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Modelling the Mobility Changes Caused by Perceived Risk and Policy Efficiency: A Case Study in Leeds

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Abstract: In many countries, governments have implemented non-pharmaceutical techniques to limit COVID-19 transmission. Restricting human mobility is one of the most common interventions, including lockdown, travel restrictions, working from home, etc. However, due to the strong transmission ability of the virus variants, further rounds of interventions, including a strict lockdown, are not considered as effective as expected. The paper aims to understand how the lockdown policy and pandemics changed human mobility in the real scenario. Here we focus on understanding the mobility changes caused by compliance with restrictions and risk perceptions, using the mobility index from the Google report during three strict lockdown periods in Leeds, the largest city in the county of West Yorkshire, England from March 2020 to March 2021. The research proposed the time-varying z-scores and Principal Component Analysis (PCA) to simulate how local people dynamically process and perceive health risk based on multi-dimensional daily COVID-19 reports first. Further modelling highlights exponentially increasing policy non-compliance through the duration of lockdown, probably attributable to factors such as mental anxiety and economic pressures. Finally, the proposed nonlinear regression model examines the mobility changes caused by the population's dynamic risk perceptions and lockdown duration. The case study at Leeds fits data well and shows that the third lockdown policy took effect much slower than the first. At the same time, the negative impact of the epidemic on population mobility decayed 40% in the third lockdown period in contrast with the first lockdown. The risk perception estimation methods could reflect that the local population became increasingly accustomed to the COVID-19 situation, and local people rationally evaluated the risks of COVID in the third lockdown period. The results prove that simulated risk perceptions and policy decay could explain urban mobility behaviour during the mobility well during lockdown periods, which could be a reference for future decision-making processes.

Keywords: urban mobility, dynamic risk perception, data-driven model, policy analysis

1. Introduction

With the emergence and spread of the COVID-19 virus pandemic worldwide, governments have imposed strict restrictions on mobility and social activities. At the beginning of the pandemic, intensive non-pharmaceutical interventions (NPIs) were needed to control virus transmission rates whilst effective vaccines were developed and distributed. With emerging virus variants, NPI's have continued to be used in complement to vaccines, including restrictions of human mobility. With the relaxation of public policies and infection prevention measures, many countries are still experiencing persistent or additional widespread waves of the virus. In the UK, people experienced three separate strict lockdown periods in a year from March 2020 to March 2021 to limit the peak of virus transmission and protect public health capacity. The continued challenge is that some virus variants might break the vaccination protection and have super transmission rates, which are hard to control immediately. Facing over 100,000 new confirmed cases per day in Dec 2021 in the U.K., the government again considered and implemented restriction

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policies. Therefore, the aim of this research is to analyse the evidence on population compliance with the NPI's, precisely, policies around restricting mobility (work from home, only take essential travel, etc) to inform decision-makers on their efficacy and future policy design.

Existing research on mobility recovery during the lockdown showed a decreasing effect from reducing human mobility even when daily cases were rising, which means the lockdown policy could not be considered a sustainable, efficient NPI in the long term[1], [2]. This is despite many research pieces showing a positive correlation between the implementation of lockdown policy and mobility reduction in different countries or regions [3]–[6]. Thus, understanding how the real-world mobility behaviour changed during the lockdown implementation could help stakeholders make improved decisions and reduce unnecessary costs for sustainable development[7]–[10]. Some research fully explores the relationship between mobility and risk perception related to COVID-19. Across survey-based research in ten countries, risk perception is regarded as the critical feature correlated with the reported public health compliance[11]. Nelson et al. gathered online surveys and detected a positive correlation between the concern of COVID and self-quarantining behaviour in the US, Canada, and Europe at the start of the outbreak[12]. Chan et al found that areas with high risk-tolerance is positively associated with the mobility change in retail and recreation places[13].

However, to the authors' knowledge, currently published research on the quantitative causal relationship between mobility and risk perception in the population and lockdown policy is limited in several respects. First, Individual perceptions and behaviours may change with the evolving environment regarding COVID-19 severity, policy, and infrastructure implementations[14]. Since the main research methods used to monitor public risk perception are questionnaires, it is hard to consistently track the longitudinal analysis of risk perceptions and mobility behaviours. Much existing analysis relies on a point in time or some periods during the pandemic period, which will lose track of the evolving mobility and risk perceptions changes. Wise et al. tracked the participants for over a week (March 11, 2020 – March 16, 2020), finding at the start of the pandemic in the U.S., and found a significant association between risk perception and commitment to protective behaviours[15]. Another study surveyed the travel risk perception and travel behaviour in the Germany-Austria-Switzerland region in March 2020 and two weeks later[16].The most recent referenced a longitudinal study of risk perception in the U.K. tracked different participants using the same cross-sectional variables in five time-snapshots over ten months, with the results indicating that risk perception is a dynamic process and positively correlated with the health behaviours[17]. This work satisfied the longitudinal definition but failed to model the dynamic relationships between mobility and risk perceptions for the specific population. Secondly, most mobility research relies on correlative analysis that only represents the association relationships and cannot model the causality or directionality between mobility and risk perceptions, while the existing research implies the risk perception toward COVID-19 acts as an antecedent of behaviour[18]. Nouvellet et al. linked mobility at the national level to effective reproductive numbers to examine the relationships between mobility and severity (Nouvellet et al., 2021). The results suggested that lockdown policies have a diminishing impact on the control of the pandemic in many countries. However, the model utilised the number of deaths and cases to generate the reproduction number representing the severity. This is different to the way in which Kraemer et al. visualised the extracted mobility data in China in a timeline with the lockdown indicator, showing that statistical correlation between the number of cases and mobility dropped from positive to negative after implementing the control measures(Kraemer et al., 2020). Hence, it is crucial to determine and explore how the health risk perceptions and policy affect and interact with health-protecting behaviours.

To address the above research gaps concerning the lack of longitudinal data , this study selected the daily COVID-19 reports, including local cases, local deaths, national cases, and national deaths as the input for simulating populations' health risk perceptions. It also used the Google Community Mobility Report for retail and recreational facilities in

Leeds from March 2020 to June 2021 as the mobility index, which covered three strict lockdown periods, as the dependent variable data. These two different data sources can form panel data that record the population's mobility behaviour and risk perception of the pandemic because they match in the daily consistent collection frequency and focus on the population in the same local area. This isn't a strict experimental panel however, as the location population will be subject to some movement, temporary visitors etc. Another advantage is that retail and recreational mobility can reflect the population's tendency for policy non-compliance because it is defined as mobility trends for non-essential retail places like restaurants, cafes, shopping centres, theme parks, museums, libraries, and movie theatres. During three strict lockdown periods, these places were not allowed to open to the public. Hence, this mobility index only records the non-essential mobility and excludes mobility behaviours concerning essential activity such as visiting the supermarket.

