New Zealand COVID Tracer App:
Understanding the Utilization and User Sentiments

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STATEMENT OF ORIGINAL AUTHORSHIP

This is to certify that to the best of our knowledge, the content of this thesis is our own work. This thesis has not been submitted for any degree or other purposes.
We certify that the intellectual content of this thesis is the product of our own work and that all the assistance received in preparing this thesis and sources have been acknowledged.

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ABSTRACT

The NZ COVID Tracer app is a part of the Aotearoa New Zealand (NZ) Government's plan to control the COVID-19 epidemic in the nation. This study investigates people's usage and sentiment on the app from its release in May 2020 to the end of 2021. A descriptive analysis of app data is carried out to understand the usage and the changes in activities of the COVID Tracer app. And sentiment analysis on user reviews such as app stores (Google Play Store and Apple App Store) and social media platforms (Twitter and Facebook) are used to explore the views and opinions of the New Zealand population (approximately 75% of the population of 5 Million). The results revealed that the passive Bluetooth-tracing feature is utilized more consistently than the manual features.

However, the increased proportion of positive sentiments from app stores and the increased proportion of all sentiments from social media platforms are seen to increase with active app use. Results indicate how reliable the Bluetooth tracing feature is, but they do not devalue the usefulness of manual interaction because active use can enhance users' perceptions of the app. Additionally, using machine learning and deep learning techniques to predict user reviews, the best model was chosen, leading to a large number of negative reviews for app stores (LSTM and RF model) and positive reviews for social media platforms (LSTM model). But over time, it changed in response to significant events in the country and NZ COVID Tracer App. This study provides insights into the performance and usage of NZ COVID Tracer app's during the study period.

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LIST OF ABBREVIATIONS

NZ	**:**	New Zealand
ML	**:**	Machine learning
DL	**:**	Deep Learning
RF	**:**	Random Forest
DT	**:**	Decision Tree
KNN	**:**	K-Nearest Neighbours
MR	**:**	Multinomial Regression
MLR	**:**	Multiple Linear Regression
LSTM	**:**	Long Short-Term Memory
NLP	**:**	Natural Language Processing
TF-IDF	**:**	Term Frequency-Inverse Document Frequency
LDA	**:**	Latent Dirichlet Allocation
RNZ	**:**	Radio New Zealand National

Chapter 1

INTRODUCTION

The NZ COVID Tracer app is a part of the Aotearoa New Zealand (NZ) Government's plan to control the COVID-19 epidemic in the nation. The design and functionality of the app have changed throughout the pandemic, from its initial voluntary use to record and trace locations to the integration of Bluetooth, its requirement to be used when visiting locations during various alert levels through 2021, and its relaxation of use during the Omicron outbreak in 2022. The NZ COVID Tracer app's performance was examined from May 2020, when it was launched, through the end of 2021 in this thesis.

The 5 million people in New Zealand have reacted well to the app effort, with over 3,550,000 app registrations overall as of December 31, 2021 (Ministry of Health - Manat Hauora, n.d.). Despite the large number of app registrations, the public's actual use of the app's features might not be numerically equivalent. As of December 31, 2021, only 1,450,129 active devices were recorded in a single day (Ministry of Health - Manat Hauora, n.d.). Active devices are those that are used by the user to complete manual tasks like scanning or diary entries.Usage patterns can also fluctuate depending on circumstances. This thesis intends to analyze the NZ COVID Tracer app's performance from its launch in May 2020 to the end of 2021 and to evaluate how the app is perceived by the general public through user evaluations. The thesis aims to provide a response to the question: How did the general public utilize and view the app between May 2020 and December 2021?

Background

The New Zealand Ministry of Health introduced the NZ COVID Tracer app in May 2020 to facilitate quicker contact tracing for COVID-19 community cases. By scanning official QR codes located on-site or manually entering the details, the app enables users to create a digital journal of the locations they've been. Beginning on December 10, 2020, the app activated a Bluetooth capability that allows them to virtually shake hands with other nearby Bluetooth-capable mobile devices. With the many pandemic stages, app upgrades, and new features, the app's design and usage are evolving. Table 1 provides an overview of significant incidents involving the NZ COVID Tracer app that were chosen from the NZ Ministry of Health website.

Table 1.Summary of significant events relating to the NZ COVID Tracer app

Date	**Event**
20 May 2020	Official launch of the NZ COVID Tracer app.
30 Jul 2020	The app was updated with an added feature that allowed users to add manual entries to their digital diary (on top of the QR code scanning feature).
19 Aug 2020	The Government made it compulsory for businesses to display the official app-compatible QR codes for premise entry doors and reception areas.
3 Sep 2020	The Government made it compulsory for all public transport providers, including buses, trains, ferries, ride-share vehicles, and operators, to provide QR codes for passengers.
23 Nov 2020	The app was updated to no longer require users to sign-up for an account or set up a password to use the app. All existing users no longer need to sign in periodically.
10 Dec 2020	A Bluetooth feature was added to the app.
22 Aug 2021	The Government announced that record-keeping, including scanning with the COVID Tracer app or manual signing, will now be mandatory for most events and businesses at all alert levels in response to the detection of the Delta variant

C h a p t e r 2

LITERATURE REVIEW

During the early phases of the pandemic, two investigations were undertaken on the NZ COVID Tracer App. The research examined the NZ COVID Tracer app's user experience and the obstacles to and enablers of the general NZ public's usage of the app [1],[2].

Both investigations were carried out prior to Bluetooth's new feature being introduced (Dec 10 2020). Between July and September 2020, [1] performed a survey of 373 persons and discovered that 31% of those surveyed reported using the app regularly, 24% occasionally, 21% had installed but had not used it, and 24% had not installed the app.

There are two primary categories of barriers: those linked to installation and those related to use of the app. These include technical, privacy, and security concerns as well as behavioral and societal barriers including users' forgetfulness and businesses' lack of support for utilizing QR codes. [1]. The largest city in New Zealand, Auckland, was chosen for the interview, and 34 users of the NZ COVID Tracer app were contacted by Facebook. Five key themes emerged from the analysis: perceived benefits, usage patterns, privacy, social impact, and the need for group action. Low alert levels and minor privacy issues when using the app cause a reduction in usage. Under circumstances of high threat, calls to civic responsibility are likely to motivate the adoption of a mobile contact tracing app.

Further study is required to fully comprehend how the NZ COVID Tracer app is used because there are research gaps in both studies. The [2] research only interviewed 34 users. The experiences of the 34 participants may not represent those of all New Zealanders who have downloaded the COVID Tracer app or be representative of studies that were limited to inhabitants of the Auckland region rather than the full country of New Zealand. [1] The research included a larger number of participants (n = 343), although the app component was only a small portion of the larger COVID-19 Health and Stress survey. Only two questions on the app were included in the survey: (1) a closed-ended question about usage frequency, and (2) an open-ended question about their choice to use or not use the app. 'Text-based replies may have reduced the depth of data presented,' the research said as a study restriction. [1].

These gaps highlight the need for more study to fully comprehend the NZ COVID Tracer App’s utilization and the necessity for additional research utilizing extensive NZ COVID Tracer App-related data.

Different strategies and policies have been developed to increase the number of people using this application. For instance, in several countries, residents are now required to install contact tracing apps in order to access public spaces like shopping malls, transportation, hospitals, and other public places [4].

The user reviews for the NZ COVID Tracer app were also analyzed for this study. App stores like Google Play and Apple Store provide consumers the option to rate and review the apps they download (McIlroy et al., 2015).It's feasible to derive user experience inferences from the analysis of a large number of user evaluations that might not be duplicated by solicited methods (such organized interviews and surveys) (Gebauer et al., 2008; Hedegaard & Simonsen, 2013). Users can leave reviews in an open-ended format in app stores without following a predetermined structure, and they can express as much praise or criticism about the app as they choose (Palomba et al., 2015; Tan et al., 2020a). Additionally, these user reviews are self-reports that provide insights into the users' experiences rather than being just summaries (Hedegaard & Simonsen, 2013). The results of several studies' analyses that app store data have improved numerous areas, including requirements engineering, planning, software design, security, and testing (Martin et al., 2016).As an example, a study by Tan et al. (2020a) on app store user reviews has shown insights into customers' perspectives of what makes disaster apps helpful.

As every app contains reviews from its users, those reviews are helpful to academics and other app stakeholders. The NZ App also includes reviews from its users. Based on the evaluations, it is possible to determine how users feel about the app and what sort of habits they have when using it. One of the main functions of NLP is sentiment analysis, often known as opinion mining. Each review contains either good, neutral, or negative feelings. (Fang & Zhan, 2015)

Due to their exponential expansion, reviews cannot be manually mined for potential information (Ranjan and Mishra (2020)). Sentiment analysis, by machine learning algorithms employing NLP, is used to explicitly uncover and interpret emotions. This study quantifies university students' app market activity and looks at the sentiment analysis of app reviews. They used the TF-IDF text representation system to apply machine learning algorithms, and their performance was assessed using group learning techniques

Chapter 3

METHODOLOGY

This study intends to examine the performance of the NZ COVID Tracer app and obtain an understanding from the viewpoints of its users. In the planned research, user reviews from app stores and social media platforms as well as data from the New Zealand Ministry of Health would be analyzed. It is feasible to deduce information about the user experience from social media posts that cannot be reproduced by solicited and organized surveys. (Gasteiger et al., 2021; Tretiakov & Hunter, 2021).

