33%) are recorded as neutral, meaning the authors (residents and visitors) are indifferent about the situation. On the other hand, tweets with 0.000 scores are negative and represent complaints or displeasures from residents and visitors (Hutto & Gilbert, 2014). The three scores sum up to 1. For better accuracy, the standardized compound matric scores (sums of all the lexicon ratings) are normalized between -1 and +1 (Kumar et al., 2018). This means = or > 0.05 is a positive sentiment polarity, > - 0.05 and < 0.05 is neutral, and = or < - 0.05 is negative.

Within each of the identified topics in each case study, there were positive, neutral and negative UGC tweets. Table 6.3 contains the summations of all normalized and weighted composite scores (sentiment polarity) for each topic. Table 6.4 shows the identified community challenges and their ranks based on the frequency of their negative sentiment polarity. While Figures 6.2, 6.3 and 6.4 show the sentiments polarities in each case study, the thematic cluster of community challenges and intensity of community challenges in each case study respectively.

The codes used for the VADER sentiment analysis are contained in Chapter 5 and Appendix B. See Hutto and Gilbert (2014) for more information on the parameters and scoring of the VADER model on Python.

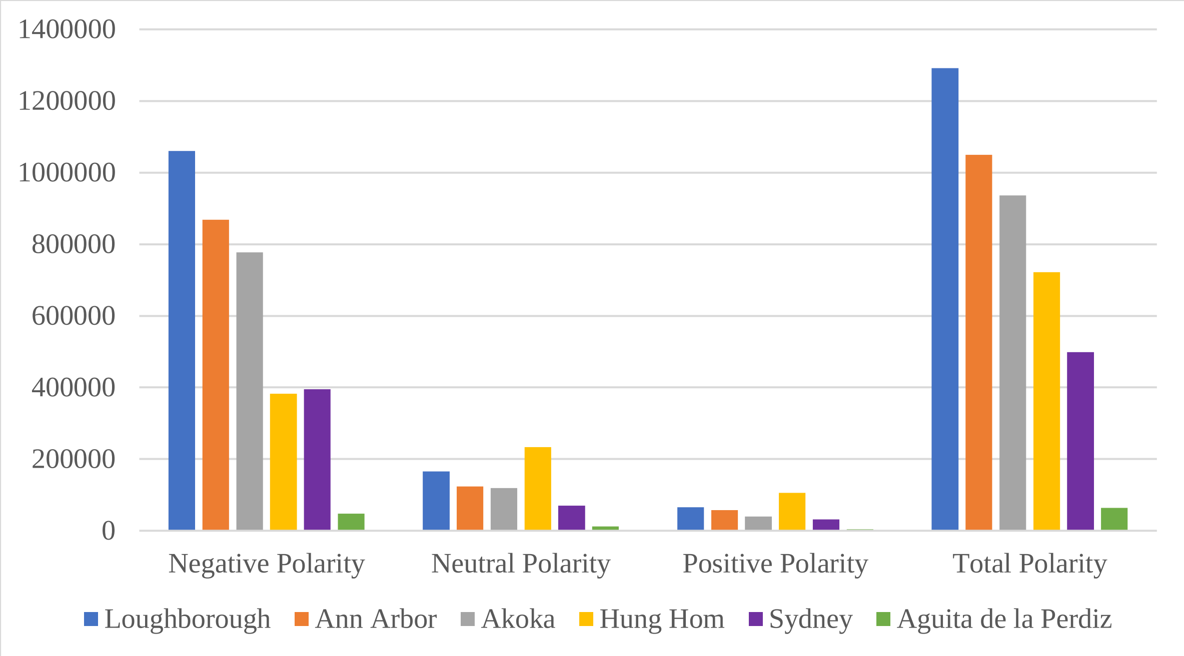

Figure 6.2 Sentiment polarities calculated from the Normalized Weighted Composite Scores (NWCS)

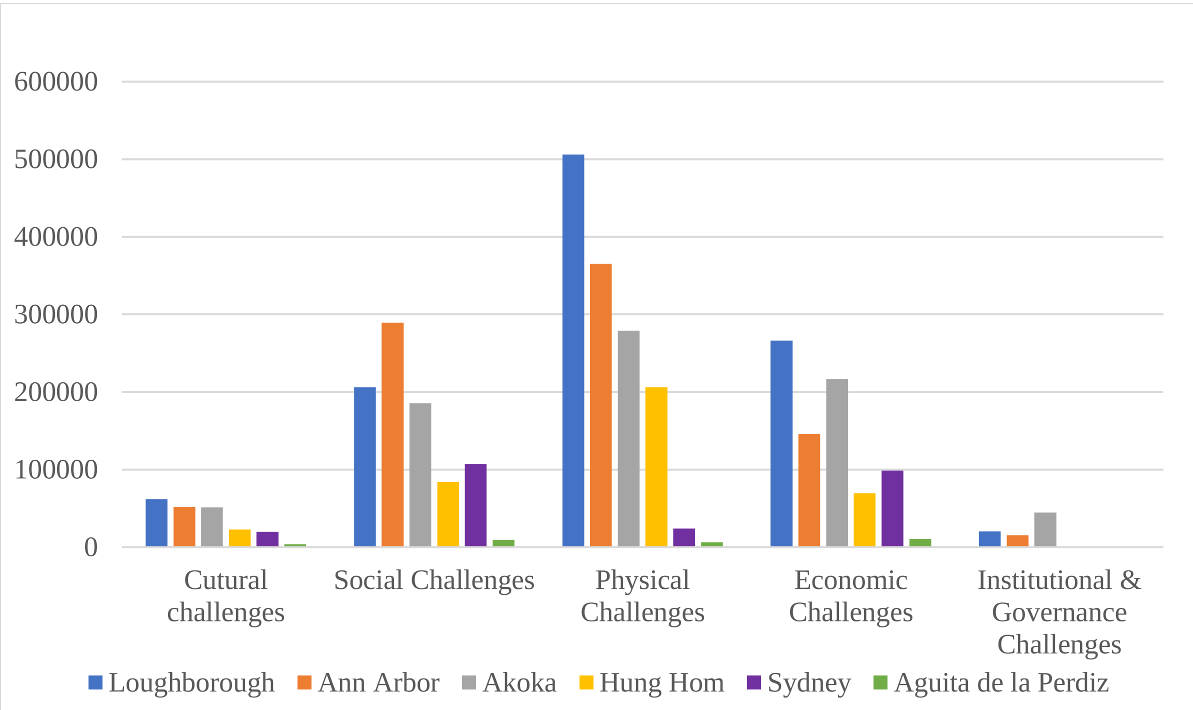

Figure 6.3 Thematic clusters of community challenges in university towns

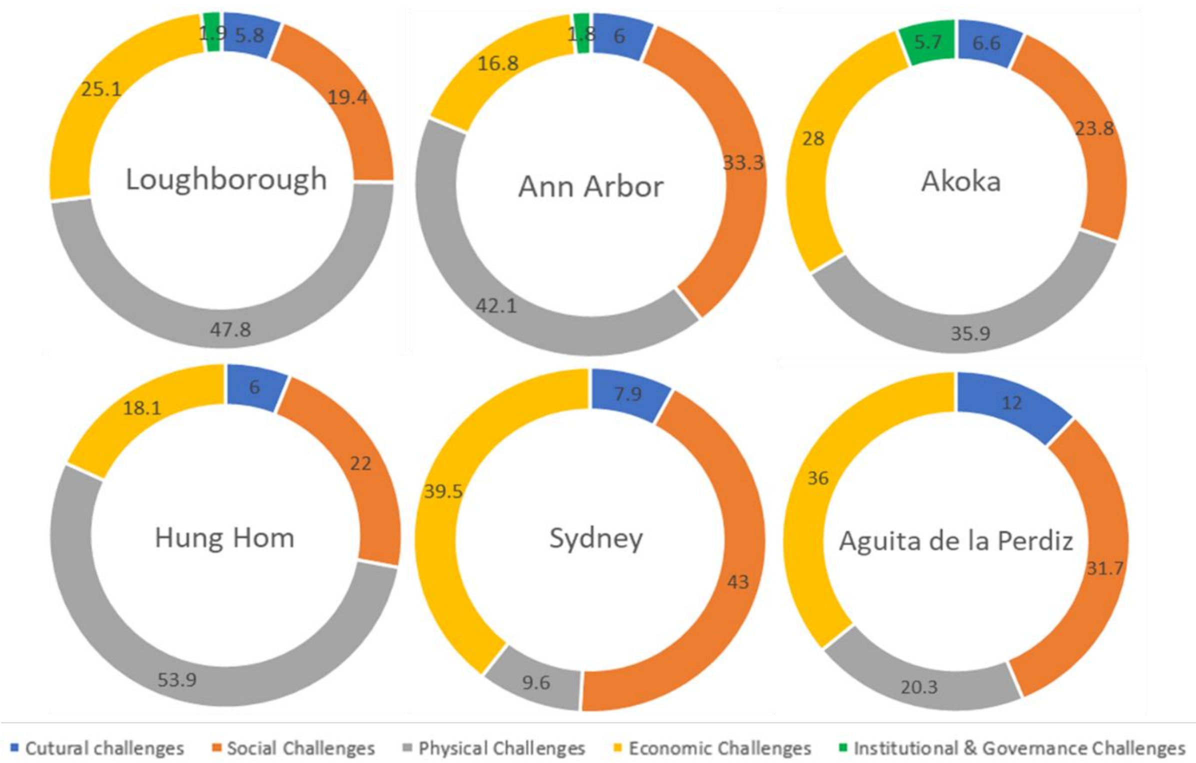

Figure 6.4 Charts showing the intensity of community challenges in percentages in the case studies.

Table 6.3 Sentiment polarity for 4,561,311 tweets mined from six university towns in UK, US, Nigeria, Hong Kong, Australia, and Chile from 01 January 2010 to 31 December 2020

Case Study	S/N	Topics	negTweets	neuTweets	posTweets	∑Tweets
		Cultural				
	1	C01	10,524	14,756	4,898	30,178
	2	C02	16,976	1,492	58	18,526
	3	C03	15,026	1,021	77	16,124
	4	C06	5,652	7,635	1,964	15,251
	5	C08	13,769	7,184	308	21,261
		Social				
	6	S01	110,457	5,715	180	116,352
	7	S03	59,820	4,602	1,022	65,444
	8	S05	8,976	4,792	1,241	15,009
	9	S07	10,872	6,197	1,042	18,111
	10	S08	9,992	2,824	2,073	14,889
	11	S10	5,766	3,624	5,362	14,752
Loughborough, UK		**Physical**				
	12	P01	122,825	17,924	2,109	142,858
	13	P02	15,184	4,625	1,207	21,016
	14	P03	56,625	12,612	1,766	71,003
	15	P04	78,563	11,162	1,526	91,251

	16	P06	46,021	6,012	14,488	66,521
	17	P07	98,852	1645	29	100,526
	18	P09	11,524	5,167	962	17,653
	19	P10	68,066	5,160	1,025	74,251
	20	P12	8,383	2,186	1,424	11,993
		Economic				
	21	E01	91,251	3,164	852	95,267
	22	E02	9,391	1,526	865	11,782
	23	E03	38,726	3,784	1,521	44,031
	24	E04	55,692	1,506	22	57,220
	25	E05	13,668	11,114	15,526	40,308
	26	E06	8,644	2,282	580	11,506
	27	E07	10,536	3,014	441	13,991
	28	E08	8,904	2,511	601	12,016
	29	E09	29,413	5,723	342	35,478
		Institution & Governance				
	30	I02	9,725	3,516	1,425	14,666
	31	I03	10,526	1,526	725	12,777
Total			**1,060,349**	**166,001**	**65,661**	**1,292,011**
Ann Arbor, USA		**Cultural**				
	1	C01	11,241	8,251	2,061	21,553
	2	C04	16,340	5,561	751	22,652
	3	C06	11,514	12,351	2,007	25,872
	3	C08	13,005	3,102	901	17,008
		Social				
	5	S01	70,045	2,414	96	72,555
	6	S02	20,961	4,669	1,251	26,881
	7	S03	53,817	2,619	1,201	57,637
	8	S05	14,769	9,226	3,326	27,321
	9	S06	23,141	5,622	2,001	30,764
	10	S07	48,323	1,627	52	50,002
	11	S08	16,521	9,523	5,622	31,666
	12	S09	9,313	4,098	1,003	14,414
	13	S10	23,816	5,783	3,512	33,111
	14	S11	8,784	4,531	4,211	17,526
		Physical				
	15	P01	97,234	2,152	983	100,369
	16	P02	10,238	4,242	1,856	16,336
	17	P03	40,711	1,400	621	42,732
	18	P04	79,518	4,343	2,514	86,375
	19	P06	27,825	7,551	11,412	46,788
	20	P07	73,512	1,008	56	74,576

	21	P09	8,075	1,523	571	10,169
	22	P10	28,029	5,161	811	34,001
		Economics				
	23	E01	92,562	5,044	2,155	99,761
	24	E03	11,164	3,509	1,421	16,094
	25	E04	36,543	2,131	1,017	39,691
	26	E05	5,729	1,217	4,506	11,452
		Institution & Governance				
	27	I01	8,674	2,451	882	12,007
	28	I03	6,751	2,328	993	10,072
Total			**868,155**	**123,437**	**57,793**	**1,049,385**
Akoka, Nigeria		**Cultural**				
	1	C01	4,526	2,643	1,004	8,173
	2	C03	7,022	1,012	28	8,062
	3	C04	13,352	4,478	421	18,251
	4	C05	5,521	6,104	710	12,335
	5	C07	5,202	3,758	1,112	10,072
	6	C08	7,158	1395	33	8,586
	7	C09	8,520	1,241	850	10,611
		Social				
	8	S01	61,503	8,109	443	70,055
	9	S02	8,111	733	512	9,356
	10	S03	44,874	2,012	128	47,014
	11	S04	28,777	12,824	1,024	42,625
	12	S07	11,741	5,539	872	18,152
	13	S08	5,545	2,368	1,263	9,176
	14	S09	4,799	3,000	204	8,003
	15	S10	11,900	3,776	2,111	17,787
	16	S11	8,012	3,652	109	11,773
		Physical				
	17	P01	79,721	2,254	6,451	88,426
	18	P02	31,041	1,782	1,972	34,795
	19	P03	18,955	6,645	292	25,892
	20	P04	8,563	5,172	2,516	16,251
	21	P05	8,934	4,441	623	13,998
	22	P06	5,662	2,120	1,223	9,005
	23	P07	57,204	1,217	103	58,524
	24	P08	4,726	3,512	984	9,222
	25	P11	48,461	2,583	152	51,196
	26	P12	15,965	3,026	1,023	20,014
		Economic				
	27	E01	79,176	1326	651	81,153

	28	E02	10,672	1,231	3,648	15,551
	29	E03	19,980	2,641	1,002	23,623
	30	E04	74,590	1,320	101	76,011
	31	E05	24,432	562	4,118	29,112
	32	E08	7,821	1,085	1,031	9,937
		Institution & Governance				
	33	I01	28,731	9,204	992	38,927
	34	I02	8,882	4,516	1,863	15,261
	35	I03	6,993	1,682	218	8,893
Total			**777,072**	**118,963**	**39,787**	**935,822**
Hung Hom, Hong Kong		**Cultural**				
	1	C01	6,632	20,571	2,121	29,324
	2	C06	16,261	15,751	16,752	48,764
		Social				
	3	S02	2,301	16,304	8,408	27,013
	4	S03	6,015	10,502	754	17,271
	5	S07	18,027	6,232	2,703	26,962
	6	S11	14,222	18,150	7,191	39,563
	7	S12	43,452	5,798	1,783	51,033
		Physical				
	8	P01	29,522	16,025	6,176	51,723
	9	P03	11,032	4,002	1,012	16,046
	10	P04	26,821	9,991	4,512	41,324
	11	P05	31,992	2,016	875	34,883
	12	P07	47,885	23,653	17,723	89,261
	13	P08	56,623	18,637	15,962	91,222
	14	P10	2,162	20,015	3,244	25,421
		Economic				
	15	E01	34,112	10,681	1,206	45,999
	16	E03	2,572	18,618	1,871	23,061
	17	E04	28,190	7,074	488	35,752
	18	E05	4,332	9,801	13,021	27,154
Total			**382,153**	**233,821**	**105,802**	**721,776**
		Cultural				
	1	C01	11,465	2,215	7,323	21,003
	2	C03	6,013	2,120	219	8,352
	3	C07	2,190	4,542	1,251	7,983
		Social				
	4	S01	33,231	6,559	231	40,021
	5	S03	22,338	2,451	762	25,551
	6	S06	11,526	5,632	1,404	18,562
	7	S07	33,243	4,237	2,143	39,623

Sydney, Australia	8	S08	4,046	2,516	501	7,063
	9	S10	2,981	1,621	2,392	6,994
		Physical				
	10	P01	47,031	3,020	471	50,522
	11	P03	4,234	1,251	142	5,627
	12	P04	25,123	3,203	1025	29,351
	13	P05	4,220	6,142	2,051	12,413
	14	P06	26,410	5,171	521	32,102
	15	P07	48,921	2,422	718	52,061
	16	P09	2,722	1,421	1022	5,165
	17	P10	11,102	1,403	1,501	14,006
		Economic				
	18	E01	43,484	1,206	2,312	47,002
	19	E03	2,961	1,341	724	5,026
	20	E04	39,991	2,871	1011	43,873
	21	E05	8,420	4,350	3251	16,021
	22	E06	3,771	4,520	1,861	10,152
Total			**395,423**	**70,214**	**31,836**	**498,473**
Aguita de la Perdiz, Chile		**Cultural**				
	1	C02	1,521	745	254	2,520
	2	C05	2,011	471	510	2,992
		Social				
	3	S02	3,124	859	161	4,144
	4	S03	2,861	1,050	341	4,252
	5	S07	3,405	1015	172	4,592
		Physical				
	6	P01	5,412	1,251	108	6,771
	7	P03	4,439	721	91	5,251
	8	P04	5,039	681	211	5,931
	9	P05	1,424	742	55	2,221
	10	P07	5,697	1,462	61	7,220
	11	P11	1,265	564	113	1,942
	12	P12	1,123	558	333	2,014
		Economic				
	13	E01	4,571	424	37	5,032
	14	E04	3,961	751	91	4,803
	15	E05	516	224	961	1,701
	16	E07	1,003	350	88	1,441
	17	E09	571	335	111	1,017
Total			**47,943**	**12,203**	**3,698**	**63,844**

Table 6.4 Identified community challenges and their ranks based on the frequency of their negative sentiment polarity from VADER.

