Public Concern About COVID-19 Through Search Queries

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Abstract COVID-19 has uprooted lives and livelihood, causing widespread panic across communities and societies. Emerging reports suggest that people living in rural areas are more susceptible to COVID-19 in some countries. However, there is a lack of quantitative evidence that can shed light on whether residents from rural areas are more concerned about COVID-19 than residents from urban areas. One way to address this issue is via examining online search queries to analyze changes in concern towards COVID-19. Therefore, this study investigated the attitudes toward COVID-19 from different Japanese prefectures by aggregating and analyzing Yahoo Japan search queries. We quantitatively define COVID-19 concern (Localized Concern Index [LCI] and Excessive Localized Concern Index [ELCI]). Our results demonstrate that the concern indices are able to measure public concern about COVID-19 in rural and urban areas from different perspectives, and there are regional differences in these concerns.

Key words COVID-19, quantitative analysis, search terms, data mining

1 Introduction

The Novel Coronavirus, also known as COVID-19, is an ongoing outbreak of an infectious disease that has been threatening global health since end December 2019. Its outbreak has posed critical challenges for public health, research, and medical communities [1]. As of December 14, 2020, COVID-19 has already affected 218 countries and territories with over 72 million confirmed cases, and has claimed over 1.6 million lives [2]. COVID-19 has uprooted many lives, even causing psychological trauma [3, 4] on a large scale.

During any outbreak of infectious diseases, the population's psychological reactions play a critical role in shaping both spread of the disease and the occurrence of emotional distress and social disorder during and after the outbreak [5]. In previous studies, Ahorsu et al. [6] developed the Fear of COVID-19 Scale (FCV-19S) through qualitative interviews to assess individuals' fears towards COVID-19. Gao et al. [7] found that that greater concern towards COVID-19 (frequent exposure towards COVID-19-related social media) was positively associated with adverse mental health outcomes.

Worryingly, the use of the Internet and social media has increased dramatically due to the enforcement of "social distancing" and "staying home" in many areas, and the search for updates on the COVID-19 has correspondingly increased [8]. However, there is a lack of quantitative evidence that can shed light on the population's psychological reactions towards COVID-19. In addition, one would think that residents of urban areas would show more concern towards COVID-19 due to crowds and easy access to transportation. Yet, emerging reports suggest that people who live in rural areas may be more vulnerable to COVID-19 than residents of urban areas(1) (2).

Therefore, we aimed to quantitatively analyze the Japanese public's psychological reactions towards COVID-19, i.e., concern for COVID-19, through search queries of Yahoo Japan users, paying particular attention to differences between rural and urban areas. Accordingly, we first developed a "concern index" to measure this concern. We used this concern index to investigate the level of concern towards COVID-19 in each prefecture in Japan (i.e., Localized Concern Index [LCI] and Excessive Localized Concern Index[ELCI]). In order to evaluate the feasibility of these concern indices, we then examined prefecture-level correlations with several indicators of ruralization and public health outcomes.

In this paper, Section 2 details our process for defining the equation of concern for COVID-19, Section 3 describes the results of our quantitative equation and the correlation co-

1 Oct, 22, 2020; The New York Times, https://nyti.ms/33AEWb1
2 Oct, 9, 2020; The Japan Times, https://bit.ly/33DaNIc

Search query	Rank change index
novel_coronavirus	18.87
シャープ マスク (Sharp's face mask)	18.74
新型コロナウイルス (novel coronavirus)	17.99
コロナ 感染者数 (coronavirus cases)	17.96
東京都 コロナウイルス感染者 (Tokyo coronavirus cases)	17.63

Table 1: Top five rapidly ascending search queries and their *rank change index* in April 2020 compared to April 2019.

efficients for results and indicators, and Section 4 discusses some possible implications of this research.

