Promoting a Safe Return to University Campuses during the COVID-19 Pandemic: Crowdsensing Room Occupancy

Gianni Tumedei*

Department of Computer Science and Engineering, University of Bologna
Bologna, Italy
gianni.tumedei@studio.unibo.it

Francesco Boschi*

Department of Computer Science and Engineering, University of Bologna
Bologna, Italy
francesco.boschi2@studio.unibo.it

Catia Prandi

ITI / LARSyS, Dept. of CS and Engineering, University of Bologna
Bologna, Italy
catia.prandi2@unibo.it

Luís Gomes

Department of Computer Science, University of Minho
Braga, Portugal
luisgomes24.97@gmail.com

Rui Calheno

Department of Computer Science, University of Minho
Braga, Portugal
ruiac66@gmail.com

Rui Abreu

INESC-ID, Faculty of Engineering of the University of Porto
Porto, Portugal
rma@fe.up.pt

Shuhao Ma

ITI / LARSyS
Lisbon, Portugal
imshuhao.ma@gmail.com

Valentina Nisi

ITI / LARSyS, Instituto Superior Técnico, University of Lisbon
Lisbon, Portugal
valentina.nisi@tecnico.ulisboa.pt

Nuno Nunes

ITI / LARSyS, Instituto Superior Técnico, University of Lisbon
Lisbon, Portugal
nunojnunes@tecnico.ulisboa.pt

Augusto Esteves

ITI / LARSyS, Instituto Superior Técnico, University of Lisbon
Lisbon, Portugal
augusto.esteves@tecnico.ulisboa.pt

ABSTRACT

We describe the work behind a privacy-preserving, crowdsensing approach that promotes social distancing upon the return of students to University. Our main motivation is enabling visualizations that predict room occupancy based on the number of connected devices to particular access points, via anonymous reports about these predictions, and via an unenforced booking system that allows users to communicate their intents about room use.

CCS CONCEPTS

• **Human-centered computing** → **Collaborative and social computing systems and tools**; *Visualization systems and tools*; Human computer interaction (HCI).

KEYWORDS

crowdsensing, covid-19, room capacity, capacity prediction

*Both authors contributed equally to this research.

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than the author(s) must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from permissions@acm.org.

GoodIT '21, September 9–11, 2021, Roma, Italy

© 2021 Copyright held by the owner/author(s). Publication rights licensed to ACM.

ACM ISBN 978-1-4503-8478-0/21/09...\$15.00

<https://doi.org/10.1145/3462203.3475911>

ACM Reference Format:

Gianni Tumedei, Francesco Boschi, Catia Prandi, Luís Gomes, Rui Calheno, Rui Abreu, Shuhao Ma, Valentina Nisi, Nuno Nunes, and Augusto Esteves. 2021. Promoting a Safe Return to University Campuses during the COVID-19 Pandemic: Crowdsensing Room Occupancy. In *Conference on Information Technology for Social Good (GoodIT '21), September 9–11, 2021, Roma, Italy*. ACM, New York, NY, USA, 6 pages. <https://doi.org/10.1145/3462203.3475911>

1 INTRODUCTION AND RELATED WORK

The COVID-19 pandemic had a considerable impact across sectors. Higher education was no exception, and a particularly critical space as it enables a regular exchange of international faculty and students which has been found to account for up to 15% of all infections [7]. The lockdowns in response to the pandemic interrupted conventional educational activities in most OECD and partner countries, and lasted from 10 weeks to well over a year [14]. While a body of work has looked at the various challenges behind transitioning teaching, learning, and assessment to a remote, online setting [6, 8, 15], our efforts focus instead in mitigating the spread of COVID-19 during the various reopening stages of Universities.

Work in this area has looked at mitigating COVID-19 through the early detection of infection via self-reports of symptoms [12] or speech or cough analysis using everyday mobile devices [10]; hand washing reminders and analysis via wrist-worn devices [13]; or contact tracing [1]. We complement these efforts by looking at the social distancing guidelines put in place upon the return of faculty and students to University campuses around the world [14], and

Figure 1: A diagram depicting the overall structure of our back-end. Access point events, together with user occupancy feedback and bookings, feed into our machine learning models for accurate occupancy predictions.

how we can leverage mobile crowdsensing approaches to facilitate compliance. Mobile crowdsensing, or participatory sensing, is an established and appealing paradigm for urban sensing where users leverage their mobile devices to collectively share implicit and explicit data of interest to a group or community. This coupling of sensed and inputted data tends to wield an higher coverage and better context awareness when compared to traditional sensor networks [2]. The use of crowdsensing in the context of the COVID-19 pandemic is not new. Cecilia et al. [3] describe several projects that rely on this paradigm to enforce a lockdown (e.g., COVID-Sensing.com), look at social distancing via contact tracking (e.g., I-MOVE-COVID-19), or monitor the evolution of the pandemic (e.g., CoronaMadrid). Examples of the latter can also be seen in Kielenyu et al. [11].