Code	Community challenges	Frequency (Negative Sentiment Polarity)	Ranking within case studies						VADER Overall Rank
			Lough-borough	Ann Arbor	Akoka	Hung Hom	Sydney	Aguita de la Perdiz	
P01	Illegal subdivision of family homes & apartments into housing with multiple occupancies	381,745	1	1	1	3	2	2	1
E01	High rental prices	345,156	4	2	2	6	3	5	2
P07	High environmental pollution – Noise, air pollution and indiscriminate waste/garbage disposal	332,071	3	4	5	2	1	1	3
S01	Increased anti-social behaviour and social disorder.	275,236	2	5	4	-	5	-	4
E04	High cost of living (goods and services)	238,967	10	9	3	9	4	6	5
P04	Defacing neighborhoods with graffiti, posters, writings and rental boards and advertisements	223,627	5	3	18	7	8	3	6
S03	Increased level of alcoholism, drugs peddling and abuse.	189,725	9	6	7	17	9	8	7
P03	Community slumification due to decline in housing renovations and environmental maintenance	135,996	7	8	12	18	20	4	8
S07	Displacement/replacement of established residents (gentrification)	125,611	18	7	16	14	6	7	9
P10	On-street parking and traffic congestion	109,359	6	11	-	15	13	-	10
P06	Increased population density	105,918	8	10	30	-	7	-	11
E03	Change in consumer behaviour and taste leading to changes in business models & structures.	75,403	11	23	13	16	22	-	12
P08	Increased incidents of protests leading to vandalism of the physical environment.	61,349	-	-	28	1	-	-	13
E05	High influx of commercial activities	57,097	12	26	11	12	12	15	14
P02	Changes in community land use	56,463	16	22	10	-	-	-	15
P11	Pressure on public transport	49,726	-	-	6	-	-	14	16
P05	Congestion and overcrowding on the streets and in public places including shops.	46,570	-	-	21	10	14	12	17
S10	Establishments of night-time entertainment ventures at the detrimental impacts of residential amenities	44,463	24	12	17	-	19	-	18
C01	Demographic changes leading to more youths	44,388	14	19	33	11	10	-	19
S12	Lack of social interactions among groups	43,452	-	-	-	4	-	-	20

I01	Weak and disjointed community leadership	37,405	-	25	9	-		-	21
S08	Increased competition for privately rented apartments	36,104	23	13	29	-	18	-	22
S06	Marginalization of permanent residents	34,667	-	14	-	-	11	-	23
S02	High level of crime due to the vulnerability & carelessness of the youthful population	34,497	-	16	27	13	-	9	24
C08	Inconsideration and lack of place attachment	33,932	15	21	32		-	-	25
C06	Cultural diversity and lifestyle conflicts	33,427	21	17		5	-	-	26
S11	Segregation and social stratification	31,018		20	23	8	-	-	27
E09	Low tax generation from the community since students are exempted from taxation.	29,984	13	-	-	-	-	17	28
C04	Aversion of crime and barriers to community policing caused by a transient population	29692	-	18	15	-	-	-	29
S04	Increased level of prostitution and sexually transmitted diseases	28,777	-	-	8	-	-	-	30
C03	Lack of community cohesion and integration due to the transient nature of the student population	28,061	20	-	34	-	16	-	31
P12	Ghost community during off-term periods	25,471	29	-	14	-	-	13	32
I03	Challenges to existing urban plans and policies	24,270	27	28	31	-	-	-	33
S05	Loss of social services like reduction in catchment areas for public schools, elderly care, etc	23,745	22	15	-	-	-	-	34
P09	Increased pressure on urban basic services due to higher population than planned for	22,321	19	27	-	-	21	-	35
E02	Lucrative student housing business deters access to affordable housing for non-student residents.	20,063	30	-	19	-	-	-	36
I02	Neglect by politicians due to low voting power.	18,607	25	-	20	-	-	-	37
C02	Declining moral and community values	18,497	17	-	-	-	-	11	38
E08	Seasonal customer base (on and off term periods)	16,725	28	-	26	-	-	-	39
S09	Lack of year-round goods & services due to the resort-economy nature of the community	14,112	-	24	35	-	-	-	40
E06	Seasonal demand for students' accommodation	12,415	31	-	-	-	15	-	41
E07	Seasonal scarcity of manpower in shops, restaurants, bars, etc	11,539	26	-	-	-	-	16	42
C09	Increased racism, tribalism and religious challenges	8,520	-	-	24	-	-	--	43
C05	Differing standards of acceptable behaviours by different social groups	7,532	-	-	22	-	-	10	44
C07	Divergent perceptions on what makes up communal obligations	7,392	-	-	25	-	17	-	45

6.4 Result validation

Data for this validation was collected through an international expert survey. See chapter 3, section 3.2.2 for the survey procedure, respondents' profile and other details. Section B of the 392 valid questionnaires received from the 23 countries was analysed and used for this chapter. The questionnaire is attached as Appendix A.

The Cronbach's alpha for section B was 0.879 (all the questionnaire surveys) and 0.803 (only those from the 6 case study countries). By statistical standards, Cronbach's alpha scores above 0.7 are accepted (Norusis, 2010). The mean values, standard deviation scores, normalized mean values, and ranking of all community challenges are shown in Table 6.5. All the mean values and normalized mean values were more than the 3.5 and 0.5 average (Darko, 2019) respectively. This means none of the 45 community challenges was collectively rejected by the 392 experts.

Table 6.5 Validated and ranked community challenges in university towns

Code	Community challenges	VADER Overall Rank	Ranking by experts in all 23 countries				Ranking by experts in the 6 countries			
			Mean Value	Standard Deviation	Normalized Mean Value	Rank	Mean Value	Standard Deviation	Normalized Mean Value	Rank
P01	Illegal subdivision of family homes & apartments into housing with multiple occupancies	1	4.172	1.241	0.976	2	4.190	1.062	0.998	3
E01	High rental prices	2	4.186	0.962	1.000	1	4.191	0.224	1.000	1
P07	High environmental pollution – Noise, air pollution and indiscriminate waste/garbage disposal	3	4.156	0.921	0.949	5	4.190	0.862	0.998	2
S01	Increased anti-social behaviour and social disorder.	4	4.160	1.231	0.956	3	4.158	0.251	0.945	6
E04	High cost of living (goods and services)	5	4.156	0.288	0.949	4	4.181	0.413	0.983	4
P04	Defacing neighbourhoods with graffiti, posters, writings and rental boards and advertisements	6	4.149	0.081	0.937	7	4.140	0.613	0.915	8
S03	Increased level of alcoholism, drugs peddling and abuse	7	4.147	0.112	0.934	9	4.131	0.251	0.900	10
P03	Community slumification due to the decline in housing renovations and environmental maintenance	8	4.152	0.177	0.942	6	4.173	0.571	0.970	5
S07	Displacement/replacement of established residents (gentrification)	9	4.141	0.167	0.924	10	4.135	0.155	0.907	9
P10	On-street parking and traffic congestion	10	4.149	0.231	0.937	8	4.141	0.352	0.917	7
P06	Increased population density	11	4.132	1.003	0.908	13	4.122	1.216	0.885	12
E03	Change in consumer behaviour and taste leading to changes in business models & structures.	12	4.119	0.315	0.886	17	4.128	1.008	0.895	11
P08	Increased incidents of protests leading to vandalism of the physical environment.	13	4.101	0.432	0.856	20	4.093	0.251	0.837	17
E05	High influx of commercial activities	14	4.139	0.152	0.920	11	4.115	0.624	0.874	13
P02	Changes in community land use	15	4.129	1.085	0.903	14	4.100	0.263	0.849	15
P11	Pressure on public transport	16	4.125	0.155	0.896	15	4.109	0.213	0.864	14
P05	Congestion and overcrowding on the streets and in public places including shops.	17	4.135	0.262	0.913	12	4.096	0.362	0.842	16
S10	Establishments of night-time entertainment ventures at the detrimental impacts of residential amenities	18	4.112	0.332	0.874	18	4.087	1.201	0.827	19
C01	Demographic changes leading to more youths	19	4.122	0.421	0.891	16	4.081	0.521	0.817	20
S12	Lack of social interactions among groups	20	4.112	1.025	0.874	19	4.090	0.241	0.832	18
I01	Weak and disjointed community leadership	21	4.084	1.045	0.827	25	4.055	0.914	0.774	28
S08	Increased competition for privately rented apartments	22	4.090	0.128	0.837	23	4.069	0.269	0.797	24
S06	Marginalization of permanent residents	23	4.055	0.261	0.778	30	4.079	0.323	0.814	21

S02	High level of crime due to the vulnerability & carelessness of the youthful population	24	4.058	0.383	0.783	29	4.058	0.824	0.779	27
C08	Inconsideration and lack of place attachment	25	4.081	0.056	0.822	26	4.061	0.731	0.784	26
C06	Cultural diversity and lifestyle conflicts	26	4.087	0.199	0.832	24	4.075	0.518	0.807	22
S11	Segregation and social stratification	27	4.099	1.074	0.852	21	4.070	0.419	0.799	23
E09	Low tax generation from the community since students are exempted from taxation.	28	4.091	0.361	0.839	22	4.046	0.982	0.759	31
C04	Aversion of crime and barriers to community policing caused by a transient population	29	4.040	1.042	0.752	33	4.050	1.043	0.766	30
S04	Increased level of prostitution and sexually transmitted diseases	30	4.031	1.427	0.737	34	4.041	1.099	0.751	32
C03	Lack of community cohesion and integration due to the transient nature of the student population	31	4.053	1.054	0.774	31	4.051	1.011	0.767	29
P12	Ghost community during off-term periods	32	4.077	1.118	0.815	27	4.063	1.231	0.787	25
I03	Challenges to existing urban plans and policies	33	4.069	1.226	0.801	28	4.019	1.306	0.714	40
S05	Loss of social services like reduction in catchment areas for public schools, elderly care, etc	34	4.011	1.118	0.703	36	4.038	1.082	0.746	34
P09	Increased pressure on urban basic services due to higher population than planned for	35	4.043	1.301	0.757	32	4.038	1.055	0.746	33
E02	Lucrative student housing business deters access to affordable housing for non-student residents.	36	4.011	1.230	0.703	38	4.027	1.070	0.728	38
I02	Neglect by politicians due to low voting power.	37	4.027	1.377	0.730	35	4.027	1.103	0.728	39
C02	Declining moral and community values	38	3.983	1.401	0.655	41	4.029	1.190	0.731	37
E08	Seasonal customer base (on and off term periods)	39	4.008	1.231	0.698	39	3.899	1.222	0.515	43
S09	Lack of year-round goods & services due to the resort-economy nature of the community	40	3.952	1.001	0.603	42	4.034	1.026	0.739	36
E06	Seasonal demand for students’ accommodation	41	3.952	1.007	0.603	43	4.007	1.009	0.694	41
E07	Seasonal scarcity of manpower in shops, restaurants, bars, etc	42	4.011	1.180	0.703	37	4.038	1.231	0.746	35
C09	Increased racism, tribalism and religious challenges	43	3.990	1.220	0.667	40	3.989	1.025	0.664	42
C05	Differing standards of acceptable behaviours by different social groups	44	3.597	1.153	0.000	45	3.899	1.302	0.515	44
C07	Divergent perceptions on what makes up communal obligations	45	3.921	1.032	0.550	44	3.589	1.247	0.000	45

6.5 Discussion

The UGC from the six case studies show that university towns face similar challenges globally. This was confirmed by the experts' validation since none of the community challenges was rejected either by experts within the countries of the case study or those from other countries with experience in community resilience. Some of the community challenges such as increased racism, tribalism and religious challenges (C09) and increased level of prostitution and sexually transmitted diseases (S04) were unique to only Akoka (Nigeria), but the remaining community challenges were reported in at least two of the case studies as seen in Table 6.2.

Loughborough with the highest number of mined UGC (see Table 6.1) has the highest negative polarity (complaints) followed by Ann Arbor, then Akoka, Hung Hom, Sydney and Aguita de la Perdiz (see Figure 6.5). But overall, Akoka has the highest number of community challenges (35 challenges), followed by Loughborough (31 challenges), Ann Arbor (28 challenges), Sydney (22 challenges), Hung Hom (18 challenges) and Aguita de la Perdiz (17 challenges). Thematically, the challenges were grouped into cultural, social, physical (environmental), economic, and institutional and governance challenges. Figure 6.6 shows that most community challenges identified were physical/environmental, followed by social, economic challenges, cultural and institutional and governance challenges, respectively. However, no institutional and governance challenges were identified from the data in Sydney and Aguita de la Perdiz. Figure 6.7 shows that 47.8% of the community challenges identified in Loughborough were physical/environmental, 21.1% have to do with the community's economy, 19.4% were social, 5.8% were cultural and only 1.9% of the community challenges were institutional and governance challenges. In Ann Arbor, 42.1% were physical, 33.3% were social, 16.8% were economic, 6% were cultural and only 1.8% were institutional and governance challenges. Akoka has 35.9% of her identified community challenges as physical, 28% economic, 23.8%

social, 6.6% cultural and 5.7% institutional and governance issues. Hung Hom has more than half of her community challenges (53.9%) as physical, 22% were social, 18.1% were economic and 6% institutional and governance-related challenges. Sydney has 43% social challenges, 39.5% economic, 9.6% physical and 7.9% cultural. Lastly, Aguita de la Perdiz has 36% economic challenges, 31.7% social, 20.3% physical and 12% cultural.

Generally, the overall ranking by the sentiment analyzer (VADER), the ranking by the experts in the 23 countries (total) and those from the 6 case study countries do not differ much. Although the community challenges were ranked slightly different in the three separate rankings as shown in Table 5, the top 10 community challenges remain the same across the three rankings. These top 10 community challenges are; Illegal subdivision of family homes & apartments into housing with multiple occupancies (E01), high environmental pollution – Noise, air pollution and indiscriminate waste/garbage disposal (P07), increased anti-social behaviour and social disorder (S01), high cost of living (goods and services) (E04), defacing neighbourhoods with graffiti, posters, writings and rental boards and advertisements (P04), increased level of alcoholism, drugs peddling and abuse (S03), community slumification due to the decline in housing renovations and environmental maintenance (P03), displacement/replacement of established residents (gentrification) (S07), and on-street parking and traffic congestion (P10).

a. Assessment of all major community resilience dimensions

Communities have complex multiple dimensions (Cimellaro et al., 2016). This novel framework was able to identify and analyses challenges under the five major dimensions of resilience (cultural, social, physical/environmental, economic and institution and governance) in all the university towns.

b. Assessing spatiotemporal dynamism of the community challenges

Capturing time horizons and knowing the specific areas where the residents and visitors' sentiments were generated helps the community managers to assess the challenges better. Since the UGC big data from microblogs like Twitter come with metadata that contains the date and time of tweets generated within a specified spatial radius, the negative polarities can be modelled using Microsoft Excel 3-D Clustered Columns for further analysis and assessment. Figure 6.5 shows a polarity-based model of residents' monthly complaints from January 1st, 2010 to December 31st 2020 in Loughborough, UK. The data for P07 (negative sentiments for Loughborough = 98,852 tweets) in Table 6.3 was grouped into months before it was modelled. The model shows a clear pattern that follows the term periods of Loughborough University and College. The complaints reduce during the summer term and semester three (April to August) and also in December, periods when the university town is almost empty. Over the last 10 years, the complaints about noise and indiscriminate waste disposal have increased in line with the growth of student residents in the town. This model can be generated to analyse every one of the 45 community challenges.

