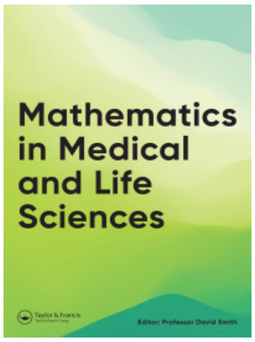

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RESEARCH ARTICLE

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Monitoring university student response to social distancing policy during the SARS-CoV-2 pandemic using Bluetooth: the RADAR study

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ABSTRACT
This paper is part of a special issue on Behavioural Epidemiology.
Aim: We use the *Remote Assessment of Disease and Relapses* platform (RADAR) to collect Bluetooth contact and location data from university students. We test the ability of this technology to objectively capture social interaction, explore the propensity of students to respond to changing COVID-19 regulations, and investigate association between Bluetooth contact and mood.
Methods: RADAR data are coded by time period to reflect shifting COVID-19 restrictions. Mean contacts per event across setting, student living arrangement and over time are explored using non-parametric tests and generalised additive models. Individual-level associations between psychological measures of mood and Bluetooth contacts are considered.
Results: Students in halls of residence had higher contacts than students in private accommodation. Mean contacts per event peak in lockdown, driven by a rise in outdoor contacts. Indoor contacts peak during the earlier Tier 3 restrictions, similar to trends in Google Mobility data. We find weak evidence of correlation between positive mood and Bluetooth contact amongst students based in halls.
Conclusions: Passive tracking of Bluetooth contacts can provide insight into the behavioural response to changing public health interventions. Our results are consistent with students responding to policy changes similarly to the wider community.

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Social contact; pandemic; psychological measures; universities; SARS-CoV-2; respiratory disease transmission

PLAIN LANGUAGE SUMMARY
We explore whether Bluetooth detection data can be used to monitor social contacts of university students. We asked university students to download the RADAR mobile app to regularly report their GPS location, and the number of detectable Bluetooth devices, to a central computer. Each time a RADAR app returns data we call an "event". Using the location data to label each event as either indoor or outdoors, and on or off campus, we explore changes in the number of reported Bluetooth contacts during a period marked by distinct shifts in COVID-19 policy. We found that students who usually live in halls of residence had higher Bluetooth contacts per event, but these dropped as stricter restrictions were introduced. Amongst the students in our study, outdoor Bluetooth detections per event peaked later, during national lockdown, than indoor events, similar to trends in visits to settings across the UK provided by Google. By linking with a survey exploring mental health, we found tentative evidence that Bluetooth contacts were associated with positive mood in students living in halls of residence. Tracking Bluetooth contacts may therefore provide a useful way to explore changing infection risk and mental health in key groups during a pandemic. However, low uptake and large amounts of missing data suggest further work is needed to use this Bluetooth tracking technology effectively.

1. Introduction

In summer 2020, Universities were earmarked as settings where SARS-CoV-2 may spread rapidly [1–3]. When in-person teaching resumed in Autumn 2020, contract tracing and isolation of contacts were key control measures [4,5]. Despite these measures, high rates of infection were observed amongst students at some universities [6]; prevalence often exceeded that in the surrounding communities [7]. The rising prevalence of SARS-CoV-2 in most

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regions from early September 2020 [4] eventually triggered further restrictions on social interactions [5]. Given social contacts are key drivers of respiratory disease transmission, we were motivated to explore the ability and propensity of university students to respond to COVID-19 regulations in a British campus-based University.

Contact diaries, interview-like questionnaires [8], and/or online surveys [9], are often used to count daily contacts that may result in the spread of a respiratory infection. These methods all require active engagement of participants and are liable to recall biases [10,11]. Passive collection of location and Bluetooth contact data via smart phones provides an alternative. Commercial footfall data such as Google mobility data, which provides information on the relative frequency of visits to different settings [12–14], and therefore an alternate proxy of contact data [15], was widely and successfully used within epidemic models to capture mass behaviour changes [16]. Facebook movement data was also used to predict surges in infection [17]. However these data streams have many limitations; they don't provide information on contact at the setting level (e.g. university), are mute on the nature of contacts, and provide only a crude classification of the setting (e.g. parks versus retail [18]). Due to privacy laws, publicly available data usually don't provide any information on individual-level changes in behaviour.

There is growing interest in the use of low-energy Bluetooth sensors to monitor contact between individuals in targeted settings such as schools [19], university halls of residence [20], hospitals [21], care facilities [22] and cruise ships [23]. Sensors may be integrated within smart phones or watches, or via wearable tags. In theory signals can be analysed to determine the distance and duration of contacts [24], and in the case of wearable sensors, even the posture of the participant [19]. Participation is often limited by privacy concerns regarding surveillance [20]. Nonetheless previous studies have reported positively on the potential for such technology to be used for contact tracing [21], understanding social contact networks [20,23], and exploring the potential efficacy of other infection–prevention interventions [23].

We adapted the open-source health platform for the *Remote Assessment of Disease and Relapses* (RADAR) [25] to track student's Bluetooth contacts via their smart phone in Autumn 2020. Consenting students volunteered their GPS coordinates when downloading the app which enabled calibration of their location via GPS, and subsequent classification of the location of their contacts into indoor/outdoor and on/off-campus. This feature of the software platform contrasts with contract tracing apps employed in the UK [26] and worldwide, where data privacy settings prevented such location-tracking, and provides a novel data set for exploring the behavioural response of university students to the evolving pandemic context in late 2020. In this paper, we use this data set to address the questions: Can we use mobile Bluetooth sensor technology to objectively measure social contacts? Did university students respond to the changing COVID-19 restrictions in Autumn 2020? Was the ability or propensity to change social behaviour different for students living in private accommodation and halls of residence? Are student contact patterns correlated with their psychological wellbeing?