Data Sources

The use of a small sample size or restricted scope in a comprehensive survey to assess users' experiences with the NZ COVID Tracer app has been a shortcoming of prior research. By examining three more substantial data sources with wider scopes, this study seeks to advance existing understanding of app use. The data sources for this study involve, (1) the NZ Ministry of Health of daily statistics on usage, (2) the user reviews from the Google and iOS app stores on the NZ COVID Tracer app and (3) the user reviews from the social media platforms such as Facebook and Twitter.

I. The NZ Ministry of Health of daily statistics on usage,

   https://www.health.govt.nz/covid-19-novel-coronavirus/covid-19-data-and-statistics/covid-19-nz-covid-tracer-app-data

II. User reviews from the Google and iOS app stores on the NZ COVID Tracer app and,

   1. https://play.google.com/store/apps/details?id=nz.govt.health.covidtracer&hl=en&gl=US
   2. https://apps.apple.com/nz/app/nz-covid-tracer/id1511667597

III. The user reviews from the social media platforms such as Facebook and Twitter.

NZ Ministry of Health's app usage data

The New Zealand Ministry of Health makes available app usage statistics on their website in the form of a daily-updated CSV spreadsheet. With variables like app registrations and poster scans, this spreadsheet covers data starting on May 19, 2020. New data variables were made accessible as the app's functionalities grew.

Table 2. Data variables from the Ministry of Health on the NZ COVID Tracer app

Variable	Description	Data available from
App registrations	The total registrations for the specified date span	19 May 2020
Poster scans	The total number of QR codes that app users have scanned in the last 24 hours	19 May 2020
Daily entries	The total number of manually entered data points submitted within a 24-hour period by all app users	7 Jul 2020
Active device count	The number of devices that either added a manual diary entry or scanned QR codes within a 24-hour period	24 Jun 2020
Bluetooth tracing numbers	The number of distinct devices participating in Bluetooth contact tracing and having Bluetooth enabled.	12 Dec 2020

User reviews from Google Play Store and Apple App Store

User reviews of NZ COVID tracer app are collected from Google play store and Apple store for the study period. The 'Date of the review', 'Rating score of 1 to 5', and 'Content of the user review' are the data variables of the app stores. The study used 4,106 reviews in total.

The count and percentage of total reviews across app stores are shown in Table 3.

Table 3. User reviews from Google Play and Apple Store

App stores	Total Reviews	Percentage
Google Play	3,552	86.51%
Apple Store	554	13.49%
Total	4,106	100.00%

User Reviews from the Social Media Platforms Such As Facebook and Twitter

Different scraping methods can be used to scrap the user reviews from social media platforms such as Facebook and Twitter. Additionally, combining all reviews from social media sites produced a single dataset with data variables such as "Date," "Comments," and "Source." The study used 2,313 reviews in total. The count and percentage of total reviews across all social media platforms are shown in Table 4.

Table 4. User reviews from the social media platforms

Social media	Total Reviews	Percentage
Facebook	1364	58.97%
Twitter	949	41.03%
Total	2313	100.00%

Data Analysis

The thesis offers three different contributions. In order to comprehend the utilization and variations in activity of the COVID Tracer app, a descriptive study of the NZ Ministry of Health data is first conducted using numerical and graphical approaches. In order to understand how users perceive the app from its first release to the end of 2021, sentiment analysis is done on user reviews from the Google Play Store and Apple Store. Thirdly, by analyzing the sentiment of user reviews from platforms such as Facebook and Twitter that were submitted for the app, will give the clear picture of app users' opinions in the social media platforms. Additionally, it describes how app users' attitudes alter in each situation during a specific time period.

Descriptive Analysis of the Ministry of Health Data

The Ministry of Health statistics were gathered using numerical and graphical techniques. The initial research focused on Cumulative app registrations, which are the total daily app registrations from May 19 to December 31, 2021. This figure is crucial because it displays the total number of app registrations, which corresponds to the maximum number of mobile devices that might possibly have the app loaded.

Based on the assumption that each registration represents a person who uses the NZ COVID Tracer app, this figure serves as the starting point for understanding app usage. Due to the risk of double counting, it is important to keep in mind that the real number of app users may be fewer than the total number of app registrations. Examples include having numerous phones, getting a new phone and installing the app while getting rid of an older one, or people reinstalling after uninstalling. The data's disadvantage is that it does not distinguish between these circumstances; rather, it merely keeps track of each app registration.

Then, using descriptive numerical analysis, the data variables in Table 2 were given their average, maximum and minimum values, and standard deviation. To get further insight into how the app is used, additional indications were generated. An indicator may be the average daily scans and manual entries made by each active user. Calculating the average daily scans and manual input per active user is one indicator. Additionally, proportions of the total number of apps registered to the number of active, Bluetooth-enabled devices were calculated. More information on these indicators is provided in Table 5.

Table 5. Indicators for figuring out how app is used

Indicators	Formula	Description
Daily scans per active device	$= \frac{\sum_1^n scan/active\ device}{n_{days\ of\ observation}}$	This is the average number of poster scans by active app users each day.

Daily manual entries per active device	$= \frac{\sum_{1}^{n} manual\ entry/active\ device}{n_{days\ of\ observation}}$	These are the typical daily manual entries made by an engaged app user.
Average active use ratio	$= \frac{\sum_{1}^{n} \frac{active\ device}{cummulative\ app\ registrations}}{n_{days\ of\ observation}}$	The typical percentage of active applications (i.e., apps where users actively use QR scanning or diary entries)
Average Bluetooth ratio	$= \frac{\sum_{1}^{n} \frac{Bluetooth\ enabled\ apps}{cummulative\ app\ registrations}}{n_{days\ of\ observation}}$	The average proportion of apps that have Bluetooth enabled

In order to track variations in activity related to the NZ COVID Tracer app, the data variables were also plotted over time using graphic approaches. Significant visible changes in the trend line were examined and contrasted with important occurrences in New Zealand.

Sentiment Analysis on User Reviews

One of the main areas of natural language processing is sentiment analysis, which is effective for identifying people's ideas, sentiments, behaviors, emotions, assessments, or attitudes about certain goods or services, problems, events, or themes (Liu & Zhang, 2012). The NZ COVID Tracer App reviews in app stores and on social media platforms were sentimentally analyzed to get a better understanding of app users' perspectives and expectations in terms of positive, negative, or neutral feedback.

The opinions of app users will evolve over time for a number of reasons. For instance, a fresh update to the app may raise user opinion of it in a favorable way (sometimes it might be a negative perception too). Therefore, tracking the sentiments regarding the app over time is useful. The sentiment analysis was mainly concerned with how users perceived the app throughout the course of time, from its release to the end of 2021. Once the sentiments throughout time have been identified, significant fluctuations can then be further examined to determine the events or scenarios that may have contributed to those fluctuations.

Sentiments of app users will change over time due to various reasons. For example, a new update to the app can cause an increase in the positive perception of the app (sometimes it might cause a negative perception too). Therefore, it is informative to track the sentiments towards the app over time. The sentiment analysis focused on investigating users' perception of the app through time from its release to the end of 2021. Once the sentiments over time are identified, significant fluctuation can be further analyzed to identify events or scenarios that may have caused those.

Data on app user reviews from May 2020 to December 2021 were gathered from; the App stores and social media platforms for sentiment analysis. A user's rating of an app is a reliable reflection of how users perceive it. However, it is restricted to a small number and might not accurately capture the user's sentiment (Maks & Vossen, 2012). As a result, the text-based user review information was subjected to sentiment analysis. A user's opinion of an app is conveyed when they leave a review for it. However, individually going through every review and figuring out the sentiment is quite time-consuming and could produce very individualized results. When reading the same review, two persons could draw two distinct conclusions about the sentiment. We classified the sentiment of each review using one deep learning (DL) classifier and the four most popular machine learning (ML) classifiers to prevent subjective interpretation.

The aim of sentiment analysis through ML and DL approaches deals with labelled data and helps in the creation of models using supervised learning algorithms, such as K-nearest neighbours(KNN), decision trees (DT), multinomial logistic regression (MLR), and bidirectional long short-term memory (LSTM).

- Decision Tree (DT) algorithm is a very specific type of probability tree that is used to make a decision. A DT includes some symbols such as Alternative Branches, Decision Nodes, Chance Nodes and End Nodes. There are Pros and Cons of Decision Tree. Pros are Transparent, Efficient and Flexible Cons are Complex, Unstable and Risky.

(https://asana.com/resources/decision-tree-analysis)

- Multinomial Naive Bayes (MNB) algorithm is a Bayesian learning approach which is most popular in Natural Language Processing (NLP). MNB is used for documents to perform textual and statistical analysis of the contents.

- K Nearest Neighbors (KNN) is a non-parametric, supervised learning algorithm. Mostly used to classify a data point, on how its neighbours are classified. KNN is used for both classification and regression.

- Random Forest (RF) is a supervised learning algorithm. RF is used as an ensemble learning method. Random Forest is used for both classification or regression
- Long short-term memory (LSTM) is an artificial neural network. LSTM is used in the fields of artificial intelligence and deep learning. LSTM has feedback connections. LSTM provides a large range of parameters such as learning rates, input and output biases.

By performing 2-fold cross-validation with hyper tuning parameters, trained and evaluated each model on the Vectorized documents. Then, compare their performance using four evaluation metrics: accuracy, precision, recall, and F1 score. F1 score is a preferred measure since it is the harmonic mean of precision and recall, hence taking into account the impact of each class on the overall score.