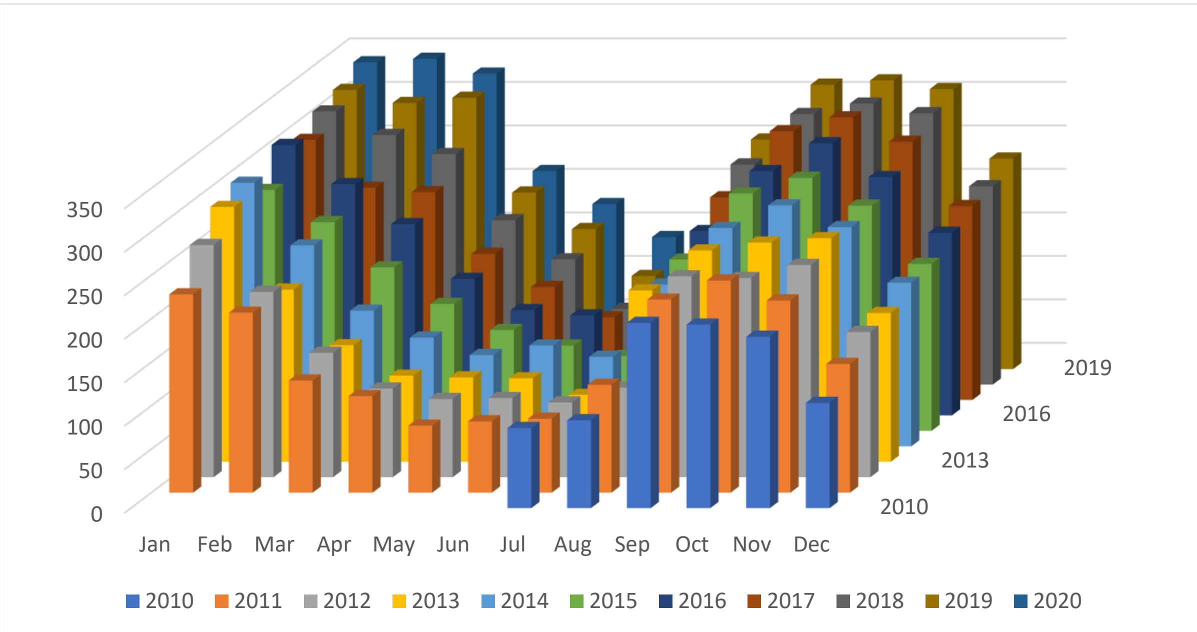

Figure 6.5 Polarity-based model for high environmental pollution (Noise & indiscriminate waste/garbage disposal) in Loughborough, UK.

c. Addressing uncertainties and ensuring public participation

Carrying out longitudinal studies to understand historical events and analysing patterns help to develop better action plans and reduce uncertainties (P. Pringle, 2011). This framework gives room for such assessments and provides an opportunity for sampling the opinions of millions of people concerning community issues. The sampled opinions were from residents, workers, and visitors, regardless of gender, race, age, religion, etc.

6.6 Chapter summary and conclusion

This chapter demonstrated how UGC from microblogs can be used to study community challenges worldwide and remotely using artificial intelligence tools like LDA and VADER.

First, a programmatic algorithm was used to mine the big data using the Twitter API and search engine. Then LDA was used to extract major topics from the data of each case study and the combined big data. These topics were used to re-mine the data, and VADER was used to analyse the sentiment polarity under each topic. The frequencies of the negative Normalized Weighted Composite Scores (NWCS) were used to rank the identified studentification-induced community challenges. An online experts survey was used to validate and rank the negative impacts of studentification globally (all the experts from the 23 countries) and within the case studies by experts only from those countries. Mean ranking, standard deviation and normalized mean values were used to rank the community challenges. The statistical results showed that all the 45 challenges clustered around the 5 community resilience dimensions were accepted as negative impacts of studentification. Apart from being comprehensive enough to identify cultural, social, physical/environmental, economic, and institutional and governance challenges in the university towns, the novel framework also provides deeper spatiotemporal analysis into each community challenge.

The next chapter demonstrates how to develop a *Composite Resilience Index* using Akoka.

CHAPTER 7: A COMPOSITE RESILIENCE INDEX FOR DEVELOPING RESILIENCE AND SUSTAINABILITY IN UNIVERSITY TOWNS[12]

Based on the mined data in Chapter 6, this chapter demonstrates how a localized *Composite Resilience Index* can be developed using AHP and Delphi for any university town. Akoka (Lagos, Nigeria) was selected as a case study.

7.1 Introduction

Studentification refers to the processes of community change and the challenges university towns face as a result of the growing students' concentration off-campus due to the inability of universities to house all their students within their campuses (Hubbard, 2008; Sage et al., 2012; Smith & Hubbard, 2014; Smith et al., 2014). These community changes often have five major dimensions which include cultural, social, physical (environmental), economic, and institution and governance (Smith, 2002, 2006a). Situmorang et al. (2020) posited that studentification leads to neighborhood decay and an increase in rental prices and cost of living, among other negative impacts that result in the gentrification of established residents within the university towns.

Studentification occurs globally in university towns due to several imperatives, which often include; the growth of the knowledge-based economy and the need for a more skilled global workforce (Foote, 2017; Smith, 2008), funding and expansion of Higher Educational Institutions (HEIs) (Foote, 2017), increased mortgage financing, low-interest rates and economic capital (Eshelby, 2015), deregulation in the real estate sector and the encouragement of the private sector to meet the housing deficit in some global economies (Hubbard, 2009),

[12] This Chapter has been developed into a journal paper but still pending submission:

1. **Abdul-Rahman**, M., Chan, E. H. W., & Wong, M. S. A Composite Resilience Index (CRI) for Developing Resilience and Sustainability in University Towns.

lack of adequate statutory enforcement of planning laws and the power to regulate free-market economies (Laidley, 2014), and finally, the shift in global ideologies in the transition from childhood to adulthood and the assumption of the right to attain a college or university degree (Smith & Holt, 2016).

Although studentification is often portrayed as a negative phenomenon both in the media and in the literature, the town-gown relationship is not all parasitic. Some of the benefits of studentification to the university towns and their residents include; the provision of a young and educated workforce, cheaper labour and increased volunteerism (Smith, 2006b), bringing diversity and vibrancy to local cultures and raising the aspirations of the local youths (Smith & Fox, 2019), enhancing the spending power, improving the local economy, creating more jobs and sustaining the local retail businesses (Holton, 2015), supporting the local real estate sector and its associated trades (agency, insurance, finance etc) and driving up demands for quality housing provision (Laidley, 2014), as well as making the town more attractive to tourists and investors (He, 2014). However, shreds of evidence from earlier studies show that the negative impacts of studentification over the years outweigh the benefits (Dewi & Ristianti, 2019; Hu et al., 2019; C. Sun et al., 2018).

To provide a solution, the resilience of the university towns must be increased for the communities within them to identify their challenges and vulnerabilities and build local capacity to withstand the chronic stresses induced by studentification. Resilient communities suffer less from the negative impacts of studentification and can build sustainability easily through absorption of the stresses (through resistance or adaptation), and still be able to maintain their functions (Twigg, 2009). To develop community resilience to studentification, this chapter looked at the challenges Akoka, a university town in Lagos-Nigeria, goes through and proposed a Composite Resilience Index (CRI) by identifying and analyzing the elements of a resilient university town and the risk reduction elements proposed by the town's residents and visitors, using user-generated contents from Twitter, the Delphi method, and Analytical Hierarchy Process (AHP) modelling.

The proposed CRI would help Akoka to become resilient, generally contribute to reducing bias in assessing the level of resilience against studentification, provide a methodology for other university towns to develop their own CRI, and contribute to the resilience body of knowledge.

7.1.1 Studentification in Akoka, Lagos, Nigeria

Akoka, one of the 6 case studies, is located 6°31'40.9"N and 3°23'34.4"E. Akoka is the home to the University of Lagos and the Federal College of Education in Lagos, Nigeria. According to population estimates in 2020, 52,251 people live in Akoka, the majority of which are students and staff of the Higher Educational Institutions (HEIs) (Bondarenko, 2020). The university town has drastically changed over the years to cater for the needs of HEIs located in it and the University of Lagos has taken over the identity of the town.

Data analysis from chapter 6 shows Twitter big data analysis of 935,822 user-generated contents (Tweets) from residents and visitors to the town from 01 January 2010 to 31 December 2020 (10 years). It also shows 35 community resilience challenges the town faces as a result of studentification. The 35 community challenges in Akoka, their ranking by the residents and visitors as well as the result of sentiments analysis (polarities) are presented in Table 7.1. The negative tweets (negTweets) represent displeasure, the neutral tweets (neuTweets) mean the residents are indifferent about the situation, while the positive tweets (posTweets) mostly contain the residents and visitors' views on how to fix the community resilience challenges. This chapter explored the positive tweets to draw out criteria and elements of a resilient community and elements of risk reduction.

These community resilience challenges vary from one university town to the other. Therefore, every CRI needs to be localized based on the specific challenges affecting the university town and the local solutions that work in such a place (Sherrieb et al., 2010; Twigg, 2009).

Figure 7.1 Map of Nigeria showing Lagos and Akoka.

Table 7.1 Twitter Data Analytics (Result from Topic Modelling and Sentiment Analysis of 935,822 Tweets

S/N	Perceived Negative Impacts of Studentification in Akoka, Lagos - Nigeria	Rank	negTweets	neuTweets	posTweets	Σ Tweets
1	Illegal conversion of family apartments to Homes with Multiple Occupancy (HMO) & studios	1	79,721	2,254	6,451	88,426
2	High rental prices	2	79,176	1326	651	81,153
3	High cost of living (goods and services)	3	74,590	1,320	101	76,011
4	Increased anti-social behaviour and social disorder.	4	61,503	8,109	443	70,055
5	High environmental pollution – Noise and indiscriminate waste/garbage disposal	5	57,204	1,217	103	58,524
6	Pressure on public transport (Peak periods and school closing hours)	6	48,461	2,583	152	51,196
7	Increased level of alcoholism, drugs peddling and abuse.	7	44,874	2,012	128	47,014
8	Increased level of prostitution and sexually transmitted diseases	8	28,777	12,824	1,024	42,625
9	Weak and disjointed community leadership	9	28,731	9,204	992	38,927
10	Changes in community land use	10	31,041	1,782	1,972	34,795
11	High influx of informal commercial activities	11	24,432	562	4,118	29,112
12	Community slumification due to the decline in housing renovations and environmental maintenance.	12	18,955	6,645	292	25,892
13	Change in consumer behaviour and taste leading to changes in business models & structures.	13	19,980	2,641	1,002	23,623
14	Ghost community during off-semester periods and holidays	14	15,965	3,026	1,023	20,014
15	Aversion of crime and barriers to community policing caused by a transient population	15	13,352	4,478	421	18,251
16	Displacement/replacement of established residents (gentrification)	16	11,741	5,539	872	18,152
17	Establishments of night-time entertainment ventures at the detrimental impacts of residential amenities	17	11,900	3,776	2,111	17,787
18	Defacing neighbourhoods with graffiti, posters, writings and rental boards and advertisements	18	8,563	5,172	2,516	16,251
19	Lucrative student housing business deters access to affordable housing for non-student residents.	19	10,672	1,231	3,648	15,551
20	Neglect by politicians due to low voting power.	20	8,882	4,516	1,863	15,261
21	Congestion and overcrowding on the streets and in public places including shops.	21	8,934	4,441	623	13,998
22	Differing standards of acceptable behaviours by different social groups	22	5,521	6,104	710	12,335
23	Segregation and social stratification	23	8,012	3,652	109	11,773
24	Increased racism, tribalism, and religious challenges	24	8,520	1,241	850	10,611

25	Divergent perceptions on what makes up communal obligations	25	5,202	3,758	1,112	10,072
26	Seasonal customer base (on and off term periods)	26	7,821	1,085	1,031	9,937
27	High level of crime due to the concentration of vulnerable young people with a lack of security awareness	27	8,111	733	512	9,356
28	Increased incidents of protests leading to vandalism of the physical environment.	28	4,726	3,512	984	9,222
29	Increased competition for privately rented apartments	29	5,545	2,368	1,263	9,176
30	Increased population density	30	5,662	2,120	1,223	9,005
31	Challenges to existing urban plans and policies	31	6,993	1,682	218	8,893
32	Inconsideration and lack of place attachment	32	7,158	1395	33	8,586
33	Demographic changes leading to more youths	33	4,526	2,643	1,004	8,173
34	Lack of community cohesion and integration due to the transient nature of the student population	34	7,022	1,012	28	8,062
35	Seasonal availability of some retail and service provision (resort economy)	35	4,799	3,000	204	8,003
	Total		**777,072**	**118,963**	**39,787**	**935,822**

Key

NegTweets – Negative Tweets

NeuTweets – Neutral Tweets

posTweets – Positive Tweets

Σ Tweets – Total Tweets

7.1.2 Developing a localized Composite Resilience Index based on Analytical Hierarchy Process

Theoretically and conceptually, we adopted the definition of resilience steaming from the ecological resilience concepts (Holling, 1973; Crawford Stanley Holling, 1996; Holling & Gunderson, 2002). This frames community resilience as the ability of the community to withstand or adapt to shocks or stresses, reorganize itself, undergo some structural changes and still be able to maintain its function and identity (B. Walker et al., 2006). Community resilience is often seen as a step closer to risk reduction and sustainability. However, building community resilience remains a challenge despite the numerous theoretical underpinnings over the years due to the complex nature of human communities (as adaptive ecological systems), especially when they are processes and outcomes from the ecological and social perspective (Adger, 2000; Manyena, 2006). To date, only a few studies within the community resilience literature (eg Susan L Cutter et al. (2008); Sherrieb et al. (2010)) provide suggestions on how the ecological resilience concept can be quantified and used to build community resilience at the local level.

This chapter proposed a novel approach to developing a CRI for Akoka, by synthesizing residents and visitors' views on building community resilience into elements of resilient community and risk reduction elements using AHP. AHP is a methodology used to fix complex problems involving multiple scenarios, criteria and actors (Satty, 1980). AHP is a human cognitive tool used to determine the relative importance of alternatives using paired comparison and assigning weights to indicators (Cardona & Carreño, 2011). In the community and resilience nexus, AHP has been used to develop indices for the management of coastlines (Ryu et al., 2011), for solving urban decay (Lee & Chan, 2008) and for disaster resilience, risk reduction and management (Carreño et al., 2007; Chen et al., 2009).

AHP was used in this chapter to prioritize the criteria and elements that best describe a resilient Akoka community from the user-generated contents (Twitter location-based historic big data) containing potential criteria and elements of a resilient community and elements of risk reduction. A framework was designed (Figure 2) and used to determine the outcome indicators of the CRI for resilience against the negative impacts of studentification in Akoka. The use of social media big data to mine the opinions of residents and visitors to the university town as well as using selected members of the town and experts from the HEIs to develop an index using AHP is the first of its kind in Nigeria and the studentification corpus.

7.2 Materials and Methods

A hierarchical framework was proposed with three tiers representing components that best describe a resilient university town in an AHP model (Figure 7.2). The first tier represents the overall goal of the university town or the aim the CRI was designed to achieve (a resilient university town). The second tier contains the criteria determined based on the five community resilience dimensions (Smith, 2002, 2006a). These include Cultural Criteria (CC), Social Criteria (SC), Physical Criteria (PC), Economic Criteria (EC), and Institution and Governance Criteria (IGC). The third and last tier contains attributes elements under each of the criterion in the second tier. These attribute elements include Elements of a Resilient Community (ERC) and Elements of Risk Reduction (ERR). Table 7.2 contains the attribute elements under each criterion.

The number of elements for comparison under each criterion was limited to a maximum of seven as prescribed by Saaty (2000). This empowered the decision-makers to reduce the number of ERC and ERR to a maximum of seven components.