2. Methods

2.1. Monitoring platform

The RADAR-base is a multipurpose platform for remote monitoring. It consists of a non-intrusive mobile app, which records data from the mobile sensors, and a backend responsible for retrieving the data streams gathered [25]. Previously, it has been used within the University for remote sensing in various mental health-related studies, some requiring National Health Service (NHS) ethics approval for its use with participants [27]. For this study, we utilise the RADAR-base's open-source licence and its flexibility to being locally deployed, allowing the installation in one of the University's computer centres. Once the RADAR application is installed on a mobile device, it must be paired to the instance that will serve as backend and will receive and store the participant's' data. For this study, the app was only configured for deployment on Android devices. Students living in halls of residence were anticipated to have high numbers of contacts due to their congregate living arrangements [1,2]. Motivated by this concern, the active survey function of the app was utilised, and participants were asked to nominate whether they lived in a hall of residence or private accommodation.

The RADAR app allows the user to withdraw partially or totally from the study. For partial withdrawal, the participant can either change the app settings disabling the access to the sensors or switch off the sensor desired (Bluetooth and GPS location settings are generally easily accessible by the user).

2.2. Experimental design

Due to the sensing capabilities of both RADAR-based [25] mobile phones, we use Bluetooth as the technology tool. Bluetooth is a low-power communication technology that allows data transfer over short distances. Being low-power limits both transfer speeds and coverage area. However, it is reliable due to its low latency and error correction methods. Bluetooth radios with standardised protocol are widely available in most modern computing and portable devices [28] and have a range of approximately 10 m when Line-of-Sight exists [29]. If the signal has to travel through thick materials, or the geometry of the environment changes rapidly, the coverage distance decreases proportionally [30]. Counts of handshakes with Bluetooth-enabled devices in the vicinity of a participant's mobile phone may be considered a proxy for their social contact [29]. As mentioned, in contrast to the Google/Apple Exposure Notification API [12], launched to enable digital contact tracing [13], we record the user's GPS location simultaneously with the Bluetooth handshake data.

2.3. Recruitment, participants and study period

This research was granted ethical approval by the University of Nottingham Faculty of Medicine and Health Sciences ethics committee (FMHS 96-0920) on 25/9/2020. Data collection using the RADAR-base began on October 2, 2020, and concluded formally on November 11, 2020, although some participants continued providing data into 2021. Coincidentally this study period straddled two distinct changes in the local COVID-19 regulations, summarised in Table 1. Initially the University was under Tier 2 restrictions; hospitality, retail and educational settings were open, but, with the exception of support bubbles, only gatherings of up to six people allowed (the "rule of six" [31]). On October 26, 2020, the Government announced the surrounding region was to enter Tier 3 (effective 3 days later, on October 29, 2020). During Tier 3 restrictions education, retail and hospitality remained open, and the rule of six remained, but gatherings were only permitted in outdoor public spaces (not indoors or in private gardens) [32]. A second national lockdown was announced on October 31, 2020, and became effective on November 5, 2020, during which only essential activities were allowed (hospitality and retail closed but education remained open) and outdoor gatherings were no longer permitted [33]. This lockdown remained in place until December 1, 2020.

Our RADAR participants were a subset of ($n = 893$) students who were enrolled in a longitudinal study which involved three waves of survey data collection on demographic, mood (anxiety, depression, loneliness, positive mood and stress) and COVID-19 vaccination intentions, as reported elsewhere [34]. Participants were asked to fill in an online survey (https://www.onlinesurveys.ac.uk/). Emotional loneliness was measured with a single item [35], depression was measured using a PHQ-9 score [36], anxiety via the GAD-7 score [37], positive mood by the scale of positive and negative experiences (SPANE) [38] and stress via the perceived stress scale (PSS) [39].

Table 1. Summary of study periods and their relationship to local and national COVID-19 regulations. Dates are provided in the format dd/mm/yyyy.

Period	Dates	COVID-19 restrictions	
1	02/10/20 – 28/10/20	Tier 2	Hospitality, retail and educational settings open, gatherings of up to 6.
2	29/10/20 – 04/11/20	Tier 3	Hospitality, retail and educational settings open, gatherings of up to 6 in outdoor public spaces only.
3	05/11/20 – 01/12/20	National lockdown	Educational settings open, no gatherings allowed.

Loneliness items were converted to a numeric variable (with higher scores mapped to more frequent experience of loneliness), and totals used as continuous measures for all other psychological measures.

2.4. Data pre-processing

The RADAR app was programmed so that participants return Bluetooth contact and location data up to every 10 minutes. We retain only the first record for each participant in each hourly period. Each Bluetooth contact event is then classified, using a location detector developed using Google maps, as indoors or outdoors, and on or off the University campus.

We further classify each Bluetooth contact event as occurring in one of three time periods of interest, coinciding with local changes COVID-19 regulations. Period 1, from the October 5, 2020, to October 27, 2020 (tier 2), Period 2, from October 27, 2020, to November 4, 2020 (tier 3), and Period 3 from November 5, 2020, until the December 1, 2020, inclusive (national lockdown) (see Tables 1 and A.1). We use only wider survey data that overlaps with the period of the RADAR study, i.e. the first wave of data collection in October 2020, linking this to RADAR Bluetooth contact data where students had (non-missing) data in Period 1.

2.5. Data analysis

We present summary statistics for Bluetooth contacts by period and setting category (indoor/outdoor, on/off campus) for all students, and students living in halls of residence or private accommodation. We perform an exploratory analysis of the data by using non-parametric hypothesis test for shifts in location of the distribution of contacts per event in each period using Kruskal–Wallis and Wilcoxon Rank Sum tests (with Bonferroni correction for multiple comparison within a stratum). We include a sub-analysis of the results from individuals who contribute data in all time periods (see Supplementary Information § A.3).

We then use Generalised Additive Models [40] with a zero-inflated negative binomial response distribution, trialling different regression formulae, to generate explanatory models for our data set. Adopting GAMs allows us to include thin-plate splines to infer the form of (penalised) smooth temporal functions. We assume a maximum basis size for the smoother $K = 5$. Models are fitted in a Bayesian framework using the *brms* package [41]. We evaluate model success using Leave One Out Cross Validation [42].

Finally, we explore the Kendall τ_b rank correlation between mean Bluetooth contacts and univariate psychological measures available from the active survey data (namely loneliness, depression, positive mood, anxiety and stress) (see Section 3.4). We do not correct for multiple comparisons in this exploratory analysis. Analyses are performed using *R* version 4.1.3.

