sustainability

Article

Novel Use of Social Media Big Data and Artificial Intelligence for Community Resilience Assessment (CRA) in University Towns

Mohammed Abdul-Rahman [1,2,3,*], Mayowa I. Adegoriola [1], Wilson Kodwo McWilson [1], Oluwole Soyinka [4] and Yusuf A. Adenle [5]

1 Department of Building and Real Estate, The Hong Kong Polytechnic University, Hong Kong, China
2 Department of Urban and Regional Planning, University of Lagos, Lagos 101017, Nigeria
3 AI Africa Lab, Lagos 101017, Nigeria
4 School of Public Policy and Global Affairs, University of British Columbia, Vancouver Campus, Vancouver, BC V6T 1Z2, Canada
5 Department of Geography and Resource Management, Chinese University of Hong Kong, Hong Kong, China
* Correspondence: 18042561r@connect.polyu.hk; Tel.: +852-6761-2834

Abstract: University towns face many challenges in the 21st century due to urbanization, increased student population, and higher educational institutions' inability to house all their students on-campus. For university towns to be resilient and sustainable, the challenges facing them must be assessed and addressed. To carry out community resilience assessments, this study adopted a novel methodological framework to harness the power of artificial intelligence and social media big data (user-generated content on Twitter) to carry out remote studies in six university towns on six continents using Text Mining, Machine Learning, and Natural Language Processing. Cultural, social, physical, economic, and institutional and governance community challenges were identified and analyzed from the historical big data and validated using an online expert survey. 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. The study also contributes to knowledge of research in the new normal by proving that longitudinal studies can be completed remotely.

Keywords: machine learning; natural language processing; text mining; social media; studentification; sustainability

Citation: Abdul-Rahman, M.; Adegoriola, M.I.; McWilson, W.K.; Soyinka, O.; Adenle, Y.A. Novel Use of Social Media Big Data and Artificial Intelligence for Community Resilience Assessment (CRA) in University Towns. *Sustainability* **2023**, *15*, 1295. https://doi.org/10.3390/su15021295

Academic Editors: Olugbenga Timo Oladinrin, Chaminda Pathirage, Ayokunle Olanipekun and Muhammad Qasim Rana

Received: 10 November 2022
Revised: 30 December 2022
Accepted: 4 January 2023
Published: 10 January 2023

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 [1,2]. In most countries, such as 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 [1,3]. According to Brooks, Byford, and Sela [1], the United Kingdom's commercialization of higher education has changed the narratives. Students now "see degrees as private investments rather than public good". To obtain the best "investment", students now travel far away from home in search of "quality" when making their higher education choices. Related to this, Kinton, Smith, Harrison, and Culora [2] emphasised that global competition among HEIs for student "customers" have made universities more responsive, increased their teaching quality and focused on providing more conducive learning environments. For students, framing "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 geographies. Housing developments are 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 [2,4,5].

"Studentification", a term coined by British geographer Darren P. Smith in 2002, has been globally used to describe the significant processes of urban change and the challenges university towns face due to the growing students' concentration off-campus. This is due to the inability of universities to house all their students within their campuses [4,6–8]. Some of the impacts of studentification have been well documented in the research corpus for the last two decades, but they were mainly woven around housing studies. Hence, most existing studies mainly discuss the economic, social, and environmental negative impacts of housing and students' accommodation and proffer solutions around the same issues using human geography and social theories [2,9–15]. For university towns to be sustainable, they have to be resilient against the chronic stresses and shocks affecting them [16]. Building resilience requires a holistic assessment in all the dimensions of resilience [17,18]. Review of extant studentification literature shows that there are no studies looking at the negative impacts of studentification from the community resilience perspective, providing holistic community assessment, or identifying community challenges from textual big data using artificial intelligence [19].

To fill this identified research gap, this study proposed a novel Community Resilience Assessment (CRA) framework that uses Artificial Intelligence (AI) tools to identify and holistically assess community challenges within university towns. The research answered the questions of the possibility of using AI and textual big data to assess community challenges and the reliability of using such an assessment in university towns suffering from the negative impacts of studentification. We chose six university towns as case studies. Namely: 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's big data. Figure 1 shows the geo-location of the six case studies.

Figure 1. Map showing the location of the six case studies. Source: Authors' fieldwork.

This study gives a global overview of university towns' challenges due to studentification beyond the housing issues often discussed in the literature. It also shows that AI and textual big data from microblogs can provide an easy, cheap, and more accurate way of conducting community resilience assessments. Section 2 of this paper shows the literature review and other related work, Section 3 explains the methodology, Section 4 shows the results from the case studies, Section 5 discusses the findings, and Section 6 gives the summary and conclusion as well as the limitations and areas for future research.

2. Theoretical and Conceptual Background

2.1. Studentification: Practical Challenges and Benefits

Studentification leads to urban changes over time. According to Smith [20] and Situmorang et al. [21] these changes have five key dimensions: social, cultural, physical, economic, and 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 new sub-cultures in the area. Physically, the environment may either be upgraded to cater to the new teaming customers (especially in retail and service infrastructure) or downgraded to a slum over time. And economically, housing stock changes to accommodate the student population lead to higher densities and inflation of property and rental prices. Local businesses also change their models over time to satisfy the needs of the students. With such rapid new complexities in the university towns, governance issues gradually manifest.

Although studentification is often portrayed as a negative phenomenon in the media and research, the town-gown relationship is not all parasitic. Some of the benefits of studentification to the university towns and their residents include the following: the provision of a young and educated workforce, cheaper labour and increased volunteerism [22]; adding more diversity and vibrancy to local cultures and raising the aspirations of the local youths [23]; enhancing the spending power, improving the local economy, creating more jobs and sustaining the local retail businesses [24]; supporting the local real estate sector and its associated trades (agency, insurance, finance, etc.) and driving up demands for quality housing provision [25]; as well as making the town more attractive to tourists and investors [26]. However, this study only looks at the practical challenges studentification has on university towns and their residents.

2.2. The Concept of Sustainability, Resilience, and Community Resilience Assessment

Defining sustainability depends on the framing and dimension. A common framework with substantial nexus with resilience is "the triple bottom line", which conceptualizes that societies should not make decisions about their future based only on economic returns but also on environmental protection, social justice, and equity [27]. The principle of the triple bottom line suggests that human settlements must be environmentally bearable, socially equitable, and economically viable for the current generations and the future ones yet unborn [28]. According to UN-Habitat [29], resilience is essential to sustainability. That is why United Nations Sustainable Development Goal 11 (UNSDG 11) categorically mandated the 193 UN member nations to strive to make their human settlements inclusive, safe, resilient, and sustainable. In urban planning, the "*concept of resilience*" is defined as the ability of human settlements to prepare and plan for, absorb, recover from, and more successfully adapt to environmental, social, and economic adverse events [30]. Community resilience, therefore, is learning from the past, understanding current situations and using that information to minimize future negative impacts. Influenced by the above philosophy and the global call to develop a sustainable world, as well as the increasing challenges of human settlements, resilience research and the concept of community resilience assessment are fast becoming popular in global policy and scientific research and discourse [31].

Community Resilience Assessment (CRA) is an assessment carried out to identify and analyze the challenges human communities face [32]. CRAs are summative or formative toolkits, indexes, scorecards, and frameworks that identify and analyze socio-cultural, economic, environmental, and institutional community resilience challenges [31]. Sharifi [31] posited that good CRA methodologies should be able to identify community challenges in all dimensions of resilience, capture spatiotemporal dynamism, address uncertainties, and seek the opinions of the people involved. In the last two decades, more than 100 CRA methodologies (toolkits, indexes, scorecards, and frameworks) have been created by different organizations for different purposes, countries, or regions. No CRA methodology was explicitly developed to identify or assess community challenges in university towns. However, few can be modified to identify and evaluate specific challenges within university towns, such as natural disasters and climate change impacts.

2.3. The Use of Artificial Intelligence and User-Generated Content from Social Media Microblogs in Community Resilience Assessment

Processes in the built environment have seen a lot of disruptions in the 21st century [33]. This is mainly due to the new challenges human settlements face in the 21st century, coupled with the drive for smarter cities, the widespread use of AI, and the explosive data generation in the fourth industrial revolution [34]. Today, billions of data points are generated in cities globally because of the increase in internet usage and smart gadgets (Internet of Things) [35]. The rising complexities and challenges of our cities in this information age require new innovative methods because most traditional approaches can no longer harness the potential of the big data generated in our cities [36]. To rise to the occasion, professionals and researchers in the built environment now use AI systems to automate traditional processes and make them more efficient and smarter [37].

In simple terms, the vast and constantly expanding field of AI refers to machines or computers mimicking cognitive functions that humans associate with the human mind, such as learning and solving problems [38]. AI applications are being used in almost every sector. In urban planning, AI is used in security surveillance and smart transport systems (including traffic management) [39], robotics, automation and installation of infrastructure [40], health care delivery [40], garbage collection [41], air quality monitoring [42], and disaster management [43], among others. On the other hand, Machine Learning (ML) is a subfield of AI that trains machines to learn from experiences and make intelligent decisions with or without supervision [44]. One of such functions is learning human languages, communicating with humans, and reading human emotions [45]. This subfield of ML is called Natural Language Processing (NLP). Figure 2 summarizes the AI, ML, and NLP relationships.