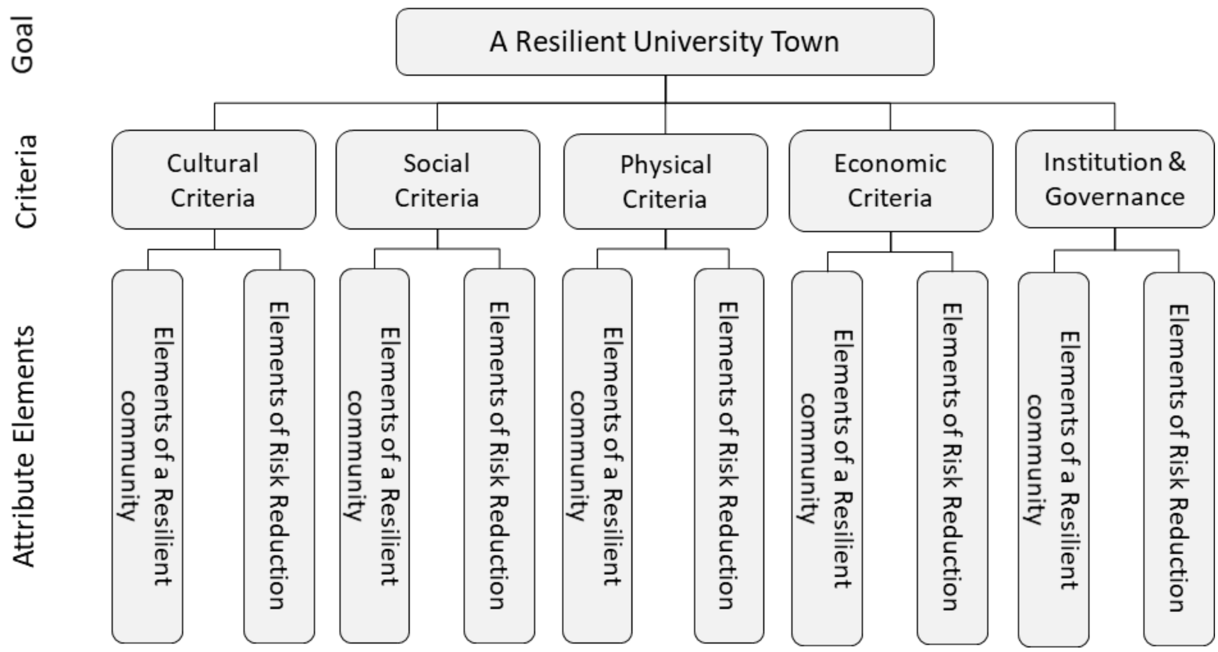

Figure 7.2. The AHP model used for prioritization

Table 7.2 Components of a resilient university town based on residents and visitors' aspiration for Akoka

Criteria		Elements of a Resilient Community (ERC)		Elements of Risk Reduction (ERR).	
CC	Cultural Criteria	CCERC1	Low crime rate and respect for law and order	CCERR1	Effective community co-policing
		CCERC2	Acceptable standards of behaviour by all groups	CCERR2	Increasing the safety and security awareness of the students' community
		CCERC3	Place attachment and considerations for others	CCERR3	Setting community standards and enlightening the public on such standards
		CCERC4	Unified and acceptable communal objectives	CCERR4	Improving social capital within the communities
		CCERC5	Community cohesion between students and non-student residents	CCERR5	Properly integrating students into the local communities through events
		CCERC6	Tribal, racial, and religious tolerance by all	CCERR6	Preaching the gains of cultural and religious diversity within the town
SC	Social Criteria	SCERC1	Orderliness and good social behaviour by all residents	SCERR1	Enacting strict laws to curb social disorders
		SCERC2	Well managed and secure students' clusters	SCERR2	Working with HEIs and property owners to manage off-campus major students clusters
		SCERC3	A drug-free town with reduced alcohol consumption and abuse	SCERR3	Crackdown on drug peddlers and users and enacting laws prohibiting the sale of alcohol to persons under 18
		SCERC4	Zero tolerance for prostitution on and off-campus	SCERR4	Prohibiting & enlightening students against prostitution
		SCERC5	Reduced competition for privately rented apartments	SCERR5	Increasing the number of purpose-built students' accommodation in the town
		SCERC6	Regulated night-time entertainment ventures in the town	SCERR6	Prohibiting the conversion of communal land-uses and commercial properties to cater for students' nightlife
		SCERC7	Protected and well-maintained family leisure parks and amenities		
PC	Physical Criteria	PCERC1	Prohibition of conversion of family homes to housing with multiple occupancies	PCERR1	Enforcement of planning laws that prohibit illegal conversion of land uses and family homes and private apartments to housing with multiple occupancies
		PCERC2	Preservation of the town's original land use according to the masterplan	PCERR2	Urban renewal and upgrade of rundown areas within the town
		PCERC3	Constantly upgraded communities	PCERR3	Increasing the carrying capacities of the existing urban basic services and expansion of shopping/commercial areas
		PCERC4	Reduced congestion and overcrowding in public spaces and commercial areas	PCERR4	Regulating the population density through urban planning and planning laws
		PCERC5	A balanced and well-distributed population density	PCERR5	Reduction of noise pollution from students' clusters
		PCERC6	Reduced environmental pollution	PCERR6	Improving the waste management systems within the town and creating more awareness on waste recycling
		PCERC7	A better public transport system	PCERR7	Improving the traffic management systems, introducing more mass transit buses and working with HEI to schedule the closing hours
EC	Economic Criteria	ECERC1	Regulated rental prices within the university town	ECERR1	Introduction of a rental and price (goods and services) control mechanism in the town
		ECERC2	Provision of more affordable housing for non-students' residents	ECERR2	Creating more opportunities and giving incentives to affordable housing developers to enter the property market in the town
		ECERC3	Affordable cost of living	ECERR3	Setting up a task force to control and regulate informal commercial activities in the town
		ECERC4	Controlled informal commercial activities		
IGC	Institution and Governance Criteria	IGCERC1	Good community leadership	IGCERR1	Participatory leadership involving the local government, non-students' residents, the students' representatives, the HEIs and other groups
		IGCERC2	A politically grounded community	IGCERR2	Giving students who are eligible to vote the right to vote within the community instead of going back to their original homes to vote
		IGCERC3	Up-to-date physical plans and policies	IGCERR3	Periodically review and update the town's master plan

7.2.1 The decision-makers

The twenty-three decision-makers comprised seventeen resilience and sustainability experts from the two HEIs in Akoka, two senior management officers in charge of students' affairs in the two HEIs, one town planner in the local government office and three local community leaders. The studentification phenomenon was easier for them to understand because of its huge impacts on the local communities within the university town and their knowledge and experiences. Delphi method was used for the prioritization process (Chen et al., 2018; Linstone & Turoff, 1975; Skulmoski et al., 2007).

7.2.2 Weights of alternative criteria and elements in the AHP model

The weights of alternative criteria and elements for achieving a resilient university town were calculated in a consistent matrix using paired comparison and ratio-scale. The formula is:

$$\frac{n(n-1)}{2} \qquad (1)$$

Where n = number of alternatives or size of the matrix (a_1, a_2, $a_3 \ldots a_n$). see Saaty (2000) and Vargas (1991).

This study, therefore, had 10 comparisons involving 5 alternative criteria each with 3 to 21 comparisons of alternative elements. The products of the paired comparisons represent the judgements of the decision-makers over another pair based on a pair-wise rating scale (Table 3) with values ranging from 1-9 (Dragićević et al., 2015; Satty, 1980; Vargas, 1991). In cases where decision-makers decide that both alternatives i and j are equally important, the comparison formula becomes aij=aji=1. But when alternative i is considered to be extremely important compared to j, then a_{ij}=9 and a_{ji}-1/9 . The distribution of these score in a square matrix gave us the reciprocal matric in equation 2 (Alonso & Lamata, 2006).

$$A = [a_{ij}] = \begin{Bmatrix} 1 & a_{ij\ldots} & a_{1n} \\ {}^{1}/_{a_{ij}} & 1\ldots & a_{2n} \\ \vdots & \vdots & \vdots \\ {}^{1}/_{a_{1n}} & {}^{1}/_{a_{2n}} & 1 \end{Bmatrix} \tag{2}$$

Where A = [a_{ij}] represents the intensity of decision-makers preferences for one alternative over another a_{ij} and for all compared alternatives ij=1,2,3,4,…n. The comparison was conducted over three rounds until there was stability in the sum of scores. To generate good approximations for the elements' weights for each alternative, comparison scores of the alternative criteria and elements were multiplied in each row of the reciprocal matrix, and taking the nth root of the products as follows:

$$\text{Element weight} = \sqrt[n]{a_{ij} \cdot a_{nj} \cdots a_{nn}} \tag{3}$$

The summations of weights in a column were used to calculate the normalized eigenvector w_{ij} for each alternative as shown below:

$$w_{ij} = \frac{Element\ weight}{\sum Element\ weights\ in\ column} \tag{4}$$

When w_{ij} was multiplied by matrix A or by the maximum eigenvalue λ_{max}, a new priority eigenvector nw_{ij} was formed (Saaty, 1990).

The significance of the criteria and elements in achieving a resilient university town was determined by a high nw_{ij} value for each criterion and element. This is the sum of the products of the normalized w_{ij} in each column and the elements in each row as seen in equation 5.

$$nw_{ij} = \sum\nolimits_{ij=1,2}^{n} a_{ij}\, w_{ij} \tag{5}$$

Since this is a consistent matrix, the values of nw_{ij} for each criterion and element represent the weights.

Table 7.3 The rating scale for pair-wise comparison

Scale	Degree of preference	Explanation
1	An equal level of importance	Two criteria or elements equally contribute to the goal
3	Moderate level of importance	A criterion or element is slightly favoured over another criteria or element
5	Essential level of importance	A criterion or element is strongly favoured over another criteria or element
7	Very strong level of importance	A criterion or element is very strongly favoured over another criteria or element
9	An extreme level of importance	The evidence favouring one criterion or element over another is of the highest possible order of affirmation
2,4,6,8	Intermediate values between alternatives	When a compromise is needed between two criteria or elements

7.2.3 Building consensus on the criteria and elements

The final scores were determined using the Delphi technique (Chiu et al., 2019; Wey & Huang, 2018; Yau & Chiu, 2015). The scores of the paired comparisons for all the criteria and elements were calculated based on their geometric means. All scores were entered into the matrix once a consensus was met. Both nw_{ij} values and the consensus scores were accepted once they meet a certain degree of consistency determined by the Consistency Index (CI) (equation 6 below).

$$CI = (\lambda_{max} - n)/(n - 1) \quad (6)$$

Where λ_{max} is the maximum eigenvalue calculated by taking the average of all eigenvalues and *n* represents the number of criteria and elements listed for prioritization. The eigenvalues are individually calculated using equation 7 below.

$$\lambda = \frac{nw_{ij}}{Normalized\ w_{ij}} \quad (7)$$

The CI was then compared to the consistency Random Index (RI) of the paired comparisons in the matrix to generate the Consistency Ratio (CR) presented in Table 4, using equation 8. The CR is used to determine the acceptability of the scores and weights of the criteria and elements.

A decisionmaker's judgement or prioritization was accepted to be valid if the CR score or weight is ≤ 0.10 (Alonso & Lamata, 2006; Vargas, 1991).

$$CR = \frac{CI}{RI} \tag{8}$$

Table 7.4 Random index of consistency for n = 10 (Saaty, 1990, 2000; Satty, 1980)

Size of matrix (n)	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Random Index (RI)	0.00	0.00	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49

The criteria and elements were selected using a top-down approach. This entails the selection of alternative elements for achieving a resilient university town and subjecting them to comparison once their criteria are prioritized by the decision-makers. New nw_{ij} values with consistency ratios ≤ 0.10 (now assigned as respective weights) are used for ranking both the criteria and elements within the AHP model.

Within the AHP model, an analytical process was used to adopt criteria and elements with ≥ 70 per cent representation within the second and third tier of the model. This percentage was introduced to provide an optimal number of components in each hierarchy and to reduce the criteria and elements to only those with high importance for the achievement of the overall community goal in tier one. Criteria and elements below this benchmark were discarded. The percentage represents the sum of the ratio of individual criteria and elements weights and the overall weight, as expressed in the equation:

$$\sum \frac{Individual\ nw_{ij}}{Overall\ nw_{ij}} \geq 70\% \tag{9}$$

7.3 Results

The matrix at the second tier of the AHP model (criteria for building a resilient community) was consistent with a CR value of 0.07 (Table 5). From the computed weights, "Physical Criteria (PC)" and "Institutional and Governance Criteria (IGC)" ranked the highest and lowest respectively. The top-ranked criteria; “Physical Criteria (PC)”, “Economic Criteria (EC)”, “Social Criteria (SC)” and “Cultural Criteria (CC)” were picked based on the sum of their weights which represented 92% of the total weights in tier two of the AHP model. The alternative elements of these four criteria were further subjected to prioritization and selection. Elements of a resilient community; PCERC1, PCERC3, PCERC4, PCERC6 and PCERC7 and elements for risk reduction; PCERR5, PCERR6, PCERR1, PCERR3 and PCERR7 make up 90% and 81% respectively of the Physical Criteria (PC) for achieving a resilient university town. Both groups of elements have CR scores of 0.03 and 0.10 (Table 6).

Prioritizations were further conducted for Economic Criteria (EC), Social Criteria (SC) and Cultural Criteria (CC) as shown in Table 6. For economic criteria (EC), elements of a resilient community; ECERC3, ECERC1 and ECERC4 and elements for risk reduction ECERR1, ECERR2 and ECERR3 represented 81% and 99% of the total elements respectively. Both groups also have 0.07 and 0.09 CR scores.

For social criteria (SC), the elements SCERC1, SCERC3, SCERC6, SCERC2 and SCERC4 were selected as elements of a resilient community, while SCERR1, SCERR3 and SCERR5 were selected as elements of risk reduction (Table 6). Both groups of elements accounted for 88% and 74% and have 0.07 and 0.02 CR scores respectively. Finally, the elements of a resilient community CCERC1, CCERC3, CCERC5 and CCERC6, and risk reduction elements CCERR1, CCERR5, CCERR4 and CCERR6 (Table 6) accounted for 83% and 80% respectively of all attributes within the Physical Criteria for achieving a resilient university town. Both groups of elements have CR scores of 0.07 and 0.08 respectively.

Table 7.5 Ranking the criteria for a resilient university town using weights (priority vector values nw_{ij})

Code	Criteria	Weight	Rank
CC	Cultural criteria	0.73	4
SC	Social criteria	0.88	3
PC	Physical criteria	1.81	1
EC	Economic criteria	1.49	2
IGC	Institution and governance criteria	0.40	5
		λ_{max} = 4.12	
		CI = 0.08	
		CR = 0.07	

Table 7.6 Ranks and weights of the elements that make up the selected criteria for a resilient university town

Criteria	Elements of a Resilient Community (ERC)		Weights	Ranks	Elements of Risk Reduction (ERR)		Weights	Ranks
PC	PCERC1	Prohibition of conversion of family homes to housing with multiple occupancies	1.55	1	PCERR1	Enforcement of planning laws that prohibit illegal conversion of land uses and family homes and private apartments to housing with multiple occupancies	1.22	3
	PCERC2	Preservation of the town's original land use according to the masterplan	0.28		PCERR2	Urban renewal and upgrade of rundown areas within the town	0.79	
	PCERC3	Constantly upgraded communities	1.32	3	PCERR3	Increasing the carrying capacities of the existing urban basic services and expansion of shopping/commercial areas	1.10	4
	PCERC4	Reduced congestion and overcrowding in public spaces and commercial areas	0.97	5	PCERR4	Regulating the population density through urban planning and planning laws	0.70	
	PCERC5	A balanced and well-distributed population density	0.42		PCERR5	Reduction of noise pollution from students' clusters	1.63	1
	PCERC6	Reduced environmental pollution	1.51	2	PCERR6	Improving the waste management systems within the town and creating more awareness on waste recycling	1.38	2
	PCERC7	A better public transport system	1.21	4	PCERR7	Improving the traffic management systems, introducing more mass transit buses and working with HEI to schedule the closing hours	0.99	5
		λ_{max} = 7.26; CI = 0.03; CR = 0.03				λ_{max} = 7.81; CI = 0.14; CR = 0.10		
EC	ECERC1	Regulated rental prices within the university town	1.26	2	ECERR1	Introduction of a rental and price (goods and services) control mechanism in the town	1.32	1
	ECERC2	Provision of more affordable housing for non-students' residents	0.40		ECERR2	Creating more opportunities and giving incentives to affordable housing developers to enter the property market in the town	1.19	2
	ECERC3	Affordable cost of living	1.51	1	ECERR3	Setting up a task force to control and regulate informal commercial activities in the town	0.61	3
	ECERC4	Controlled informal commercial activities	1.08	3		λ_{max} = 3.12; CI = 0.06; CR = 0.10		
		λ_{max} = 4.25; CI = 0.08; CR = 0.09						
SC	SCERC1	Orderliness and good social behaviour by all residents	1.55	1	SCERR1	Enacting strict laws to curb social disorders	1.61	1
	SCERC2	Well managed and secure students' clusters	1.27	4	SCERR2	Working with HEIs and property owners to manage off-campus major students clusters	0.60	
	SCERC3	A drug-free town with reduced alcohol consumption and abuse	1.49	2	SCERR3	Crackdown on drug peddlers and users and enacting laws prohibiting the sale of alcohol to persons under 18	1.58	2
	SCERC4	Zero tolerance for prostitution on and off-campus	0.91	5	SCERR4	Prohibiting & enlightening students against prostitution	0.66	
	SCERC5	Reduced competition for privately rented apartments	0.34		SCERR5	Increasing the number of purpose-built students' accommodation in the town	1.32	3

	SCERC6	Regulated night-time entertainment ventures in the town	1.44	3	SCERR6	Prohibiting the conversion of communal land-uses and commercial properties to cater for students’ nightlife	0.36	
	SCERC7	Protected and well-maintained family leisure parks and amenities	0.57			λ_{max} = 6.13; CI = 0.03; CR = 0.02		
		λ_{max} = 7.57; CI = 0.10; CR = 0.07						
CC	CCERC1	Low crime rate and respect for law and order	1.59	1	CCERR1	Effective community co-policing	1.54	1
	CCERC2	Acceptable standards of behaviour by all groups	0.61		CCERR2	Increasing the safety and security awareness of the students' community	0.68	
	CCERC3	Place attachment and considerations for others	1.45	2	CCERR3	Setting community standards and enlightening the public on such standards	0.63	
	CCERC4	Unified and acceptable communal objectives	0.46		CCERR4	Improving social capital within the communities	1.29	3
	CCERC5	Community cohesion between students and non-student residents	1.33	3	CCERR5	Properly integrating students into the local communities through events	1.40	2
	CCERC6	Tribal, racial, and religious tolerance by all	1.01	4	CCERR6	Preaching the gains of cultural and religious diversity within the town	0.98	4
		λ_{max} = 6.45; CI = 0.09; CR = 0.07				λ_{max} = 6.52; CI = 0.10; CR = 0.08		

7.4 Discussions

7.4.1 Harmonizing the criteria and alternative elements in an AHP model using a Delphi technique

The Delphi technique was used to get the consensus on the scores of paired comparisons within the AHP model. The multi-stakeholder decision-making process was fully harmonized after three rounds with the help of a strong facilitator. The decision-makers were of various educational backgrounds with varying experiences and knowledge of both the university town and the resilience domain, so a facilitator was needed to expound and organize the opinions of the decision-makers until consensus was met on all criteria and alternative elements.