To dynamically model mobility behaviour during the lockdown, the proposed model will consider the two most significant perspectives influencing mobility behaviours and policy compliance: confirmed cases and personal psychological characteristics, based on the research results from the U.K. [17]. The originality of the research is the use of a time-varying z-score and PCA to simulate how people perceived the pandemic severity through multi-dimensional daily reports and history information, whose results can be validated by satisfying the general trends of risk perception in the U.K. [17]. The proposed model also quantitively describes that the non-compliance for lockdown increased exponentially as the policy continued over time, which is consistent with the survey results during the first lockdown in the U.K. [19]. Finally, the method provided a way to explain how daily reports and lockdown duration quantitively affected population mobility during the lockdown and to predict the trend towards mobility recovery.

2. Materials and Methods

This section firstly introduces the data used in this research and how we process the data before fitting the model. Then, the methods for generating the perceived risk perception and policy non-compliance are presented. Finally, the nonlinear regression model is presented, which describes how modelling factors influence mobility.

2.1 Data

The mobility index used in this study is from Google's COVID-19 Community Mobility Report, collected from Google's users who have turned on their location history[1]. The mobility index corresponding to "the mobility changes for each day of the week" is continuous in terms of percentage relative to the median of each specific day during the baseline period from January 3 to February 6, 2020 (approximately seven weeks before introducing the first national lockdown). There are six mobility categories: retail and recreation, groceries and pharmacies, parks, transit stations, workplaces, and residential. We chose to focus on the mobility index of retail and recreation places as it is directly relevant to the lockdown as the key element of the policy was the close of all non-essential shops. This category includes places such as cinemas, restaurants, shopping centres etc. It is worth mentioning that supermarkets are not included in this category. So it can represent the effectiveness of the lockdown policy.

The COVID-19 data is gathered from the government website of the U.K[2]. The website supports the daily updates about the local cases, local death numbers and national cases and death numbers. The vaccine information was recorded from Jan 2021. The current research didn't involve vaccine data because most lockdown periods were before the vaccine distribution.

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[1] Google LLC *"Google COVID-19 Community Mobility Reports"*. https://www.google.com/covid19/mobility/ Accessed: <2021-12-10>.

[2] https://coronavirus.data.gov.uk/

In summary, the research data consists of two elements: the mobility index and the COVID-19 reports. The research approach is outlined in Section 2.2 and generates dynamic risk perceptions perceived by daily COVID-19 reports as one of the independent variables. The dependent variable is the mobility index of retail and recreation places. The specific data pre-processing and introduction is explained in the case study section and Appendix (A1).

2.2 Dynamic risk perception towards COVID-19 estimated by time-varying z-score

Dynamic risk perceptions are required to model the continuous changes in mobility, which are challenging to collect directly through use of a survey. Hence, the research referred to the time-varying z-score to simulate how people process the COVID-19 information and perceive the risk. Since the data was collected through the Google service on mobile devices, the research assumes the users of these devices can access daily COVID-19 reports, including local daily cases, local daily deaths, national daily cases, and national daily deaths from the media with a reliable probability. The size of these factors will affect the public's perception of risk towards COVID-19. For instance, mobile phone users will receive subscribed news summarising COVID-19 reports from the previous day. The users will perceive and process the latest information and compare it with the historical information, then today's risk perceptions against COVID-19 will be assessed. In practice, there have been multiple information channels with prominent COVID-19 daily reports, such as TV news channels, online and hard copy newspapers and more. The following explanatory factors(variables) are considered to influence the dynamic risk perception:

- Local daily cases
- Local daily death numbers
- National daily cases
- National daily death numbers

These four factors are all a daily updated index, and the cumulative death or cases are excluded because they have high collinearity with the time(see Appendix A2). The order of magnitudes is different for each selected variable due to the volume sizes between local and national data, especially for national daily cases and local daily deaths. Furthermore, risk perception in the psychological scale is always conducted on the 5-point Likert scale[11], [17]. It is also important to normalise the variables to compare measurements with different units. Therefore, variables measured on different scales do not contribute equally to the analysis, and it's is necessary to re-scale the variables. One helpful data process method is the standard scaler (i.e. z-score), making the variables with zero-mean and unit variance. The Z-Score has been used in economic research as a risk measure that reflects a bank's likelihood of bankruptcy[20]. The advantage of using this approach is that, if the data is sequenced in order of time, it is possible to analyse the data according to the most recent set of observations, or to give different weights, exploring z-score variants to track dynamic changes in the data, which is the so-called time-varying method. The time-varying z-score can be calculated by adjusting the moving mean and standard deviation with whole history samples or given window size[20]–[22].

This research tests three different methods to calculate the time-varying z-score for each variable's time series. According to the definition of z-score calculation, the adjustments are applied in the calculation methods for the sample mean and standard deviation. For example, the local daily case is a sequence $\{X_t\}$, t from 1 to T, where T is the lockdown duration. The three proposed algorithms use the moving average/standard deviation with specific window size(Algorithm 1), the moving average/standard deviation with all history information(Algorithm 2) and the exponentially weighted moving average/standard deviation (Algorithm 3). After accessing the datum $\{X_t\}$ in the different algorithms, there are different dynamic risk perceptions generated by the local daily cases.

Algorithm 1

$Input\ \{X_t\}, N$

$X_0 = 0$

$For\ t\ in\ 1,2, \dots ,T:$

$IF\ t < N:$

$\overline{X_t} = X_t$

$se_t = 0$

$ELSE:$

$$\overline{X_t} = \frac{\sum_{t-N}^{t-1} X_i}{N}$$

$$se_t = \sqrt{\frac{1}{t-1} \sum_{t-N}^{t-1} (X_i - \overline{X_t})^2}$$

$IF\ se_t = 0:$

$R_t = 0$

$ELSE:$

$$R_t = \frac{X_t - \overline{X_t}}{se_t}$$

$Output\ \{R_t\},\ t = 1,2, \dots ,T$

Algorithm 1. Dynamic perceived risk perception by moving average and moving standard deviation with window size as N.

Algorithm 2

$Input\ \{X_t\}$

$X_0 = 0$

$For\ t\ in\ 1,2, \dots ,T:$

$$\overline{X_t} = \frac{\sum_{1}^{t-1} X_i}{t-1}$$

$$se_t = \sqrt{\frac{1}{t-1} \sum_{1}^{t-1} (X_i - \overline{X_t})^2}$$

$IF\ se_t = 0:$

$R_t = 0$

$ELSE:$

$$R_t = \frac{X_t - \overline{X_t}}{se_t}$$

$Output\ \{R_t\},\ t = 1,2, \dots ,T$

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Algorithm 2. Dynamic perceived risk perception by moving average and moving standard deviation with all historical samples.

Algorithm 3

$Input\ \{X_t\}, N$

$X_0 = 0$

$\alpha = 2/(N+1)$

$EMA_0 = X_1$

$For\ t\ in\ 1,2, \dots ,T:$

$\delta_t = X_t - EMA_{t-1}$

$EMA_t = EMA_{t-1} + \alpha * \delta_t$

$EMVar_t = (1-\alpha)(EMVar_{t-1} + \alpha * {\delta_t}^2)$

$IF\ EMVar_t = 0:$

$R_t = 0$

$ELSE:$

$$R_t = \frac{X_t - EMA_t}{{\delta_t}^2}$$

$Output\ \{R_t\},\ t = 1,2, \dots ,T$

Algorithm 3. Dynamic perceived risk perception by exponentially weighted moving average and exponentially weighted moving standard deviation with window size as N.