Table 2. Summary statistics for the number of Bluetooth contacts per contact event [N_{events}, mean, median (IQR)] by period and indoor status.

	Period 1	Period 2	Period 3
All	8186, 14.81, 9 (4, 17)	1515, 16.47, 8 (4, 15)	8225, 14.88, 9 (4, 15)
		Setting	
Indoor	4800, $15.07^{\star\dagger}$, 10 (4, 18)	755, $14.91^{\star\square}$, 8 (4, 16)	4004, $12.11^{\dagger\square}$, 8 (4, 12)
Outdoor	3386, $14.44^{\dagger}$, 8 (4, 16)	760, $18.02^{\square}$, 8 (4, 14)	4221, $17.5^{\dagger\square}$, 11 (11,18)
On campus	405, $21.05^{\dagger\star}$, 17 (9,25)	72, $20.07^{\star}$, 10.5 (6, 20.5)	1133, 13.59, 13 (9, 17)
Off campus	7781, 14.48, 9 (4,16)	1443, 16.29, 8 (4, 14)	7092, $15.08^{\dagger}$, 8 (4,14)
		Living arrangements	
Halls	2309, $19.73^{\dagger}$, 13 (8, 21)	597, 23.03, 12 (8, 23)	3759, $16.25^{\dagger}$, 12 (8, 18)
Private	5877, $12.87^{\dagger\star}$, 8 (2,14)	918, $12.2^{\star}$, 6, (2,11.75)	4466, $13.72^{\dagger}$, 7 (2,12)

N_{events} counts the total number of successfully recorded contact events in the post-processed data (this is capped at one entry per student per hour, so at most $N_{students}$ × days in period × 24 in a given period). Within each row, a matching pair of superscripts indicates a difference in location of the Bluetooth measures at 5% significance.

3. Results

3.1. Student participation

A total of 67 students were recruited for the study, of whom 29 lived in student accommodation (either managed by the University or a third party), 37 lived in private accommodation and one student had unknown accommodation type. Of these 67 students, 62 had linkable data from the first wave (October 5, 2020, to November 1, 2020) of the TRACK-COVID study [34]: 28 students in halls of accommodation and 34 in private accommodation. Of these students, only 24 students returned location and Bluetooth data to the server at least once in Period 1.

3.2. RADAR data

Participation varied over the study period (see Figure 1), with only 29 students providing RADAR data in all time periods. The distribution of recorded Bluetooth contacts is highly skewed; many instances in which zero or very small numbers of Bluetooth handshakes were recorded, and the occasional event recording hundreds of Bluetooth handshakes (see Figure A.1, Supplementary Information). The maximum number of students contributing non-missing data on a given day peaked at 31 students on October 20, 2020. We present the number of unique contributing students by day (i.e. the number of students who successfully return paired Bluetooth and location data on each day) (Figure 1a) and the mean number of Bluetooth contacts per event by day (Figure 1 b).

Table 2 summarises Bluetooth contact data for all students binned by period and stratified by contact location. Overall, mean contacts per event peaked at 16.47 in Period 2, but median contacts per event were lower in Period 2 than the periods straddling it. Kruskal–Wallis (KW) tests for difference in means confirm no significant difference between distributions by Period across all data at the 5% significance level.

When stratifying by whether events occur indoors or outdoors, KW tests indicate significant difference between Periods ($p < 0.001$) in each stratum. Mean contacts per indoor event were lower in Period 2 than Period 1 [difference in location 1.00, 95% CI (2.20×10^{-5}, 2.00)], in Period 3 than Period 2 (difference in location 1.00, 95% CI (3.92×10^{-5}, 2.00)) [as well lower in Period 3 than Period 1, difference in location 1.00, 95% CI (3.92×10^{-5}, 2.00)]. Mean contacts per outdoor event decreased from Period 2 to Period 3 [difference in location 2.00, 95% CI (1.00, 3.00)] and were lower in Period 1 than Period 3 [difference in location 2.00, 95% CI (2.00, 2.00)].

On campus contacts per event were lowest in Period 3, and significantly lower than those in Period 1 [difference in location 4.00, 95% CI (2.00, 5.00)] Period 2 contacts per event on campus were lower than Period 1 [difference in location 4.00, 95% CI (4.91×10^{-5}, 7.00)]. The Kruskal–Wallis test indicates some difference in the location of distributions for off campus contacts per event by Period, which is closest to reaching significance when comparing Period 3 and Period 1 ; however, the magnitude of difference in location [3.91×10^{-5}, 95% CI (5.86×10^{-5}, 0.100)] indicates that this is not a meaningful difference.

Overall students living in halls of residence had higher Bluetooth contacts per event than students in private