2 Methodology

2.1 Target Queries

First, we explored people's COVID-19 concerns by analyzing search queries over different time periods. We selected the search queries of Yahoo Japan's users in April-May 2019 and April-May 2020. This time period was determined due to the Japanese government's declaration of a state of emergency in April 2020[(3)]. In addition, since the elderly (over the age of 65) are at a significantly greater risk of adverse COVID-19 outcomes [9], we speculated that there may be more COVID-19-related search queries from this group. Hence we started the analysis by targeting the search queries of people over 65 years old. We extracted the search queries of this elderly population for the two aforementioned time periods and ranked them in reverse order according to the search counts. This resulted in a ranking index of search queries that ascend and descend as defined by the following *rank change index*,

$$\textit{Rank change index}(q) = \frac{\log(\text{No. of } q \text{ in } 2020 + 2)}{\log(\text{No. of } q \text{ in } 2019 + 2)}$$

The larger the index, the fewer the search counts for this query in 2019 or the greater the search counts in 2020, and vice versa. A constant of two was added to both the numerator and denominator, to avoid instances with zeros (uncountable) in search counts. Table 1 indicates the top five rapidly ascending search queries in April 2020 compared to April 2019. As expected, these terms appear to be COVID-19 related.

Consistently, of the top 100 queries in the ascending query list, 76 queries contained COVID-19-related keywords (e.g., "コロナ [coronavirus]," "マスク [mask]"), and of these, 33 queries contained the prefecture names with "コロナ感染者 (coronavirus cases)." A query pattern such as prefecture name + "coronavirus cases" clearly displays prefecture's information, and reflects the user's concern towards COVID-19 to some extent as well. Figure 1 indicates the distribution of the top 100 ascending queries, and Table 2 indicates some queries samples in this study.

Search query	Rank change index
東京都 コロナウイルス感染者 (Tokyo coronavirus cases)	17.63
神奈川県 コロナ感染者 (Kanagawa coronavirus cases)	16.26
埼玉県 コロナウイルス感染者 (Saitama coronavirus cases)	16.18
福岡県 コロナウイルス感染者 (Fukuoka coronavirus cases)	16.11
茨城県 コロナウイルス感染者 (Ibaraki coronavirus cases)	15.84

Table 2: Target queries samples.

2.2 Baseline Queries

However, when we calculated the search counts of the target queries comprising of prefecture name and "coronavirus cases" from January to September 2020, we found that the search counts in Tokyo were much higher than the other

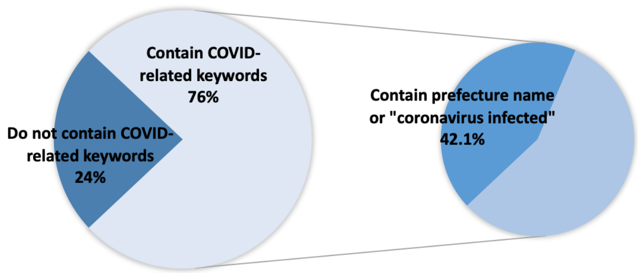


Figure 1: Distribution of the top 100 of the ascending queries.

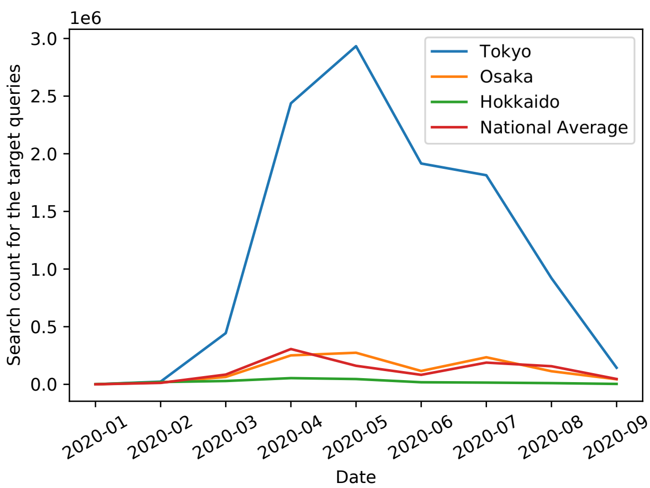


Figure 2: Search counts for targeted queries in *Tokyo, Osaka, Hokkaido* and national average.

3 https://japan.kantei.go.jp/ongoingtopics/_00025.html

prefectures and the national average, as shown in Figure 2. One possibility was due to Tokyo having a larger population, which meant that frequencies of general search counts were higher compared to other less-populated prefectures. We speculated that this excessive disparity would inevitably have an impact on our subsequent calculations. To mitigate this effect, for each prefecture, we proposed a baseline of search queries that is relatively stable in search counts from January to September. The baseline queries are in the form of **"prefecture name + X"**, where **"X"** refers to any keywords as long as the variance of their search counts by month is as small as possible. Hence we compared and counted the search counts of queries for the above form from January to September, and then identified the top three queries with the smallest variance in the search counts for nine months as the baseline queries.