For algorithm 1, the research uses N=7, 14, 28 respectively to represent the population's short/medium/long memory when producing the risk perception from daily reports. For algorithm 2, since all historical data are deemed equal, the built risk perception represents the long-memory population's risk perception. As for algorithm 3, even though every historical sample is considered, the weight of each sample decreases exponentially from the earliest to the oldest. The N = 7,14,28 represents that the first N datum points in an EMA represent about 86% of the total weight in the calculation when $\alpha = 2/(N+1)$.

Recall that the variables considered form four sequences: local case, local death, national case, national death. To avoid the dimension explosion fitting the model(see S3) and simulate the population considering the four variables together, the last step for generating the perceived COVID-19 risk is Principal Component Analysis(PCA). The complete process generating the perceived risk perception by daily reports is shown in Figure 1. The four variables will use the same algorithm to generate the risk perceptions and then be compressed into one dimension as the final variable that will be used to represent the intraday risk perceptions toward COVID-19 influencing mobility.

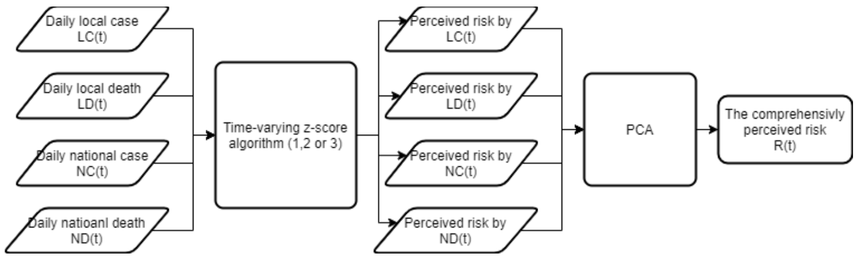

Figure 1. The perceived risk generation process. Four time series will be the input to the time-varying z-score in section 2.2, and the output corresponds to perceived risks. The second step implements the PCA to reduce the four time series into one, which is the comprehensively perceived risk to be used.

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3. The case study and results

3.1. Model configuration

This section implements a detailed case study to analyse the retail and recreational mobility changes among three national strict lockdown periods in Leeds from March 2020 to March 2021. The complete COVID-19 rules are summarised in Figure 2 from the authority source[23].

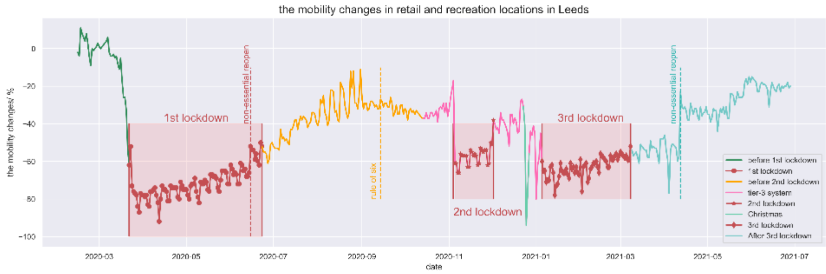

Figure 2. The mobility changes of retail and recreation locations in Leeds. The first lockdown started on March 23 2020 and ended on June 23, 2020. The second lockdown lasted one month, from October 31 2020, to December 2 2020. And the last lockdown continued from January 6 2021, to March 8 2021.

The research implemented three algorithms with different window sizes to generate the dynamic perceived risk R(t) and to model the local aggregated mobility changes in each lockdown period. The R(t) developed by various methods is validated and discussed in Appendix (A3).

From Figure 2, the mobility of retail and recreation places showed periodic variations. The periodicity is found to be seven days caused by weekdays and weekends, which could be explained that people tend to go to retail and recreation places more on weekdays (S2). Since the objective is to find the trends in mobility behaviours influenced by policy and risk perceptions, the mobility index data was smoothed by applying the centred 7-day moving-average method to eliminate the weekly periodicity. There are two independent variables the research focuses on: the policy duration, t, and dynamic risk perceptions, R(t). The regression model is based on the general linear model as

$$M_t = c + \beta_1\varphi_1(t) + \beta_2\varphi_2(t) + \cdots + \beta_n\varphi_2(t) + \alpha R(t),\ t \in (1, T) \qquad (1)$$

, where T is the lockdown duration, and $R(t)$is the dynamic risk perception generated by the proposed methods.

Under full compliance, the assumed lockdown policy effect was that mobility should drop to the low level and stay there, which is inversely proportional to the lockdown time. So the first regression term is assigned as the $\frac{1}{t}$. However, the real situation in some lockdown periods of Leeds reviewed was that after the sharp drop in the beginning, mobility recovered at a slower rate through the lockdown days. The proposed model assumes that the mobility recovered at a fixed rate, which assigns the second term $\varphi_2(t) = t$. So, in conclusion, the first proposed linear regression model is

$$M_t = c + \beta_1\frac{1}{t} + \beta_2 t + \alpha R(t),\ t \in (1, T) \qquad (2)$$

Furthermore, according to Ganslmeier's work[19], the lockdown policy's non-compliance increased at an exponential rate in the U.K. Hence, the alternative model is

$$M_t = c + \beta_1\frac{1}{t} + e^{\beta_2 t} + \alpha R(t),\ t \in (1, T) \qquad (3)$$

,which is a nonlinear model.

The case study compared the goodness of model fitting and selected the proper one by fitting two regression models with the same data. In total, we have seven kinds of perceived risk generated by different algorithms and window sizes in table 1. The window size is chosen as 7, 14, 28 and all history data representing the various memory capacities. The objective is to compare the model results and search for the proper risk perception feature in each lockdown period and which modelling term, linear or nonlinear, is more precise.

3.2. Model results

By fitting the model into three lockdown periods by equation 2 using the Statsmodels [24], the results are shown in **Error! Reference source not found.**. There are seven dynamic perceived risks for each lockdown period. A correct, well-fitting model should have statistical significance for each parameter, and especially the estimated parameter β_2 should be negative, keeping consistency with other researchers' conclusions[17], [18], which means risk perception should negatively affect mobility. For the first lockdown period, two fitted models have a negative coefficient for the perceived risk perceptions with lower p-values. However, the p-values are all above 0.1, meaning that they are non-significant. As for the second lockdown period, the only negative parameter exists in the model using all history samples equally. The p-value again fails. For the third lockdown, the model utilised the exponentially weighted moving risk to satisfy the model evaluation conditions, including all parameters reaching a certain significance. Figure 3 displays the fitting performances of the best models in each lockdown period.