Table 6. Calculation of evaluation metrics

Accuracy	Ratio of True Positives and True Negatives to all the Positive and Negative (TP, TN, FP, FN) observations.	(TruePositive + TrueNegative)/ (TruePositive + FalseNegative + TrueNegative + FalsePositive)
Precision	Measure the percentage of positively predicted labels that are actually correct.	TruePositives / (TruePositives + FalsePositives)
Recall	Ability of the model to correctly predict the positives out of all the actual positives.	TruePositives / (TruePositives + FalseNegatives)

F- Score	Measure the model score as a function of precision and recall score.	(2 * Precision * Recall) / (Precision + Recall)

Hyper parameter tuning is basically about finding the optimal set of hyper parameter values for a learning algorithm while applying it to any dataset in order to maximize the performance of the model by reducing the default loss function. The table below shows the hyper parameters which are used for this study.

Table 7. Hyper parameters for each model

Model	**Hyper Parameters**
RF	n_estimators, max_depth, Min_samples_leaf, Criterion, Max_features, max_leaf_nodes, Min_samples_split, n_jobs, bootstrap, class_weight, max_samples
DT	max_features, max_depth, Min_samples_leaf, Criterion, splitter, Min_samples_split, max_leaf_nodes, class_weight
KNN	n_neighbors, weights, leaf_size, algorithm, n_jobs
MR	Multi_class, Solver, C, Max_iter, class_weight
LSTM	Epoch, lose function, Batch Size, Embedded dim, Dropout, Recurrent Dropout

Labeled training data

A challenge with using ML and DL approaches for sentiment analysis is that they need labeled training data, data consisting of reviews and the corresponding sentiments, which isn't included in the user reviews from the NZ COVID Tracer app. Additionally, DL requires a considerable amount of data to understand parameters (Pan et al., 2020) and as more training data will result in better accuracy, sentiment labels have been added to three data sets.

(1) User reviews of Google Play Store apps from Kaggle ;

- ➢ Google Play store reviews have been downloaded from Kaggle website and this dataset contains the '10 best food apps' user reviews.

  (https://www.kaggle.com/code/basu369victor/sentiment-analysis-with-googleplaystoreapp-reviews/data)

(2) User reviews of Nykaa apps from Kaggle ; and

- ➢ Nykaa app review dataset has been downloaded from Kaggle, these reviews were scraped from the Google Play Store for the E-Commerce company known as Nykaa, ending August 2021. In this Nykaa app reviews, randomly 2000 Neutral labelled reviews are taken for the training dataset.

  (https://www.kaggle.com/datasets/nirant/nykaa-app-review-sentiment/metadata?select=test_nykaa_review_sentiment.csv)

(3) User reviews of the MySejahtera COVID tracer app in Malaysia from the App stores

- ➢ Scraped My Sejahtra app's user reviews from google play store using python and took only the review with ratings 1&5, manually labelled with the help of python and chooses rating 1 as Negative and rating 5 as Positive. (https://play.google.com/store/apps/details?id=my.gov.onegovappstore.mysejahtera, https://apps.apple.com/us/app/mysejahtera/id1504055630)

The procedure used to generate the training dataset is depicted in the following figure

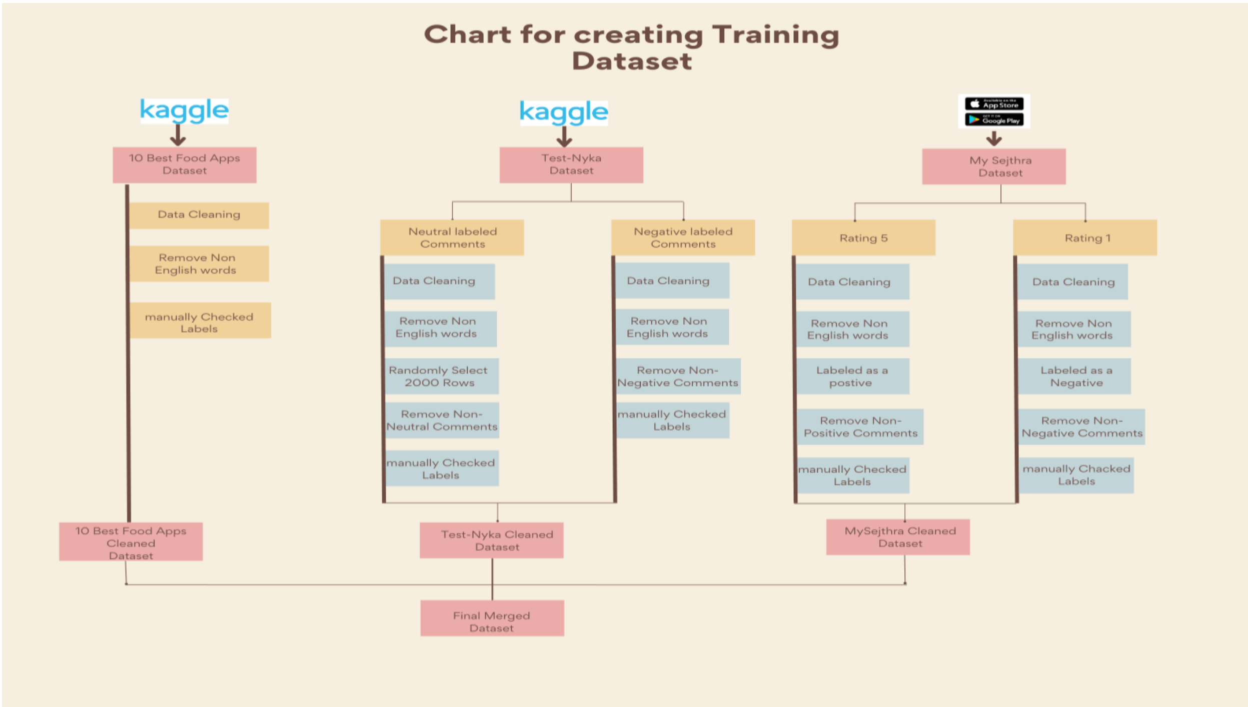


Figure 1

Each data set consists of user reviews of different apps that are text-based and are labeled as having a favorable, negative, or neutral sentiment. Following the fusion of the three data sets, Table 8 displays the distribution of all reviews. There are 32,189 experimental data with labels representing 17,135, 10,07, and 5,047 positive, negative, and neutral attitudes, making up 53.23%, 31.09%, and 15.68% of the total.

Table 8. The distribution of the merged data set

	Positive reviews	**Negative reviews**	**Neutral reviews**
Count	17,135	10,007	5,047
Proportion	53.23%	31.09%	15.68%

Data Preprocessing

Using natural language processing (NLP) techniques, the following preparation operations were carried out on the data to prepare it for analysis and training: Delete negative reviews Remove all punctuation, symbols, and excess spaces, less characters that are repeated Delete the HTML and URL, Take away numbers, Expand contractions(e.g., won\’t - will not), Convert words to lowercase, Remove stop words (e.g., am, is, are, the, an, will, shall, let, may, can, it, with, of, this, and, as, etc.), Utilize the WordNet Lemmatizer to lemmatize words and eliminate duplicates. The total number of reviews was decreased to 32183 after preprocessing.

Data Vectorization

Next, Vectorized the text and retrieved unigrams using the Term Frequency-Inverse Document Frequency (TF-IDF) technique for ML models. When assigning terms or words weight, it considers both frequency and relevancy. Texts are Vectorized using the pad sequences method for the DL model.

Training and Testing

The data set was then split into two sets, with 20% functioning as a testing set and 80% functioning as a training set. The models were trained using the training data, and cross-validation was used to optimize the hyper-parameters of each model class. The testing data was used to identify the performance of each model, once an optimal model from each model class was obtained. The last two steps of the sentiment analysis are (1) using the best model to forecast the reviews' sentiment and (2) validating the findings. In order to validate the model, users' ratings of each review, on a scale of 1 to 5 were used.

The sentiment analysis code is available on GitHub, and the platform utilized was Python in Google Colab. The Results section below provides the sentiment analysis's findings.

Latent Dirichlet Allocation (LDA) topic modelling on user reviews from app stores

The Latent Dirichlet Allocation (LDA) topic model represents a document as a distribution of many topics. It portrays each topic as a distribution of many words by extracting semantic links hidden in text.

Chapter 4

FINDINGS AND RESULTS

Descriptive Analysis Results

The number of cumulative app registrations from app launch in 2020 to December 31 of 2021 was 3,531,037 - the maximum number of apps that may have been installed. If it is considered that each app registration equates to one user having the app, the data shows that there is a high app uptake in New Zealand (about 75% of a population of 5 Million).

In table 9 the Ministry of Health Data are summarized numerically and descriptively. There are typically 37,648 manual entries and 1,086,339 scans each day from all app users. However, just 554,360 users actively use their apps each day for scanning or manual entries, on average. Bluetooth contact tracing was enabled on an average of 1,559,428 devices every day. These findings suggest that the app's passive function (Bluetooth contact tracing) is used more frequently than its user-active capabilities (i.e., scanning and diary entries).

Table 9. Descriptive numerical summary of Ministry of Health data variables

	Average	**Max**	**Min**	**Standard Deviation**
App registrations per day	6,184	233,200	302	17,850
Scans per day (from all users)	1,086,339	3,962,782	1,407	895,366
Manual entries per day (from all users)	37,648	255,338	5	31,562
User active devices per day	554,360	1,450,129	4,800	373,932
Bluetooth enabled devices per day	1,559,428	2,401,547	351,430	562,272

During the study period, there are 6,184 registrations every day on average. The standard deviation of 17,850 registrations, maximum observation of 233,200 registrations per day, and minimum observation of 302 registrations per day, however, when the number of registrations has not been constant over this time. Plotting the app registrations over time reveals prominent peaks (See Figure 2).