This was to balance the impact of excessive disparity by using the quotient of the baseline query and our target query, since the search counts of target queries is large for urbanized prefectures like Tokyo, where the search count frequencies of baseline queries are also large.

2 3 Localized Concern Index

Following which, our query-based equation to quantify the level of concern of COVID-19, i.e., the **Localized Concern Index (LCI)** equation, is defined for each prefecture $pref$ as follows:

$$LCI_{pref} = \frac{Count(tq) + 1}{Count(bq)}$$

Where tq_{pref} and bq_{pref} for the target query and the baseline query of each prefecture, respectively, and $Count(.)$ is a function that count the number of a query. We took the logarithmic result for the LCI calculation, and suggest that a higher LCI means a higher frequency of baseline-controlled, prefecture-specified COVID-19-related queries, which in turn reflects a larger level of concern for COVID-19 for that prefecture.

Prefecture	LCI	Prefecture	LCI
Tokyo	7.04	Miyazaki	0.63
Ibaraki	5.90	Ehime	0.87
Fukuoka	5.54	Mie	0.96
Saitama	5.31	Miyagi	1.02
Okayama	4.92	Wakayama	1.07

Table 3: Top prefectures with the highest and the lowest LCI.

Figure 3(a) shows a map of our LCI results for 2020 from January to September. Table 3 shows top prefectures with the highest and the lowest LCI, as well as those the darkest and the lightest colors in Figure 3(a). In addition, we examined LCI across three phases following the timing the state of emergency: (1) before the state of emergency (January-March), (2) during the state of emergency (April-June), (3) after the state of emergency (July-September). Figure 3(b), 3(c) and 3(d) shows ours results by prefectures for each phase. In general, it illustrates a gradual increase in LCI with time.

2 4 Excessive Localized Concern Index

One criticism of the LCI is that it is highly influenced by the COVID-19 situation in each prefecture. As such, *Tokyo* being the most populous city in Japan and the hardest hit, naturally has the highest search counts for target queries mentioned in Section 2 1, and correspondingly, LCI. However, attitudes towards COVID-19 are not always rationale, and anecdotal evidence has shown heightened, seemingly irrational concern towards COVID-19 in rural areas[4].

For this reason, we attempted to improve our LCI equation examine COVID-19 concern beyond the direct influence of actual COVID-19 cases. We argue that this would quantify the excessive concern towards COVID-19 beyond the risk of actual infection. To do so, we modified the LCI to account for the number of new cases per month in each prefecture by the population of that prefecture to calculate the percentage of infected patients, i.e., (No. of monthly new cases)/population.

As Gamonal Limcaoco et al. [10] mentioned that the pandemic of COVID-19 is raising people's anxiety levels, the revised LCI should reflect a deeper level of anxiety or fear towards COVID-19, that we define as "excessive" concern.

In summary, the **Excessive Localized Concern Index (ELCI)** for each prefecture $pref$ is as follows,

$$ELCI_{pref} = LCI_{pref} \Bigg/ \left(\frac{\text{monthly new cases}_{pref} + 1}{\text{population}_{pref}} \right)$$

Similarly, we took the logarithmic result for the ELCI calculation.