First-lockdown			Params	T-test	P-value	Adj_r2
First-lockdown	exponentially weighted moving risk, N=7	c	-85.99	-146.08	0.00	0.91
		β1	37.48	18.50	0.00	
		β2	0.26	26.78	0.00	
		α	-0.15	-0.77	0.44	
	exponentially weighted moving risk, N=14	c	-85.86	-144.46	0.00	0.91
		β1	37.22	18.35	0.00	
		β2	0.26	26.06	0.00	
		α	-0.19	-1.21	0.23	
	exponentially weighted moving risk, N=28	c	-85.99	-156.39	0.00	0.91
		β1	37.51	18.99	0.00	
		β2	0.26	26.68	0.00	
		α	-0.15	-1.24	0.22	
	moving risk , N=7	c	-85.86	-157.41	0.00	0.91
		β1	37.25	19.01	0.00	
		β2	0.27	29.72	0.00	
		α	0.21	1.92	0.06	
	moving risk , N=14	c	-85.75	-147.62	0.00	0.91
		β1	37.08	18.60	0.00	
		β2	0.26	28.94	0.00	
		α	0.27	1.71	0.09	
	moving risk , N=28	c	-85.36	-141.47	0.00	0.91
		β1	36.09	17.86	0.00	
		β2	0.26	28.75	0.00	
		α	0.52	2.59	0.01	
	moving risk , N=All	c	-85.24	-168.53	0.00	0.93
		β1	35.27	19.34	0.00	
		β2	0.30	29.26	0.00	
		α	0.89	4.92	0.00	

Second-Lockdown			Params	T-test	P-value	Adj_r2
Second-lockdown	exponentially weighted moving risk, N=7	c	-60.85	-27.58	0.00	0.76
		β1	34.81	7.65	0.00	
		β2	0.11	1.02	0.32	
		α	0.16	0.23	0.82	
	exponentially weighted moving risk, N=14	c	-60.76	-27.99	0.00	0.76
		β1	34.74	7.70	0.00	
		β2	0.12	1.06	0.30	
		α	0.31	0.62	0.54	
	exponentially weighted moving risk, N=28	c	-60.96	-27.84	0.00	0.76
		β1	34.91	7.68	0.00	
		β2	0.12	1.06	0.30	
		α	-0.02	-0.04	0.97	
	moving risk , N=7	c	-61.09	-28.31	0.00	0.76
		β1	34.87	7.74	0.00	
		β2	0.15	1.24	0.23	
		α	0.34	0.63	0.53	
	moving risk , N=14	c	-60.76	-27.99	0.00	0.76
		β1	34.74	7.70	0.00	
		β2	0.12	1.06	0.30	
		α	0.31	0.62	0.54	
	moving risk , N=28	c	-60.96	-27.84	0.00	0.76
		β1	34.91	7.68	0.00	
		β2	0.12	1.06	0.30	
		α	-0.02	-0.04	0.97	
	moving risk , N=All	c	-60.48	-27.34	0.00	0.76
		β1	34.21	7.51	0.00	
		β2	0.05	0.37	0.72	
		α	-0.74	-0.82	0.42	

Third-Lockdown			Params	T-test	P-value	Adj_r2
Third-lockdown	exponentially weighted moving risk, N=7	c	-71.17	-122.23	0.00	0.82
		β1	14.92	8.61	0.00	
		β2	0.22	15.36	0.00	
		α	-0.16	-0.70	0.49	
	exponentially weighted moving risk, N=14	c	-71.51	-125.77	0.00	0.82
		β1	15.47	9.11	0.00	
		β2	0.23	15.80	0.00	
		α	0.26	1.22	0.23	
	exponentially weighted moving risk, N=28	c	-70.90	-122.00	0.00	0.83
		β1	14.47	8.49	0.00	
		β2	0.21	13.98	0.00	
		α	-0.33	-1.80	0.08	
	moving risk , N=7	c	-70.95	-118.81	0.00	0.82
		β1	14.57	8.43	0.00	
		β2	0.22	14.86	0.00	
		α	-0.17	-1.40	0.17	
	moving risk , N=14	c	-71.16	-126.03	0.00	0.82
		β1	14.91	8.72	0.00	
		β2	0.22	15.85	0.00	
		α	-0.16	-1.00	0.32	
	moving risk , N=28	c	-71.41	-129.48	0.00	0.82
		β1	15.31	9.07	0.00	
		β2	0.23	16.87	0.00	
		α	-0.22	-1.14	0.26	
	moving risk , N=All	c	-71.18	-127.29	0.00	0.82
		β1	14.91	8.74	0.00	
		β2	0.24	11.32	0.00	
		α	0.43	1.04	0.30	

Table 1. The linear model results of each generated risk perception in three lockdown periods.

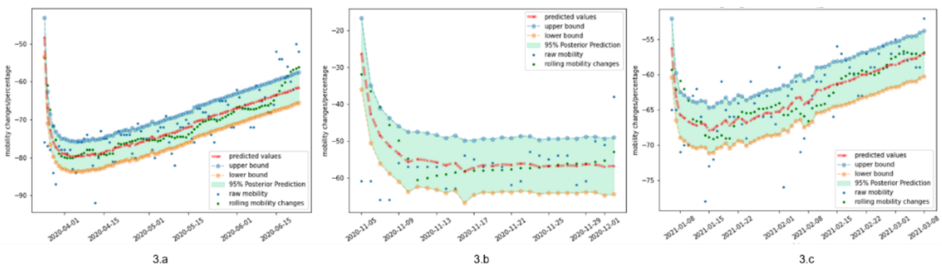

Figure 1. The linear model fitting results in three lockdown periods. The light green area covers the 95%-confidence-level lower and upper confidence bounds. The green points are the rolling mobility data, whereas blue points are raw mobility data. The red dash line composes of the predicted values. Figure 3.a and 3.c depicts the mobility changes in the first and the third lockdown period using the risk perception generated in the exponentially weighted way(N=28). Figure 3.b displayed mobility changes in the second lockdown with equally weighted moving risk perception(N=all).

From Figure 1, based on the linear regression, all three selected models can capture the trends of the mobility changes with R^2 as 0.91, 0.76 and 0.83 in the corresponding lockdown period. For the first lockdown, the mobility index quickly dropped almost 40% compared with before and then recovered at a nearly linear speed. The mobility index dropped 40% too for the second lockdown period but didn't rebound. However, the mobility showed a similar trend in the first lockdown again. Moreover, the mobility drop in the third lockdown period is much smaller than before.

The nonlinear model results are summarised in Table 1. The standards to select the proper model are still based on the negativity of α and the statistical significance of each variable. In the first lockdown period, the best nonlinear model using all history information to generate the risk perception can reach high statistical significance for all parameters and gain sound fitness. However, in the second lockdown, the risk perception term fails to pass the t-test. The dynamic risk perception generated by algorithm 3 with N=28 performs best among other risk perceptions in the third lockdown, the same as in linear model results.