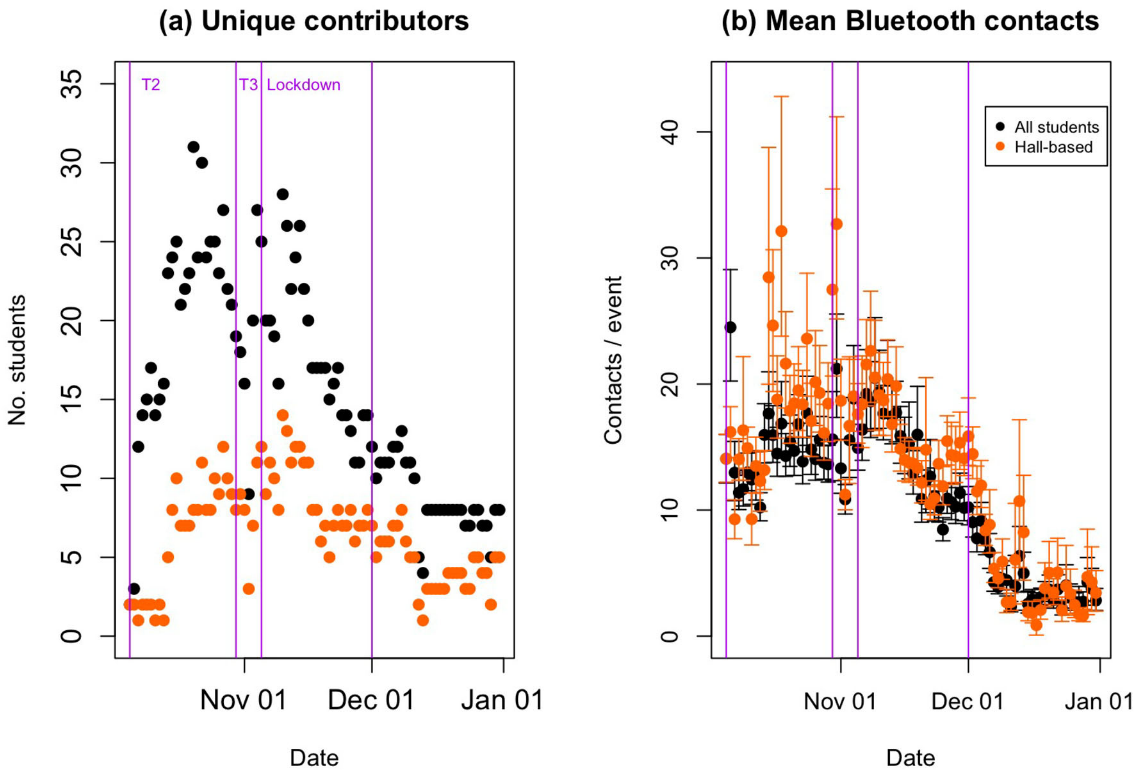

Figure 1. (a) Number of unique students contributing by day until the end of 2020. (b) Mean Bluetooth contacts per event by day (solid points) with error bars indicating 95% confidence intervals estimated using 1000 bootstrapped samples for each day. Vertical (purple) lines indicate the beginning of the data collection period, transition into Tier 3, transition into national lockdown, and the end of national lockdown.

accommodation. Contacts per event are lower in Period 3 than Period 1 [difference in location 1.00, 95% CI (1.00, 2.00)] for hall-based students. Contacts per event for students living in private accommodation decrease from Period 1 to Period 2 (difference in location 1.000068, 95% CI (1.47×10^{-5}, 2.00)), but are higher in Period 3 than Period 1 [difference in location 1.00, 95% CI (6.13×10^{-5}, 1.00)] (see Table 2).

Although we have been able to classify students by their living arrangement, their place of residence at the onset the study period, students may have returned "home" during term due to changes in frequency of face-face teaching, or in anticipation of another lockdown. We can gauge the extent to which this occurred by examining the number of hall-based students who visited campus in each study period (28 hall-based students returned data on campus in Period 1, 8 in Period 2 and 13 in Period 3), indicating that fewer students may be occupying their halls of residence in later Periods.

3.3. Generalised additive models

Aggregating data by Period may hide temporal trends, particularly around the very short Tier 3 period. Here we adopt a generalised additive model that (optionally) allows the mean contacts/event to vary smoothly with time. Each model has the form:

Table 3. GAM regression models. Here $f_{\text{date},x}$ indicates a temporal smooth conditional on the categorical covariate x.

Model	Predictor
1	$\beta_0 + x_{\text{living}}\beta_{\text{living}} + x_{\text{indoor}}\beta_{\text{indoor}} + x_{\text{campus}}\beta_{\text{campus}}$
2	$\beta_0 + f_{\text{date}}(x_{\text{date}})$
3	$\beta_0 + f_{\text{date}}(x_{\text{date}}) + x_{\text{living}}\beta_{\text{living}} + x_{\text{indoor}}\beta_{\text{indoor}} + x_{\text{campus}}\beta_{\text{campus}}$
4	$\beta_0 + f_{\text{date,indoor}}(x_{\text{date}}) + x_{\text{living}}\beta_{\text{living}} + x_{\text{campus}}\beta_{\text{campus}}$
5	$\beta_0 + f_{\text{date,living}}(x_{\text{date}}) + x_{\text{indoor}}\beta_{\text{indoor}} + x_{\text{campus}}\beta_{\text{campus}}$

$$\mathbb{E}(Y) = g^{-1}\left(\beta_0 + \Sigma_{j=1}^{J} f_j(x_j)\right), \quad (1)$$

where Y is the response (number of Bluetooth contacts), g^{-1} is the inverse link and response function (zero inflated negative binomial), x_j are the covariates, f_j are the smoother functions for each covariate and β_0 is the intercept. We trial different forms for the predictor as in Table 3, assuming default *brms* priors in each [41]. Models 2–4 all include a temporal smooth component (i.e. a non-linear function f_{date}, either as the only predictor (Model 2), or in addition to assuming all other covariates are fixed (f_j linear in x_j) (Model 3). In Model 4 (5) f_{date} is estimated independently for the levels of β_{living} (β_{outdoor}).

The comparison of fitted GAM models using leave-one-out cross validation is in favour of Model 4, though the expected log pointwise predictive density for Model 3 is within 4 standard errors, suggesting this model performs similarly [42] (Table A.7). In both Models 3 and 4, contacts measured for off campus events are on average higher than contacts for campus events (Model 3: $\beta_{\text{campus}} = -0.11$, 95% credibility interval $(-0.17, -0.05)$, Model 4: $\beta_{\text{campus}} = -0.05$, 95% credibility interval $(-0.11, 0.01)$) and mean contacts per event are significantly higher for students living in halls of residence compared to private accommodation ($\beta_{\text{living}} = -0.31$, 95% CI $(-0.34, -0.27)$) (see Tables A.4 and A.5). When we enforce the temporal smooth to be independent of indoor setting (Model 3), modelled mean contacts per event peak in Period 3 (Figure 2, left panel). When we allow the temporal smooth to be stratified by β_{indoor} (Model 4), modelled mean contacts per indoor event peak in Period 2/Tier 3, while mean contacts for outdoor events peak in Period 3/national lockdown (Figure 2, middle panel). In the right panel of Figure 2, we show Google Mobility data for the UK [43]. Google mobility data estimates record changes (from a January 3 to February 6, 2020, baseline) in the frequency of visits to indoor settings (which we assume correspond to the average of “Retail & recreation”, “Workplaces”, “Residential” and “Grocery & pharmacy” data streams) and outdoor settings (which we assume correspond to the “Parks” data stream for Google users enabling “Location History” tracking [18][1]) (see middle and right panels of Figure 2).