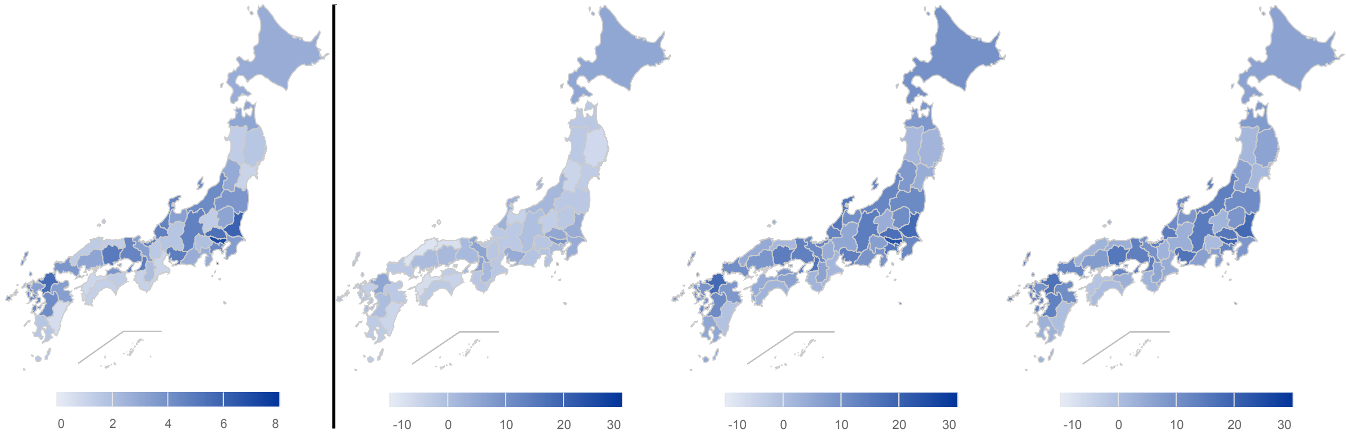
3 Results

3 1 ELCI Results by Prefectures

We made the same processing as in Section 2 3. Figure 4(a) shows ELCI results map from January to September, and Table 4 shows top prefectures with the highest and the lowest ELCI, and Figures 4(b), 4(c) and 4(d) show ELCI results by prefectures for three phases, respectively. Please refer to the Tables A· 1, A· 2, A· 3, and A· 4 for LCI and ELCI values for all prefectures.

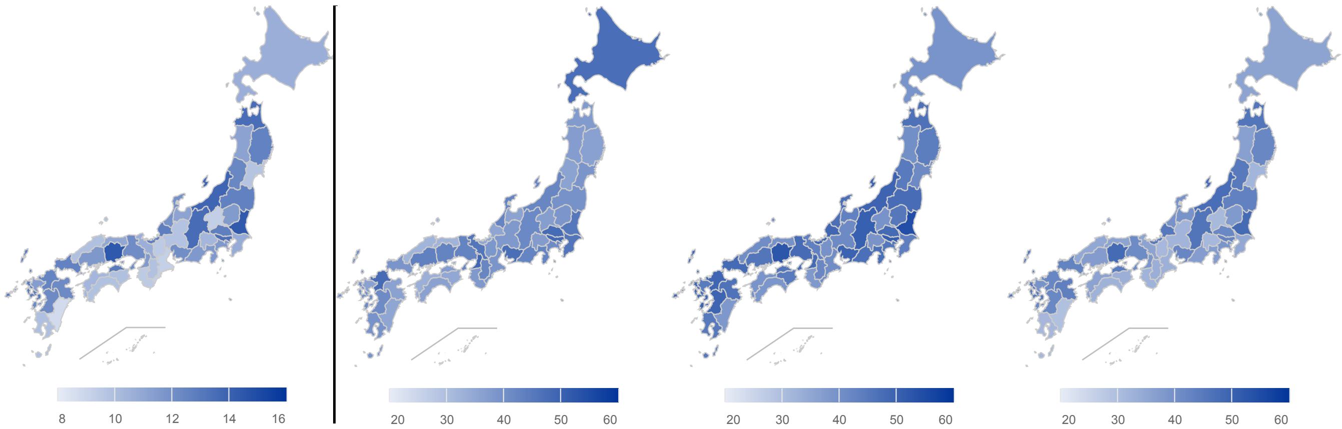
In particular, among of all the prefectures, we selected 4

4 Sep, 1, 2020; Bunshun Online (Japanese), https://bit.ly/2LTxf90



(a) Whole phase (Jan-Sep). (b) **Before** the state of emergency (Jan-Mar). (c) **During** the state of emergency (Apr-Jun). (d) **After** the state of emergency (Jul-Sep).

Figure 3: LCI results by prefectures.



(a) Whole phase (Jan-Sep). (b) **Before** the state of emergency (Jan-Mar). (c) **During** the state of emergency (Apr-Jun). (d) **After** the state of emergency (Jul-Sep).

Figure 4: ELCI results by prefectures.

Prefecture	ELCI	Prefecture	ELCI
Okayama	14.36	Miyazaki	8.68
Ibaraki	14.31	Ehime	9.18
Niigata	13.78	Gunma	9.23
Nagano	13.48	Okinawa	9.30
Aomori	13.46	Shiga	9.43

Table 4: Top prefectures with the highest and the lowest ELCI.

prefectures for specific display: *Tokyo, Osaka, Niigata* and *Ibaraki*, as shown in Figure 5. As a criterion for distinguishing between urban and rural areas, we used the number of farm households. According to a survey by the Statistics Bureau of Japan(5), *Tokyo* and *Osaka* have the lowest number of farm households in Japan, while *Ibaraki* and *Niigata* have the highest number of farm households. This suggests that *Niigata* and *Ibaraki* have relatively lower urbanization rates than *Tokyo* and *Osaka*. Nevertheless, Figure 5 indicates that some urban areas (i.e., *Tokyo* and *Osaka*) have relatively lower concern index than some rural areas (i.e., *Ibaraki*) in terms of general trends.