First-lockdown			Params	T-test	P-value	
First-lockdown	exponentially weighted moving risk, N=7	c	-80.80	-257.13	0.00	Adj_R2:0.928804, MSE: 275.8
		β1	26.82	16.53	0.00	
		β2	0.04	98.74	0.00	
		α	0.03	0.16	0.87	
	exponentially weighted moving risk, N=14	c	-80.81	-254.62	0.00	Adj_R2:0.9288283, MSE: 275.8
		β1	26.84	16.50	0.00	
		β2	0.04	95.71	0.00	
		α	0.03	0.23	0.82	
	exponentially weighted moving risk, N=28	c	-80.74	-284.16	0.00	Adj_R2:0.9292953, MSE:273.9
		β1	26.71	16.74	0.00	
		β2	0.04	98.04	0.00	
		α	-0.09	-0.79	0.43	
	moving risk , N=7	c	-81.06	-249.99	0.00	Adj_R2:0.9308883, MSE:267.8
		β1	27.31	16.96	0.00	
		β2	0.04	108.51	0.00	
		α	-0.16	-1.63	0.11	
	moving risk , N=14	c	-81.14	-230.50	0.00	Adj_R2:0.930973, MSE:267.4
		β1	27.43	16.89	0.00	
		β2	0.04	106.25	0.00	
		α	-0.24	-1.66	0.10	
	moving risk , N=28	c	-80.81	-209.02	0.00	Adj_R2:0.9287917, MSE:275.9
		β1	26.83	15.74	0.00	
		β2	0.04	101.17	0.00	
		α	-0.02	-0.10	0.92	
	moving risk , N=All	c	-82.00	-188.55	0.00	Adj_R2:0.9376691, MSE:241.5015
		β1	29.56	17.46	0.00	
		β2	0.03	103.51	0.00	
		α	-0.51	-3.52	0.00	

Second-Lockdown			Params	T-test	P-value	
Second-lockdown	exponentially weighted moving risk, N=7	c	-62.22	-44.76	0.00	Adj_R2:0.7969454, MSE:279.4
		β1	35.67	9.35	0.00	
		β2	0.06	3.97	0.00	
		α	-0.02	-0.02	0.98	
	exponentially weighted moving risk, N=14	c	-62.06	-46.08	0.00	Adj_R2:0.7997176, MSE:275.6
		β1	35.42	9.35	0.00	
		β2	0.06	4.26	0.00	
		α	0.40	0.58	0.57	
	exponentially weighted moving risk, N=28	c	-62.17	-46.92	0.00	Adj_R2:0.7980499, MSE:277.9
		β1	35.52	9.34	0.00	
		β2	0.07	4.25	0.00	
		α	0.27	0.37	0.72	
	moving risk , N=7	c	-62.06	-48.24	0.00	Adj_R2:0.8050882, MSE:268.2
		β1	35.20	9.44	0.00	
		β2	0.07	5.12	0.00	
		α	0.52	1.01	0.32	
	moving risk , N=14	c	-62.02	-45.08	0.00	Adj_R2:0.7992887, MSE:276.2
		β1	35.47	9.35	0.00	
		β2	0.06	3.96	0.00	
		α	0.26	0.53	0.60	
	moving risk , N=28	c	-62.30	-46.22	0.00	Adj_R2:0.7976699, MSE:278.4
		β1	35.74	9.44	0.00	
		β2	0.06	4.21	0.00	
		α	-0.16	-0.30	0.77	
	moving risk , N=All	c	-62.23	-45.72	0.00	Adj_R2:0.7978839, MSE:278.1
		β1	35.64	9.37	0.00	
		β2	0.06	2.85	0.01	
		α	-0.29	-0.34	0.73	

Third-Lockdown			Params	T-test	P-value	
Third-lockdown	exponentially weighted moving risk, N=7	c	-68.81	-205.31	0.00	Adj_R2:0.8426589, MSE:137
		β1	9.81	6.68	0.00	
		β2	0.04	45.33	0.00	
		α	-0.02	-0.08	0.94	
	exponentially weighted moving risk, N=14	c	-68.84	-216.08	0.00	Adj_R2:0.8442878, MSE:135.6
		β1	9.84	6.81	0.00	
		β2	0.04	47.02	0.00	
		α	0.16	0.78	0.44	
	exponentially weighted moving risk, N=28	c	-68.69	-213.16	0.00	Adj_R2:0.8502894, MSE:130.4
		β1	9.55	6.69	0.00	
		β2	0.04	41.17	0.00	
		α	-0.30	-1.72	0.09	
	moving risk , N=7	c	-68.75	-194.97	0.00	Adj_R2:0.8431947, MSE:136.6
		β1	9.70	6.56	0.00	
		β2	0.04	43.10	0.00	
		α	-0.06	-0.45	0.65	
	moving risk , N=14	c	-68.77	-210.94	0.00	Adj_R2:0.8438013, MSE:136
		β1	9.72	6.68	0.00	
		β2	0.04	46.66	0.00	
		α	-0.10	-0.66	0.51	
	moving risk , N=28	c	-68.93	-211.99	0.00	Adj_R2:0.8470236, MSE:133.2
		β1	9.96	6.94	0.00	
		β2	0.04	50.23	0.00	
		α	-0.23	-1.29	0.20	
	moving risk , N=All	c	-69.40	-140.70	0.00	Adj_R2:0.8486247, MSE:131.8
		β1	10.84	6.89	0.00	
		β2	0.04	35.37	0.00	
		α	-0.48	-1.50	0.14	

Table 1. The nonlinear model results of each generated risk perceptions in three lockdown periods.

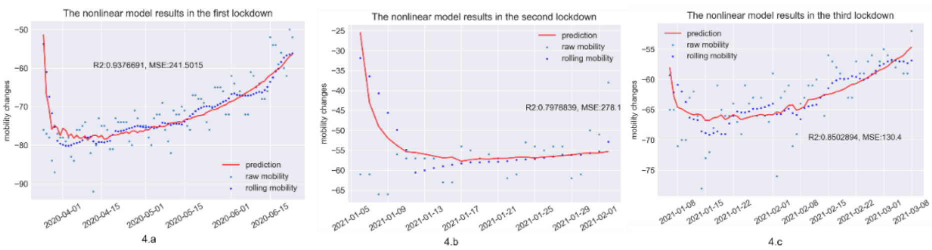

Figure 2. The nonlinear model results in each lockdown period. The red line is the predictive mobility. The blue points represent the mobility after applying the 7-day moving-average. And the cyan points are the raw mobility scatter plot.

The three model fitting results with the best performance in three periods are illustrated separately in Figure 2. From the perspectives of MSE and R square, the models can capture the fundamental trends in each lockdown period, and even better than the linear models.

After implementing a range of models, we could finally select well-fitting, correct nonlinear models that successfully describe the mobility changes in the first and third lockdown periods. The estimated regression model with the best performance for the first lockdown period is nonlinear:

$$M_t = -82 + 29.56\frac{1}{t} + e^{0.03t} - 0.51R_{all}(t)\,,\ t \in (1, T_1) \qquad (4)$$

, where $R_{all}(t)$ is estimated by using all history information (**Error! Reference source not found.**) and $T_1 = 91$ is the length of the first lockdown policy. It is reasonable because people were nervous about the unknown risk and virus due to the beginning of the pandemic. Hence, people tended to hold long-lasting memory for the COVID-19 spread.

And the selected regression model for the third lockdown is also nonlinear because of its better goodness of fit:

$$M_t = -68.69 + 9.55\frac{1}{t} + e^{0.04t} - 0.3R_{ew}(t)\,,\ t \in (1, T_3) \qquad (5)$$

, where $R_{ew}(t)$ is estimated by using the exponentially weighted moving average/standard deviation with N=28 (**Error! Reference source not found.**) and $T_3 = 62$ is the length of the third lockdown policy. This implies that people would use the recent information to evaluate the COVID-19 severity and risk, rather than all historical information.