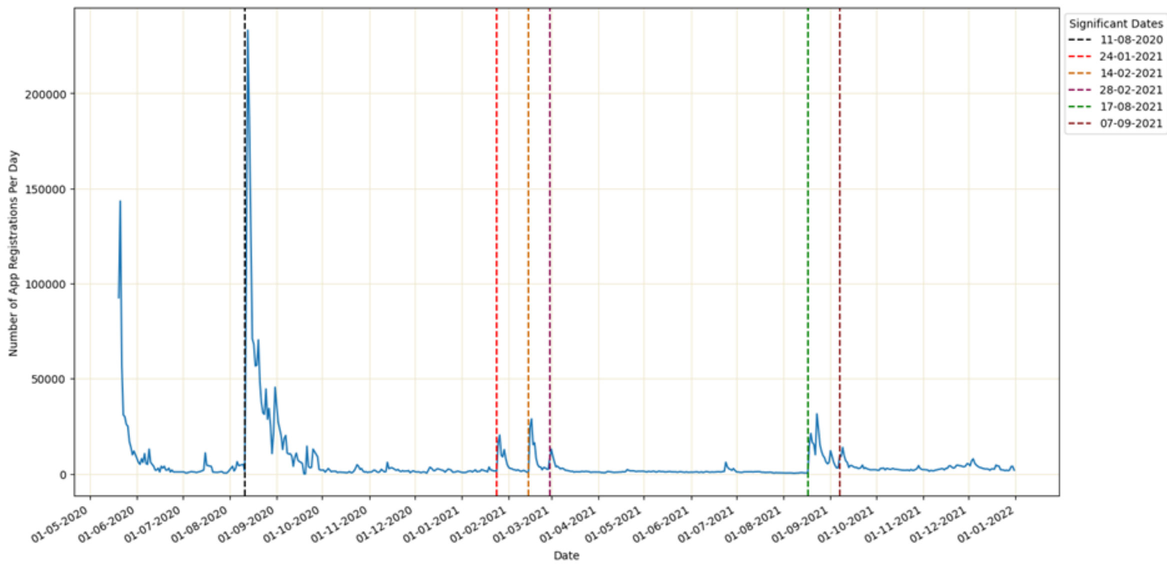


Figure 2.App registrations per day through the study period; vertical lines indicate dates associated with trend changes

There was a significant increase in registrations during the app's launch, with 143,405 registrations on 20 May 2020. Once they stabilized at 2,000 per day, registrations quickly decreased. August sees a noticeable uptick after that. The research period is marked by recurring patterns of rapid increase-decrease-stabilization. According to an analysis, there are rapid rises with significant COVID-related events in NZ. The following timeline of events was collected from information on the RNZ website and the NZ Government's Unite Against COVID-19 website (n.d.-a):

- **11 Aug 2020** - Since NZ was moved to Alert Level 1, four additional COVID-19 cases have been recorded in the community as a first case under community case.
- **24 Jan 2021** - The first COVID-19 community case since November 2020 in NZ records.
- **14 Feb 2021** - Three new COVID-19 cases have been reported in the community. Auckland moved to Alert Level 3 at 11:59 pm. The rest of NZ moved to Alert Level 2.0
- **28 Feb 2021** - A new lockdown is implemented in Auckland, and the city is returned to Alert Level 3 as a consequence of more community cases. The rest of NZ moved to Alert Level 2.

- **17 Aug 2021** - At 11:59 p.m., all of New Zealand was placed on Alert Level 4 due to the discovery of Delta in the community.

- **23 Jun 2021** - On the way back to Australia, a traveler from Sydney had a COVID-19 positive test result. Wellington moves to Alert Level 2. The rest of NZ remained on Alert Level 1.

These findings demonstrate how app registration uptake is related to important events. High variances are seen for the other data variables in a manner similar to this (see Table 5 for a summary). These findings suggest that app usage varied during the period of the study.

The daily total of captured scans is shown in Figure 2. It demonstrates that scanning considerably increased after August 11, 2021, when the first community case was discovered in New Zealand and COVID-19 was effectively eliminated with no community cases and went to Alert Level 1. Before August 11, there were roughly 26,000 scans per day. The fact that there were 1 million scans per day on average from August 11 to December 2020 indicates that people were scanning more regularly. While there are fluctuations in the number of scans during the period, they have stabilized at hundreds of thousands per day rather than returning to their pre-August 2020 levels. On September 7, 2021, New Zealand (with the exception of the Auckland region) shifted from lockdowns to Alert Level 2, which was a substantial change in scanning. More people were moving and searching as the population emerged from total lockdown. Between September 7 and December 31, 2021, there were 2.6 million scans performed on average per day. Due to the fact that most people stay at home on Christmas Day and most businesses close, there will be a noticeable decline in business on December 25, 2021.

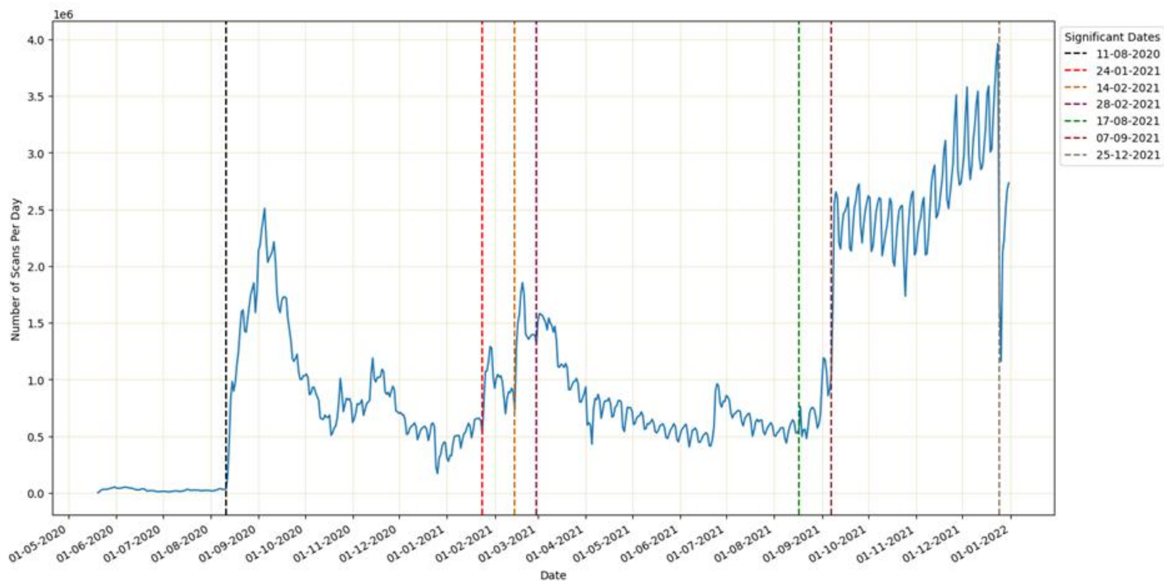


Figure 3. The number of scans per day through the study period; vertical lines indicate significant dates

The calculated indicators in Table 10 give insight on how people use the apps. An active device only scans 1.97 times a day. Even less frequently, with only 0.09 entries per device per day on average, do users use the manual diary option? Only 20% of the potential total of over 3.5 million registered apps use their smartphones actively. Comparatively, 35% of participants had Bluetooth turned on during the research time.

Table 10. Indicators of app usage

Indicator	**Results**
Daily scans per active device	1.97
Daily manual entries per active device	0.09
Average active use ratio	0.20
Average Bluetooth ratio	0.35

However, it's possible that these utility ratios have changed over time. Figure 3 shows a time-plot of the total app registrations, the number of user active devices, and the total number of Bluetooth-enabled devices for further analysis. The blue line denotes the extent to which the app may be used. The figure displays gaps between the active devices (Orange line), Bluetooth-enabled devices (green line), and the maximum potential (blue line). By the end of 2021, approximately 3.5 million devices used the NZ COVID Tracer app, however many of them are still not being utilized for scanning or diary entries. Also, Bluetooth was not turned on in a huge portion of devices.