5 https://www.stat.go.jp/english/data/nenkan/69nenkan/1431-08.html

3 2 Correlations with LCI and ELCI

To establish the differentiated patterns of associations for the LCI and ELCI, we examined Prefecture-level correlations with both indices. As our research questions involves the distinction between urban and rural areas, we included corresponding measures that examine the prevalence of farming, ease of accessibility, population change, and public health outcomes. We argue that rural areas can be indicated by higher prevalence of farming households, farming area, and rice production. Conversely, urban areas can be seen by higher population density, ease of accessibility (proportion of reachable area within one hour) and rate of population change (urban areas should see population growth, while rural areas should see population decline). Finally, prefectural

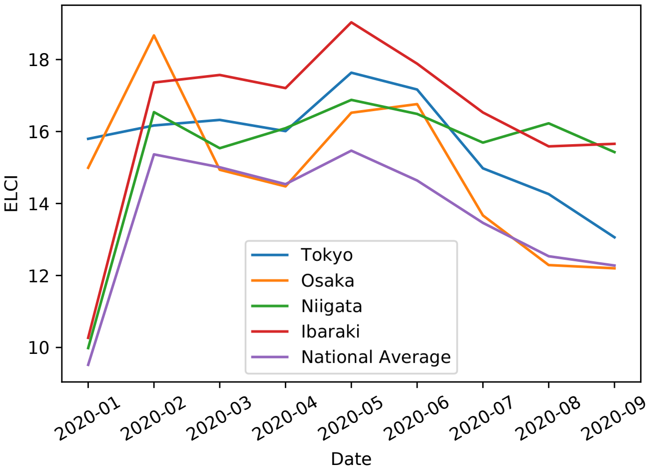


Figure 5: ELCI results of *Tokyo, Osaka, Niigata, Ibaraki* and national average from January to September.

public health was measured by the number of cumulative COVID-19 cases per 1 million residents (as of September 30, 2020), proportion of population that reported general symptoms (non-COVID-19-related), number of ambulance dispatches, and number of daily outpatients.

Our results suggest that LCI was significantly correlated with COVID-19 infection risk (cumulative cases), and urbanized prefectures. The latter was seen through the population density, ease of accessibility: LCI was higher in prefectures that have high proportion of reachable area within one hour, and in prefectures that had growing populations. By contrast, ELCI was higher in prefectures that were more rural. This was marked by prefectures that had higher numbers of farming households, and rice production.

Table 5 shows the correlation coefficient results.

3.3 Age-Based ECLI Results

We investigated ECLI results for three different age groups as well: (1) age 25-44, (2) age 45-64, and (3) age over 65. At this point, the *population* in the ECLI equation is replaced by the number of people in each age group. Figure 6 shows elderly people over years of age 65 pay less concern than the 25-44 and 45-64 age groups, while 25-44 and 45-64 age groups have almost the same concern for COVID-19.

4 Discussion

4.1 Nature of LCI and ELCI

As expected, LCI appeared to represent overall concern towards COVID-19. To a large extent, this was influenced by the actual prevalence of COVID-19 within the prefecture. Similarly, this is heightened in prefectures that are dense, highly accessible and that are growing in population. Most likely, these are reflections of urbanized prefectures that have highly developed infrastructure and are attracting migrations from younger workers due with more job opportunities.

Indicator		**LCI**	**ELCI**
No. of farm households	Pearson's r	0.147	0.403
	p-value	0.323	0.005
Rate of population change	Pearson's r	0.522	0.022
	p-value	$<.001$	0.886
Farmland percent	Pearson's r	0.235	0.232
	p-value	0.111	0.116
Rice production	Pearson's r	0.020	0.309
	p-value	0.895	0.034
Reachable area within one hour	Pearson's r	0.585	0.258
	p-value	$<.001$	0.080
Travel time from Tokyo to major stations in each prefecture	Pearson's r	-0.264	-0.164
	p-value	0.073	0.270
Reported symptoms	Pearson's r	-0.053	-0.160
	p-value	0.725	0.289
Daily outpatients	Pearson's r	-0.146	-0.019
	p-value	0.326	0.897

Table 5: Correlation coefficients of the whole phase LCI and ELCI and some indicators.