However, for the second lockdown period, none of the proposed models could reach the statistical significance for parameter α. The proper regression results in linear and nonlinear models have almost the same effect. To be comparable with the other two models, here the selected model is also chosen as nonlinear for sketching the mobility changes in the second lockdown in Leeds:

$$M_t = -62.23 + 35.64\frac{1}{t} + e^{0.06t} - 0.29R_{all}(t)\,,\ t \in (1, T_2) \qquad (6)$$

, where $R_{all}(t)$ is estimated by using all history information (**Error! Reference source not found.**) and $T_2 = 28$ is the length of the second lockdown policy.

By comparing the best nonlinear models selected among three lockdown periods from equation 4 to 6, the changes of parameters can be interpreted as the evolving process of public attitudes toward COVID-19 and lockdown policy. The parameter β_1 represents the rate of policy efficiency, i.e., the decay rate of mobility index. The values of β_1 increased from 29.56 in the first lockdown to 35.64 in the second lockdown and then dropped back to 9.55, implicating that the policy took effect in different lockdown periods. In the long term, the lockdown efficiency in the third lockdown was far lower than at the beginning stage, explaining the lockdown fatigue phenomenon. And for parameter β_2, which can be interpreted as the policy non-compliances sensitivity of lockdown time, it has the same trend with β_1. In the first lockdown period, β_1 is 0.03 but raised to 0.06 in the second lockdown. The potential reason could be the impatience of lockdown[2] and the high demand for mobility before the Christmas holidays. However, in the third lockdown, β_1 dropped back to 0.04. It might be explained as that more and more people realised the importance of lockdown or the public was getting used to the lockdown life in the COVID-19. As for the α, parameter of risk perception's effect, it decayed from 0.51 to 0.3, almost a 40% drop, which indicates that people were less affected by COVID-19 cases than the initial epidemic. The possible reasons could be that at first, people were becoming familiar with the COVID, which didn't have a high fatality rate. Secondly, the vaccine project had started in Dec 2020. Many elder people (high-risk group) were vaccinated and protected at that time. It is worth noting that the dynamic risk perceptions in the first two lockdown periods, equation 4 and 6, used algorithm 2 (i.e. using all historical information to perceive current risks), and algorithm 3 is more suitable in the third lockdown (equation 5). It suggests that after coexisting with the virus a year, the local population travel choices wouldn't be influenced by their long-lasting memory of former situations and that they were focused on the current scenes in considering the risks.

3.3. Result discussion

The best linear model used the risk perception generated by the 28-day moving average and standard error for the first lockdown. However, the parameter of the risk perception is non-significant (P = 0.22), which is not as good as the nonlinear model(P=0). Using the risk perception generated by all history information, the nonlinear model has the best performance. It can be interpreted as that most people had a strong protective mind at the beginning of the epidemic and were cautious. So, the public will consider all the history information to judge the current risk, which is not too long to remember. And also, as for the policy non-compliance term ($e^{0.03t}\, vs\ 0.26 * t$), the exponential term has the consistent conclusion with the previous survey results [19], which means the non-compliance increased faster and faster in the first lockdown period.

For the second lockdown, both the best model among linear and nonlinear's don't have a significant p-value for risk perception term, which means the risk perception variable in the second lockdown is not crucial. The possible reason could be that the second lockdown was inserted between the 3-tier lockdown and Christmas holidays. There may have many uncertainties for estimating the risk perceptions and other psychological concerns. For example, some people might avoid going outside because of the severe epidemic. However, also some people might insist on going out for visiting family members or shopping because of the coming released holiday period.

As for the third lockdown period, both the best linear and nonlinear models use the risk perception generated by exponentially weighted moving (EWM) z-score(N=28). Even the exponentially weighted moving z-score has a window size, it doesn't mean the method only takes N previous data points. However, it still considered all history data points, just decreasing weights. The good performances of EWM_28 risk perception can be explained that the local people would judge the COVID-19 severity more realistically during the third lockdown than people were able to in the initial stage. That would be rational as it had been a year at that time since the first wave in the U.K., and people would have a few memories of the beginning stage and care more about the prevailing situation.

4. Conclusions

The research explores the mobility changes caused by lockdown policy duration and dynamic risk perceptions. Our analysis also provided three algorithms simulating the local public's daily risk perceptions toward COVID-19 by using the official dashboard data. The case study is implemented in Leeds, which experienced three strict lockdown periods over a year. After tuning the hyper-parameters of different risk perception generation algorithms and comparing linear with nonlinear models, three selected proper nonlinear models respectively capture the mobility trends well in different lockdown periods. The model results reflect that the local population could adapt to the lockdown lives in the COVID era. The recent lockdown policy becomes less potent in restricting retail and recreation mobility than in the first lockdown. In addition, during the most recent lockdown policy, the dynamic risk perceptions were estimated well in an exponentially weighted way. Compared with the former model using all history information, the exponentially weighted approach is more rational, representing people focusing on their current lives rather than only being concerned about the epidemic. Also, the parameter, which quantifies the negative influence on mobility caused by risk perceptions, in the third lockdown is lower 40% than in the first lockdown. The possible reason for this decline might be promoting vaccination that decreased the fatality rate, and people prefer to believe the pandemic is becoming harmless.

However, the present research still has certain limitations. First, the risk perception generation method is based on simple assumptions that people feel dangerous when cases or deaths increase. The real risk conceptions should be triggered by a comprehensive psychology process and personal social experience. Second, the model didn't involve other COVID-19 dashboard data, such as the vaccination data and the number of people in hospitals. Third, the vaccination project started with the third lockdown period, so it should influence mobility and risk perceptions. The future work would focus on the real causal inference between each pair of factors and explore the actual mobility dynamics under the COVID-19 situation to investigate better public policy.

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Data Availability Statement

The research data mentioned in this study is open-access, and here are links

1.Google LLC *"Google COVID-19 Community Mobility Reports"*. https://www.google.com/covid19/mobility/ Accessed: <date>.

2.https://coronavirus.data.gov.uk/

Conflicts of Interest

The authors declare no conflict of interest.

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Appendix

A1.Data pre-processing for mobility index.

Google's COVID-19 Mobility Report records the movement trends since February 15 2020 in different nations and regions, aggregating the anonymised data from users who turn on the location history setting. The mobility is measured based on the frequency and duration of visits to places as the same as to calculate popular times in Google Maps. The Google report data describes the mobility change compared with the median value from the baseline period from January 3 to February 6 2020, in the percentage format. If values are negative, the mobility on this date is less than the baseline scenario, vice versa.

The trends are recorded and classified into different categories: retail and recreation, groceries and pharmacies, parks, transit stations, workplaces, and residential. The data is open for downloading and research. The whole mobility trend history is plotted together with six kinds of places shown in Figure A3. One apparent observation is that curves have periodic patterns.