3.4. Individual associations between mood and bluetooth contact

We finda moderate but significant correlation between individual median Period 1 Bluetooth contacts per event and SPANE total (positive mood) ($\tau_b = 0.417$, 95% CI $(0.083, 0.751)$)). Moderate, correlations are also noted with loneliness ($\tau_b = -0.373$, 95% CI (,−0.623,−0.124)) and total GAD ($\tau_b = -0.351$) amongst students living in halls of residence ; however, these do not reach significance at the 5% level (95% CI $(-0.805, 0.104)$). No significant associations with median Bluetooth contact were noted amongst students in private accommodation, or for the linked study sample as a whole (see Table 4).

4. Discussion

We report on paired Bluetooth contact and location data for over 20,000 events from 67 students during October–December 2020. Enrolment in this study was significantly smaller than those in the wider study, indicating some reluctance to permit sharing of Bluetooth contact data. Participation also varied over the course of the study, with at peak 31/67 providing data on a given day. There are many possible reasons for missing instances of Bluetooth contact data for students enrolled in the study; loss of internet connection, deactivation of sensors, or disabling tracking within the app. The RADAR app can be a significant drain on battery life, which may cause students to disable tracking. The Bluetooth sampling rate is inversely correlated the RADAR application’s battery usage. While fine temporal sampling may be of interest to determine the epidemiological significance of contact events, as currently designed, sampling every 10 minutes likely contributed to the high rates of missing data. Optimising app performance and communicating on with study participants about its use to minimise missing data may therefore be useful for future work in this space. Nonetheless, by treating each contact event as independent, we were able to assemble a large data set and explore setting-dependent temporal trends that did not rely on self-reported social contact.

To facilitate the exploration of student ability to adhere to COVID-19 social distancing policy, we have coded the settings of recorded events as either indoor or outdoor, and on campus or off-campus. Our post-hoc analyses suggest that students responded to the changing COVID-19 regulations. In particular, when aggregating data by Period, Bluetooth contacts per event in indoor settings were highest in Period 1. In contrast, mean Bluetooth contacts per event in outdoor settings peaked in Period 2, suggesting that students may have been substituting indoor contacts with permissible (albeit with restrictions) outdoor socialisation. Given the approximate radius of 10

Table 4. Kendall tau rank correlation coefficient between mood measures and individual median Period 1 Bluetooth contacts, together with 95% confidence intervals. Numeric values are truncated to three significant figures.

	Living	τ_b	95% CI
GAD total	All	−0.108	(−0.399, 0.183)
	Halls	−0.351	(−0.805, 0.104)
	Private	0.069	(−0.316, 0.454)
Loneliness	All	−0.107	(−0.372, 0.158)
	Halls	−0.373	(−0.623, −0.124)
	Private	0.040	(−0.362, 0.442)
SPANE total	All	0.121	(−0.175, 0.417)
	Halls	0.417	(0.083, 0.751)
	Private	−0.105	(−0.568, 0.358)
PSS total	All	−0.099	(−0.358, 0.160)
	Halls	−0.261	(−0.585, 0.063)
	Private	−0.013	(−0.395, 0.370)
PHQ total	All	−0.053	(−0.284, 0.178)
	Halls	−0.234	(−0.552, 0.084)
	Private	0.019	(−0.312, 0.350)

[1] We ignore the “Transit” data stream, which may be a mixture of indoor and outdoor settings, however the qualitative trends in mobility data are not sensitive to this choice.

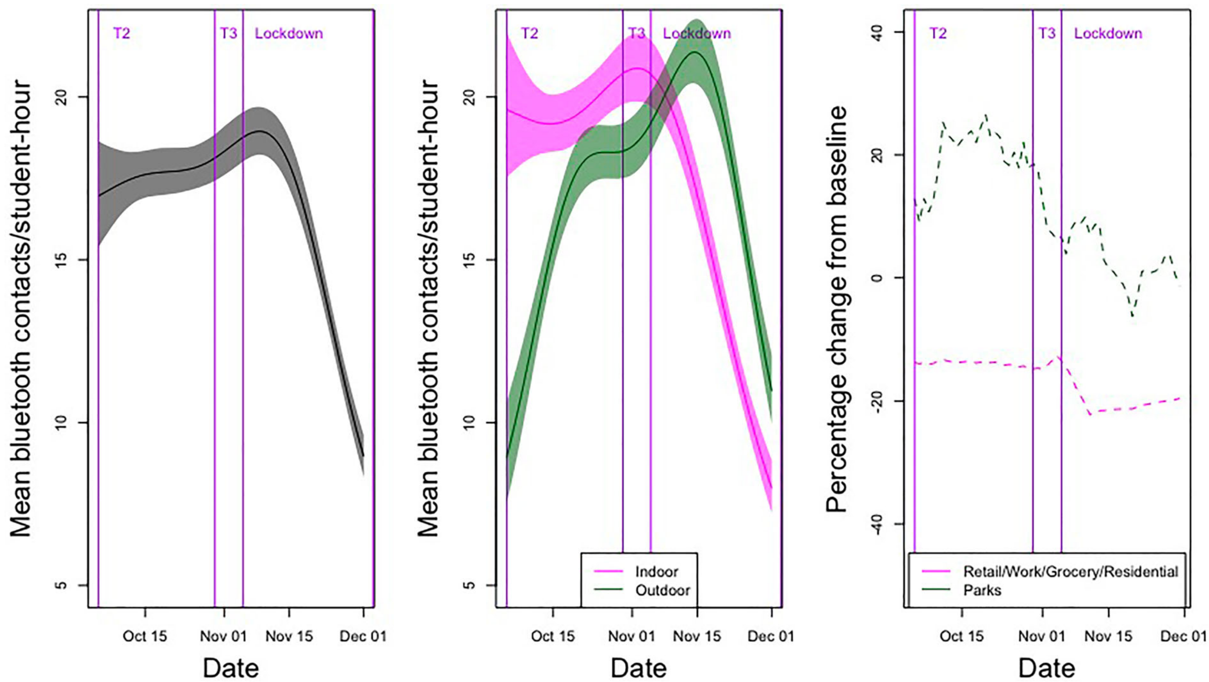

Figure 2. Comparison of GAM Model 3, with single temporal smooth (*left panel*), GAM Model 4 (with temporal smooth conditional on β_{indoor}, *middle panel*), and UK Google mobility data in Parks and the average of Retail, Work and Grocery visits (*right panel*). Conditional GAM effects are for off campus, indoor contacts for students residing in halls; due to the additive nature of the GAM, the temporal trend consistent across settings.

m for Bluetooth detection, it is important to note that the detection of a Bluetooth contact event does not imply that the participant was not observing social distancing policy.