Social media microblogs have become a key medium of communication and expression with the increased use of Internet of Things (IoT) and smartphones. This has made User-Generated Content (UGC) from Twitter, WeChat, Facebook, and Instagram a huge part of research in areas such as marketing, commerce, tourism, and health [46]. For example, Alharbi et al. [47] used Twitter big data, ML, and NLP methods to study the opinions of Apple phone users. Their research examines users' sentiments to determine if they are happy or sad about using the new iPhones. Using a similar methodology and Twitter big data, Asghar et al. [48] also studied people's automobile preferences. Generally, in commerce and marketing, companies use UGC to understand customers' perceptions and satisfaction and how their goods and services are compared with other similar products in the market [49].

In the health and human settlements nexus, Carlos et al. [50] used Twitter data to study the outbreaks of dengue fever in Brazil, while Shah et al. [51] used data from medical microblogs to analyse the sentiments patients have toward their physicians in the UK. And in travel and tourism, Nilashi et al. [52] used data from social media microblogs and ML to study travellers' decision-making processes and develop a system to recommend hotels tailored to their preferences. Similarly, Sun et al. [53] also used big data from social media to study trends and tourists' opinions in China. Ahani et al. [54] also used a similar methodology to study customer behaviour and customer satisfaction in the hotel industry to develop a better marketing plan and recommend strategies for hotel owners to increase customer satisfaction and retention.

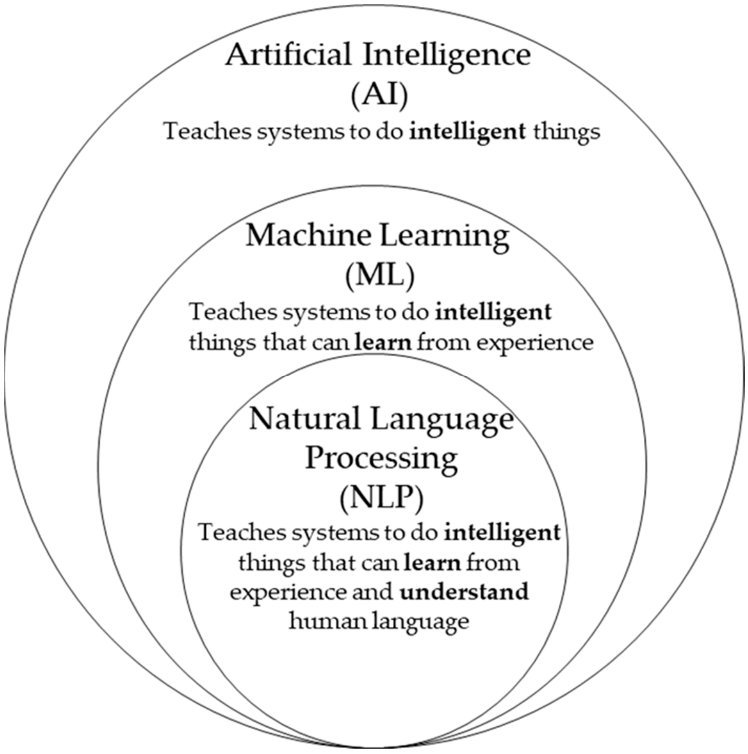

Figure 2. The AI—ML—NLP nexus.

In an attempt to use similar methodologies above for urban planning and management Abdul-Rahman et al. [55] developed a framework to simplify pre-processing of social media big data using Text Mining ™, ML, and NLP. Their study showed that UGC from Twitter can be used to identify community challenges using AI. Similar to studies in marketing and tourism, people also share their opinions and sentiments on how they feel about their communities, what challenges their communities experience, and what they think the solutions are. This study expanded Abdul-Rahman, Chan, Wong, Irekponor, and Abdul-Rahman [55] study and methodology to develop a CRA framework for university towns. Apart from its efficiency, the novelty of this proposed framework lies in its ability to provide spatiotemporal analysis of community challenges among the five dimensions of resilience.

Among all social media microblogs, Twitter is commonly used for text mining because of the rich textual UGC, the size of the data, and the ease of using the Twitter API [56]. This study also used big data from Twitter.

3. Materials and Methods

Since this study adopted an existing AI-based framework with high accuracy [55], only key modified codes and procedures were repeated here. However, apart from adapting the framework to identify and assess the negative impacts of studentification in multiple case studies, the original approach's validation step was also modified to online experts' validation. This makes validation easier, faster, and cheaper.

The methodological framework in Figure 3 comprises the following steps:

(a) *Getting started*—The user connects the computer (*Local Host*) to the internet.
(b) *Connecting to case study and Python environment*—User receives geographical coordinates from case study and launches Python v3 (or a newer version) (Python Software Foundation, Beaverton, OR, USA), launches PyQuery, and Lxml.

(c) *Text mining*—The User downloads the *Optimized-Modified-GetOldTweets3-OMGOT* (https://github.com/marquisvictor/Optimized-Modified-GetOld-Tweets3-OMGOT, accessed on 24 December 2022) library from GitHub and follows the instructions in the *ReadMe file* to mine public UGC from Twitter. *Optimized-Modified-GetOldTweets3-OMGOT* is a python-based open-source tool containing a set of programmatic algorithms designed by Abdul-Rahman, Chan, Wong, Irekponor, and Abdul-Rahman [55] to streamline searches and bypass the rate limits of the Twitter APIs, allowing the download of unlimited historic tweets generated from a specific geo-location using the PyQuery tool, from terminal or command prompt. The algorithms download both the UGC (tweets) and their metadata into Microsoft Excel files (.csv) directly to the *Local Host*. Since the data is downloaded to .csv file(s), it can easily be transferred outside of the Python environment for further data analysis. In this study, only tweets in the English language were downloaded.

(d) *Topic Modelling—Latent Dirichlet Allocation (LDA)* (https://github.com/lda-project/lda, accessed on 24 December 2022) An ML and NLP Python-based tool were used to split the big data downloaded in step (c) into major topics. These topics represent major discussion themes within the selected case study areas based on Twitter UGC. 45 themes (topics) were identified. The 45 topics were converted to keywords and used to re-mine the textual data "per topic" using the *Use Cases* in the *ReadMe file*. Data from each topic was then saved in a separate .csv file. This step helps to validate the previously mined data and break down the big data into manageable sizes for further analysis. Blei et al. [57], Chuang et al. [58], Sievert–Shirley [59], Moody et al. [60], Momtazi [61], Abdul-Rahman, Chan, Wong, Irekponor, and Abdul-Rahman [55] and Asghari, et al. [62] all published great papers on how to use LDA.

(e) *Sentiments Analysis*—Each topic folder in step (d) was analyzed for sentiment polarity using *Valence Aware Dictionary and sEntiment Reasoner* (VADER) (https://github.com/cjhutto/vaderSentiment, accessed on 24 December 2022). VADER is an ML and NLP open-source tool that analyses textual data according to their sentiment polarity (positive, negative, and neutral) and intensity [63]. Negative comments from the community residents and visitors represent displeasure and community challenges. Due to the unstructured nature of the social media data, VADER is one of the best NLP tools for analysing sentiments from social media UGC [47,48].

(f, g and h) *Survey and Data Validation*—VADER is trained and validated by the developers [64], and Abdul-Rahman, Chan, Wong, Irekponor, and Abdul-Rahman [55] showed that the output has high accuracy. However, to further reduce bias and narrow the error margin, the assumption that the residents, workers, and visitors' displeasures about a community (negative polarities) represent the community's challenges needs to be re-validated. Physical distribution of the questionnaire survey as used by Abdul-Rahman, Chan, Wong, Irekponor, and Abdul-Rahman [55] slows down the process, therefore, this study proposed an online survey via email and twitter to experts identified through research databases and some identified from the big data based on their work on studentification and community resilience, sustainability and artificial intelligence in the 6 countries of the case studies. The survey instrument was designed and tested followed techniques used by Darko [65]. A pilot survey was carried out before the main questionnaire survey. The purpose of the pilot survey was to test the survey procedures and verify the comprehensiveness and the use of technical language [66]. The pilot survey was administered to five participants: two professors, one chief resilience officer, one post-doctoral researcher, and a doctoral researcher. These participants are all well knowledgeable in the field of CRA and the use of artificial intelligence for big data mining and natural language processing. After the pre-testing phase, the survey instrument was perfected and administered to experts for seven months, from June 2020 to February 2021. The experts were asked to forward the questionnaire link to others they feel are eligible to answer the questionnaire within their network, including experts outside of their countries and copy the research team. A total of 392 valid responses were received. Figure 4 shows the number of responses received for validation and the extra 17 countries the survey snowballed to. The questionnaire used for this study is available online via https://theses.lib.polyu.edu.hk/handle/200/11732 (pg. 99–203), accessed on 24 December 2022. Only sections A and B were used for validation in this study. Section A was used to collect the respondents' biodata. In contrast, section B collected data on the respondents' countries and the respondents' agreements on the data grouped under the five dimensions of studentification (cultural, social, physical, economic, and institutional and governance challenges). A 5-point Likert scale (1 = strongly disagree; 2 = somewhat; disagree; 3 = neither agree nor disagree; 4 = somewhat agree; 5 = strongly agree). Four data analysis methods were used: (1) The reliability of the scales was measured using Cronbach's alpha; (2) Ranking was performed using Mean value ranking; (3) Standard Deviation scores; (4) The Mean values were normalized (Normalized value = (mean—minimum mean)/(maximum mean—minimum mean)). SPSS v26 and Python v3.10.8 were used for the validation analysis.