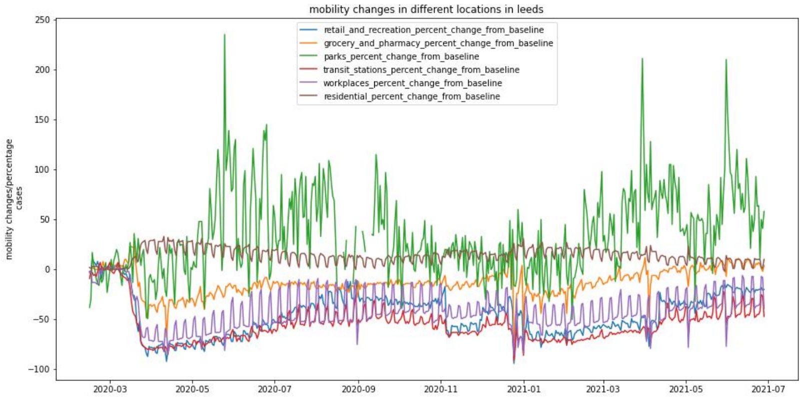

Figure A3. The mobility trends between January 15 2020, and July 3 2021, in Leeds from Google data

To see that directly, the author sliced the section between March 23, 2020, and June 23, 2020, the period from the first strict lockdown in the U.K. to the end of national hibernation announced by the primary ministry shown in **Figure A4**.

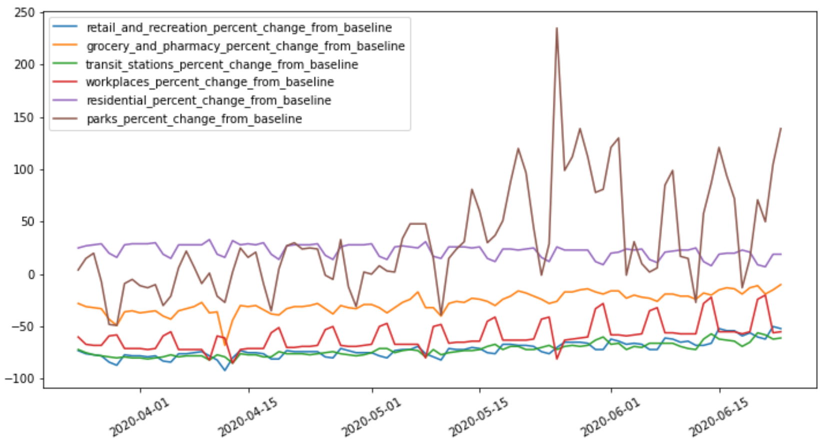

Figure A4. The mobility trends during the first lockdown in Leeds

All curves are almost flat in the first few weeks, and then the mobility for the park has shown significant vibrations and increasing trend. In addition, the workplaces and residential places exhibited complementary periodic patterns because of the weekdays and weekends. Since the policy strictly limited the indoor social activities and business service industries, the retail and recreation places should have significant mobility loss or keep at the low-level mobility. However, the increasing trend is apparent by showing the

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mobility trend for retail and recreation places in Figure A3. This is counterintuitive because the lockdown was not released during these months, and the accumulative deaths and cases of COVID-19 are increasing. The possible reasons could be people's risk perception toward COVID-19 and the natural policy decay rate.

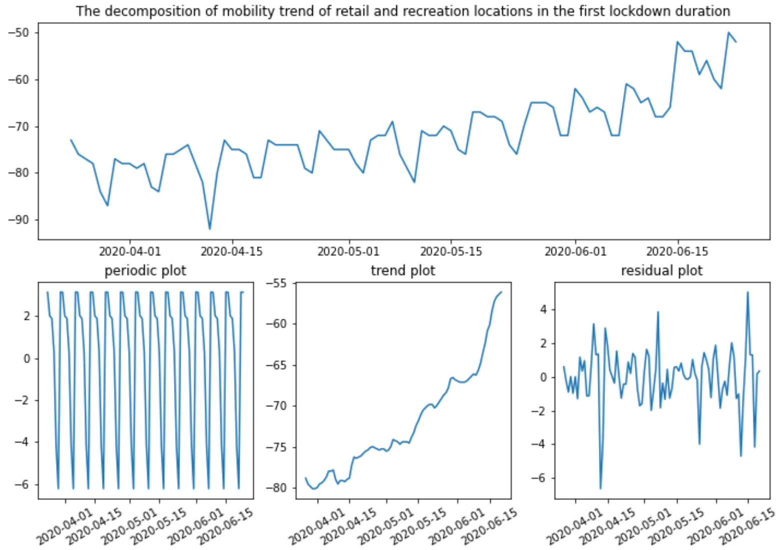

Figure A5 The decomposition of retail and recreation mobility during the first lockdown period in Leeds

For the dependent variable: the mobility of retail and recreation in Leeds, there is an option to smooth it by moving average or not. Because from Figure A5, the trend curve is more transparent without the vibrations, it is worthy of improving the model's prediction ability. To better illustrate the periodic pattern of retail and recreation mobility, we partitioned the data into seven weekdays and observed the mobility distribution of each day shown in Figure A6. The apparent drop in weekends can be observed, which matches the phenomenon in Figure A5. Also, the moving average result shows that the window size as seven could reduce the periodicity.

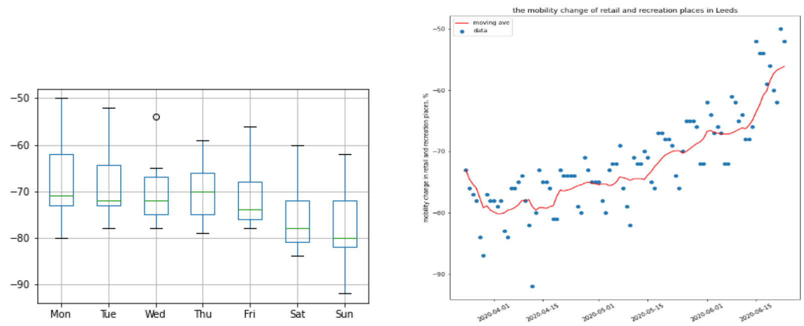

Figure A6. The mobility boxplot of each weekday and the mobility data using moving average (window size = 7)

Hence, the moving average with a window size of seven is meaningful. The effect of moving average is to smooth the curve and decrease the influence of exogenetic factor, weekday, on the model. Furthermore, the experiments show that the model fitted with rolled mobility data has better evaluations than raw mobility data.

So, in conclusion, for the dependent variable (mobility index), the moving average with window 7 of mobility will smooth the objective curve and improve the model fitting performance.

A2.Feature selection: reducing collinearity

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Only data processing on variables is not enough to eliminate multicollinearity. Figure A7 shows that the policy time variable has high correlation coefficients with cumulative COVID-19 variables near to positive one. That makes sense because the cumulative features always increase over time. So the solution is to eliminate the cumulative COVID-19 statistics and keep the variable 'policy time' only.