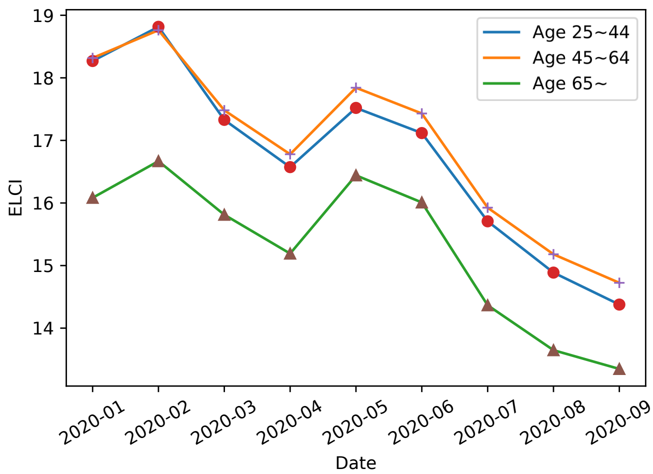


Figure 6: ELCI results for ages 25-44, 45-64, and over 65.

As such, these fast-paced, young, and dense prefectures naturally present a greater risk of COVID-19 infection, and the increased concern on search queries observed through the LCI is no surprise.

However, once we remove the variance explained by including daily increases in COVID-19 cases in the equation, we observed the opposite effect. ELCI ceased to reflect COVID-19 risk from urban areas, and showed no significant relationship with cumulative COVID-19 cases. Furthermore, the pattern of significant correlations revealed an association with rural prefectures. The larger the proportion of farming households and the larger the rice production, the higher the public concern towards COVID-19 that is beyond that explained by risk of infection. Now, why does ELCI reflect increased ruralization? We posit an explanation in the form of collectivism afforded by farming, and specifically rice farming societies [11, 12]. These societies tend to be more collectivistic, where residents have greater psychological desire to protect the community from internal and external threats. COVID-19 is one such threat, so rural communities may thus have greater vigilance and concern in preventing COVID-19 from becoming prevalent in these communities. This is also consistent with prior studies that have established links between COVID-19 concern and collectivism [13], and collectivism with COVID-19 prevention behavior [14].

Such an explanation may have potential policy implications. Specifically, the discrepancy between the LCI and ELCI shows that more care must be given towards considering public attitudes towards COVID-19 between rural and urban communities. If ELCI is indeed a result of collectivism and greater vigilance against COVID-19, this may also imply a broader adoption of preventive measures, i.e., hand-washing, mask-wearing. By contrast, the LCI does not seem to be similarly indicative of such concern. Public campaigns that promote such behaviour may therefore use differing strategies when targeting rural versus urban societies, for greater effectiveness.

Interestingly, we note that measures of public health in Table 5 did not correlate significantly with ELCI. This suggests that the preexisting or general health of a prefecture's population do not appear to affect public concern towards COVID-19.

4.2 Preliminary Analysis of Age-Based Results

Japan, as one of the fastest-aging countries, has the highest proportion of elderly people in the world [15]. Emerging studies suggested that elderly people are more susceptible to COVID-19 and likely to have poor outcomes [9]. However, we note that individuals over 65 have reduced ELCI scores, suggesting that their concern might be lower than the 25-44 and 45-64 age group. One possibility could be a confound of Internet literacy, where users above 65 may have less proficiency with using the Internet, or simply less accustomed to using search terms and queries for topics of concern. However, more research is needed to contextualize this result.

4.3 Effectiveness of Search Queries as Public Concern Indicators

Finally, we evaluate the usefulness of our method of extracting search queries and combining them with actual COVID-19 infection rates in quantifying public concern. We first note the limitations of our approach. Our method of extracting prefecture information from search queries relies on searches for prefecture name + "coronavirus cases", and not location-based information like IP addresses. This may not necessarily be representative of queries from residents from these prefectures, but also queries from non-residents who may be interested in the COVID-19 situation for these prefectures (e.g., a user who may be travelling to these prefectures). Nevertheless, the correlations for LCI and ELCI demonstrate external validity, as LCI and ELCI were both associated with constructs that could be explained by previous research. This joins a growing body of literature that uses web-based search queries to track public health (e.g., Murayama et al. [16]), but the ELCI adds a dimension of using prefecture-level infection rates to control for expected outcomes. This is then effectively able to quantify public concern at a deeper level, that we propose is explained by the collectivistic psychological tendencies of a society.