A rating scale for the pair-wise comparison (Table 7.3) was adopted for easy scoring. This made it easier for the decision-makers to assign quantitative measurements to the qualitative data (alternatives). Since the paired comparisons were in a consistent matrix, alternatives placed diagonally across from each other (equation 2) were scored using the rule of thumb. This means when a prioritization favours the alternative on the left-hand side, an absolute score was given (1-9), but when the alternative on the right-hand side gets prioritized, a reciprocal score was assigned (1/2 – 1/9) (Teknomo, 2006).

7.4.2 The Prioritized criteria and elements for a resilient Akoka town

Although the four major criteria for achieving a resilient university town are similar to the five core dimensions of resilience (Sharifi, 2016; Smith, 2002, 2006a), their importance was never investigated, measured or ranked for achieving resilience in any university town or community against the negative impacts of studentification.

The Physical Criteria (PC) was the most important criterion for describing a resilient Akoka. This is because the impacts of studentification on the environment are usually the highest in most university towns around the world (Dewi & Ristianti, 2019; Kinton et al., 2018). The decision-makers came to a consensus defining a resilient Akoka town to be one in which the conversion of family homes to Housing with Multiple Occupancies (HMOs) is prohibited to reduce the competition for residential housing, control the increase in rental prices and reduce the gentrification of non-students' residents (PCERC1). Other elements that represent a resilient Akoka town include reduced environmental pollution (noise from students clusters and talking loudly on the streets, playing loud music from their car stereos and homes, defacing the environment with graffiti and posters as well as indiscriminate waste disposal) (PCERC6), constantly upgrading the run-down areas of the town (buildings, roads and infrastructure) to reduce the *broken-window* effect in the town (Harcourt & Ludwig, 2006) (PCERC3), functional mass transport system to reduce traffic congestions during rush hours (PCERC4), and reduced congestions and overcrowding in public spaces and commercial areas like shops and markets.

To reduce the physical (environmental) risks imposed by studentification in Akoka town, the decision-makers proposed reduction of noise in students clusters (off-campus halls) (PCERR5), improving the waste management system within the town and continuously enlightening the residents on recycling and other best practices (PCERR6), enforcements of existing planning laws that prohibit the illegal conversion of land-uses and family homes to HMOs without proper permits (PCERR1), increasing and upgrading the carrying capacities of existing urban basic services and shopping facilities within the town (PCERR3) and improving the traffic management systems, introducing more mass transit buses and working with HEI to schedule their closing hours so that not all students resume lectures same time in the morning and all of them end their lectures at the same time in the afternoon (PCERR7).

The Economic Criteria (EC) was the second most important criterion prioritized by the decision-makers. This is because studentification often leads to a higher population density and competition for scarce resources (Baron & Kaplan, 2010; Hubbard, 2009; Prada, 2019).

Prioritized elements that define a resilient Akoka town include affordable cost of living (ECERC3), regulated rental prices within the town (ECERC1) and controlled informal sector activities such as selling alcohol to underage students or commercial activities by the walkways that cause human traffic (ECERC4). The decision-makers also proposed the introduction of a rental and price (goods and services) control mechanism in the town to regulate inflation due to high demand and check the artificial manipulation of the market (ECERR1), creating an enabling environment for real estate investors and giving them incentives to develop more affordable housing in places that are less congested within the town (ECERR2) and setting up a task force to control and regulate the activities of the informal traders within the town (ECERR3), as the risk reduction elements to eliminate the studentification-induced economic shocks and stresses in Akoka.

Studentification also affects the socio-cultural fabric of the communities within the university towns, especially those with a high concentration of undergraduate students' population (Fabula et al., 2017; Hubbard, 2008; Woldoff & Weiss, 2018). To be resilient against the social and cultural negative impacts of studentification in Akoka, the decision-makers chose Social Criteria (SC) and Cultural Criteria (CC) as the third and fourth criteria to make Akoka resilient. Under the SC, prioritized elements for a resilient town include orderliness and good social behaviour (SCERC1), a drug-free town with regulated alcohol consumption to reduce alcohol abuse (SCERC3), regulated night-time entertainment ventures to reduce night-time noise and insecurities (SCERC6), well managed and secure students clusters including purpose-built students accommodation quarters (SCERC2) and a zero-tolerance for prostitution on and off-campus which is common within university towns in Nigeria (SCERC4). To reduce social risks and promote resilience in Akoka, the decision-makers proposed the enactments of strict laws to curb social disorder (SCERR1), a crackdown on drug peddlers and users, and enacting a law prohibiting the sale of alcohol to persons under 18 years of age (SCERR3) and increasing the number of purpose-built students' accommodation in the town to reduce the pressure on family homes and to cluster the students in specific areas for easy management (SCERR5).

Culturally, the decision-makers also envisioned a resilient Akoka with a low crime rate and respect for law and order (CCERC1), place attachment and consideration for all (CCERC3), community cohesion between students and non-student residents (CCERC5) and a place with great tolerance for tribal, cultural, racial and religious diversity (CCERC6). To achieve the Cultural Criterion (CC) envisioned, the decision-makers prioritized effective community co-policing (CCERR1), integrating the students into the local communities through events (CCERR4), improving the social capital within the communities (CCERR5) and preaching the gains of cultural and religious diversity within the town (CCERR6).

7.4.3 Framing the index and matrices

A framework (Figure 7.3) was developed for the Outcome Indicators (OI) of the CRI using the important criteria and their associated elements in sub-section 7.4.2. The OI serves as a tool to evaluate and build the resilience of the university town. However, viewing resilience based on its outcomes alone creates limitations (Manyena, 2006). These include limitations in terms of human involvement and limitations in decentralizing the process of developing community resilience. To overcome these limitations, Process Indicators (PI) were added to the overall CRI (S. Kafle, 2010). Since the AHP model only provides the OI (Figure 7.4), the PI components were adopted from the Integrated Community-Based Risk Reduction (ICBRR). The ICBRR model (Figure 7.5), used by the Canadian and Indonesian Red Cross Society (S. K. Kafle, 2010; Kafle, 2012), contains 10 key steps (processes) for implementing the Elements of Risk Reduction (ERR) in the proposed AHP model which makes up the OI. As a result, the proposed CRI (Figure 7.6) for building a resilient and sustainable university town was developed based on the four criteria and their elements from the AHP model (OI) and the PI that contains the implementation processes.

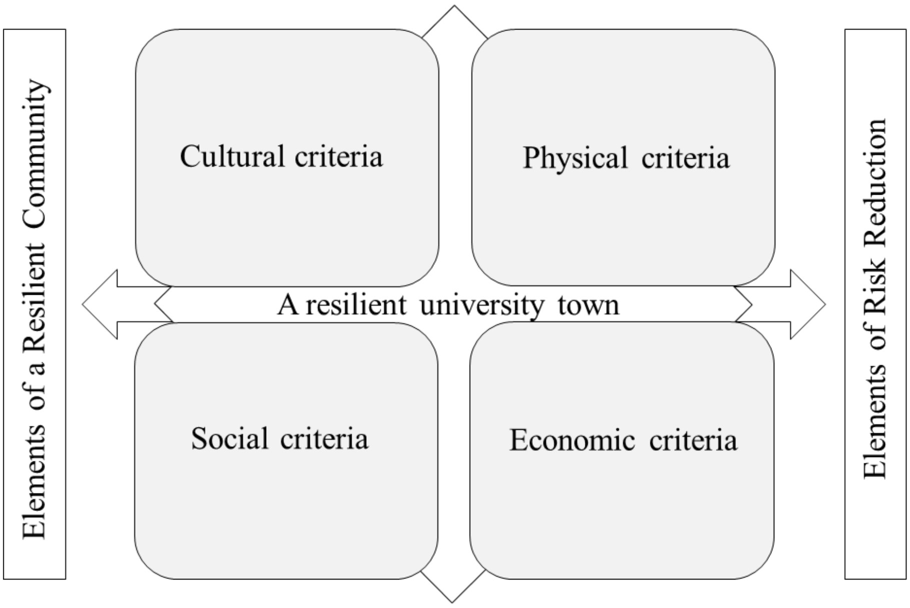

Figure 7.3 The Analytic Hierarchy Process framework for the Outcome Indicator

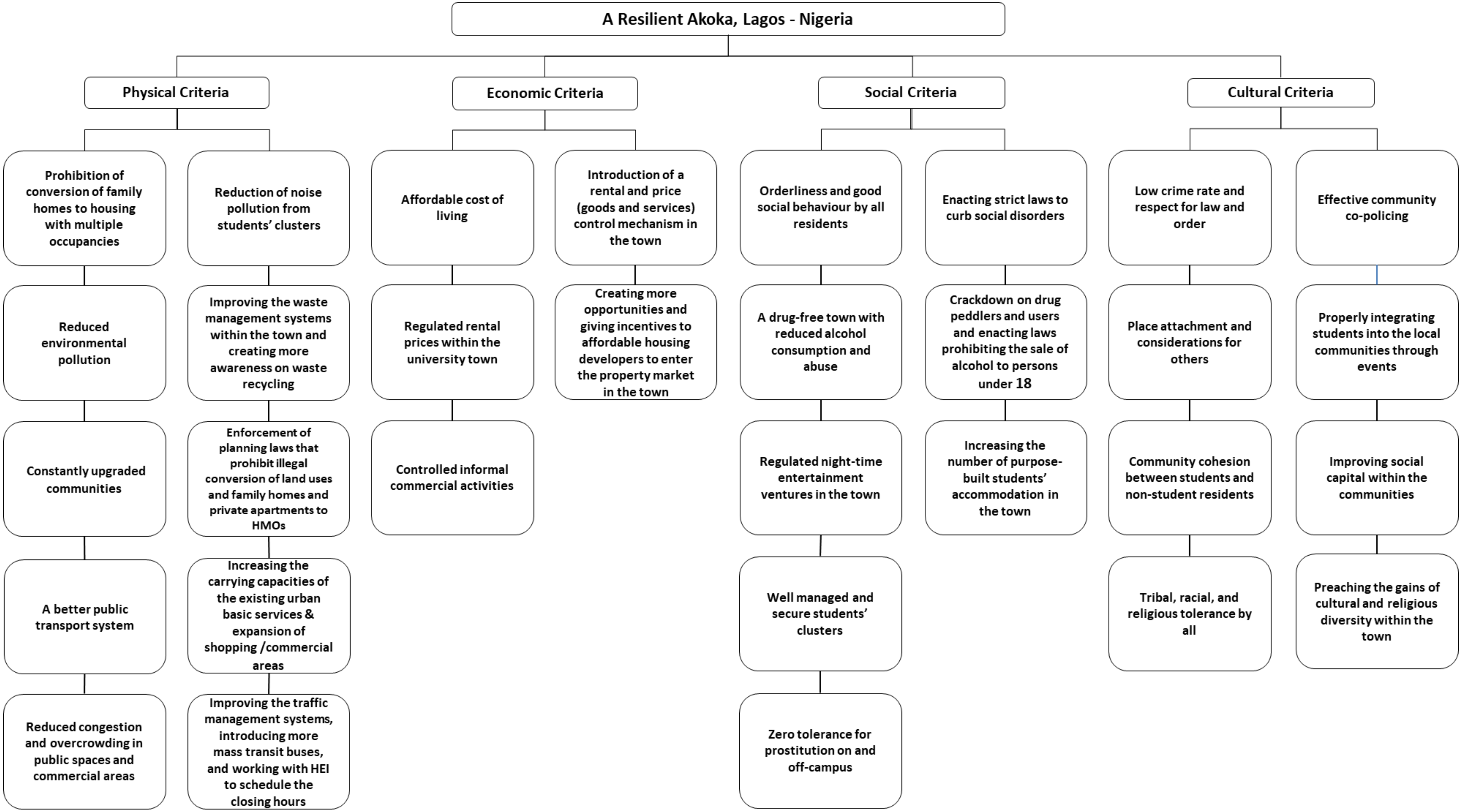

Figure 7.4 The output indictors from the AHP model

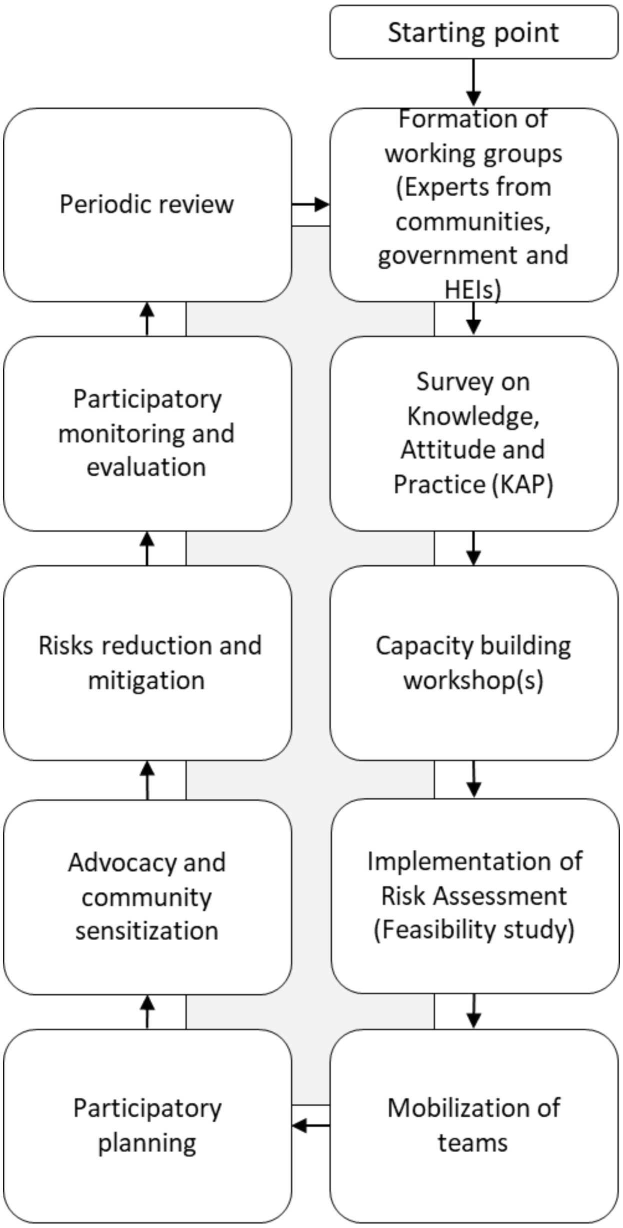

Figure 7.5 Process indicators adapted from ICBRR (S. K. Kafle, 2010; Kafle, 2012)

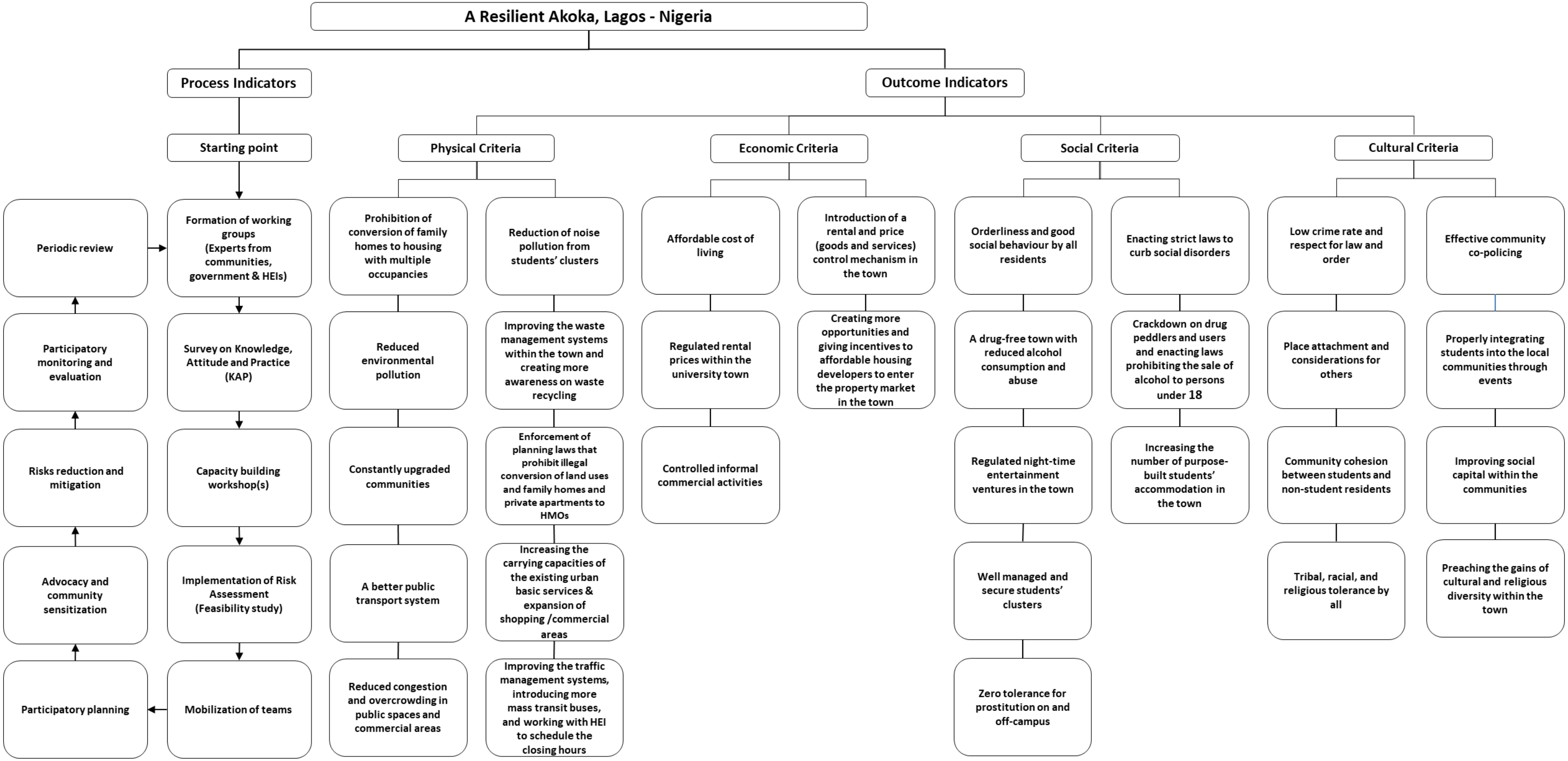

Figure 7.6 A Composite Resilience Index (CRI) for Akoka, Lagos – Nigeria.