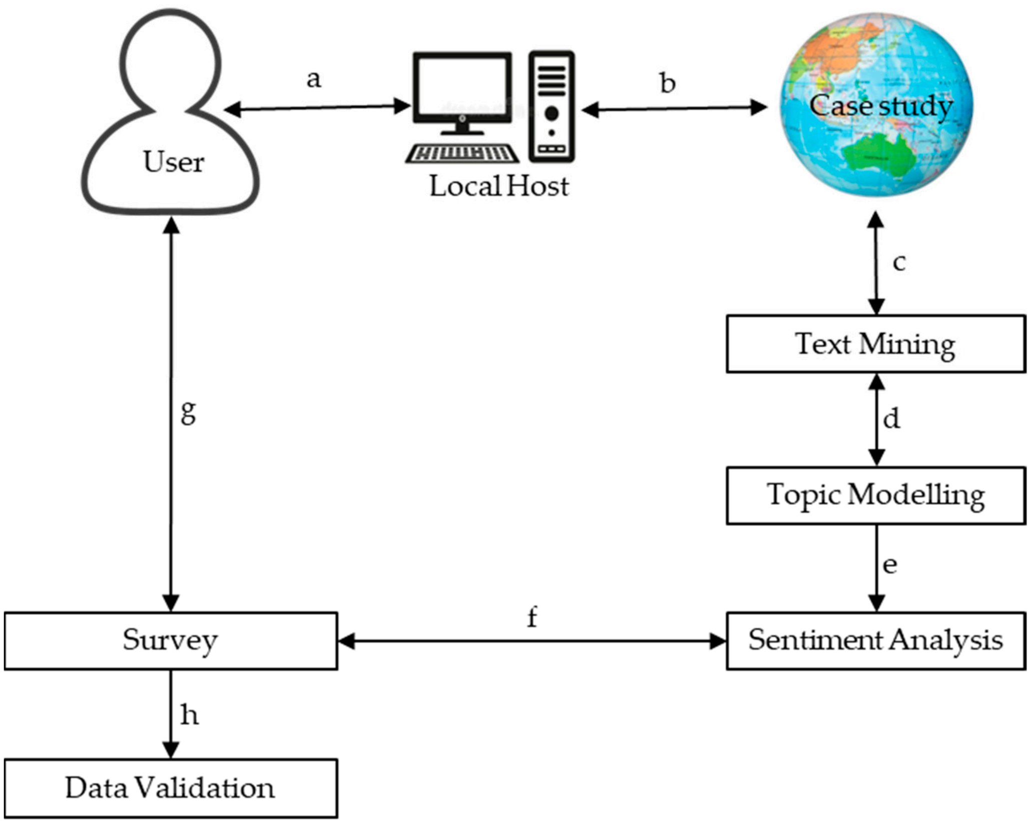

Figure 3. The methodological framework adapted from Abdul-Rahman, Chan, Wong, Irekponor, and Abdul-Rahman [55].

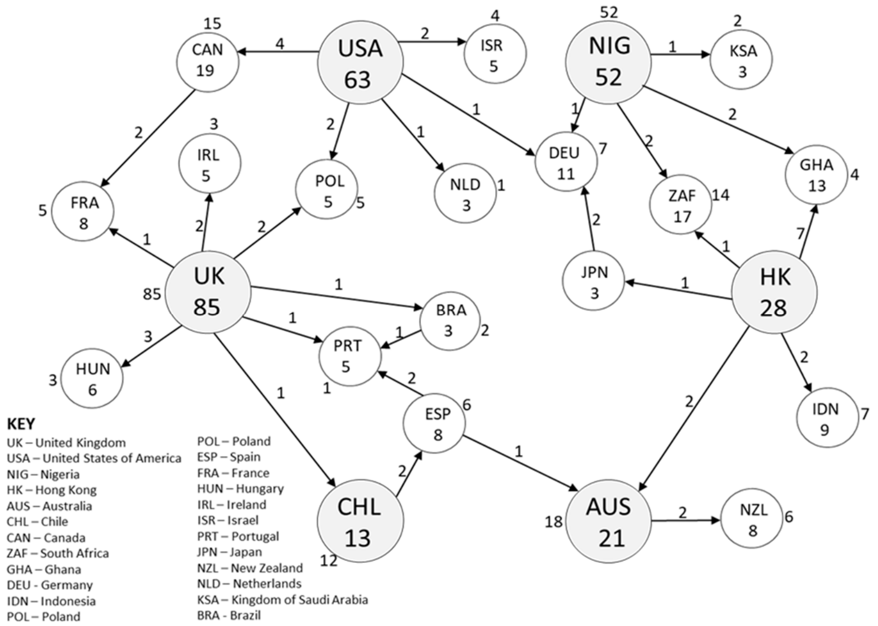

Figure 4. Network showing how the questionnaire survey snowballed from the six countries into 23.

4. Results

4.1. Data Mining using the Optimized-Modified-GetOldTweets3-OMGOT Library

Ten years of Twitter's historic UGC within the six case study areas was downloaded (from 1 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 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

4.2. Topic Modelling and Identifying Community Challenges Using Latent Dirichlet Allocation

A total of 45 topics were identified from the first mining datasets combined (total) using LDA. The topic modelling was also performed per case study. A total of 31 of the 45 issues 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 Abdul-Rahman, Chan, Wong, Irekponor and Abdul-Rahman [55]). A total of 4,561,311 tweets were mined under the 45 topics (99.65% of the first mining). A total of 15,796 tweets were automatically excluded because they did not fit into any of the primary 45 topic clusters, and the topics they were under didn't have significant data under them. See Table 2 for the final output and Appendix B for the coding scripts.

Table 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	8173	29,324	21,003	-
	C02	Declining moral and community values	18,526	-	-	-	-	2520
	C03	Lack of community cohesion & integration due to the transient nature of the student population	16,124	-	8062	-	8352	-
	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	-	-	2992
	C06	Cultural diversity and lifestyle conflicts	15,251	25,872	-	48,764	-	-
	C07	Divergent perceptions on what makes up communal obligations	-	-	10,072	-	7983	-
	C08	Inconsideration and lack of place attachment	21,261	17,008	8586	-	-	-
	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	9356	27,013	-	4144
	S03	Increased level of alcoholism, drugs peddling and abuse.	65,444	57,637	47,014	17,271	25,551	4252
	S04	Increased level of prostitution and sexually transmitted diseases	-	-	42,625	-	-	-
	S05	Loss of social services such as 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	4592
	S08	Increased competition for privately rented apartments	14,889	31,666	9176	-	7063	-
	S09	Lack of year-round goods & services due to the resort-economy nature of the community	-	14,414	8003	-	-	-

Table 2. *Cont.*

Theme	Code	Generated Topics	Number of Mined Tweets per Case Study					
			Lough-Borough	Ann Arbor	Akoka	Hung Hom	Sydney	Aguita de la Perdiz
	S10	Establishments of night-time entertainment ventures at the detrimental impacts of residential amenities	14,752	33,111	17,787	-	6994	-
	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	6771
	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	5627	5251
	P04	Defacing neighbourhoods with graffiti, posters, writings and rental boards and advertisements	91,251	86,375	16,251	41,324	29,351	5931
	P05	Congestion and overcrowding on the streets and in public places including shops.	-	-	13,998	34,883	12,413	2221
	P06	Increased population density	66,521	46,788	9005	-	32,102	-
	P07	High environmental pollution—Noise, air pollution and indiscriminate waste/garbage disposal	100,526	74,576	58,524	89,261	52,061	7220
	P08	Increased incidents of protests leading to vandalism of the physical environment.	-	-	9222	91,222	-	-
	P09	Increased pressure on urban basic services due to higher population than planned for	17,653	10,169	-	-	5165	-
	P10	On-street parking and traffic congestion	74,251	34,001	-	25,421	14,006	-
	P11	Pressure on public transport	-	-	51,196	-	-	1942
	P12	Ghost community during off-term periods	11,993	-	20,014	-	-	2014

Table 2. *Cont.*

Theme	Code	Generated Topics	Number of Mined Tweets per Case Study					
			Lough-Borough	Ann Arbor	Akoka	Hung Hom	Sydney	Aguita de la Perdiz
Economic	E01	High rental prices	95,267	99,761	81,153	45,999	47,002	5032
	E02	Lucrative student housing business deters access to affordable housing for non-student residents.	11,782	-	15,551	-	-	-
	E03	Change in consumer behaviour & taste leading to changes in business models & structures.	44,031	16,094	23,623	23,061	5026	-
	E04	High cost of living (goods and services)	57,220	39,691	76,011	35,752	43,873	4803
	E05	High influx of commercial activities	40,308	11,452	29,112	27,154	16,021	1701
	E06	Seasonal demand for students' accommodation	11,506	-	-	-	10,152	-
	E07	Seasonal scarcity of manpower in shops, restaurants, bars, etc.	13,991	-	-	-	-	1441
	E08	Seasonal customer base (on and off term periods)	12,016	-	9937	-	-	-
	E09	Low tax generation from the community since students are exempted from taxation.	35,478	-	-	-	-	1017
Institution & 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	8893	-	-	-
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

4.3. 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 displeasure from residents and visitors [63]. 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 [64]. This means = or >0.05 is a positive sentiment polarity, >−0.05 and <0.05 is neutral, and = or <−0.05 is negative.