We used generalised additive models with thin plate splines to further examine temporal trends in the data. A GAM model with a single smooth (Model 3) suggests that, overall, mean contacts per event peaked during lockdown. However, if we allow the smoother to be conditional on whether a setting is indoors or outdoors, then we recover trends that are similar to those in UK-wide mobility data: indoor contacts rising under Tier 3 restrictions, an initial increase in outdoor contacts during lockdown, and indoor contacts falling before outdoor contacts after the introduction of a national lockdown. We note that our GAM Model 3 does not describe the *proportion* of contact events that occur indoors or outdoors, but the change in mean Bluetooth contacts for contact events recorded indoors or outdoors. In contrast, the Google mobility data quantifies the change in frequency of visits to each setting compared to a pre-pandemic baseline, and should only be qualitatively compared to our results.

Students in halls of residence had higher contacts per event in all Periods. Mean contacts per event were higher off-campus than on-campus, consistent with explorations of settings of highest SARS-CoV-2 transmission risk in a similar population [8]. Differences in contact trends per event may also reflect changes in the delivery of teaching during the autumn term, with decreasing proportions of hall-based students recording on campus contact events. We do not have baseline data on students' changing social behaviour over the period of the academic year, and it is possible that not all of the observed changes are driven by changes in pandemic policy. While we note similar trends between settings, periods and student living arrangements amongst student who contribute data in each Period (see Supplementary Information § A.3), we have not attempted to model or correct for the representativeness of our data with respect to student characteristics, and treat each contact event independently. Participants may not be representative of the student population, and the relative contribution of different student groups may change over time. We have not considered any role of infection on Bluetooth contacts, which can for example, drive anomalies in mobile phone data [44].

We found tentative evidence that mood is associated with the median Bluetooth contact per contact event for students living in halls of residence; loneliness and anxiety were associated with fewer Bluetooth contacts per contact event, and positive mood was associated with higher Bluetooth contacts per contact event. The *direction* of the associations we report is consistent with another study exploring the impact of social interaction and mood (see, e.g. [45], for a study in older adults). We are unable to identify the potentially complex casual relationships between social experiences and psychological measures. We have not controlled for infection history, which may systematically differ by student residential setting [46]. Nor we have controlled for, e.g. exposure to nature, which pre-pandemic studies have indicated can increase positive mood [47]. In a study of German students during the SARS-CoV-2 pandemic, Hopp et al. [48] found lower emotional loneliness amongst students whose close contacts were similar to them, further hinting that raw counts of contact events may be insufficient to predict this outcome. Further interdisciplinary work exploring the relationship between and mental health, social and other activity, and infection is warranted.

We have focused on a post-hoc analysis of our data; however, real-time analysis is in principle possible. As configured, the RADAR app records a unique (non-identifiable) Bluetooth handshake for each contact event. Ethical considerations and privacy laws permitting, adding capability to remember previous Bluetooth handshakes with a device would open up possibility for data processing and modelling to comment on the size and structure social networks, duration of contacts, as well correcting for the possibility that contacts carry multiple Bluetooth devices. Our ability to automatically classify events by setting enabled novel insights regarding response to policy. Commercial data that is stratified by key demographic characteristics, such as Hong Kong Octopus Card transaction data used as a proxy for mobility/contact by age in modelling work, [49] may provide a useful compromise to holding potentially sensitive individual level data. Future work in this field may involve pairing data with infection and/or serology data to explore the relationship between Bluetooth contacts and infection risk [8]. Bluetooth contact data, paired with self-reported influenza-like-illness in university students, has been used to simultaneously infer network dynamics and transmission rates [50]. Such endeavours will likely be more fruitful using an experimental design that can measure contact proximity and duration.

5. Conclusion

Passive tracking of Bluetooth contacts combined with GPS data, even with small numbers of participants, can provide insights into the behavioural response to changing public health interventions. These data suggests that, at least qualitatively, students responded to policy changes similarly to the wider community; indoor Bluetooth contacts per event decreased rapidly at the beginning of lockdown, with contacts per outdoor event falling after a delay. Active survey data allowed us to stratify our proxy contact data by student living arrangement, to identify some (aggregated) differences in trends, suggesting the extension of this type of contact monitoring could help inform tailored public health policy in pandemic scenarios.

When linking individual Bluetooth contact data to survey data on mood in an exploratory analysis, we report moderate correlation between positive mood and median Bluetooth contacts per event for students living in halls of residence. Studies integrating psychological data with objective measures of social contact and presence in different types of settings may help tailor policy to accommodate the needs of different sub-populations. However, high rates of missing Bluetooth contact data indicates a need to optimise the technology available for passive, real-time surveillance of contact data for use in pandemic scenarios.

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Data availability statement

The participants of this study did not give written consent for their data to be shared publicly, so due to the potentially sensitive nature of the research, data are not available.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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References

[1] Brooks-Pollock E, Christensen H, Trickey A, et al. High COVID-19 transmission potential associated with re-opening universities can be mitigated with layered interventions. Nat Commun. 2021 Jan;12:5017. doi: 10.1038/s41467-021-25169-3

[2] Hill EM, Atkins BD, Keeling MJ, et al. Modelling SARS-CoV-2 transmission in a UK university setting. Epidemics. 2021;36:100476. doi: 10.1016/j.epidem.2021.100476

[3] Task and Finish Group on Higher Education/Further Education. Principles for managing SARS-CoV-2 transmission associated with higher education; 2020 Sept 3. Accessed: 2021-02-05.Available from: https://www.gov.uk/government/publications/principles-for-managing-sars-cov-2-transmission-associated-with-higher-education-3-september-2020.