5 Conclusion

In sum, the present research utilizes search queries from Yahoo Japan users as a means to quantify the degree of concern towards COVID-19 in rural and urban areas. We first established that Yahoo search queries were able to quantify COVID-19 related concern. Next, we defined the Localized Concern Index (LCI) and the Excessive Localized Concern Index (ELCI) as quantitative indicators of prefecture-level COVID-19 concern. The LCI was indicative of COVID-19 concern in urban prefectures, whereas the ELCI appeared to be indicative of COVID-19 concern in rural prefectures. By investigating the relationships between these concern indices and prefecture-related information, we show that the LCI and ELCI demonstrate good external validity. With this result, one potential application could be in differentiated public campaigns towards COVID-19 prevention and misinformation. I.e., Due to the different sources of concern for rural and urban areas, such campaigns should adopt different strategies for risk communication between urban and rural areas.

Acknowledgements

This study was supported in part by JSPS KAKENHI Grant Number JP19K20279 and Health and Labor Sciences Research Grant Number H30-shinkougyousei-shitei-004.

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Appendix

Prefecture	LCI	ELCI	Prefecture	LCI	ELCI
Aichi	3.82	47.04	Akita	-2.62	37.11
Aomori	-2.44	37.47	Chiba	3.64	45.65
Ehime	-7.16	33.09	Fukui	-2.61	35.21
Fukuoka	5.1	47.72	Fukushima	-2.46	39.43
Gifu	-2.61	37.81	Gunma	-3.7	36.79
Hiroshima	0.43	43.18	Hokkaido	4.83	47.16
Hyogo	0.89	42.71	Ibaraki	3.82	45.2
Ishikawa	2.45	42.34	Iwate	-5.94	36.12
Kagawa	-2.96	37.25	Kagoshima	-3.12	39.05
Kanagawa	0.68	40.84	Kochi	-2.75	35.83
Kumamoto	0.03	40.95	Kyoto	5.31	45.62
Mie	-2.1	38.77	Miyagi	-3.35	38.66
Miyazaki	-5.52	35.04	Nagano	-0.44	41.37
Nagasaki	-1.45	39.74	Nara	1.15	42.06
Niigata	1.26	42.06	Oita	-2.64	35.82
Okayama	0.83	42.58	Okinawa	2.34	41.86
Osaka	5.73	48.6	Saga	-3.95	35.79

Prefecture	LCI	ELCI	Prefecture	LCI	ELCI
Saitama	4.64	47.61	Shiga	-2.18	38.36
Shimane	-8.3	31.97	Shizuoka	-1.34	42.37
Tochigi	-2.42	38.44	Tokushima	-4.71	34.69
Tokyo	8.69	48.29	Tottori	-7.6	32.08
Toyama	-4.46	35.73	Wakayama	-2.05	37.78
Yamagata	-5.24	35.74	Yamaguchi	-2.37	38.6
Yamanashi	-1.96	37.25			

Table A· 1: LCI and ECLI values for ***Jan-Mar***.

Prefecture	LCI	ELCI	Prefecture	LCI	ELCI
Aichi	13.46	49.58	Akita	0.98	39.93
Aomori	7.98	46.45	Chiba	11.61	43.61
Ehime	3.83	38.91	Fukui	12.57	48.61
Fukuoka	17.97	48.81	Fukushima	11.19	47.48
Gifu	4.86	41.06	Gunma	3.45	39.05
Hiroshima	8.57	45.62	Hokkaido	9.6	38.88
Hyogo	13.2	47.7	Ibaraki	17.8	54.13
Ishikawa	15.4	46.86	Iwate	1.86	43.92
Kagawa	7.83	45.84	Kagoshima	4.78	44.75
Kanagawa	14.98	45.64	Kochi	2.19	38.55
Kumamoto	10.9	49.14	Kyoto	11.24	43.35
Mie	1.41	40.34	Miyagi	3.49	41.09
Miyazaki	-1	37.95	Nagano	13.77	50.21
Nagasaki	8.45	48.18	Nara	5.63	41.63
Niigata	12.06	49.46	Oita	7.94	46.3
Okayama	13.83	52.4	Okinawa	6.88	44.55
Osaka	15.9	47.76	Saga	9.02	44.42
Saitama	16.85	47.81	Shiga	3.59	39.28
Shimane	4.1	40.49	Shizuoka	8.82	46.76
Tochigi	10.34	45.09	Tokushima	5.79	44.5
Tokyo	23.24	50.81	Tottori	1.02	39.32
Toyama	10.09	43.08	Wakayama	1.85	37.87
Yamagata	7.78	44.54	Yamaguchi	10.14	47.83
Yamanashi	6.6	38.82			