Table 3. 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 & indiscriminate waste 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 neighbourhoods with graffiti, posters, writings & rental boards & 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 & environ. 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 ent. 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

Table 3. *Cont.*

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	
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	29,692	-	18	15	-	-	-	29
S04	Increased level of prostitution and sexually transmitted diseases	28,777	-	-	8	-	-	-	30
C03	Lack of community cohesion & integration due to the transient nature of the 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 such as 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-students	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	8520	-	-	24	-	-	–	43
C05	Differing standards of acceptable behaviours by different social groups	7532	-	-	22	-	-	10	44
C07	Divergent perceptions on what makes up communal obligations	7392	-	-	25	-	17	-	45

Within each of the identified topics in each case study, there were positive, neutral, and negative UGC tweets. Table A1 in Appendix D contains the summations of all normalized and weighted composite scores (sentiment polarity) for each topic. Table 3 shows the identified community challenges and their ranks based on the frequency of their negative sentiment polarity. While Figures 4–6 show the sentiments polarities in each case study, the thematic cluster of community challenges and the intensity of community challenges in each case study, respectively.

The codes used for the VADER sentiment analysis are also contained in Appendix C. See Hutto and Gilbert [63] for more information on the parameters and scoring of the VADER model on Python.

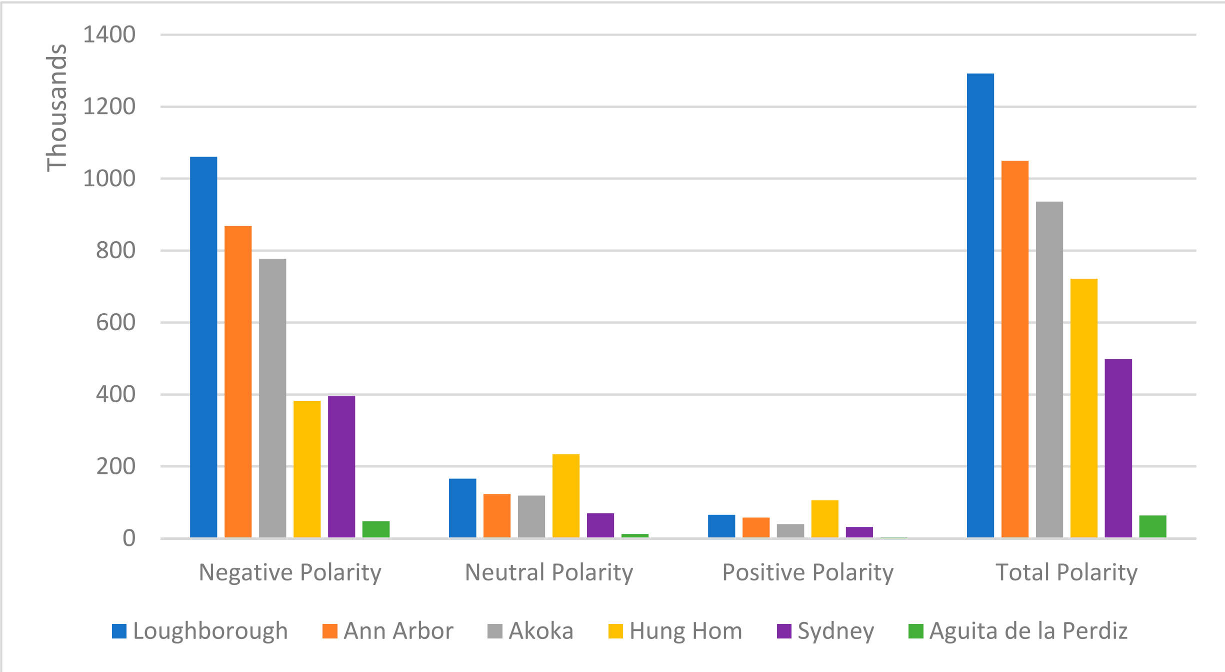

Figure 5. Sentiment polarities calculated from the Normalized Weighted Composite Scores (NWCS).

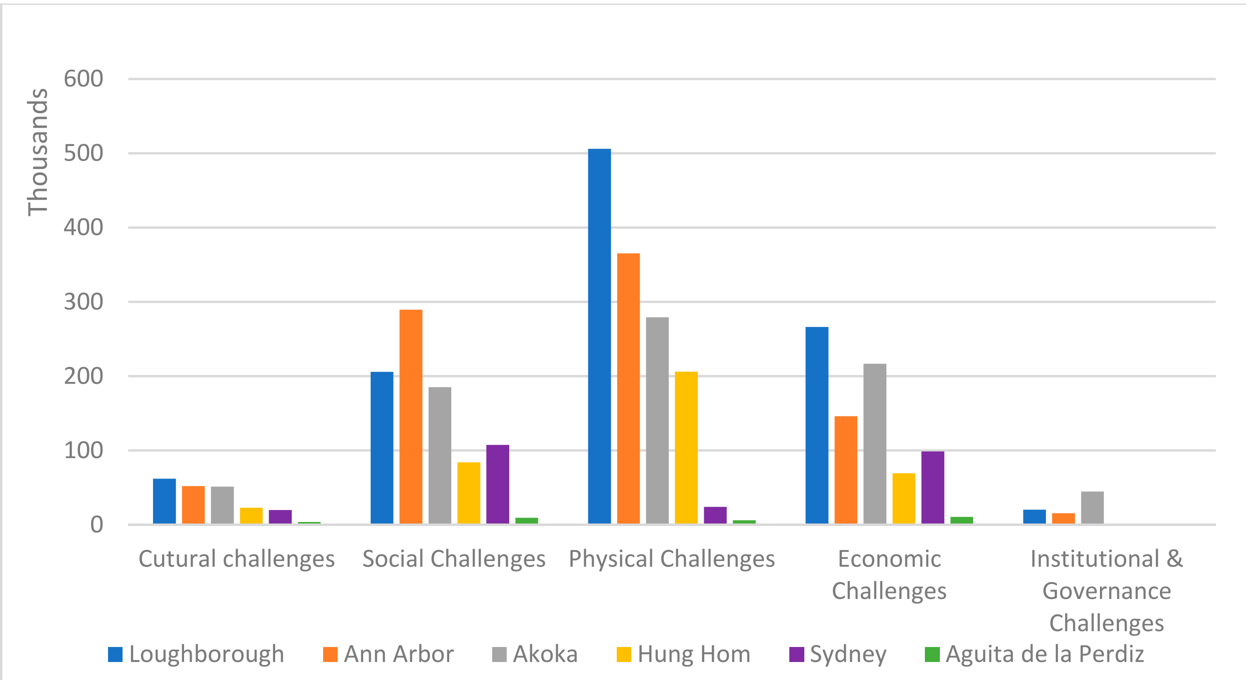

Figure 6. Thematic clusters of community challenges in university towns.

4.4. Result Validation

To test the reliability of the scales, Cronbach's Alpha (CA) was calculated using Howard [67] Python methodology. The CA values for the subscales were 0.799 (cultural), 0.972 (social), 0.957 (physical), 0.869 (economic), and 0.798 (institutional and governance). By statistical standards, CA scores above 0.7 are said to have good internal consistency [68]; therefore, the validation data is reliable. Table 4 shows the respondents' profile, while the mean values, standard deviation scores, normalized mean values, and ranking of all community challenges are shown in Table 5. All the mean and normalized mean values were more than the 3.5 and 0.5 average [65], respectively. This means none of the 45 community challenges was collectively rejected by the 392 experts, who were mainly from academia or research institutes and had more than 5 years of experience working as researchers, urban planners, or in the community resilience domain. The majority of the experts also have experience either developing CRA methodology or using one.

Table 4. Respondents' profiles for validation.

Data on Survey Respondents	Responses	Percentage
Category		
Academia/research institute	189	48.2
Consulting/private sector	42	10.7
Public sector/government agency or department	36	9.2
Intergovernmental organization/international NGO	97	24.8
Others	28	7.1
Profession		
Academic/researcher	128	32.7
Urban planner	112	28.6
Resilience project manager/officer	51	13.0
Architect	29	7.4
Economist/development economist	12	3.0
Sociologist	22	5.6
Engineer (civil, construction, etc.)	27	6.9
Others	11	2.8
Years of experience		
1–5 years	36	9.2
6–10 years	91	23.2
11–15 years	102	26.0
16–20 years	55	14.0
Above 20 years	108	27.6
Type of involvement in community resilience & Sustainability		
Development of as assessment methodology	191	48.7
Use of an assessment method	138	35.2
Both of the above	51	13.0
Others	12	3.1

Table 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

Table 5. *Cont.*

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
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 such as 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

5. Discussion

5.1. General Overview of Community Challenges in University Towns

The UGC from the six case studies shows that university towns face similar challenges globally. This was confirmed by the experts' validation since none of the community challenges was rejected. Some of the community challenges, such as increased racism, tribalism, and religious challenges (C09) and increased levels of prostitution and sexually transmitted diseases (S04) were unique to only Akoka (Nigeria). At the same time, the lack of social interactions among groups (S12) was unique to only Hung Hom (Hong Kong). The rest of the community challenges were reported in at least two case studies, as seen in Table 2.