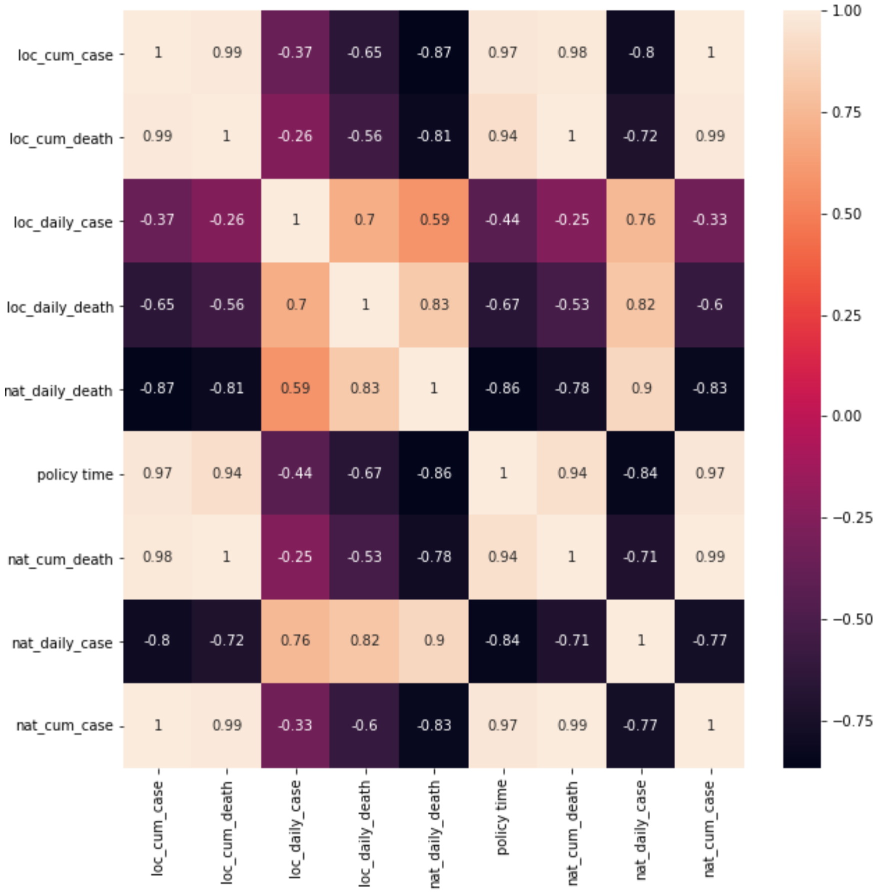

Figure A7. The correlation heatmap of independent variables

A3.The dynamic risk perceptions by time-varying z-score and PCA

The research has proposed three algorithms to simulate the risk perceptions, and each algorithm has several hyperparameters to choose from. This section listed the dynamic risk perception results of each algorithm.

There are two steps for generating the dynamic risk perception. The first step is using the proposed time-varying z-score algorithms for four sequences separately. For algorithm 1, the z-score is calculated by using moving average and standard deviation. There are three alternatives for the hyperparameter, window size, 7, 14 and 28, representing the length of public memory. As for algorithm 2, there is no hyperparameter to tune, so only one result is generated by algorithm 2. Similarly, algorithm three also has a window size as the hyperparameter to tune even if it used all historical data. To fairly compare the effect of each algorithm, window size options are still 7, 14 and 28. Table A1 shows the names of these risk perceptions.

Table A1. The risk perceptions to examine in the case study. [3]

[3] mz: moving z-score; emz: exponentially weighted moving z-score.

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Algorithm	Window size	Risk perceptions
	7	mz_7
Algorithm 1	14	mz_14
	28	mz_28
Algorithm 2	-	mz_all
	7	emz_7
Algorithm 3	14	emz_14
	28	emz_28

The visualisation results are divided into three lockdown periods to study and demonstrate in Figure A8. There are apparent gaps between risk curves generated by moving z-score and exponentially weighted moving z-score. The emz curves are higher than the mz ones no matter the window size at the middle of each lockdown period.

Also, the research tried to valid the simulated dynamic risk perceptions by comparing the general trends discovered in the U.K. (Schneider et al., 2021). In Figure A9, the left is from the Schneider et al. longitudinal survey results across the U.K. from Mar 2020 to Jan 2021. According to the mean value in each time point, the public's risk perception peaked in March 2020 and then decayed until September 2020, before increasing back in Jan 2021, where was still lower than the initial level. The risk perception generated by the emv_28 method could capture the similar trend exactly shown in the right in Figure A9.

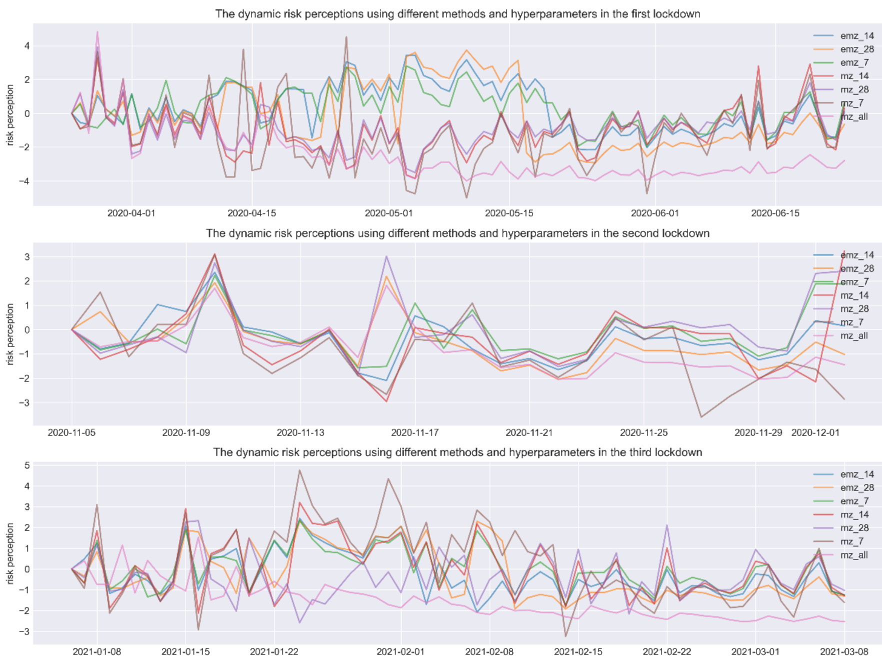

Figure A8. The dynamic risk perceptions generated by different methods in three lockdown periods.

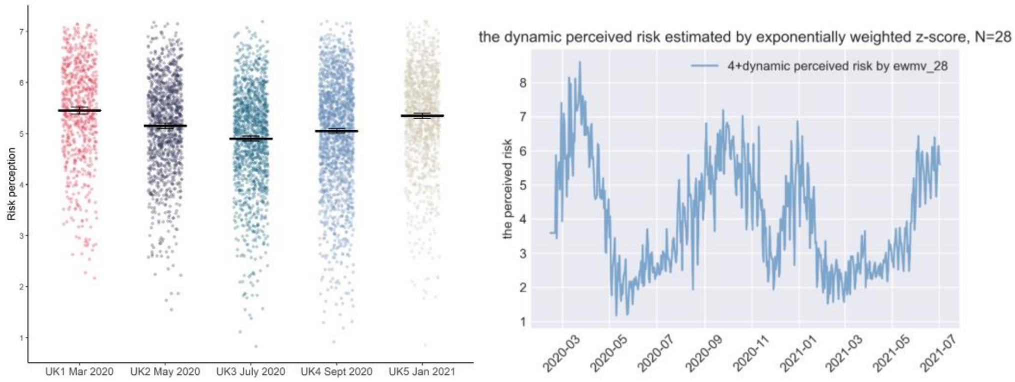

Figure A9. The risk perception comparison between survey results and emz_28.

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