Table A· 2: LCI and ECLI values for ***Apr-Jun***.

Prefecture	LCI	ELCI	Prefecture	LCI	ELCI
Aichi	16.09	41.87	Akita	1.22	36.39
Aomori	7.32	45.55	Chiba	8.19	34.64
Ehime	-1.52	35.58	Fukui	14.26	44.96
Fukuoka	16.42	41.93	Fukushima	10.57	43.02
Gifu	3.1	31.85	Gunma	2.03	30.76
Hiroshima	7.17	37.21	Hokkaido	5.71	35.53
Hyogo	13.56	40.97	Ibaraki	18.07	47.77
Ishikawa	10.89	39.09	Iwate	5.4	41.69
Kagawa	12.19	44.26	Kagoshima	2.46	31.21
Kanagawa	12.7	38.59	Kochi	0.2	32.4
Kumamoto	13.12	41.63	Kyoto	9.41	35.54
Mie	3.83	32.77	Miyagi	1.06	31.77
Miyazaki	-0.13	29.42	Nagano	14.28	45.7
Nagasaki	13.18	44.84	Nara	5.3	33.21
Niigata	13.53	47.35	Oita	10.36	43.4
Okayama	15.2	47.91	Okinawa	6.82	30.57
Osaka	13.82	38.16	Saga	9.06	39.12
Saitama	15.08	41.58	Shiga	2.32	31.04
Shimane	2.14	34.53	Shizuoka	6.43	37.12
Tochigi	8.39	37.53	Tokushima	2.84	32.91
Tokyo	19.13	42.3	Tottori	2.93	35.39
Toyama	8.22	39.11	Wakayama	2.24	32.2
Yamagata	6.2	44.69	Yamaguchi	11.35	42.68
Yamanashi	0.34	31.14			

Table A· 3: LCI and ECLI values for ***Jul-Sep***.

Prefecture	LCI	ELCI	Prefecture	LCI	ELCI
Aichi	4.75	12.06	Akita	1.28	11.13
Aomori	3.01	13.46	Chiba	3.37	10.77
Ehime	0.87	10.29	Fukui	4.64	12.73
Fukuoka	5.54	12.47	Fukushima	3.69	12.63
Gifu	1.66	9.76	Gunma	1.29	9.23
Hiroshima	3.07	11.62	Hokkaido	2.73	10.65
Hyogo	4.45	12.11	Ibaraki	5.90	14.31
Ishikawa	4.51	11.85	Iwate	1.62	12.55
Kagawa	3.67	12.91	Kagoshima	1.63	9.93
Kanagawa	4.35	11.57	Kochi	1.17	9.84
Kumamoto	4.11	12.20	Kyoto	3.32	10.64
Mie	0.96	9.18	Miyagi	1.02	9.70
Miyazaki	0.63	8.68	Nagano	4.62	13.48
Nagasaki	4.18	12.89	Nara	1.99	9.82
Niigata	4.19	13.78	Oita	3.29	12.20
Okayama	4.92	14.36	Okinawa	2.90	9.29
Osaka	4.76	11.53	Saga	3.24	11.40
Saitama	5.31	12.71	Shiga	1.46	9.43
Shimane	1.40	9.88	Shizuoka	2.73	11.56
Tochigi	3.07	11.49	Tokushima	1.34	9.87
Tokyo	7.04	13.37	Tottori	1.26	10.93
Toyama	3.23	11.09	Wakayama	1.07	9.45
Yamagata	2.83	12.36	Yamaguchi	3.69	12.56
Yamanashi	1.88	10.29			

Table A· 4: LCI and ECLI values for ***the whole phase (Jan-Sep)***.