Loughborough, with the highest number of mined UGC (see Table 1), has the highest negative polarity (complaints), followed by Ann Arbor, then Akoka, Hung Hom, Sydney, and Aguita de la Perdiz (see Figure 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 shows that most community challenges identified were physical/environmental, followed by social, economic, cultural, and institutional and governance challenges. However, no institutional and governance challenges were identified from the data in Sydney and Aguita de la Perdiz. Figure 7 shows that 47.8% of the community challenges identified in Loughborough were physical/environmental, 25.1% had 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% as social, 18.1% as economic, and 6% as institutional and governance-related challenges (due to studentification). 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.

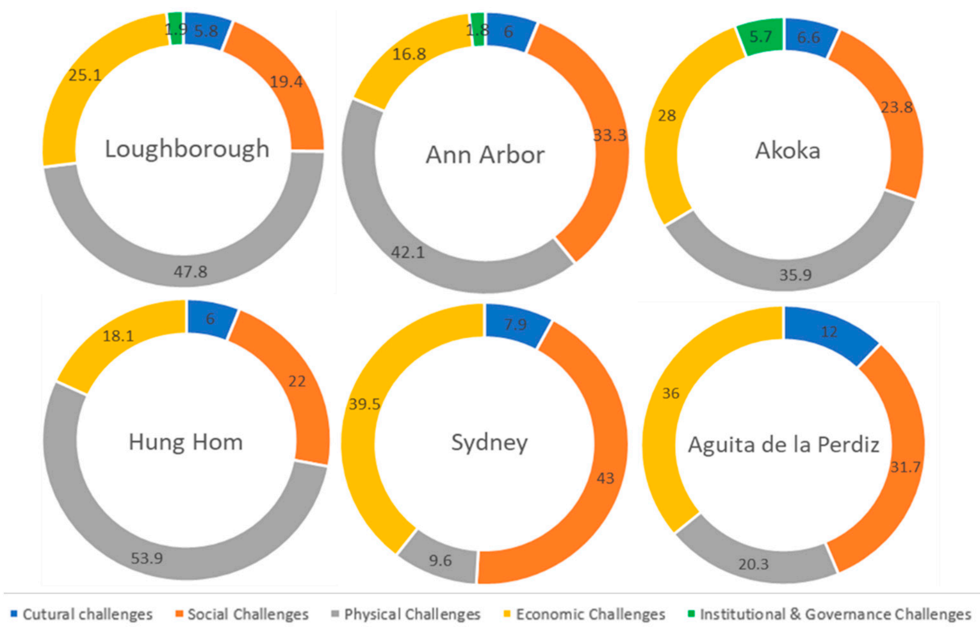

Figure 7. Charts showing the intensity of community challenges in percentages in the case studies.

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 differently 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 include the following: the illegal subdivision of family homes and apartments into housing with multiple occupancies (P01); high rental prices (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 (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).

These results show that the intensity of community challenges varies from one community to the other, but overall most university towns experience similar challenges due to studentification. This points to the fact that students have similar behaviours regardless of the country or region [69,70]. This novel CRA framework allows university towns to collaborate and co-produce solutions against studentification challenges, share best practices and learn coping mechanisms from one another, especially those with similar challenges [71].

5.2. Novelty and Implications of the Proposed CRA Methodology

a. Assessment of all major community resilience dimensions

Communities have multiple complex dimensions [72]. This novel framework identified and analysed challenges under the five major dimensions of resilience (cultural, social, physical/environmental, economic, and institution and governance) in all the university towns. This allows community planners and managers to study community resilience challenges holistically and zoom deeper into individual community challenges or resilience dimensions.

b. Assessing the spatiotemporal dynamism of the community challenges

Capturing time horizons and knowing the specific areas where the residents' and visitors' sentiments were generated will help the community managers better assess the challenges and focus on "hotspots". Since the UGC big data from microblogs such as Twitter come with metadata that contains the date and time of tweets generated within a specified spatial radius, the negative polarities can be modelled further after sentiments analysis using Microsoft Excel 3-D Clustered Columns to show spatiotemporal dynamics. Figure 8 shows a polarity-based model of residents' monthly complaints from 1 January 2010 to 31 December 2020 in Loughborough, UK. The data for P07 (negative sentiments for Loughborough = 98,852 tweets) from figure of Appendix C 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 reduced during the summer term and semester three (April to August) and also in December when the university town was 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 any of the community challenges identified.

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 [73]. 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.

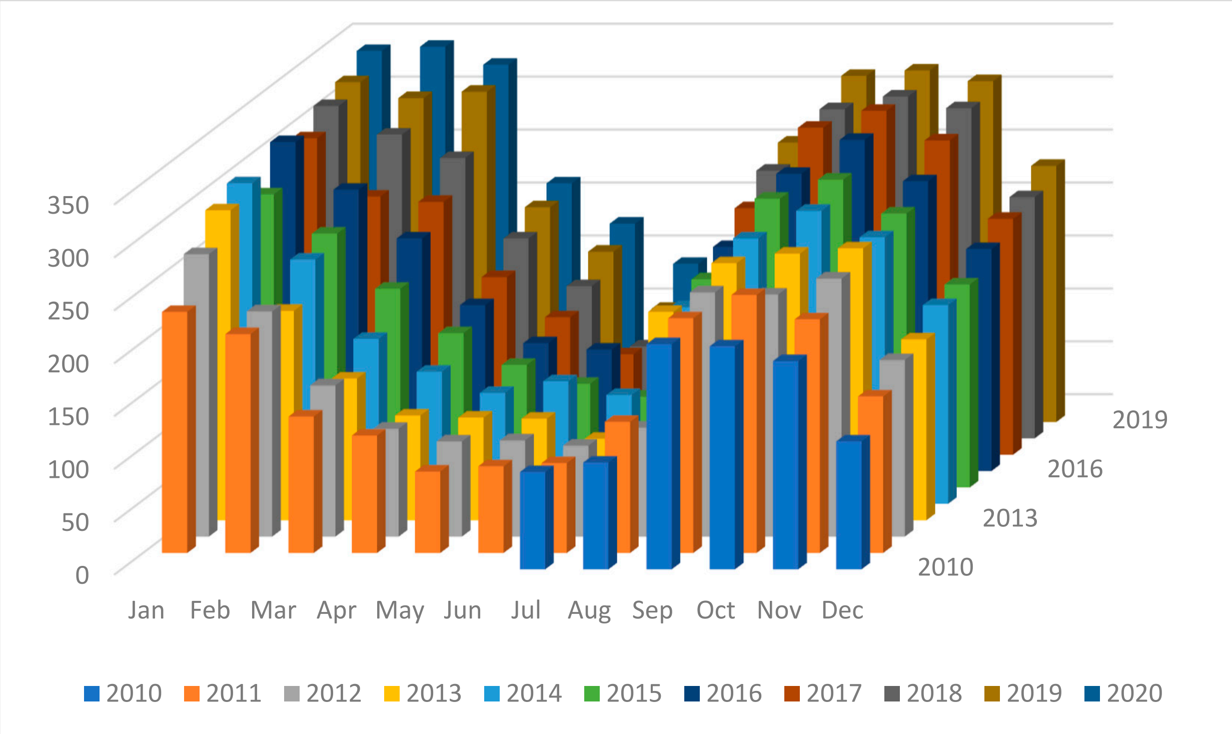

Figure 8. Polarity-based model for high environmental pollution (Noise and indiscriminate waste/garbage disposal) in Loughborough, UK.

6. Summary and Conclusions

By adapting and modifying the novel framework for pre-processing location-based social media data by Abdul-Rahman, Chan, Wong, Irekponor, and Abdul-Rahman [55], this study demonstrated UGC from microblogs can be used to identify community challenges using AI (ML and NLP) tools such as LDA and VADER. Six university towns were used as case studies.

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 issue. The negative Normalized Weighted Composite Scores (NWCS) frequencies were used to rank the identified community challenges. An online expert survey was conducted to validate and rank the negative impacts of studentification. Mean ranking, standard deviation, and normalized mean values were used to rank the community challenges. The statistical results showed that all 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, this novel framework also provides a deeper spatiotemporal analysis of each community challenge. Using a large opinion poll (sample size) helps minimize errors and increases the accuracy of the data.

This study contributes to the community resilience body of knowledge by providing a simple, fast, cheap, and efficient way of conducting CRA remotely. This novel methodology can be used by urban planners, community managers, community-based organizations, and universities. It can be used to identify community challenges and make university towns resilient and sustainable.

This methodological framework works better in well-connected urban university towns where more people are connected to the internet and the use of social media is high. This limitation will not render the methodology useless, but it will affect the amount of data available for analysis if the framework is used in a rural community with low Internet connectivity. Future works may include using APIs from other microblogs such as WeChat and Facebook. The framework can also be improved to predict future trends based on historical data. Geographic Information System (GIS) can also be used to overlay the data on the base maps of the case studies to run more analysis and visualization.