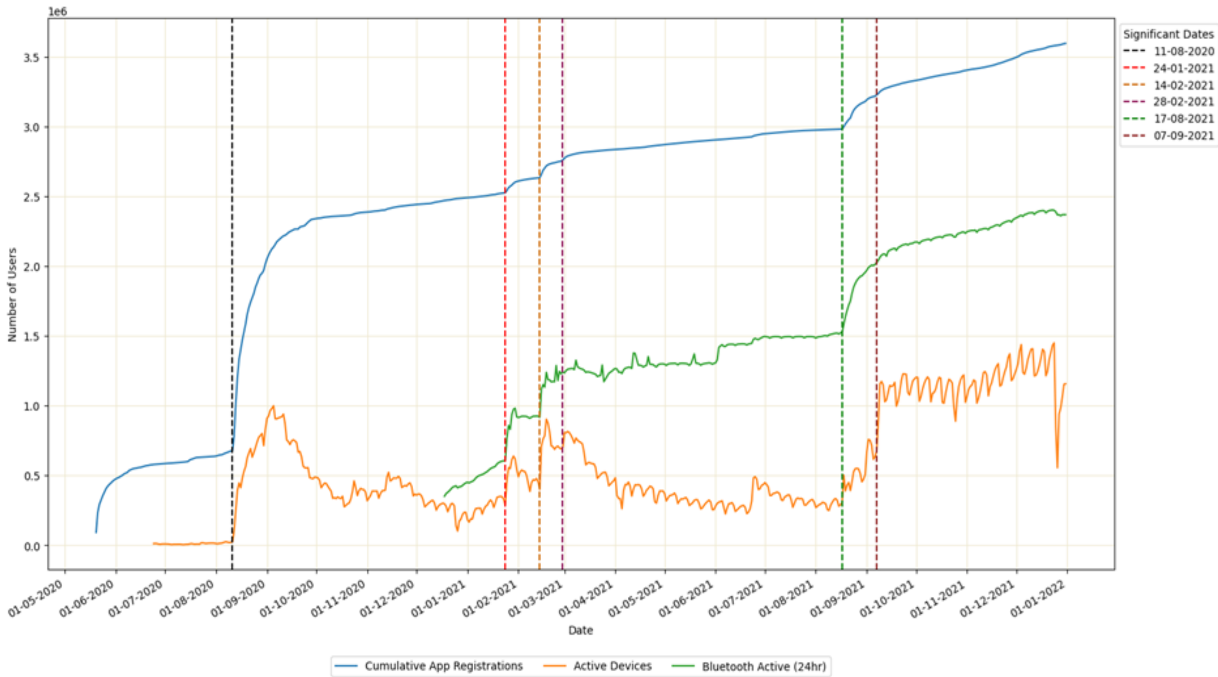


Figure 4. App utility through time

The blue line portrays the cumulative app registration through time. The orange line shows the active devices (i.e., scan or diary entry) per day. The green line indicates the Bluetooth-enabled devices per day through the study period; vertical lines indicate significant dates.

The ‘active use ratio’ (the active devices to cumulative registrations) and Bluetooth ratio (the number of Bluetooth-enabled devices over cumulative registrations) are plotted through time in Figure 5.

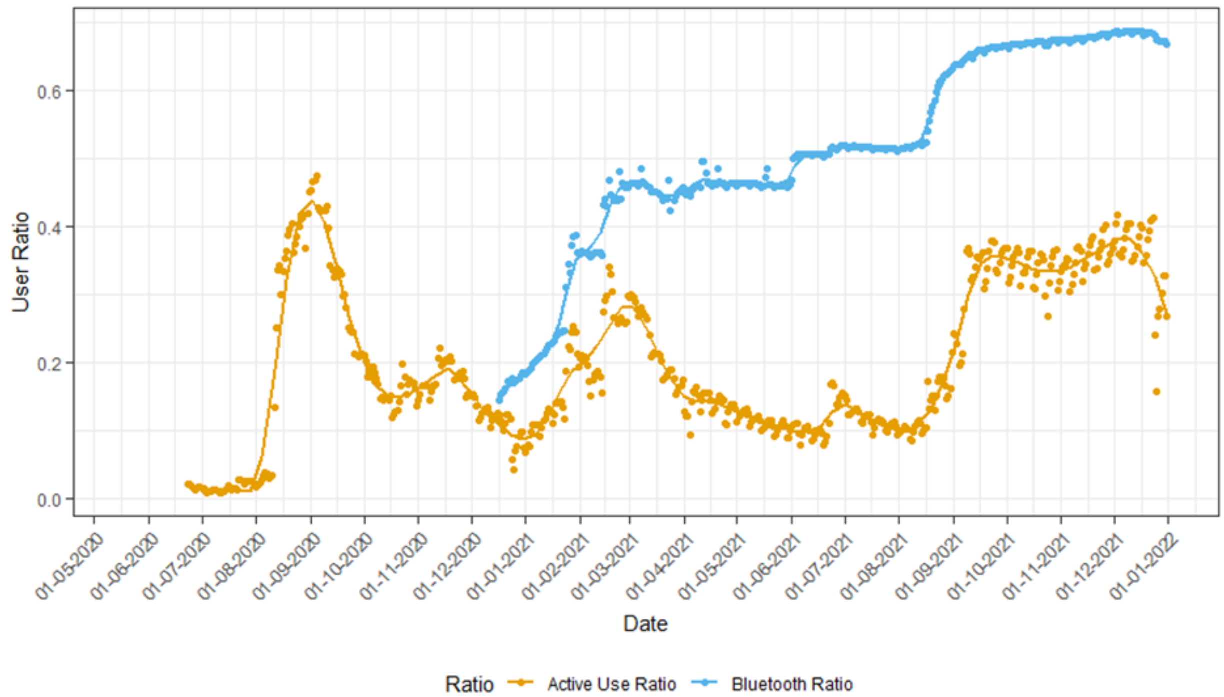


Figure 5.Active use ratio and Bluetooth ratio through time

The government declared it mandatory for all public transportation providers, including buses, trains, ferries, ride-share vehicles, and operators, to give QR codes for passengers on September 4, 2020, when the active ratio reached its maximum value of 0.474. After that peak, the active use percentage fluctuated over time but in general grew over time, particularly in the latter part of 2021. In contrast, the Bluetooth ratio climbed steadily over time with little variation. Compared to the manual features of the app, the Bluetooth capability appears to be seeing a more steady growth in usage.

Sentiment analysis results

App stores

Five classification models are compared in the study: RF, DT, KNN, MLR, and LSTM. Table 11 displays the classification outcomes for each model, and Table 12 displays the accuracy of each classifier. These outcomes show how each model performed using the test set of data.

Table 11. . Classification results of the models on performance evaluation metrics

	Positive			Negative			Neutral		
Model	**P**	**R**	**F**	**P**	**R**	**F**	**P**	**R**	**F**
RF	0.94	0.94	0.94	0.91	0.95	0.93	0.91	0.81	0.85
DT	0.93	0.93	0.93	0.91	0.92	0.91	0.83	0.81	0.82
KNN	0.82	0.90	0.86	0.86	0.60	0.70	0.62	0.78	0.69
MLR	0.92	0.95	0.94	0.92	0.94	0.93	0.91	0.77	0.83
LSTM	0.94	0.96	0.95	0.94	0.94	0.94	0.89	0.84	0.86

Table 12. Accuracy values obtained by each classifier

Model	**Results**
RF	0.93
DT	0.91
KNN	0.79

MLR	0.92
LSTM	0.93

The merged data set, which consists of sentiment labels for positive, negative, and neutral opinions, clearly demonstrated that both RF and LSTM models looked excellent in terms of accuracy (93%). Precision, Recall, and F-measure (P-R-F index) performance measures show that LSTM outperforms in positive classification (P = 0.94, R = 0.96, F = 0.95) as compared to negative classification (P = R = F = 0.94). In terms of F-measure, LSTM is more accurate in negative and neutral classification than RF. Both models, however, are equally accurate. KNN is the least accurate (79%) and has the lowest P-R-F index across all three classes of the five classifiers. Therefore, when compared to the other four models, KNN does not perform well on the data set. When DT and MLR were compared, MLR performed almost as well, with an accuracy of 92% and F-measures for positive, negative, and neutral classification, of 0.94, 0.93, and 0.83 respectively. Overall, it can be said that the accuracy and performance criteria were best achieved by the RF and LSTM models. Thus, the sentiments of the user reviews of the NZ COVID Tracer app were predicted using both models.

Although the sentiment of reviews and user ratings may not always coincide (Maks & Vossen, 2013), they can be utilized to confirm the results of the best models (RF and LSTM). Reviews with ratings of 4 or 5 are typically interpreted as being positive, reviews with ratings of 1 or 2 as being negative, and reviews with ratings of 3 as being neutral. The sentiments predicted by RF and LSTM were compared with those determined by user rating using this criterion. This analysis determined the similarity of two sentiments and validated the two models; RF provided a similarity of 69.47% and LSTM provided a similarity of 68.84%.

The patterns and trends of the sentiments were observed using graphical techniques. The changes of the proportions of three sentiments is depicted in Figures 5 and 6. These plots can identifying major fluctuations in the sentiments (Figure 5) and can illustrate how the perception of the app has changed during the study (Figure 6)

The proportion of sentiments over a week during the research period is depicted in Figure 5. The ratio is derived by dividing the number of reviews for a sentiment category for a week divided by that week's total number of reviews. Prior to the first week of March 2021, the proportion of negative sentiments constantly exceeded the proportion of positive sentiments. Positive and negative sentiments show a cross point during the week of March 1, 2021; from that point on, the positive sentiments occasionally exceed the negative sentiments. Fewer reviews on the week may have caused the fluctuation. However, an investigation of NZ's COVID-19 event history revealed frequent modifications to the alert level are over the month of February 2021. Auckland went under lockdown and returned to Alert Level 3, while the rest of New Zealand moved to Alert Level 2, on February 28, 2021. The shifting COVID-19 scenario in NZ may also be related to the shift in sentiment. Increased app registrations, scanning, and Bluetooth usage were also seen on this occasion (see Figures 1, 2, and 3). In this instance, the app's enhanced usefulness and the swing toward a higher proportion of positive sentiment. Future research should validate this relationship by looking into it more deeply.

The increasing gap between positive and negative sentiments from May 25 to June 2021 is another noteworthy result in Figure 6. It should be mentioned that in May 2021, the Ministry of Health issued the app's revised Version 5.0.0. According to the communications about Version 5.0.0, updates were made to make the app more useful and user-friendly; improvements included on dashboard, digital diary, and Bluetooth tracing (Ministry of Health - Manat Hauora, 2021). The higher proportion of positive sentiments during this period may reflect how users generally supported the May 2021 app update.