[4] Public Health England. Weekly coronavirus disease 2019 (COVID-19) surveillance report Summary of COVID-19 surveillance systems Week 40, 2020; 2020.Available from: https://assets.publishing.service.gov.uk/media/5f76ed9bd3bf7f7c2921be81/Weekly_COVID19_Surveillance_Report_week_40.pdf.

[5] UK Government. The health protection (coronavirus, restrictions) (England) regulations 2020; 2020. Accessed: 2021-05-22.Available from: https://www.legislation.gov.uk/uksi/2020/350/regulation/6/2020-03-26.

[6] UCU. Monitoring cases of Covid-19 in UK higher and further education; 2020. Accessed: 2020-11-15.Available from: https://www.ucu.org.uk/covid-dashboard.

[7] Leeman D, Flannagan J, Chudasama D, et al. Effect of returning university students on COVID-19 infections in England, 2020. Emerging Infect Dis. 2022;28(7):1366–1374. doi: 10.3201/eid2807.212332

[8] Fairbanks EL, Bolton KJ, Jia R, et al. Influence of setting-dependent contacts and protective behaviours on asymptomatic SARS-CoV-2 infection amongst members of a uk university. Epidemics. 2023;43:100688. doi: 10.1016/j.epidem.2023.100688

[9] Smith LE, Potts HW, Amlot R, et al. Patterns of social mixing in England changed in line with restrictions during the COVID-19 pandemic (September 2020 to April 2022). Sci Rep. 2022;12(1):10436. doi: 10.1038/s41598-022-14431-3

[10] Hoang T, Coletti P, Melegaro A, et al. A systematic review of social contact surveys to inform transmission models of close-contact infections. Epidemiol (Camb, MA). 2019;30(5):723–736. doi: 10.1097/EDE.0000000000001047

[11] Mastrandrea R, Barrat A. How to estimate epidemic risk from incomplete contact diaries data? PLoS Comput Biol. 2016;12(6):e1005002. doi: 10.1371/journal.pcbi.1005002

[12] Apple. Apple and Google partner on COVID-19 contact tracing technology; 2020 Apr.Available from: https://www.apple.com/newsroom/2020/04/apple-and-google-partner-on-covid-19-contact-tracing-technology/.

[13] Google. Exposure notification API launches to support public health agencies; 2020 May.Available from: https://blog.google/inside-google/company-announcements/apple-google-exposure-notification-api-launches/.

[14] Google. COVID-19 community mobility reports; 2022.Available from: https://www.google.com/covid19/mobility/.

[15] Nouvellet P, Bhatia S, Cori A, et al. Reduction in mobility and COVID-19 transmission. Nat Commun. 2021;12(1):1–9. doi: 10.1038/s41467-021-21358-2

[16] Barnard RC, Davies NG, Jit M, et al. Modelling the medium-term dynamics of SARS-CoV-2 transmission in England in the Omicron era. Nat Commun. 2022;13(1):4879. doi: 10.1038/s41467-022-32404-y

[17] Zachreson C, Mitchell L, Lydeamore MJ, et al. Risk mapping for COVID-19 outbreaks in Australia using mobility data. J R Soc Interface. 2021;18(174):20200657. doi: 10.1098/rsif.2020.0657

[18] Aktay A, Bavadekar S, Cossoul G, et al. Google COVID-19 community mobility reports: anonymization process description (version 1.1). 2020 Nov. 3. doi: 10.48550/arXiv.2004.04145arXiv: 2004.04145[cs].Available from: http://arxiv.org/abs/2004.04145 (visited on 06/04/2024).

[19] Girolami M, Mavilia F, Delmastro F. Sensing social interactions through BLE beacons and commercial mobile devices. Pervasive Mob Comput. 2020;67:101198. doi: 10.1016/j.pmcj.2020.101198

[20] Chronis I, Madan A, Pentland A. Socialcircuits: the art of using mobile phones for modeling personal interactions. In: Proceedings of the ICMI-MLMI'09 Workshop on Multimodal Sensor-Based Systems and Mobile Phones for Social Computing; 2009. p. 1–4.

[21] Curtis SJ, Rathnayaka A, Wu F, et al. Feasibility of bluetooth low energy wearable tags to quantify healthcare worker proximity networks and patient close contact: a pilot study. Infect Dis Health. 2022;27(2):66–70. doi: 10.1016/j.idh.2021.10.004

[22] Thompson CA, Daffu-O'Reilly A, Willis T, et al. "smart"BLE wearables for digital contact tracing in care homes during the COVID-19 pandemic – a process evaluation of the contact feasibility study. Implement Sci Commun. 2023;4(1):155. doi: 10.1186/s43058-023-00533-0

[23] Pung R, Firth JA, Spurgin LG, et al. Using high-resolution contact networks to evaluate SARS-CoV-2 transmission and control in large-scale multi-day events. Nat Commun. 2022;13(1):1956. doi: 10.1038/s41467-022-29522-y

[24] Lovett T, Briers M, Charalambides M, et al. Inferring proximity from bluetooth low energy RSSI with unscented Kalman smoothers; 2020. arXiv preprint arXiv:2007.05057.