Author Contributions: Conceptualization, M.A.-R. and Y.A.A.; methodology, M.A.-R., Y.A.A. and O.S.; software, M.A.-R.; validation, W.K.M. and M.I.A.; formal analysis, visualization and data curation, M.A.-R., Y.A.A. and W.K.M.; writing—original draft preparation and writing—review and editing, M.A.-R., O.S. and M.I.A. All authors have read and agreed to the published version of the manuscript.

Funding: This research work was part of a larger doctoral study titled "A community Resilience Assessment Framework for University Towns" supported by a PhD studentship from the Research Institute for Sustainable Development (RISUD) and the Department of Building and Real Estate of the Hong Kong Polytechnic University [research grant: G-R006.RJET].

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Informed consent was obtained from all respondents involved in the study.

Data Availability Statement: Not applicable.

Acknowledgments: The authors acknowledge Professor Edwin H.W. Chan and Professor Man Sing Wong's supervision, for their advice and mentorship for the PhD thesis "A community Resilience Assessment Framework for University Towns", which led to the development of this manuscript.

Conflicts of Interest: The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

Appendix A

1. Data mining codes.

```
#First Mining for LDA
python GetOldTweets3.py --near "coordinates from centre of case study" --within
4km --lang es --since 2010-01-01 --until 2020-12-31
```

```
#Second Mining using Keywords for Sentiment Analysis
python GetOldTweets3.py --near " coordinates from centre of case study " --within
4km --lang es --since 2010-01-01 --until 2020-12-31 --querysearch "keywords"
```

2. Codes for text cleaning
    a. Loading the dataset

```
df = pd.read_csv('file name')
```

    b. Data cleaning and noise reduction

```
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

doc_clean = [clean(doc).split() for doc in doc_complete]
```

c. 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]
```

Appendix B

Codes for Topic Modelling using LDA

```
#Initializing the LDA Model with gensim library
Lda = gensim.models.ldamodel.LdaModel

#Training the LDA model on the document term matrix
ldamodel = Lda(doc_term_matrix, num_topics=50, id2word = dictionary, passes=50)
print(ldamodel.print_topics(num_topics=50, num_words=5))
```

Appendix C

Codes for Sentiment Analysis Using VADER

```
#Import VADER library
> pip install vaderSentiment

#Launch the sentiments analyzer
from vaderSentiment.vaderSentiment import SentimentIntensityAnalyzer
analyser = SentimentIntensityAnalyzer()