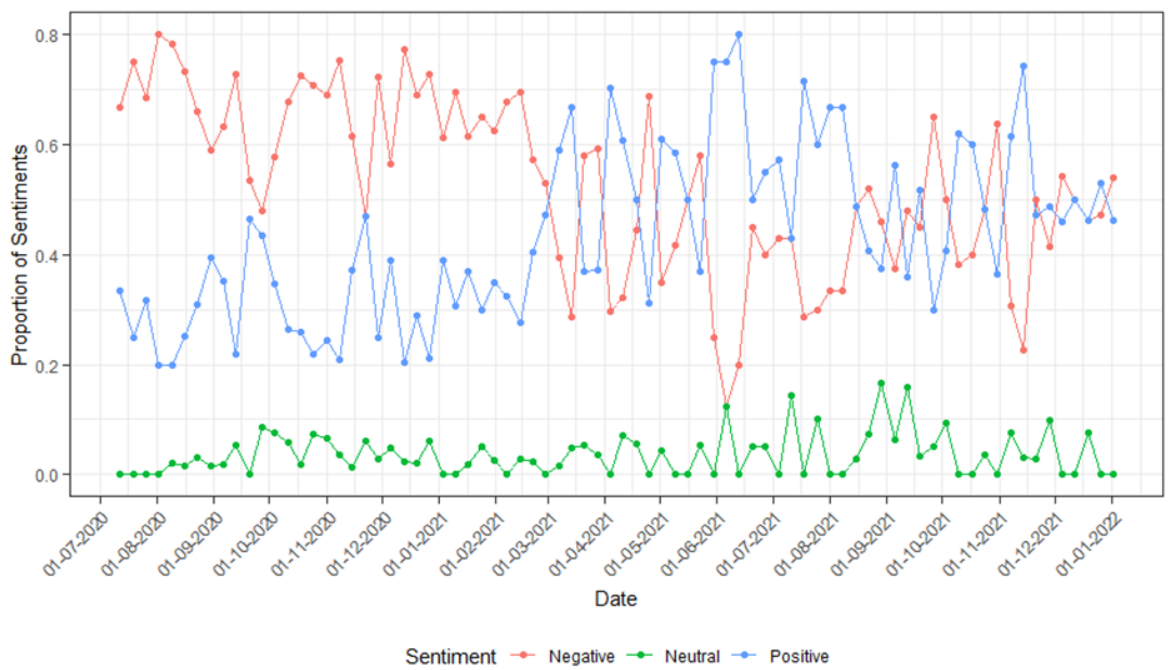


Figure 6. Weekly proportion of each sentiment

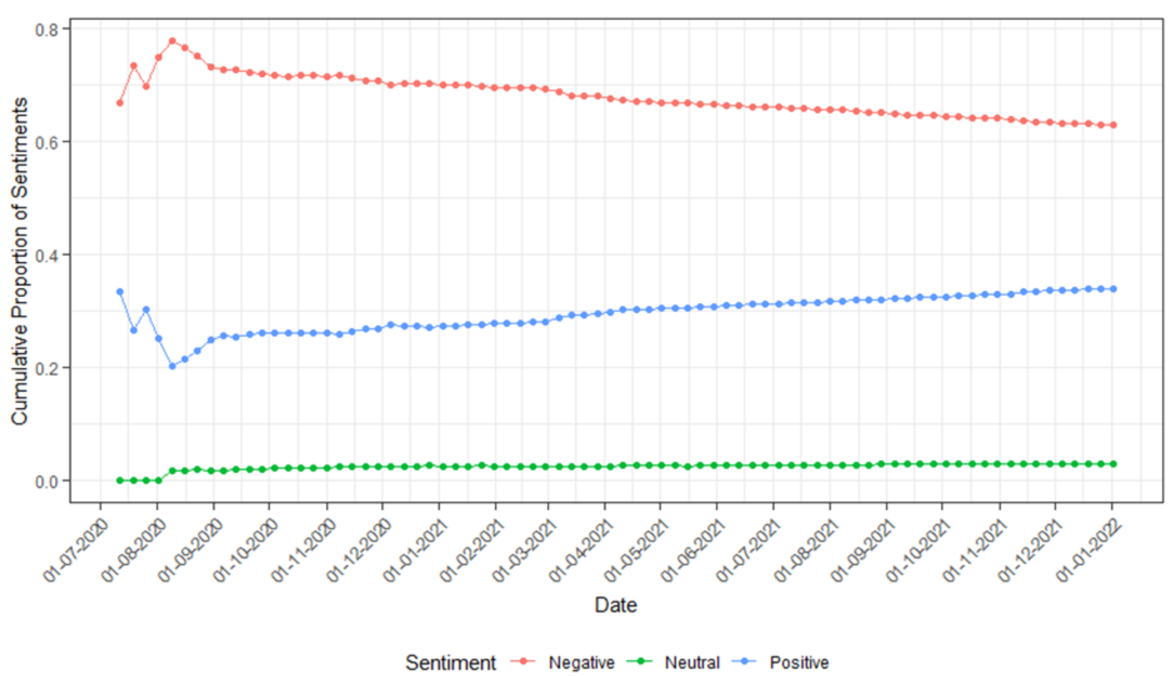


Figure 7.Cumulative proportion of each sentiment over time

In order to look for trends in the sentiments, Figure 7 shows the cumulative proportion of each sentiment over time. A sentiment category's cumulative proportion is computed by dividing the overall number of reviews up to a certain date by the overall number of reviews up to that date. Positive feelings are trending upward in Figure 7, while negative sentiments are trending downward, and neutral sentiments show neither an upward nor a downward trend. This suggests that, despite the user evaluations' overall negative sentiment, user perception is improving over time.

Social media platforms

As for the App stores, sentimental analysis for social media platforms also performed by using the same models such as RF, DT, KNN, MLR, and LSTM

Table 13. Results of models on performance evaluation metrics

	Negative			Neutral			Positive		
Model	P	R	F1-S	P	R	F1-S	P	R	F1-S
RF	0.91	0.95	0.93	0.90	0.81	0.85	0.94	0.94	0.94
DT	0.91	0.91	0.91	0.83	0.81	0.82	0.92	0.93	0.93
KNN	0.86	0.60	0.70	0.62	0.78	0.69	0.82	0.90	0.86
MR	0.92	0.94	0.93	0.91	0.77	0.83	0.92	0.95	0.94
LSTM	0.93	0.92	0.93	0.85	0.86	0.86	0.94	0.94	0.94

Table 14. Accuracy values are obtained by each classifier.

Model	**Results**
RF	**0.92**
DT	**0.91**
KNN	**0.79**
MR	**0.92**
LSTM	**0.93**

RF model and LSTM models performed equally well on the merged data set that consists of sentiment labels. RF model test accuracy is 92% and LSTM test accuracy is 93%, From 1% LSTM model is well but RF model is also too well. From the performance metrics: Precision, Recall, and F1-Score, RF positive classification is (P = 0.94, R = 0.94, F1-Score = 0.94) and LSTM also (P =0.94 R =0.94 F1-Score = 0.94). Performance metrics are same for both. LSTM is more accurate than RF for Neutral and Negative sentiments in terms of F-measure. When comparing DT and MLR, MLR has an accuracy of 92% and F-measures of (P-0.92, R-0.94, F1-S-0.93) for Negative (P-0.91, R-0.77, F1-S-0.83) for Neutral and (P-0.92, R-0.95, F1-S-) 0.94 for Positive labels. Among the five classifiers, KNN has the least test accuracy which is 79% and the lowest Performance measures (P, R, F1-Score)). Finally, it can be concluded that both RF and LSTM models are best in accuracy and performance metrics and models can be used to predict the sentiments of the social media user reviews (Facebook and Twitter) of the NZ COVID Tracer app.

When making predictions, generally assume that a review with a rating 4 or 5 indicates positive sentiments, a rating of 1 or 2 indicates negative sentiment, and a rating of 3 represents neutral sentiment. The sentiments are predicted using this criterion for both RF and LSTM models.

Figure 3 depicts how the sentiments (Positive, Negative, and Neutral) have changed over time. The plots help in spotting significant changes in sentiment and can provide insight into how the app's perception has evolved over the period of the study.