7.4.4 Proposed weighted linear combination measurement for the index

The CRI matrics followed a Weighted Linear Combination (WLC) process for both the OI and PI. The OI were given weights based on the intensification of the indicator scores taken from nw_{ij} values which determined the elements' ranks in the AHP model. The linear scaling method was used as shown in equation 10.

$$W_n = (W_{act} - W_{min})/(W_{max} - W_{min}) \qquad 10$$

Where W_n is the criterion or element's normalized weight. W_{act} is the original weight, and W_{min} and W_{max} are the minimum and maximum weights within the group.

While computing the matric for the four criteria and their elements, ECERR3 was not selected because its normalized weight was zero. This left the economic criteria with only two risk reduction elements (ECERR1 and ECERR2). Table 7.7 shows the WLC outputs for all the selected criteria and elements.

The OI was calculated based on the Element Scores (ES) and ES were computed based on the attainment of a level of agreement among the decision-makers. On the scale used to attain the level of agreement, level five was the highest and one was the lowest. This scale was modified with adaptations from Twigg (2009) for ranking indicators and measuring the progress of the CRI implementation. An additional level with a zero score was added to imply the non-existence of disaster risk reduction element(s) in the town or zero progress (see Table 7.8).

Table 7.7 Selected and normalized criteria and elements for a resilient Akoka

Criteria	W_n	Elements of a Resilient Community (ERC)		W_n	Elements of Risk Reduction (ERR)		W_n
PC	0.44	PCERC1	Prohibition of conversion of family homes to housing with multiple occupancies	0.28	PCERR5	Reduction of noise pollution from students' clusters	0.29
		PCERC6	Reduced environmental pollution	0.24	PCERR6	Improving the waste management systems within the town and creating more awareness on waste recycling	0.23
		PCERC3	Constantly upgraded communities	0.19	PCERR1	Enforcement of planning laws that prohibit illegal conversion of land uses and family homes and private apartments to housing with multiple occupancies	0.20
		PCERC7	A better public transport system	0.18	PCERR3	Increasing the carrying capacities of the existing urban basic services and expansion of shopping/commercial areas	0.15
		PCERC4	Reduced congestion and overcrowding in public spaces and commercial areas	0.11	PCERR7	Improving the traffic management systems, introducing more mass transit buses, and working with HEI to schedule the closing hours	0.13
EC	0.25	ECERC3	Affordable cost of living	0.48	ECERR1	Introduction of a rental and price (goods and services) control mechanism in the town	0.53
		ECERC1	Regulated rental prices within the university town	0.29	ECERR2	Creating more opportunities and giving incentives to affordable housing developers to enter the property market in the town	0.47
		ECERC4	Controlled informal commercial activities	0.23			
SC	0.21	SCERC1	Orderliness and good social behaviour by all residents	0.25	SCERR1	Enacting strict laws to curb social disorders	0.39
		SCERC3	A drug-free town with reduced alcohol consumption and abuse	0.22	SCERR3	Crackdown on drug peddlers and users and enacting laws prohibiting the sale of alcohol to persons under 18	0.31
		SCERC6	Regulated night-time entertainment ventures in the town	0.20	SCERR5	Increasing the number of purpose-built students' accommodation in the town	0.30
		SCERC2	Well managed and secure students' clusters	0.18			
		SCERC4	Zero tolerance for prostitution on and off-campus	0.15			
CC	0.10	CCERC1	Low crime rate and respect for law and order	0.31	CCERR1	Effective community co-policing	0.32
		CCERC3	Place attachment and considerations for others	0.27	CCERR5	Properly integrating students into the local communities through events	0.27
		CCERC5	Community cohesion between students and non-student residents	0.23	CCERR4	Improving social capital within the communities	0.21
		CCERC6	Tribal, racial, and religious tolerance by all	0.19	CCERR6	Preaching the gains of cultural and religious diversity within the town	0.20

Table 7.8. Ranking Scale for the indicators

Scores	Description of level
0	Non-existence of disaster risk reduction element in the town or zero progress
1	Limited awareness of the intervention(s) and little effort to implement them
2	Awareness of the interventions and willingness to implement them, but capacity & resources remain limited
3	Capacity and all resources are available, but the implementation of interventions is slow
4	Interventions are in place, positive impacts are materializing, but interventions and their results are not sustainable
5	Interventions and their results are sustainable, the element(s) is/are contributing to making the town resilient, and it is/they are embedded in the town's relevant policies, collective attitudes and behaviours of residents

All ES within each criterion were summed up to get the Criteria Score (CS) using equation 11.

$$CS = \sum_{j=0}^{j=5} \mathrm{ERC}\left(W_i ES_j\right) + \sum_{j=0}^{j=5} ERR\ (W_i ES_j) \qquad 11$$

Where ERR represents elements of a resilient community and ERR represent elements of risk reduction. W_i represents the weights of all elements *i*, and ES_j represent elements scores *j*. All the CS were combined to give the Outcome Indicator Score (OIS) as expressed by equation 12.

$$OIS = \sum_{j=0}^{j=5} C\ (W_i CS_j) \qquad 12$$

Where C represent criteria, W_i represents the weights of all elements *i*, and CS_j represent the scores of each criterion j.

Similarly, the Process Indicator Score (PIS) was calculated using equation 12.

$$PIS = \sum_{j=0}^{j=5} P\ (W_i R_j) \qquad 13$$

Where P represents the process indicators based on the ICBRR model, W_i represents the weights of all elements *i*, and R_j represents ranks or value of the process indicator j.

The rating of both indicators (OI and PI) is based on the scale in Table 7.8. Since both indicators have W_i whose sum is 1, the W_i for each PI is 0.10.

The overall Composite Resilience Index Score (CRIS) is the combination of both OIS and PIS as shown in equation 14.

$$CRIS = OISW_i + PISW_i \qquad 14$$

Where OIS and PIS are the outcomes and process indicator scores, and W_i represents the weights of the outcome and process indicators *i*.

7.5 Chapter summary and conclusion

The negative impacts of studentification in university towns across the world have been well documented in the literature. Few university towns around the world have also implemented policies to make their towns resilient against the shocks and stresses brought about by studentification. However, there is no known index or model specifically designed to assess and develop community resilience in any university town. This motivated the need to develop a localized Composite Resilient Index (CRI) for university towns starting with Akoka, Lagos, Nigeria as a case study.

The Analytic Hierarchy Process (AHP) was used as a multicriteria decision-making tool to prioritize and select the criteria and elements that best describe a resilient Akoka. To carry out the AHP, the Delphi method was used and was coordinated by a strong facilitator to achieve the preferences of the decision-makers in selecting the final criteria and their elements. Physical, economic, social, and cultural criteria were the four criteria selected to describe the outcome indicators for a resilient Akoka, while the Integrated Community-Based Risk Reduction (ICBRR) model was adopted for the process indicators. Both outcome and process indicators were combined to form the CRI. A six-level scale was then developed to rate the existence and performance of the criteria, their elements, and the overall index. The proposed CRI is expected to contribute to community resilience assessment and building resilience in Akoka, as well as providing a methodology for other university towns to develop theirs.

The next chapter shows the summary of research findings, presents the overall framework, highlights the research significance, gives the limitations and policy recommendations.

CHAPTER 8: CONCLUSIONS AND RECOMMENDATIONS

8.1 Introduction

Based on the outcomes of all the findings in this thesis, this chapter presents a summary of the research, explains the proposed framework for community resilience assessment for university towns, gives the research significance, states the limitations and policy directions, and highlights directions for future research.

It is imperative to restate that this study aims to develop an artificial intelligence-based Community Resilience Assessment (CRA) framework for identifying and assessing community challenges and developing resilience in university towns. This aim was achieved, and the overall framework is presented in subsection 8.2.5 below.

8.2 Summary of research findings

The findings of this thesis are summarized according to the research objectives below:

8.2.1 Objective 1: Reviewed the existing literature

Objective 1, presented in chapter 2, reviewed the existing empirical studies on community resilience assessment and studentification and examined the characteristics of the existing CRA methodologies, and identified the concepts and theories related to studentification and community resilience that could be used to develop a new CRA Framework for university towns. This objective answered the first three research questions that inquired about the characteristics of existing CRA methodologies and asked if any of the existing CRA methodologies could be adapted or modified to specifically identify studentification-induced negative impacts and assess the resilience of university towns. The answer was none. Therefore, objective 1 went ahead to look for theories and concepts that could be used to design a new CRA for university towns and identified the success factors needed. Findings also show the non-existence of an AI-powered CRA framework that harnesses the use of User-Generated

Content (location-based data) from microblogs to access and build resilience.

8.2.2 Objective 2: Identified the Critical Success Factors (CSFs) for Community Resilience Assessment (CRA)

Critical success factors (CSFs) are important for the success of any project including assessing the resilience of communities to natural and human-made shocks and stresses. Due to limited studies on CSFs for community resilience assessment (CRA) and the non-existence of CSFs for CRA for university towns, this objective, presented in chapter 4, was set to identify and classify CSFs using resilience experts' opinions from both developed and developing countries and investigate if the same factors apply to the success of CRA in developed and developing countries. Thirty-one factors were identified from the community resilience literature and analyzed using feedbacks from 392 survey questionnaires from twenty-three countries. Analysis carried out to measure the agreements between experts' opinions from developed and developing countries showed no significant disagreement on most of the CSFs. Twenty-eight of the factors were found to be critical to CRA success in both developed and developing countries. The results from the Principal Component Analysis further classified the 28 CSFs into seven components. Results from this objective provide guidelines for community resilience experts to develop better CRA methodologies and help CRA project managers to improve CRA success.

This objective was presented at the 24th International Symposium on Advancement of Construction Management and Real Estate (CRIOCM 2019, Chongqing, China) and won the Best Paper Award. It was published as a book chapter by Springer Nature.

8.2.3 Objective 3: Developed an AI-Based Data Pre-Processing Framework

Over the last decade, 90 per cent of Big Data has been generated by people living in urban areas. With the advent of Internet of Things (IoT) and the increased use of the internet, Social

Media has become an integral part of people's daily lives. University towns are some of the most connected human settlements in the current industrial age due to the number of young people in those towns. Millions of unstructured data are being sent to the cloud every second from such communities, providing opinions practically on almost any discourse. This makes microblogs such as Twitter, Instagram, WeChat, and Facebook smart instruments for urban planners to harvest 'textual' data on socioeconomics, urban dynamics, transportation, land uses, resilience, studentification challenges, etc. Using the principles of Grounded Theory (adopted Mid-Range Theory for this study), this objective, presented in chapter 5, proposed an *AI-Based Data Pre-Processing Framework* for location-based data mining, cleaning and data analytics using Twitter API. The developed programmatic algorithms were tested using Hung Hom, Hong Kong, as a pilot case study. The results from the pilot study were validated using a questionnaire survey and the results showed high accuracy that Social Media Big Data can be used to study the spatiotemporal dynamism of community challenges.

This first part of objective 3 was published in Elsevier's Cities (Q1 journal).

The developed framework was used to carry out remote studies in six university towns in six continents (Loughborough in Leicestershire, UK, Akoka in Lagos, Nigeria, Ann Arbor in Michigan, USA, Hung Hom in Kowloon, Hong Kong, Sydney in New South Wales, Australia and Aguita de la Perdiz in Concepcion, Chile). Cultural, social, physical, economic and institutional and governance community challenges were identified and analysed from the historical big data and validated using an online experts survey. This part of the study is contained in chapter 6. It gives a global overview of the challenges university towns experience due to studentification and shows that artificial intelligence can provide an easy, cheap and more accurate way of conducting community resilience assessments. The objective also contributes to knowledge of research in the new normal (due to the COVID 19 pandemic) by proving that longitudinal studies can be done remotely using social media big data.

This second part of objective 3 is under review in Sage's Big Data and Society (Q1 journal).

8.2.4 Objective 4: Developed a Composite Resilience Index (CRI) for university towns, using Akoka, a case study in Lagos – Nigeria

Most higher educational institutions can no longer house their students within their campuses due to the increased number of enrolments and the unavailability of land for spatial expansion, especially in urban areas. This leads to studentification which negatively impacts university towns globally. Developing resilience makes university towns more sustainable. Thus, objective 4 proposed a localized Composite Resilience Index (CRI) for Akoka (one of the 6 case studies), a university town in Lagos, Nigeria. The composites of the index were determined by prioritizing User-Generated Content mined from the case study in objective 3 on elements of resilience and risk reduction using the Delphi method and the Analytic Hierarchy Process (AHP). The research outcomes from this objective, contained in chapter 7, showed that physical, economic, social, and cultural related criteria subjected to comparisons represented ≥ 70% of the total weights in the case study. These criteria made up the outcome indicators while the Integrated Community-Based Risk Reduction Program (ICBRR) model was adopted for the process indicators. Both outcome and process indicators made up the localized CRI for Akoka, Lagos - Nigeria. This proposed CRI would help Akoka to assess and build resilience against the negative impacts of studentification and provide a methodology for other university towns to create theirs.

8.2.5 The proposed Community Resilience Assessment Framework for university towns

The four objectives above contributed to achieving the research aim. An artificial intelligence-based Community Resilience Assessment (CRA) framework for university towns was developed. Figure 8.1 shows the proposed framework and its key features, while Figure 8.2

shows the connection between the proposed framework and the theoretical framework developed for this study.