#Launch the polarity score calculator
def sentiment_analyzer_scores(sentence):
    score = analyser.polarity_scores(sentence)
    print("{:-<40}{}".format(sentence, str(score)))
sentiment_analyzer_scores("Demographic changes leading to more youths.")
The family park is super cool----------------- {'neg': 0.0, 'neu': 0.326, 'pos':
0.674, 'compound': 0.7351}
```

Appendix D

Table A1. Sentiment polarity for 4,561,311 tweets mined from six university towns in the UK, US, Nigeria, Hong Kong, Australia and Chile from 1 January 2010, to 31 December 2020.

Case Study	S/N	Topics	negTweets	neuTweets	posTweets	∑Tweets
		Cultural				
	1	C01	10,524	14,756	4898	30,178
	2	C02	16,976	1492	58	18,526
	3	C03	15,026	1021	77	16,124
	4	C06	5652	7635	1964	15,251
	5	C08	13,769	7184	308	21,261
		Social				
	6	S01	110,457	5715	180	116,352
	7	S03	59,820	4602	1022	65,444
	8	S05	8976	4792	1241	15,009
	9	S07	10,872	6197	1042	18,111
Loughborough, UK	10	S08	9992	2824	2073	14,889
	11	S10	5766	3624	5362	14,752
		Physical				
	12	P01	122,825	17,924	2109	142,858
	13	P02	15,184	4625	1207	21,016
	14	P03	56,625	12,612	1766	71,003
	15	P04	78,563	11,162	1526	91,251
	16	P06	46,021	6012	14,488	66,521
	17	P07	98,852	1645	29	100,526
	18	P09	11,524	5167	962	17,653
	19	P10	68,066	5160	1025	74,251
	20	P12	8383	2186	1424	11,993

Table A1. *Cont.*

Case Study	S/N	Topics	negTweets	neuTweets	posTweets	∑Tweets
		Economic				
	21	E01	91,251	3164	852	95,267
	22	E02	9391	1526	865	11,782
	23	E03	38,726	3784	1521	44,031
	24	E04	55,692	1506	22	57,220
	25	E05	13,668	11,114	15,526	40,308
	26	E06	8644	2282	580	11,506
	27	E07	10,536	3014	441	13,991
	28	E08	8904	2511	601	12,016
	29	E09	29,413	5723	342	35,478
		Institution & Governance				
	30	I02	9725	3516	1425	14,666
	31	I03	10,526	1526	725	12,777
	Total		**1,060,349**	**166,001**	**65,661**	**1,292,011**
Ann Arbor, USA		**Cultural**				
	1	C01	11,241	8251	2061	21,553
	2	C04	16,340	5561	751	22,652
	3	C06	11,514	12,351	2007	25,872
	3	C08	13,005	3102	901	17,008
		Social				
	5	S01	70,045	2414	96	72,555
	6	S02	20,961	4669	1251	26,881
	7	S03	53,817	2619	1201	57,637
	8	S05	14,769	9226	3326	27,321
	9	S06	23,141	5622	2001	30,764
	10	S07	48,323	1627	52	50,002
	11	S08	16,521	9523	5622	31,666
	12	S09	9313	4098	1003	14,414
	13	S10	23,816	5783	3512	33,111
	14	S11	8784	4531	4211	17,526
		Physical				
	15	P01	97,234	2152	983	100,369
	16	P02	10,238	4242	1856	16,336
	17	P03	40,711	1400	621	42,732
	18	P04	79,518	4343	2514	86,375
	19	P06	27,825	7551	11,412	46,788
	20	P07	73,512	1008	56	74,576
	21	P09	8075	1523	571	10,169
	22	P10	28,029	5161	811	34,001

Table A1. *Cont.*

Case Study	S/N	Topics	negTweets	neuTweets	posTweets	∑Tweets
		Economics				
	23	E01	92,562	5044	2155	99,761
	24	E03	11,164	3509	1421	16,094
	25	E04	36,543	2131	1017	39,691
	26	E05	5729	1217	4506	11,452
		Institution & Governance				
	27	I01	8674	2451	882	12,007
	28	I03	6751	2328	993	10,072
	Total		**868,155**	**123,437**	**57,793**	**1,049,385**
Akoka, Nigeria		**Cultural**				
	1	C01	4526	2643	1004	8173
	2	C03	7022	1012	28	8062
	3	C04	13,352	4478	421	18,251
	4	C05	5521	6104	710	12,335
	5	C07	5202	3758	1112	10,072
	6	C08	7158	1395	33	8586
	7	C09	8520	1241	850	10,611
		Social				
	8	S01	61,503	8109	443	70,055
	9	S02	8111	733	512	9356
	10	S03	44,874	2012	128	47,014
	11	S04	28,777	12,824	1024	42,625
	12	S07	11,741	5539	872	18,152
	13	S08	5545	2368	1263	9176
	14	S09	4799	3000	204	8003
	15	S10	11,900	3776	2111	17,787
	16	S11	8012	3652	109	11,773
		Physical				
	17	P01	79,721	2254	6451	88,426
	18	P02	31,041	1782	1972	34,795
	19	P03	18,955	6645	292	25,892
	20	P04	8563	5172	2516	16,251
	21	P05	8934	4441	623	13,998
	22	P06	5662	2120	1223	9005
	23	P07	57,204	1217	103	58,524
	24	P08	4726	3512	984	9222
	25	P11	48,461	2583	152	51,196
	26	P12	15,965	3026	1023	20,014

Table A1. *Cont.*

Case Study	S/N	Topics	negTweets	neuTweets	posTweets	∑Tweets
		Economic				
	27	E01	79,176	1326	651	81,153
	28	E02	10,672	1231	3648	15,551
	29	E03	19,980	2641	1002	23,623
	30	E04	74,590	1320	101	76,011
	31	E05	24,432	562	4118	29,112
	32	E08	7821	1085	1031	9937
		Institution & Governance				
	33	I01	28,731	9204	992	38,927
	34	I02	8882	4516	1863	15,261
	35	I03	6993	1682	218	8893
Total			**777,072**	**118,963**	**39,787**	**935,822**
Hung Hom, Hong Kong		**Cultural**				
	1	C01	6632	20,571	2121	29,324
	2	C06	16,261	15,751	16,752	48,764
		Social				
	3	S02	2301	16,304	8408	27,013
	4	S03	6015	10,502	754	17,271
	5	S07	18,027	6232	2703	26,962
	6	S11	14,222	18,150	7191	39,563
	7	S12	43,452	5798	1783	51,033
		Physical				
	8	P01	29,522	16,025	6176	51,723
	9	P03	11,032	4002	1012	16,046
	10	P04	26,821	9991	4512	41,324
	11	P05	31,992	2016	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	2162	20,015	3244	25,421
		Economic				
	15	E01	34,112	10,681	1206	45,999
	16	E03	2572	18,618	1871	23,061
	17	E04	28,190	7074	488	35,752
	18	E05	4332	9801	13,021	27,154
Total			**382,153**	**233,821**	**105,802**	**721,776**

Table A1. *Cont.*

Case Study	S/N	Topics	negTweets	neuTweets	posTweets	∑Tweets
Sydney, Australia		**Cultural**				
	1	C01	11,465	2215	7323	21,003
	2	C03	6013	2120	219	8352
	3	C07	2190	4542	1251	7983
		Social				
	4	S01	33,231	6559	231	40,021
	5	S03	22,338	2451	762	25,551
	6	S06	11,526	5632	1404	18,562
	7	S07	33,243	4237	2143	39,623
	8	S08	4046	2516	501	7063
	9	S10	2981	1621	2392	6994
		Physical				
	10	P01	47,031	3020	471	50,522
	11	P03	4234	1251	142	5627
	12	P04	25,123	3203	1025	29,351
	13	P05	4220	6142	2051	12,413
	14	P06	26,410	5171	521	32,102
	15	P07	48,921	2422	718	52,061
	16	P09	2722	1421	1022	5165
	17	P10	11,102	1403	1501	14,006
		Economic				
	18	E01	43,484	1206	2312	47,002
	19	E03	2961	1341	724	5026
	20	E04	39,991	2871	1011	43,873
	21	E05	8420	4350	3251	16,021
	22	E06	3771	4520	1861	10,152
Total			**395,423**	**70,214**	**31,836**	**498,473**
Aguita de la Perdiz, Chile		**Cultural**				
	1	C02	1521	745	254	2520
	2	C05	2011	471	510	2992
		Social				
	3	S02	3124	859	161	4144
	4	S03	2861	1050	341	4252
	5	S07	3405	1015	172	4592
		Physical				
	6	P01	5412	1251	108	6771
	7	P03	4439	721	91	5251
	8	P04	5039	681	211	5931
	9	P05	1424	742	55	2221
	10	P07	5697	1462	61	7220

Table A1. *Cont.*

Case Study	S/N	Topics	negTweets	neuTweets	posTweets	∑Tweets
	11	P11	1265	564	113	1942
	12	P12	1123	558	333	2014
		Economic				
	13	E01	4571	424	37	5032
	14	E04	3961	751	91	4803
	15	E05	516	224	961	1701
	16	E07	1003	350	88	1441
	17	E09	571	335	111	1017
Total			**47,943**	**12,203**	**3698**	**63,844**

References

1. Brooks, R.; Byford, K.; Sela, K. Students' unions, consumerism and the neo-liberal university. *Br. J. Sociol. Educ.* **2016**, *37*, 1211–1228. [CrossRef]
2. Kinton, C.; Smith, D.P.; Harrison, J.; Culora, A. New frontiers of studentification: The commodification of student housing as a driver of urban change. *Geogr. J.* **2018**, *184*, 242–254. [CrossRef]
3. Brooks, R. The social construction of young people within education policy: Evidence from the UK's Coalition government. *J. Youth Stud.* **2013**, *16*, 318–333. [CrossRef]
4. Smith, D.P.; Sage, J.; Balsdon, S. The geographies of studentification:here, there and everywhere? *Geography* **2014**, *99*, 116. [CrossRef]
5. Holton, M.; Riley, M. Talking on the move: Place-based interviewing with undergraduate students. *Area* **2014**, *46*, 59–65. [CrossRef]
6. Hubbard, P. Regulating the Social Impacts of Studentification: A Loughborough Case Study. *Environ. Plan. A: Econ. Space* **2008**, *40*, 323–341. [CrossRef]
7. Smith, D.P.; Hubbard, P. The segregation of educated youth and dynamic geographies of studentification. *Area* **2014**, *46*, 92–100. [CrossRef]
8. Sage, J.; Smith, D.; Hubbard, P. The Diverse Geographies of Studentification: Living Alongside PeopleNotLike Us. *Hous. Stud.* **2012**, *27*, 1057–1078. [CrossRef]
9. Baron, M.G.; Kaplan, S. The Impact of Studentification on the Rental housing Market. In Proceedings of the 50th Congress of the European Regional Science Association, Jönköping, Sweden, 19–23 August 2010.
10. Donaldson, R.; Benn, J.; Campbell, M.; De Jager, A. Reshaping urban space through studentification in two South African urban centres. *Urbani Izziv* **2014**, *25*, S176–S188. [CrossRef]
11. Foote, N.S. Beyond studentification in United States College Towns: Neighborhood change in the knowledge nodes, 1980–2010. *Environ. Plan. A* **2017**, *49*, 1341–1360. [CrossRef]
12. Haghighi, F. Study. Be silent. Die: Indeterminate architecture and the dispositif of studentification. *J. Cult. Res.* **2018**, *22*, 55–72. [CrossRef]
13. Holton, M. Living together in student accommodation: Performances, boundaries and homemaking. *Area* **2016**, *48*, 57–63. [CrossRef]
14. Hubbard, P. Geographies of Studentification and Purpose-Built Student Accommodation: Leading Separate Lives? *Environ. Plan. A: Econ. Space* **2009**, *41*, 1903–1923. [CrossRef]
15. Kinton, C.; Smith, D.P.; Harrison, J. De-studentification: Emptying housing and neighbourhoods of student populations. *Environ. Plan. A: Econ. Space* **2016**, *48*, 1617–1635. [CrossRef]
16. Seeliger, L.; Turok, I. Towards sustainable cities: Extending resilience with insights from vulnerability and transition theory. *Sustainability* **2013**, *5*, 2108–2128. [CrossRef]
17. Burroughs, S. Development of a tool for assessing commercial building resilience. *Procedia Eng.* **2017**, *180*, 1034–1043. [CrossRef]
18. Schipper, E.L.F.; Langston, L. A comparative overview of resilience measurement frameworks. In *Analyzing Indicators and Approaches*; Overseas Development Institute: London, UK, 2015; Volume 422.
19. Abdul-Rahman, M.; Chan, E.H.W.; Li, X.; Wong, M.S.; Xu, P. Big Data for Community Resilience Assessment: A Critical Review of Selected Global Tools. In Proceedings of the 24th International Symposium on Advancement of Construction Management and Real Estate, Chongqing, China, 19–22 November 2021; pp. 1345–1361.
20. Smith, D.P. Studentification. In *The Wiley Blackwell Encyclopedia of Urban and Regional Studies*; Wiley Blackwell: New York, NY, USA, 2006; pp. 1–3.