[25] Ranjan Y, Rashid Z, Stewart C, et al. Radar-base: Open source mobile health platform for collecting, monitoring, and analyzing data using sensors, wearables, and mobile devices. JMIR mHealth uHealth. 2019;7(8):e11734. doi: 10.2196/11734

[26] Wymant C, Ferretti L, Tsallis D, et al. The epidemiological impact of the NHS COVID-19 app. Nature. 2021;594(7863):408–412. doi: 10.1038/s41586-021-03606-z

[27] Andrews JA, Craven MP, Jamnadas-Khoda J, et al. Health care professionals' views on using remote measurement technology in managing central nervous system disorders: qualitative interview study. J Med Internet Res. 2020;22(7):e17414. doi: 10.2196/17414

[28] Bhagwat P. Bluetooth: technology for short-range wireless apps. IEEE Internet Comput. 2001;5(3):96–103. doi: 10.1109/4236.935183

[29] Liu S, Jiang Y, Striegel A. Face-to-face proximity estimation using bluetooth on smartphones. IEEE Trans Mob Comput. 2013;13(4):811–823. doi: 10.1109/TMC.2013.44
[30] Anderson HR, McGeehan JP. Optimizing microcell base station locations using simulated annealing techniques. In: Proceedings of IEEE Vehicular Technology Conference (VTC). IEEE Vehicular Technology Conference (VTC). Stockholm, Sweden: IEEE; 1994. p. 858–862. doi: 10.1109/VETEC.1994.345212 ISBN: 978-0-7803-1927-1. Available from: http://ieeexplore.ieee.org/document/345212/ (visited on 08/14/2024).
[31] Rule of six comes into effect to tackle coronavirus. GOV.UK.Available form: https://www.gov.uk/government/news/rule-of-six-comes-into-effect-to-tackle-coronavirus (visited on 07/04/2024).
[32] UK Government. Returning to a regional tiered approach; 2020.Available from: https://www.gov.uk/government/speeches/returning-to-a-regional-tiered-approach.
[33] UK Government. Prime minister announces new national restrictions; 2020.Available from: https://www.gov.uk/government/news/prime-minister-announces-new-national-restrictions.
[34] Knight H, Jia R, Ayling K, et al. The changing vaccine landscape: rates of COVID-19 vaccine acceptance and hesitancy in young adults during vaccine rollout. Perspect Public Health. 2023;143(4):220–224. doi: 10.1177/17579139221094750
[35] Dawn S, Martin G. Measuring loneliness: guidance for use of the national indicators on surveys.Available from: https://www.ons.gov.uk/peoplepopulationandcommunity/wellbeing/methodologies/measuringlonelinessguidanceforuseofthenationalindicatorsonsurveys (visited on 06/17/2024).
[36] Kroenke K, Spitzer RL, Williams JBW, et al. The patient health questionnaire somatic, anxiety, and depressive symptom scales: a systematic review. Gen Hosp Psychiatry. 2010 July 1;32(4):345–359. doi: 10.1016/j.genhosppsych.2010.03.006. ISSN: 0163-8343. https://www.sciencedirect.com/science/article/pii/S0163834310000563 (visited on 06/19/2024).
[37] Spitzer RL, Kroenke K, Williams JBW, et al. A brief measure for assessing generalized anxiety disorder: the GAD-7. Arch Intern Med. 2006 May 22;166(10):1092. doi: 10.1001/archinte.166.10.1092
[38] Diener E, Wirtz D, Tov W, et al. New well-being measures: short scales to assess flourishing and positive and negative feelings. Soc Indic Res. 2010 Jan 1;97(2):143–156. doi: 10.1007/s11205-009-9493-y. ISSN: 1573-0921. (visited on 06/19/2024).
[39] Cohen S. Perceived stress in a probability sample of the United States. In: The social psychology of health. The claremont symposium on applied social psychology. Thousand Oaks(CA, US): Sage Publications, Inc; 1968. p. 31–67. ISBN: 978-0-8039-3162-6 978-0-8039-3163-3.
[40] Wood SN. Generalized additive models: an introduction with R. Boca Raton, FL: Chapman and Hall/CRC; 2017.
[41] Bürkner P-C. brms: an R package for Bayesian multilevel models using Stan. J Stat Softw. 2017;80:1–28.
[42] Vehtari A, Gelman A, Gabry J. Practical Bayesian model evaluation using leave-one-out cross-validation and WAIC; 2016 Sept 12. doi: 10.1007/s11222-016-9696-4arXiv: 1507.04544[stat].Available from: http://arxiv.org/abs/1507.04544 (visited on 05/29/2024).
[43] Google. COVID-19 community mobility reports; 2020.Available from: https://www.google.com/covid19/mobility/.
[44] Yang C, Song H, Tang M, et al. Dynamic network anomaly modeling of cell-phone call detail records for infectious disease surveillance. In: Proceedings of the 28th ACM SIGKDD Conference on Knowledge Discovery and Data Mining; 2022. p. 4733–4742.
[45] Wu C-Y, Mattek N, Wild K, et al. Can changes in social contact (frequency and mode) mitigate low mood before and during the COVID-19 pandemic? the I-CONECT project. J Am Geriatr Soc. 2022 Mar;70(3):669–676. doi: 10.1111/jgs.v70.3. ISSN: 0002-8614. https://agsjournals-onlinelibrary-wiley-com.nottingham.idm.oclc.org/doi/full/10.1111/jgs.17607 (visited on 05/27/2024).
[46] Children's Task and Finish Group. Children's Task and Finish Group: Update on Children, Schools and Transmission; 2020 Nov.Available from: https://assets.publishing.service.gov.uk/media/5fae67fb8fa8f55dec19ba48/tfc-covid-19-children-transmission-s0860-041120.pdf.
[47] Neill C, Gerard J, Arbuthnott KD. Nature contact and mood benefits: contact duration and mood type. J Posit Psychol. 2019 Nov 2;14(6):756–767. doi: 10.1080/17439760.2018.1557242. ISSN: 1743-9760. (visited on 07/15/2024).
[48] Hopp MDS, Händel M, Bedenlier S, et al. The structure of social networks and its link to higher education students' socio-emotional loneliness during COVID-19. Front Psychol. 2022 Jan 13;12. doi: 10.3389/fpsyg.2021.733867. ISSN: 1664-1078. https://www.frontiersin.org/journals/psychology/articles/10.3389/fpsyg.2021.733867/full (visited on 07/15/2024).
[49] Leung K, Wu JT, Leung GM. Real-time tracking and prediction of COVID-19 infection using digital proxies of population mobility and mixing. Nat Commun. 2021;12(1):1501. doi: 10.1038/s41467-021-21776-2
[50] Bu F, Aiello AE, Xu J, et al. Likelihood-based inference for partially observed epidemics on dynamic networks. J Am Stat Assoc. 2022 Jan 2;117(537):510–526. doi: 10.1080/01621459.2020.1790376