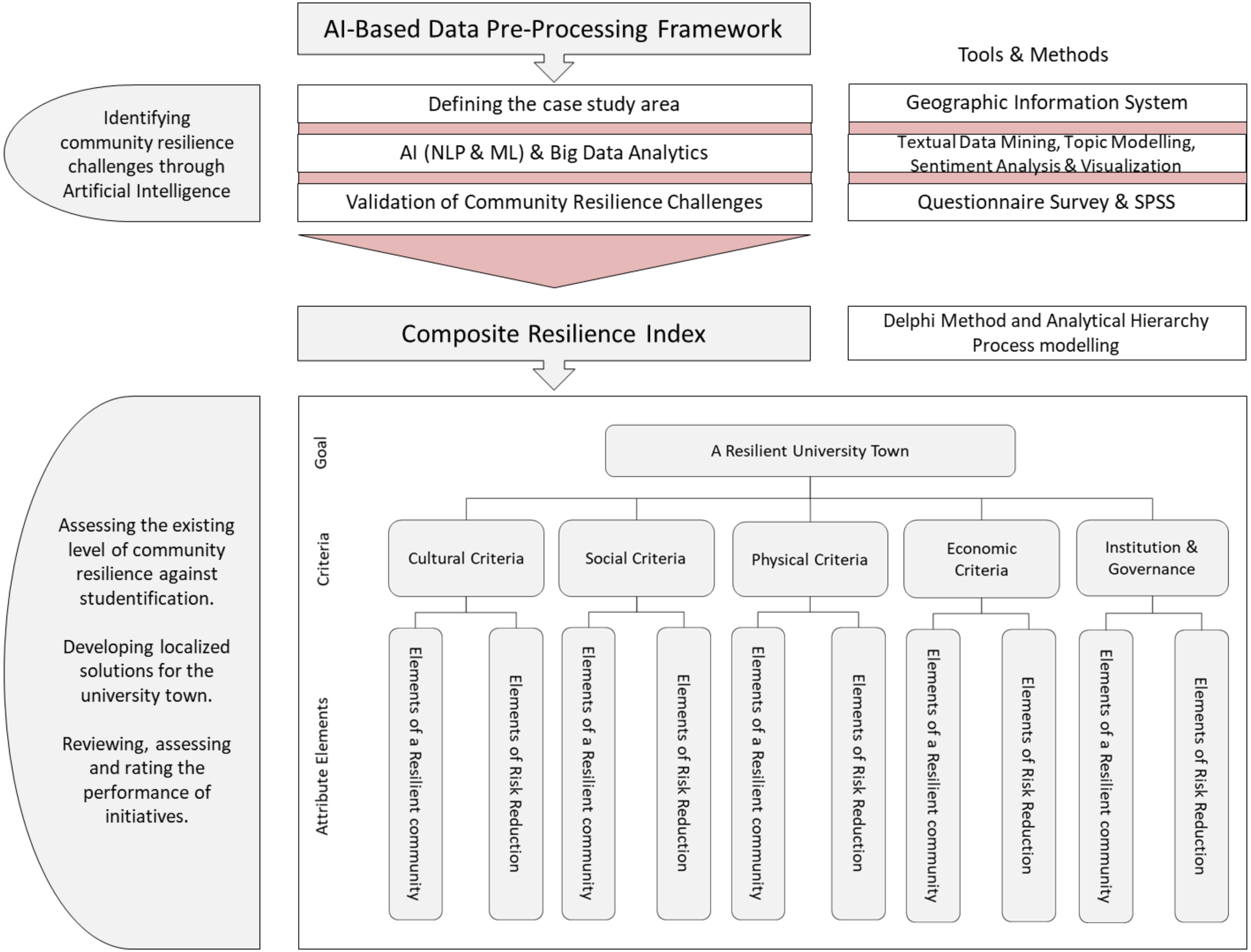

Figure 8.1 The proposed Community Resilience Assessment Framework for university towns

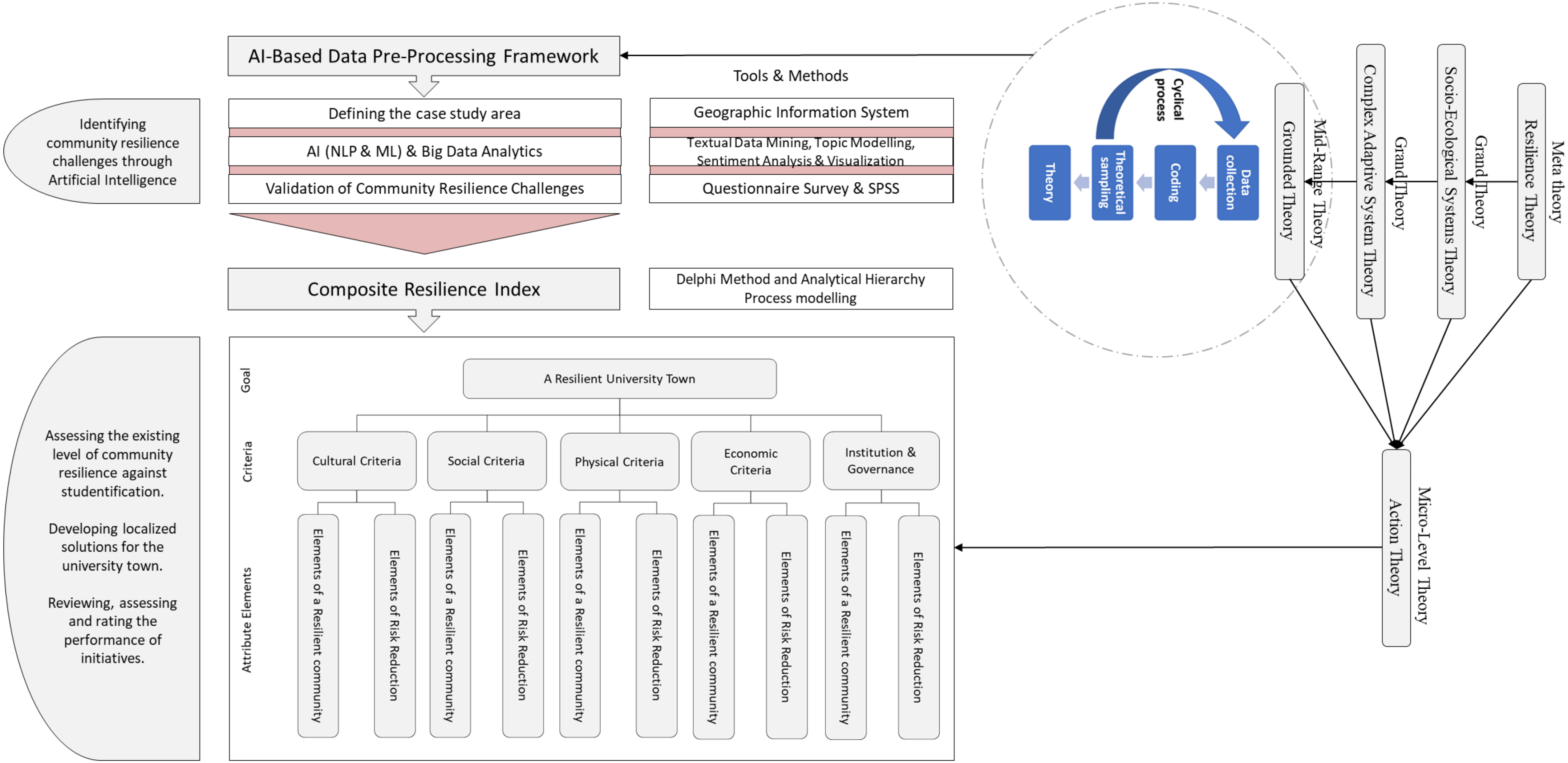

Figure 8.2 Relationship between the Proposed CRA Framework and the Theoretical Framework

8.2.5.1 The two components of the proposed framework

1. The AI-Based Data Pre-Processing Framework

As shown in Figure 8.1, this framework helps to mine location-based data, clean the data, identify community challenges through topic modelling and sentiments analysis and validate the findings through a questionnaire survey. The above processes are mirrored principles and steps of Grounded Theory which was used to drive the methodology. Instead of collecting qualitative data manually, coding it and clustering the data into themes and then analysing the themes to understand internal and external relationships to draw new theories (Grounded Theories), this study automated the processes using Artificial Intelligence (Machine Learning and Natural Language Processing). This enables the process to handle larger volumes of data (big data), reduce errors and make the analysis faster.

This framework only assesses the studentification impacts/community resilience challenges, it does not profer solutions (action plans).

2. The Composite Resilience Index

The second part of the framework (Figure 8.1) proposes a Composite Resilience Index (CRI) using the data mined, Delphi and AHP. The index assesses the existing level of community resilience against studentification and develops localized solutions for the university town based on its peculiar challenges. It can also be used to review, assess and rate the performance of initiatives in university towns. As shown in Figure 8.2, this segment of the overall proposed CRA framework is driven through Action Theory. The meta and grand theories (Resilience Theory, Socio-Ecological Systems Theory and Complex Adaptive Cycles Theory) all contribute to the study’s philosophy and bind all the pieces together from methodology to findings, discussion of results and action plans.

8.3 Research significance and contribution

This study contributes to the community resilience literature, body of knowledge and resilience research methodology by integrating new research tools and methods into resilience assessment and planning. Introducing Social Media Big Data Analytics (UGC from Microblogs) and Natural Language Processing and Machine Learning aspects of Artificial Intelligence into resilience studies and will create new research frontiers and stimulate more multidisciplinary studies in that direction.

The theoretical framework adopted for this study uses a multi-level theoretical underpinning and adoption of theories outside the boundaries of the current resilience research and traditional planning theories, this will contribute to resilience research by introducing new theories and show examples of how these theories can be used to drive resilience studies.

The research outcomes, the developed programmatic open-source algorithms, the proposed AI-Based Data Pre-Processing Framework, the proposed Composite Resilience Index, as well as the overall CRA Framework for university towns, would be useful to urban planners and city managers who wants to assess and manage the studentification crises and develop resilience in university towns globally.

8.4 Policy Suggestions

A good framework without adoption is useless (Foucault, 1988).

The following policy suggestions are recommended alongside the use of the framework:

- Joint community action comprising of local authorities, residents, school, and students to develop common visions and co-create cohesion, livability, resilience and sustainability through town-gown relationships.
- Both university and community visions need to be harmonized both in policy and practice and the joint use of this proposed framework.

- HEIs need to be accountable for their students' actions by developing code of conducts that extend beyond the walls of the HEIs.
- Exiting policies need to be reviewed to accommodate unplanned students' population growth & to upscale urban basic services.
- Research shows PBSA, Gated Students Communities and Urban Renewal actions were all not successful in combating studentification, therefore, instead of championing segregations, the following policy actions can be adopted by the government:
  a. PBSA will be denied planning permissions, except they are part of the de-studentification plan and within school-controlled areas.
  b. Extensions to illegally subdivided flats & HMOs which are already occupied by students will be denied planning permissions.
  c. Further licenses will not be granted till illegal conversions are reversed.
  d. Where licenses granted, these are subject to an occupation condition prohibiting full occupation by students.
  e. Conversions of properties to fast food outlets, pubs and other uses not originally contained in the masterplan will be resisted.
  f. Developers should seek to allocate a certain percentage of new build houses for family use.

8.5 Limitations and future research directions

8.5.1 AI-Based Data Pre-Processing Framework

The AI-Based Data Pre-Processing Framework works better in well-connected urban university towns where more people are connected to the internet and social media use is high. This limitation will not render the methodology useless but reduce the amount of available data for analysis. The more the data, the smaller the margin of error and the better the accuracy. Future research directions may include the use of other microblogs APIs (WeChat, Facebook, etc) for data mining or combining data from various microblogs for the analysis. The framework can also be improved to predict future trends based on historic data and streaming APIs. Geographic Information System (GIS) can also be used to overlay the data on the base maps of the case studies to run more analysis (eg heat maps to show intensities of complaints across space over time).

8.5.2 Composite Resilience Index

The CRI is made up of both outcome and process indicators developed through AHP. The CRI was also designed to assess the level of attainment of each indicator. This helps during the periodic review of the implementation of the CRI in the town and allows less performing elements to be adjusted or upscaled. The outcome indicators were developed from the mined UGC of the town's residents and visitors from Twitter and prioritized by twenty-three experts (decision-makers). However, the process indicators were directly adopted from the ICBRR model. This follows the assumption that since such indicators were developed using a similar procedure, tested, and widely used by the international red cross society in both developing and developed countries including Indonesia and Canada, they are suitable for use in any country and university town too.

The weights of the outcome indicators vary because they were generated from the computations in the AHP model, but the process indicators were assigned equal weights manually because the ICBRR designed them as such. This may cause some limitations to the accuracy of the measurements since the weights are used in intensifying the scores of the assessments. Although the ranking scale (Table 7.8) will reduce the effects of any bias as a result of the above, future research can be carried out to test this assumption. Another AHP modelling can also be done for the process indicators to increase the objectivity of the overall evaluation.

8.5.3 General limitations

Generally, the COVID 19 pandemic affected our lives in many ways we could not imagine. The impacts on research have created a lot of delays, include slowing down the processes of academic article reviews and feedbacks on data collections. For this study, the international experts' survey and AHP took about six and three months respectively to conclude. The manuscripts submitted to journals are also taking longer time for the review processes compared to the pre-COVID 19 era.

Restrictions on travel also affected study trips for fieldwork, so everything was done virtually. This limitation birthed innovation in the end, but a hybrid between fieldwork and virtual research might have resulted in a better outcome for the AHP model.

8.6 Chapter Summary and overall research conclusion

This chapter summarizes the thesis, explains the proposed CRA framework for university towns, shows the nexus between the proposed framework and the research's theoretical underpinning, states the significance of the study, and gives the research limitations as well as directions for further studies.

The thesis chapters end here.

APPENDICES

Appendix A – Survey Questionnaire

Dear Sir/Madam,

Invitation for Participation in an International Expert Survey

Due to the high global rate of urbanization in the 21st century and the global increase in the world's population in the last few decades, Higher Educational Institutions (HEIs) can no longer house their students within their campuses due to the increased number of enrolments and the unavailability of land for spatial expansion, especially in urban areas. Often, these HEIs' students have to live off-campus either in Purpose-Built Students Accommodations (PBSAs) or Housing with Multiple Occupancies (HMOs), preferably within the university town for ease of commuting to the HEIs. This often leads to "studentification", a term used to describe the contradictory social, economic, cultural, and spatial transformations of urbanism resulting from an influx of students into neighbourhoods around HEIs. Although studentification is not always a negative phenomenon as portrayed by the global media, extant literature shows that the negative impacts of studentification often outweigh its benefits.

This study (**A Community Resilience Assessment Framework for University Towns**) tries to investigate the negative impacts of studentification in 6 case studies, identify success factors and leverage on the power of artificial intelligence to harness location-based user-generated content from social media to build a community resilience assessment framework for university towns.

The research is part of a funded PhD project at the Department of Building and Real Estate, of the Hong Kong Polytechnic University, Hong Kong, under the supervision of Professor Edwin H. W. Chan and Sr. Dr. Man-Sing Wong, Charles. This questionnaire is expected to take about 20-30 minutes of your valuable time to complete.

All the information and data you provide will be kept in strict confidence and used solely for research purposes in accordance with the guidelines of the Human Subjects Ethics Sub-committee (HSESC) of The Hong Kong Polytechnic University (https://www.polyu.edu.hk/hsesc/index.html).

Should you have any further enquiries about this research, please feel free to contact me (Mohammed) by mobile phone number (+852) 6761- or via email: mohammed.abdulrahman@ . Thank you in anticipation for your generous assistance with this research. I am looking forward to receiving your early response.

Yours sincerely,

Mr. Mohammed Abdul-Rahman
Full-Time Doctoral Candidate
Department of Building and Real Estate
The Hong Kong Polytechnic University,
Hong Kong

Kind request:
You may also forward this survey questionnaire to other colleagues with expertise in community resilience or studentification that could contribute to the success of this research. Thank you in anticipation of your kind assistance.

SECTION A – RESPONDENTS BIODATA

For Question 1-4 below, choose 1 answer only.

1. Kindly indicate your sector.	
Academia/research institute	○
Consulting/private sector	○
Public sector/government agency or department	○
Intergovernmental organization/international NGO	○
Others	○
2. Kindly indicate your profession.	
Academic/researcher	○
Urban planner	○
Resilience project manager/officer	○
Architect	○
Economist/development economist	○
Sociologist	○
Engineer (civil, construction, etc)	○
Others	○
3. Years of experience	
1-5 years	○
6-10 years	○
11-15 years	○
16-20 years	○
Above 20 years	○
4. Type of involvement in community resilience	
Development of as assessment methodology	○
Use of an assessment method	○
All of the above	○
Others	○

SECTION B – STUDENTIFICATION IMPACTS

Question 1: Are you an expert form the underlisted university towns? Please pick one or specify your country under "others" below.

Loughborough, UK	○
Ann Arbor, USA	○
Akoka, Nigeria	○
Hung Hom, Hong Kong	○
Sydney, Australia	○
Aguita de la Perdiz, Chile	○
Others, please state below ______	○

Question 2: Based on your answer in question 1, kindly rate the following studentification challenges in your university town/community (that you indicated above) by writing the number of following scale: 1 = strongly disagree; 2 = somewhat; disagree; 3 = neither agree nor disagree; 4 = somewhat agree; and 5 = strongly agree, into the spaces.

		Lough-borough	Ann Arbor	Akoka	Hung Hom	Sydney	Aguita de la Perdiz	Others
C01	Demographic changes leading to more youths							
C02	Declining moral and community values							
C03	Lack of community cohesion and integration due to the transient nature of the student population							
C04	Aversion of crime and barriers to community policing caused by a transient population							
C05	Differing standards of acceptable behaviours by different social groups							
C06	Cultural diversity and lifestyle conflicts							
C07	Divergent perceptions on what makes up communal obligations							
C08	Inconsideration and lack of place attachment							
C09	Increased racism, tribalism and religious challenges							
Other	____________________							
S01	Increased anti-social behaviour and social disorder.							
S02	High level of crime due to the vulnerability & carelessness of the youthful population							
S03	Increased level of alcoholism, drugs peddling and abuse.							
S04	Increased level of prostitution and sexually transmitted diseases							
S05	Loss of social services like reduction in catchment areas for public schools & elderly care							
S06	Marginalization of permanent residents							
S07	Displacement/replacement of established residents (gentrification)							
S08	Increased competition for privately rented apartments							
S09	Lack of year-round goods & services due to the resort-economy nature of the community							
S10	Establishments of night-time entertainment ventures at the detrimental impacts of residential amenities							
S11	Segregation and social stratification							
S12	Lack of social interactions among groups							
Other	____________________							
P01	Illegal subdivision of family homes & apartments into housing with multiple occupancies							
P02	Changes in community land use							
P03	Community slumification due to the decline in housing renovations and environmental maintenance.							
P04	Defacing neighbourhoods with graffiti, posters, writings and rental boards and advertisements							
P05	Congestion and overcrowding on the streets and in public places including shops.							
P06	Increased population density							
P07	High environmental pollution – Noise, air pollution and indiscriminate waste/garbage disposal							
P08	Increased incidents of protests leading to vandalism of the physical environment.							