21. Situmorang, R.; Sudikno, A.; Surjono, S.; Wicaksono, A.D. Conceptual Framework of Studentification Impacts in Malang City, Indonesia. *Int. J. Adv. Sci.* **2020**, *29*, 585–593.
22. Smith, D.P. *Studentification: A Guide to Opportunities, Challenges and Practice*; Universities UK: London, UK, 2006; Volume 52.
23. Smith, D.P.; Fox, M. *Studentification Guide for North America: Delivering Hermonious Town and Gown Associations*; Loughborough University UK and Mount Allison University, Canada: Loughborough, UK, 2019; p. 73.
24. Holton, M. Adapting relationships with place: Investigating the evolving place attachment and 'sense of place' of UK higher education students during a period of intense transition. *Geoforum* **2015**, *59*, 21–29. [CrossRef]
25. Laidley, T.M. The Privatization of College Housing: Poverty, Affordability, and the U.S. Public University. *Hous. Policy Debate* **2014**, *24*, 751–768. [CrossRef]
26. He, S. Consuming urban living in 'villages in the city': Studentification in Guangzhou, China. *Urban Stud.* **2014**, *52*, 2849–2873. [CrossRef]
27. Marshall, J.D.; Toffel, M.W. Framing the elusive concept of sustainability: A sustainability hierarchy. *Environ. Sci. Technol.* **2005**, *39*, 673–682. [CrossRef] [PubMed]
28. Hoosain, M.S.; Paul, B.S.; Ramakrishna, S. The Impact of 4IR Digital Technologies and Circular Thinking on the United Nations Sustainable Development Goals. *Sustainability* **2020**, *12*, 10143. [CrossRef]
29. UN-Habitat. *Urbanization and development: Emerging Futures*; United Nations Human Settlements Programme (UN-Habitat): Nairobi, Kenya, 2016; Volume 5, p. 49.
30. National Research Council. *Disaster Resilience: A National Imperative*; The National Academies Press: Washington, DC, USA, 2012; p. 260.
31. Sharifi, A. A critical review of selected tools for assessing community resilience. *Ecol. Indic.* **2016**, *69*, 629–647. [CrossRef]
32. Houston, J.B. Bouncing Forward: Assessing Advances in Community Resilience Assessment, Intervention, and Theory to Guide Future Work. *Am. Behav. Sci.* **2014**, *59*, 175–180. [CrossRef]
33. Yigitcanlar, T.; Wilson, M.; Kamruzzaman, M. Disruptive impacts of automated driving systems on the built environment and land use: An urban planner's perspective. *J. Open Innov. Technol. Mark. Complex.* **2019**, *5*, 24. [CrossRef]
34. Lavalle, A.; Teruel, M.A.; Maté, A.; Trujillo, J. Improving Sustainability of Smart Cities through Visualization Techniques for Big Data from IoT Devices. *Sustainability* **2020**, *12*, 5595. [CrossRef]
35. Silva, B.N.; Khan, M.; Jung, C.; Seo, J.; Muhammad, D.; Han, J.; Yoon, Y.; Han, K. Urban Planning and Smart City Decision Management Empowered by Real-Time Data Processing Using Big Data Analytics. *Sensors* **2018**, *18*, 2994. [CrossRef]
36. Batty, M. Big data, smart cities and city planning. *Dialogues Hum. Geogr.* **2013**, *3*, 274–279. [CrossRef]
37. Yigitcanlar, T.; Cugurullo, F. The Sustainability of Artificial Intelligence: An Urbanistic Viewpoint from the Lens of Smart and Sustainable Cities. *Sustainability* **2020**, *12*, 8548. [CrossRef]
38. Kassens-Noor, E.; Hintze, A. Cities of the future? The potential impact of artificial intelligence. *AI* **2020**, *1*, 192–197. [CrossRef]
39. Nikitas, A.; Michalakopoulou, K.; Njoya, E.T.; Karampatzakis, D. Artificial intelligence, transport and the smart city: Definitions and dimensions of a new mobility era. *Sustainability* **2020**, *12*, 2789. [CrossRef]
40. Macrorie, R.; Marvin, S.; While, A. Robotics and automation in the city: A research agenda. *Urban Geogr.* **2020**, *42*, 1–21. [CrossRef]
41. Barns, S. *Platform Urbanism: Negotiating Platform Ecosystems in Connected Cities*; Springer: Berlin/Heidelberg, Germany, 2019.
42. Caprotti, F.; Liu, D. *Emerging Platform Urbanism in China: Reconfigurations of Data, Citizenship and Materialities*; Elsevier: Amsterdam, The Netherlands, 2019.
43. Zahra, K.; Imran, M.; Ostermann, F.O. Automatic identification of eyewitness messages on twitter during disasters. *Inf. Process. Manag.* **2020**, *57*, 102107. [CrossRef]
44. Zhou, Z.-H. *Machine Learning*; Springer Nature: Berlin/Heidelberg, Germany, 2021.
45. Chowdhary, K. Natural language processing. *Fundam. Artif. Intell.* **2020**, *1*, 603–649.
46. Kennedy, H.; Moss, G. Known or knowing publics? Social media data mining and the question of public agency. *Big Data Soc.* **2015**, *2*, 2053951715611145. [CrossRef]
47. Alharbi, A.N.; Alnnamlah, H.; Liyakathunis. Classification of Customer Tweets Using Big Data Analytics. In *Advances in Intelligent Systems and Computing, Proceedings of the 5th International Symposium on Data Mining Applications, Riyadh, Saudi Arabia, 20–22 July 2018*; Springer: Berlin/Heidelberg, Germany, 2018; pp. 169–180.
48. Asghar, Z.; Ali, T.; Ahmad, I.; Tharanidharan, S.; Nazar, S.K.A.; Kamal, S. Sentiment Analysis on Automobile Brands Using Twitter Data. *Commun. Comput. Inf. Sci.* **2019**, *932*, 76–85. [CrossRef]
49. Abumalloh, R.A.; Ibrahim, O.; Nilashi, M. Loyalty of young female Arabic customers towards recommendation agents: A new model for B2C E-commerce. *Technol. Soc.* **2020**, *61*, 101253. [CrossRef]
50. Carlos, M.A.; Nogueira, M.; Machado, R.J. Analysis of dengue outbreaks using big data analytics and social networks. In Proceedings of the 2017 4th International Conference on Systems and Informatics (ICSAI), Hangzhou, China, 11–13 November 2017; pp. 1592–1597.
51. Shah, A.M.; Yan, X.; Tariq, S.; Ali, M. What patients like or dislike in physicians: Analyzing drivers of patient satisfaction and dissatisfaction using a digital topic modeling approach. *Inf. Process. Manag.* **2021**, *58*, 102516. [CrossRef]
52. Nilashi, M.; Ibrahim, O.; Yadegaridehkordi, E.; Samad, S.; Akbari, E.; Alizadeh, A. Travelers decision making using online review in social network sites: A case on TripAdvisor. *J. Comput. Sci.* **2018**, *28*, 168–179. [CrossRef]

53. Sun, Y.; Ma, H.; Chan, E.H.W. A Model to Measure Tourist Preference toward Scenic Spots Based on Social Media Data: A Case of Dapeng in China. *Sustainability* **2018**, *10*, 43. [CrossRef]
54. Ahani, A.; Nilashi, M.; Ibrahim, O.; Sanzogni, L.; Weaven, S. Market segmentation and travel choice prediction in Spa hotels through TripAdvisor's online reviews. *Int. J. Hosp. Manag.* **2019**, *80*, 52–77. [CrossRef]
55. Abdul-Rahman, M.; Chan, E.H.W.; Wong, M.S.; Irekponor, V.E.; Abdul-Rahman, M.O. A framework to simplify pre-processing location-based social media big data for sustainable urban planning and management. *Cities* **2020**, 102986. [CrossRef]
56. Sykora, M.; Elayan, S.; Jackson, T.W. A qualitative analysis of sarcasm, irony and related #hashtags on Twitter. *Big Data Soc.* **2020**, *7*, 2053951720972735. [CrossRef]
57. Blei, D.M.; Carin, L.; Dunson, D. Probabilistic Topic Models: A focus on graphical model design and applications to document and image analysis. *IEEE Signal Process. Mag.* **2010**, *27*, 55. [PubMed]
58. Chuang, J.; Manning, C.D.; Heer, J. Termite: Visualization techniques for assessing textual topic models. In Proceedings of the International Working Conference on Advanced Visual Interfaces, Capri Island, Italy, 21–25 May 2012; pp. 74–77.
59. Sievert, C.; Shirley, K. LDAvis: A method for visualizing and interpreting topics. In Proceedings of the Workshop on Interactive Language Learning, Visualization, and Interfaces, Baltimore, MD, USA, 27 June 2014; pp. 63–70.
60. Moody, C.; Johnson, R.; Zhang, T. Mixing Dirichlet Topic Models and Word Embeddings to Make lda2vec. *arXiv* **2016**, arXiv:1605.02019.
61. Momtazi, S. Unsupervised Latent Dirichlet Allocation for supervised question classification. *Inf. Process. Manag.* **2018**, *54*, 380–393. [CrossRef]
62. Asghari, M.; Sierra-Sosa, D.; Elmaghraby, A.S. A topic modeling framework for spatio-temporal information management. *Inf. Process. Manag.* **2020**, *57*, 102340. [CrossRef]
63. Hutto, C.J.; Gilbert, E.E. VADER: A Parsimonious Rule-based Model for Sentiment Analysis of Social Media Tweet. In Proceedings of the Eighth International Conference on Weblogs and Social Media (ICWSM-14), Ann Arbor, MI, USA, 2–4 June 2014.
64. Kumar, C.V.; Ashish, B.; Amita, G. Twitter Sentiment Analysis Using Vader. *Int. J. Adv. Res. Ideas Innov. Technol.* **2018**, *4*, 485–490.
65. Darko, A. Adoption of green building technologies in Ghana: Development of a model of green building technologies and issues influencing their adoption. In *Green Building in Developing Countries*; Springer: Berlin/Heidelberg, Germany, 2019.
66. Soyinka, O.; Adenle, Y.A.; Abdul-Rahman, M. Urban informality and sustainable design of public space facilities: A case study of Hong Kong SAR of China in 2018. *Environ. Dev. Sustain.* **2021**, *23*, 16560–16587. [CrossRef]
67. Howard, M.C. Calculating Cronbach's Alpha in Python. 2022.
68. Norusis, M.J. *PASW Statistics 18 Guide tso Data Analysis*; Prentice Hall Press: Hoboken, NJ, USA, 2010.
69. Talavera, L.; Gaudioso, E. Mining student data to characterize similar behavior groups in unstructured collaboration spaces. In *Workshop on Artificial Intelligence in CSCL, Proceedings of the 16th European Conference on Artificial Intelligence, Valencia Spain, 22–27 August 2004*; pp. 17–23.
70. Limanond, T.; Butsingkorn, T.; Chermkhunthod, C. Travel behavior of university students who live on campus: A case study of a rural university in Asia. *Transp. Policy* **2011**, *18*, 163–171. [CrossRef]
71. Mathooko, F.M.; Ogutu, M. Coping strategies adopted by public universities in Kenya in response to environmental changes. *J. Manag. Strategy* **2014**, 5. [CrossRef]
72. Cimellaro, G.P.; Renschler, C.; Reinhorn, A.M.; Arendt, L. PEOPLES: A Framework for Evaluating Resilience. *J. Struct. Eng.* **2016**, *142*, 04016063. [CrossRef]
73. Pringle, P. AdaptME: Adaptation monitoring and evaluation. In *Adaptme: Adaptation Monitoring and Evaluation*; UK Climate Impacts Programme (UKCIP): Oxford, UK, 2011.