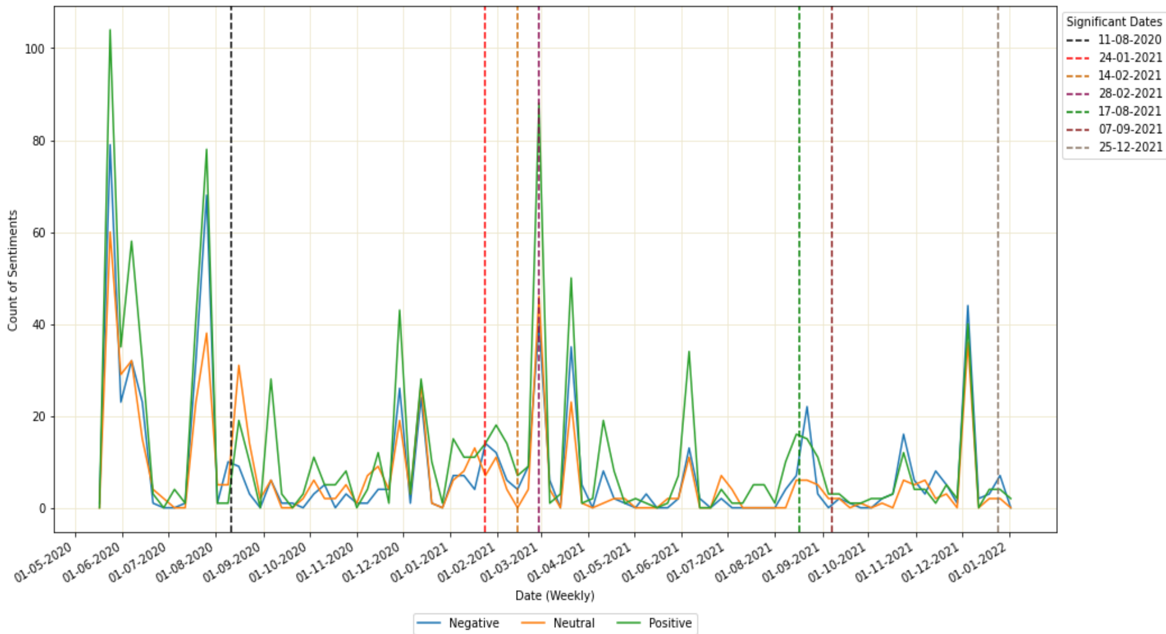


Figure 8.Sentiments over Time LSTM

There is no obvious trend in the attitudes during the study period when looking at the graph. The number of positive remarks peaked in the beginning, in the month of June 2020, and then gradually decreased over time. The amount of favorable remarks increased once again on February 28, 2021, as a result of Auckland's transition to Alert Level 3 at 6 am. The rest of New Zealand moved to Alert Level 2. When compared to the negative comments, the number of negative comments was initially high (Compared to positive its low), but over time, the number of negative comments decreased. The social media data demonstrates that app users' attitudes change over time.

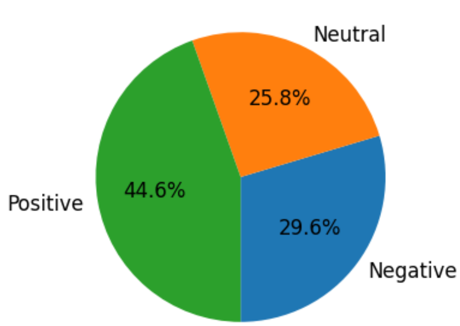


Figure 9.Summary of overall sentiment

The figure 5 shows the summary of overall sentiments in terms of the counts of positive, negative and neutral comments. Users of the NZ COVID tracer app are more likely to provide positive and negative comments than neutral ones (Negative 685, Neutral 597, and Positive 1031).

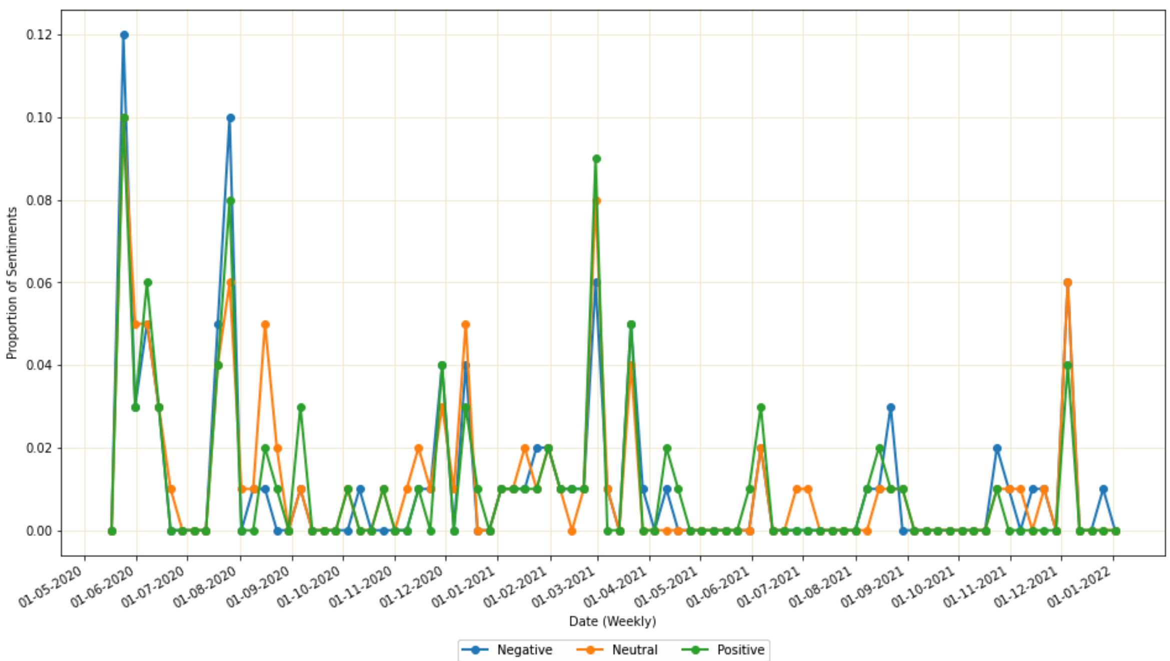


Figure 10.Weekly proportion of each sentiment

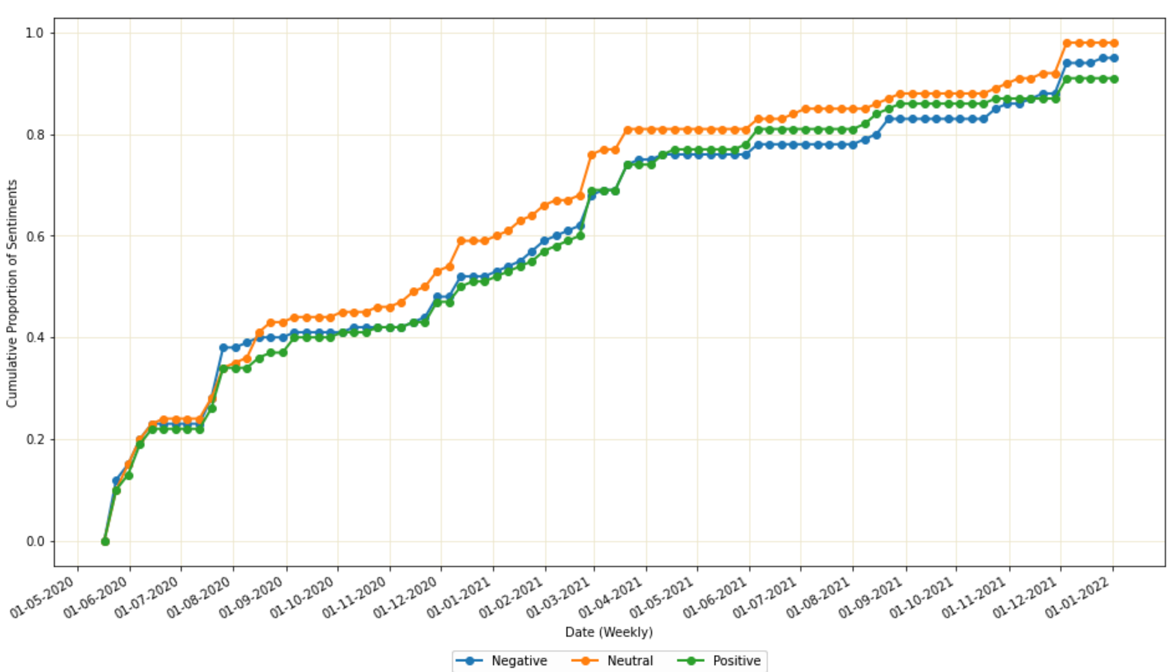


Figure 11.Cumulative proportion of each sentiment over time

The following figure 6 and 7 shows that the users typically submit comments when they are extremely satisfied or dissatisfied with the app due to the nature of users. The NZ COVID

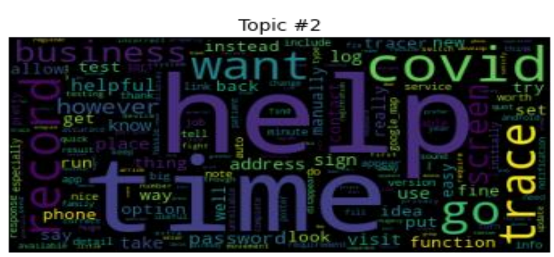
Tracer app's general attitude is positive after projecting social media data (figure 6). The NZ COVID tracer app received mostly positive feedback on social media.

Limitations are identified throughout the analysis of the subject area, mainly focused on the Sentiments, which includes predicting whether a sentiment would be positive, negative, or neutral, visualizing sentiments over time, and counting the overall sentiments of the social media data.

LDA topic modelling for app stores

LDA topic modeling is applied for app stores to classify the common words under each positive, negative and neutral comments which can help to figure out the reason the behind those sentiments.