P09	Increased pressure on urban basic services due to higher population than planned for							
P10	On-street parking and traffic congestion							
P11	Pressure on public transport							
P12	Ghost community during off-term periods							
Other	____							
E01	High rental prices							
E02	Lucrative student housing business deters access to affordable housing for non-student residents.							
E03	Change in consumer behaviour and taste leading to changes in business models & structures.							
E04	High cost of living (goods and services)							
E05	High influx of commercial activities							
E06	Seasonal demand for students' accommodation							
E07	Seasonal scarcity of manpower in shops, restaurants, bars, etc							
E08	Seasonal customer base (on and off term periods)							
E09	Low tax generation from the community since students are exempted from taxation.							
Other	____							
I01	Weak and disjointed community leadership							
I02	Neglect by politicians due to low voting power.							
I03	Challenges to existing urban plans and policies							
Other	____							

Kindly see next page…..

SECTION C – CRITICAL SUCCESS FACTORS

Kindly rate the following success factors for community resilience assessment using the following scale: 1 = not important; 2 = less important; 3 = Neutral; 4 = important; and 5 = very important.

Code	Success factors	Level of importance 1	2	3	4	5
F1	Assessment of interlinkages	○	○	○	○	○
F2	Assessment of social risk within the community	○	○	○	○	○
F3	Assessment of place attachment & sense of community and pride	○	○	○	○	○
F4	Simulation of alternate states	○	○	○	○	○
F5	Inclusive & participatory CRA process	○	○	○	○	○
F6	Evaluation of community social network	○	○	○	○	○
F7	Co-creation & co-adoption of the CRA methodology	○	○	○	○	○
F8	Inclusive & participatory action planning process	○	○	○	○	○
F9	Repeated key assessment processes (iterative process)	○	○	○	○	○
F10	Decentralized responsibilities & leadership during the CRA process	○	○	○	○	○
F11	Evaluation of the trust & reciprocity within the community	○	○	○	○	○
F12	Evaluation of crime prevention & reduction mechanisms	○	○	○	○	○
F13	Assessment of economic risks within the community	○	○	○	○	○
F14	Identification of present resilience challenges	○	○	○	○	○
F15	Assessment of upper-scale relationships	○	○	○	○	○
F16	Evaluation of available social safety-nets mechanisms	○	○	○	○	○
F17	Assessment of environmental risks	○	○	○	○	○
F18	Identification and assessment of shared assets within the community	○	○	○	○	○
F19	Prediction of future resilience challenges	○	○	○	○	○
F20	Flexibility in action planning to accommodate evolving situations	○	○	○	○	○
F21	Assessment of lower-scale relationships	○	○	○	○	○
F22	Assessment of existing institutional and governance structures	○	○	○	○	○
F23	Identification and evaluation of shared norms & value	○	○	○	○	○
F24	Identification of past resilience challenges	○	○	○	○	○
F25	Assessment of focal-scale relationships	○	○	○	○	○
F26	Integration of action plans with other existing community systems	○	○	○	○	○
F27	Assessment of community conflict resolution mechanisms	○	○	○	○	○
F28	Redundancies in the action plan to accommodate disruptions	○	○	○	○	○
F29	The resourcefulness of the action plan to respond to needs during crises	○	○	○	○	○
F30	Robustness of the action planning process	○	○	○	○	○
F31	Co-reflectiveness during plan-making	○	○	○	○	○

If you wish to receive a copy of the summary of the research findings for reference or wish to participate in consequent surveys, please provide your email below (Optional):

Kindly return the completed survey form (saved in PDF file format) to Mr. Mohammed Abdul-Rahman via email mohammed.abdulrahman@

Thank you for your valuable time and concerted effort.

THE END

Appendix B – Codes

1. Data Mining - Optimized-Modified-GetOldTweets3-OMGOT

This is a Python script for mining old and backdated Twitter messages. It bypasses the limitations/restrictions of the Twitter API. The full Repo is available on https://github.com/marquisvictor/Optimized-Modified-GetOldTweets3-OMGOT for use. It houses an improvement fork of the original GetOldTweets Library by Henrique (2016). The improvement makes running this package on Windows OS seamless with Python 3.x.

a. Components

When running this script from the command line, it typically returns the following as columns in an output.csv file that would be saved in your current working directory. It should be noted that the geo attribute returns an empty column. So, if you need to get location-based Twitter data, you will have to specify the Geographical coordinates as well as the search radius.

- id (str)
- permalink (str)
- username (str)
- text (str)
- date (date)
- retweets (int)
- favorites (int)
- mentions (str)
- hashtags (str)
- geo (str)

b. **Command Line Arguments**

This script was optimized to work more efficiently and seamlessly on both Windows CMD, and Terminal using the following command-line arguments.

- username (str): An optional specific username from a Twitter account. Without "@".
- since (str. "yyyy-mm-dd"): A lower bound date to restrict the search.
- until (str. "yyyy-mm-dd"): An upper bound date to restrict search.
- querysearch (str): A query text to be matched.
- toptweets (bool): If True only the Top Tweets will be retrieved.
- near(str): A reference location area from where tweets were generated.
- within (str): A distance radius from "near" location (e.g. 15mi).
- maxtweets (int): The maximum number of tweets to be retrieved. If no number is set here or is lower than 1 all possible tweets will be retrieved.

c. **Usage - Very Important to Understand**

Clone or download the repo to your local machine, then cd into the downloaded GetOldTweets3 folder, and open the command prompt or terminal right in that same folder. then run the following codes in the examples below. Customize or change the parameters/arguments as used in the examples below according to the needs of your project.

d. **Use Cases**

Use case 1 - Get the last 100 top tweets by username:

```
python GetOldTweets3.py --username "mo4president" --toptweets --maxtweets 100
```

Specified --username, --toptweets, and --maxtweets Which was set to 100. Meaning to retrieve the last 100 toptweets from Twitter, made by that username.

Use case 2 - Get 500 tweets by the username and bound dates:

```
python GetOldTweets3.py --username "mo4president" --since 2017-05-10 --until 2019-05-10 --maxtweets 500
```

Specified --username, --since, --until, and --maxtweets Which in this case was set to 500. And the above command retrieves 500 tweets made by the username given from May 2017 till May 2019 (2 years' worth).

Use case 3 - Get tweets by language and keyword search:

```
python GetOldTweets3.py --querysearch "football" --lang es --maxtweets 100
```

Specified --querysearch, --lang, and --maxtweets, which in this case was set to 100. And the above command retrieves 100 tweets data from twitter that has the keyword "football" in it. The language parameter here was set to Spanish 'es', meaning only Spanish tweets are stored. By default, the code retrieves all the tweets found on the querysearch keyword irrespective of the language. The language parameter acts more like a runtime pre-processing step to sieve out unwanted contents. 'en' - English, 'cn'- Chinese.

Use case 4 - Get 500 tweets by querysearch and geo-coordinates:

```
python GetOldTweets3.py --querysearch "BBNaija" --near "6.52, 3.37" --within 40km --maxtweets 500
```

Specified --querysearch, --near, --within, and --maxtweets Which in this case was also set to 500. And the above command retrieves 500 tweets data from twitter that has the keyword BBNaija, within a 40km radius of the geographical coordinate given, which happened to be Lagos Island, Lagos state, Nigeria.

2. Topic Modelling using LDA on Python

```
#Initializing the LDA Model with gensim library
Lda = gensim.models.ldamodel.LdaModel
#Then we trained the LDA model on the document term matrix
ldamodel = Lda(doc_term_matrix, num_topics=20, id2word = dictionary, passes=50)
```

```
print(ldamodel.print_topics(num_topics=20, num_words=5))
['0.912*antisocial + 0.887*neighbour + 0.861*lonely + 0.831*friends + 0.815*bored,
'0.782*tiny + 0.766*converted + 0.741*shared + 0.727*studio + 0.715*student,
'0.707*expensive + 0.695*apartment + 0.695*accommodation + 0.692*small + 0.687*agents,
'0.679*shouting + 0.671*noise + 0.668*hostel + 0.665*late + 0.664*cars,
'0.660*africans + 0.657*indians + 0.655*park + 0.655*Chinese + 0.651*building,
'0.649*graffiti + 0.647*posters + 0.647*defacing + 0.647*writing + 0.645*environment,
'0.644*costly + 0.641*food + 0.641*hunghom + 0.640*goods + 0.640*restaurant,
'0.638*congestion + 0.636*crowded + 0.636*chatting + 0.635*mobility + 0.635*traffic,
'0.633*diversity + 0.631*international + 0.631*polyu + 0.629*influence + 0.628*social,
'0.626*youthful + 0.625*young + 0.625*teenagers + 0.623*many + 0.623*children,
'0.622*commercial + 0.620*shops + 0.620*office + 0.618*space + 0.617*supermarkets,
'0.616*lawlessness + 0.605*abiding + 0.594*law + 0.594*crime + 0.587*crossing,
'0.579*relocated + 0.573*enjoying + 0.560*territories + 0.0555*moved + 0.501*serenity,
'0.499*litter + 0.497*waste + 0.493*smell + 0.486*bins + 0.478*dirty,
'0.477*parking + 0.477*road + 0.474*cars + 0.461*carpark + 0.459*events,
'0.455*youth + 0.442*stuff + 0.440*shopping + 0.438*pizza + 0.435*western,
'0.433*air + 0.428*burning + 0.425*incense + 0.420*pollution + 0.418*paper,
'0.412*smoking + 0.401*drugs + 0.398*alcohol + 0.398*sale + 0.395*drinking,
'0.393*slum + 0.390*demolition + 0.387*old + 0.381*maintenance + 0.377*landlords,
'0.370*culture + 0.370*practices + 0.368*religion + 0.365*buddha + 0.364*traditions]
```

Each line from the above LDA output is a topic with individual topic terms and weights.

Topic 1: Lack of social interactions

Topic 2: Conversion of apartments to HMO & studios

Topic 3: High rental prices

Topic 4: Noise Pollution

Topic 5: Segregation and social stratification

Topic 6: Defacing the neighbourhood with graffiti, posters, and writings

Topic 7: High cost of living (goods and services)

Topic 8: Congestion and overcrowding

Topic 9: The influence of social and cultural diversity

Topic 10: Community youthification

Topic 11: High rate of commercialization

Topic 12: Crime and lawlessness

Topic 13: Structural gentrification

Topic 14: ``Waste pollution

Topic 15: Parking challenges

Topic 16: Youthification of goods and services

Topic 17: Air pollution

Topic 18: Drugs and alcoholism

Topic 19: Slumification

Topic 20: Cultural and religious practices and norms

3. Procedures, workings, and scoring of the VADER model on Python.

The full library is hosted on GitHub[13] for use and modification by Hutto and Gilbert (2014).

The simplest way to install the library on python is to use the command line:

```
> pip install vaderSentiment
```

Once VADER is installed, launch the sentiment analyzer:

[13] https://github.com/cjhutto/vaderSentiment

```
from vaderSentiment.vaderSentiment import SentimentIntensityAnalyzer
analyser = SentimentIntensityAnalyzer()
```

Then call the polarity score analyzer using the codes below:

```
def sentiment_analyzer_scores(sentence):
    score = analyser.polarity_scores(sentence)
    print("{:-<40} {}".format(sentence, str(score)))
```

```
sentiment_analyzer_scores("The family park is super cool.")
The family park is super cool----------------- {'neg': 0.0, 'neu':
0.326, 'pos': 0.674, 'compound': 0.7351}
```

Parameters that affect sentiment intensity and VADER's handling of emojis, slangs, and emoticons

The above intensities are also affected by some key parameters explained below:

1. *Punctuations:* The use of an exclamation mark (!) increases the intensity of scores, the more the exclamation marks, the higher the intensity (magnitude) and compound scores as shown below.

```
#Baseline sentence
sentiment_analyzer_scores('The food here is good')
The food here is good----------- {'neg': 0.0, 'neu': 0.58, 'pos': 0.42,
'compound': 0.4404}

#Punctuation
Print(sentiment_analyzer_scores('The food here is good!')
Print(sentiment_analyzer_scores('The food here is good!!')
Print(sentiment_analyzer_scores('The food here is good!!!')

The food here is good--------- {'neg': 0.0, 'neu': 0.556, 'pos': 0.444,
'compound': 0.4926}
None
The food here is good--------- {'neg': 0.0, 'neu': 0.534, 'pos': 0.466,
'compound': 0.5399}
None
The food here is good--------- {'neg': 0.0, 'neu': 0.514, 'pos': 0.486,
'compound': 0.5826}
None
```

2. *Degree modifiers:* These are words that either increase or decrease the intensity of the sentence. See the example below.

```
#Baseline sentence
sentiment_analyzer_scores('The service here is good')
The service here is good-------- {'neg': 0.0, 'neu': 0.58, 'pos': 0.42,
'compound': 0.4404}

#Degree Modifiers
Print(sentiment_analyzer_scores('The service here is extremely good')
Print(sentiment_analyzer_scores('The service here is marginally good')

The food here is good----------- {'neg': 0.0, 'neu': 0.61, 'pos': 0.39,
'compound': 0.4927}
None
The food here is good---------- {'neg': 0.0, 'neu': 0.657, 'pos': 0.34,
'compound': 0.3832}
None
```

3. *Capitalization:* Using upper case letters emphasizes a sentiment, therefore, using the upper case for a word among other non-capitalized words increases the intensity. See the example below.

```
#Baseline sentence
sentiment_analyzer_scores('The food here is great!')
The food here is good--------- {'neg': 0.0, 'neu': 0.477, 'pos': 0.523,
'compound': 0.6588}

#Capitalization
Print(sentiment_analyzer_scores('The food here is GREAT!')

The food here is good--------- {'neg': 0.0, 'neu': 0.438, 'pos': 0.562,
'compound': 0.729}
```

4. *Conjunctions:* The use of conjunctions like “but” signals a shift in sentiments from the part of the sentence preceding it to the part following it. It shows mixed sentiments. The latter half of the sentence dictates the overall sentiment intensity.

```
#Capitalization
sentiment_analyzer_scores('The food here is great, but the service is
horrible')

The food here is good-------- {'neg': 0.31, 'neu': 0.523, 'pos': 0.167,
'compound': -0.4939}
```

5. *Preceding Trigram:* By examining the trigram preceding a sentiment-laden sentence, VADER catches about 90% of cases where negation flips the polarity of the text. A negated sentence would be "The neighbours here aren't that great".

6. *Emoticons, Slangs and Emojis:* VADER performs better with emojis, emoticons, slangs, and all the above, that is why it is advisable not to clean data for sentiment analysis before the analysis if need be, only the metadata like usernames and hashtags should be removed.

VADER easily detects sentiments from the above parameters which form the bulk of big data from micro-blogs, this makes the model the most ideal to use for sentiments analysis of social media data (Hutto & Gilbert, 2014; Kumar et al., 2018).

Emoticons

```
print(sentiment_analyzer_scores("Make sure you :) or :D today!"))
Make sure you :) or :D today!----------- {'neg': 0.0, 'neu': 0.294,
'pos': 0.706, 'compound': 0.8633}
```

```
print(sentiment_analyzer_scores("Today SUX!"))
print(sentiment_analyzer_scores("Today only kinda sux! But I'll get by,
lol"))

#output
Today SUX!----------- {'neg': 0.779, 'neu': 0.221, 'pos': 0.0,
'compound': -0.5461}
Today only kinda sux! But I'll get by, lol {'neg': 0.127, 'neu': 0.556,
'pos': 0.317, 'compound': 0.5249}
```

```
print(sentiment_analyzer_scores('I am 😁 today'))
print(sentiment_analyzer_scores('😊'))
print(sentiment_analyzer_scores('😥'))
print(sentiment_analyzer_scores(' ☹'))

#Output

I am 😁 today-------- {'neg': 0.0, 'neu': 0.476, 'pos': 0.524, 'compound':
0.6705}
😊---------------- {'neg': 0.0, 'neu': 0.333, 'pos': 0.667, 'compound':
0.7184}
😥---------------- {'neg': 0.275, 'neu': 0.268, 'pos': 0.456, 'compound':
0.3291}
☹---------------- {'neg': 0.706, 'neu': 0.294, 'pos': 0.0, 'compound': -
0.34}
💘---------------- {'neg': 0.0, 'neu': 1.0, 'pos': 0.0, 'compound': 0.0}
```

Sentiment analysis of Hung Hom data

The mined data from Table 1 was loaded and analyzed one after the other one using the command line below:

```
#Load dataset to data frame
df = pd.read_csv('social_interactions.csv', parse_dates = True)

#Generate sentiments
analyzer.polarity_scores(str(df['tweet_clean'][6]))

#show outputs
print("{:-<40} {}".format(df, str(score)))
```

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