Table 15. Topics for positive comments

Topic	Common words	World Cloud
1	"keep" + "excellent" + "new" + "safe" + "download" + "take" + "set" + "long" + "problem" + "time"	
2	"log" + "quick" + "version" + "work" + "idea" + "stop" + "wish" + "simple" + "give" + "hopefully"	
3	"help" + "time" + "covid" + "record" + "go" + "trace" + "want" + "business" + "screen" + "however"	

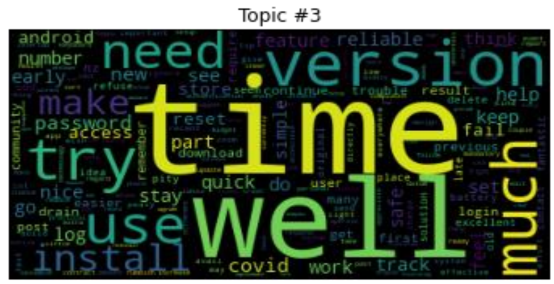
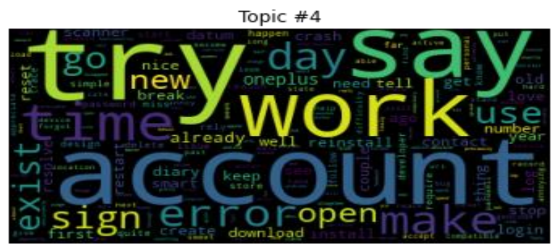
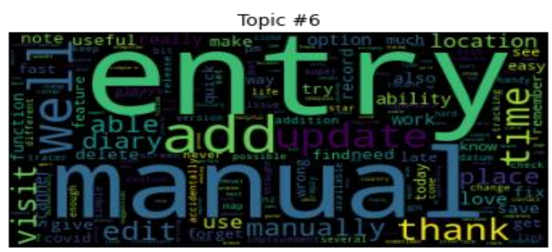
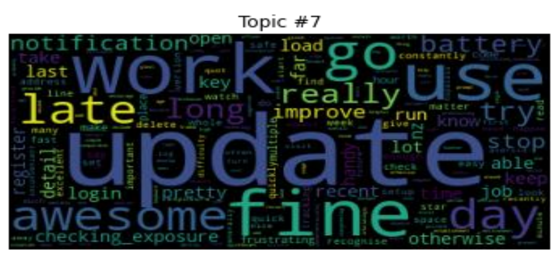
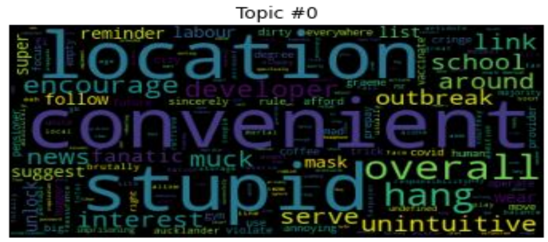
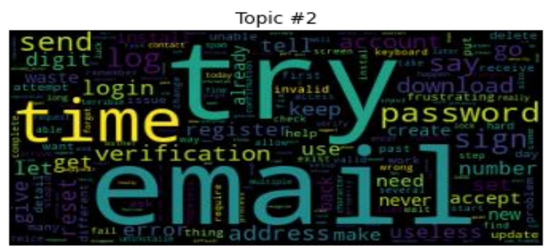
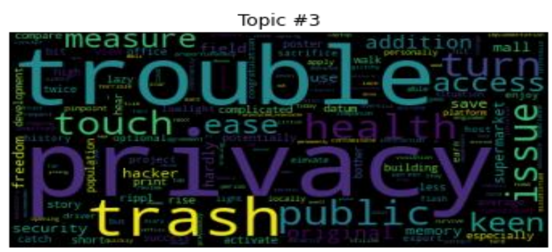
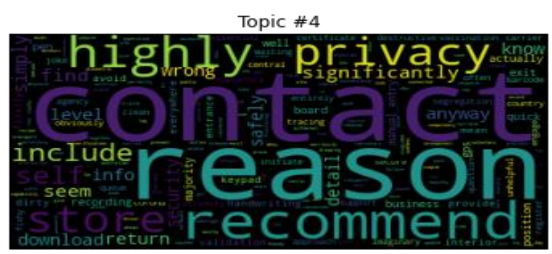
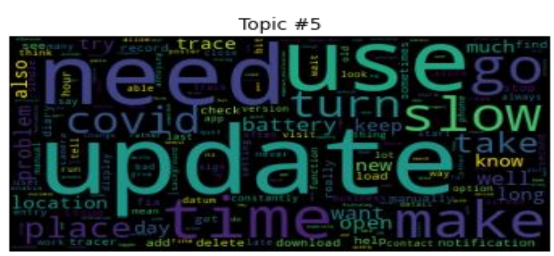
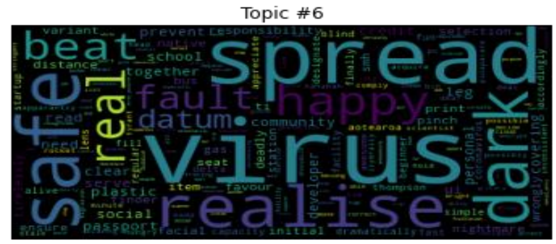
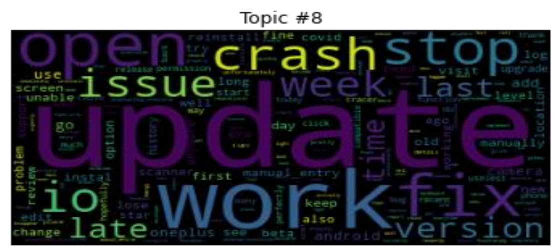
4	"time" + "well" + "version" + "try" + "much" + "use" + "need" + "install" + "make" + "password"	
5	"try" + "account" + "say" + "work" + "time" + "make" + "error" + "day" + "sign" + "use"	
6	"go" + "fast" + "open" + "need" + "leave" + "sign" + "camera" + "keep" + "put" + "verification"	
7	"entry" + "manual" + "add" + "well" + "update" + "time" + "thank" + "visit" + "edit" + "manually"	
8	"update" + "work" + "use" + "fine" + go" + "awesome" + "day" + "late" + "really" + "long"	

Table 16. Topics for negative comments

Topic	Common words	World Cloud
1	"convenient" + "stupid" + "location" + "overall" + "encourage" + "hang" +"developer" + "link" + "unintuitive" + "serve"	
2	"call" +"get" + "simple" + "information" + "yesterday" + "die" + "hand" + "important" + "remember" + "level"	
3	"try" + "email" + "time" + "password" + "log" + "send" + "sign" + "say" + "account" + "download"	
4	"privacy" + "trouble" + "trash" + "public" + "turn" + "issue" + "health" + "touch" + "access" + "measure"	
5	"contact" + "reason" + "recommend" + "highly" + "privacy" + "store" + "include" + "self" + "significantly" + "seem"	
6	"update" + "use" + "need" + "time" + "make" + "go" + "slow" + "turn" + "covid" + "place"	

7	"virus" + "spread" + "safe" +*"dark" + "realise" + "happy" + "real" + "beat" + "fault" + "datum"	
8	"terrible" + "watch" + "reply" + "developer" + "nzbn" + "feedback" +*"put" + "people" + "develop" + "privacy"	
9	"update" + "work" + "open" + "fix" + "stop" + "crash" + "io" + "issue" + "week" + "version"	
10	"poor" + "think" + "get" + "quit" + "idea" + "nz" + "typical" + "seriously" + "covid" + "compliance"	

C h a p t e r 5

CONCLUSION

A study question was posed at the beginning of the research: how did the general public utilize and interpret the app between May 2020 and the end of 2021? Although the NZ public uses apps frequently, their utility might yet be increased. For contact tracing, the fluctuating and inconsistent number of active users (scanning and diary input) may not be appropriate. In contrast, a bigger percentage of devices are Bluetooth-enabled, and the utility of Bluetooth keeps growing with time. The Bluetooth feature's consistency is encouraging because it might be more useful for contact tracing. The user reviews' sentiment analysis reveals that there are more negative comments about the app overall, but these comments have gradually decreased over time. Fluctuations favoring higher percentages of positive sentiment are linked with the app's increased utility in February–March 2021 and the app update in May 2021. This could imply that promoting active use and enhancing utility will increase user satisfaction about the app.

As the COVID-19 pandemic continues to change, this study's findings will be useful. The NZ COVID Tracer app's function in the pandemic response has changed in 2022. Due to the extensive presence of COVID-19 in the community, it is now the person's responsibility to notify their close contacts if they test positive (New Zealand Government, n.d.-b). Additionally, the government has abandoned its requirement that be scanned and displaying QR code posters (Chen, 2022). However, the app's Bluetooth functionality is still in use, since alerts may still be delivered to your phone when the Bluetooth functionality pinges (New Zealand Government, n.d.-b). The study's findings demonstrate the value of the Bluetooth functionality while also emphasizing the necessity to understand user perceptions and how they relate to actual app usage. The value of the Bluetooth functionality while also emphasizing the necessity to understand user perceptions and how they relate to actual app usage.

Facebook and Twitter data that have been scraped are used as the analysis's data set.

The prediction for social media data was done using the LSTM model because it has the highest test accuracy. Throughout the study period, sentiments have been fluctuating, and the overall sentiment summary is (Positive - 1031, Negative- 685, Neutral-597). Through social media sites like Facebook and Twitter, the NZ COVID tracer app has received more encouraging remarks.

LDA model give the set of topics with common words based on positive, negative and neutral reviews

Finally the study highlights the value of continuing to encourage users to use the app. The users of the NZ COVID Tracer app need to be encouraged to interact and have positive sentiments toward the app, even if it is not used in the same manner as it was in 2020 and 2021. . The risk is that users will completely remove the app after a period of inactivity, which could be an issue if the NZ COVID Tracer software needs to be utilized in the future for contact tracing in response to the pandemic.

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A p p e n d i x A

QUESTIONNAIRE

A p p e n d i x B

CONSENT FORM - DATA REQUEST