In this paper we describe the design and implementation of a set of crowdsensing features included in a larger mobile application for University students at Instituto Superior Técnico (IST) in Portugal that promotes social distancing via crowdsensing methods. Our main motivation is enabling the visualization of the overall room occupancy on both IST campuses so that students can make informed decisions about when to travel to University; and once there, which campus areas are safer for studying or group work. These visualizations are enabled via predictions based on the number of connected devices to particular access points, and via user reports about these predictions. These visualizations also benefit from an unenforced booking system that allows users to communicate their plans on using a particular room. Finally, and unlike the social distancing via contact tracing examples described by Cecilia et al. [3], our entire feature set was designed so it does not store or access any personal information about users and their devices. These privacy concerns are one of the major drawbacks of crowdsensing [5], and

have been shown to negatively affect users' willingness to interact with COVID-19 related applications [4].

Taken together, we contribute with insights into the design and development process of a privacy-preserving crowdsensing feature set, leading up to its deployment as part of a broader University application in early 2021. Our aim is that our process is easily replicable by other institutions looking for: (i) pragmatic ideas on how to support an orderly and safe return of faculty, staff, and students to their campuses – now and in the future when the need for such measures arises again; and (ii) ideas that remain relevant during non-pandemic times, so that the time and effort put into these developmental endeavors are not short lived.

2 CROWDSENSING ROOM OCCUPANCY

Our work expands on the "Madeira Safe to Discover"¹ mobile app, developed by several of the authors to ensure a safe visit to the island of Madeira in Portugal during the COVID-19 pandemic. This is a gamified experience [9] where visitors earn points by actively reporting on symptoms in exchange for discounted services and treats. Further, the system asks users for geolocation permission, which allows it to display how crowded different touristic attractions are in real-time. This ultimately allows visitors to implicitly adhere to distancing guidelines, to better plan their days, and to have an overall better experience.

Following the success of the app – over 300.000 downloads – we decided to provide a similar experience to the approximately 12.000 University students and 1.000 staff members of IST. This is accomplished via the "Técnico Go!" mobile app, which was developed by a multi-disciplinary research team of interaction and service designers, computer scientists, and engineers. This followed

¹<https://madeirasafetodiscover.com/app/>

Figure 2: On the left a 2d map of the campus with two rooms; one at approximately half-capacity (yellow) and the other with no user occupancy reports filled in the last hour (grey border). In the middle, and after tapping the room at half-capacity, the user can inspect how many others are there based on occupancy feedback (19), and the room capacity (44), type (*Biblioteca* or library in English), and location (ground floor of the *Informática II* building). On the right the user can inspect a plot with hourly and daily information on historical mean occupancy reports (green bars) and user intents/bookings as a gray line.

a user-centered design approach and iterative design process which started with an online questionnaire to over 200 students about their needs, fears, and wishes upon their return to campus. The resulting app allows students to anonymously report not only on COVID-19-related symptoms but also on their mental well-being, in addition to receiving relevant notifications about a safe return to campus (e.g., the latest guidelines).

The biggest departure from the original "Madeira Safe to Discover" app, and the focus of this paper, is on how we support occupancy visualization of different areas of the University. The original approach using geolocation was not feasible due to not only privacy concerns – exacerbated in the context of COVID-19 and contact tracing [4] – but also not working well indoors (i.e., at room level). Our solution relies instead on a privacy-preserving twofold approach. First, occupancy predictions are offered based on a machine learning model that looks at the number of connected devices on any given access point (past and present) – simply reporting on connected devices is not enough as each user can travel with a varying number of Wi-Fi-enabled devices. The location of these access points, and the relevant rooms and spaces they cover and

their capacity (e.g., study rooms, libraries), were manually added to the system. Finally, students and staff can provide anonymous room-level occupancy reports that not only provide minor corrections to the predictions above, but also enable finer occupancy visualizations when an access point spans multiple rooms.

An additional user report feature was also developed to allow students to anonymously communicate their intentions of using University facilities. Students can provide details about which room they wish to visit, when, and with whom (e.g., a three-student study group). The goals of this feature are threefold. First, to double-down as a *room finder* for when students share their intentions of traveling to campus but have no preference for a particular space or do not want to engage with the occupancy visualization (i.e., the system can recommend a room based on occupancy data). Second, to contribute with one more data point regarding expected occupancy. Third, to provide some functionality that would be appealing to students after a return to normalcy. That is, occupancy information is not only relevant for social distancing but can also contribute to better access to the University's infrastructure and an overall better student experience post-COVID-19 pandemic.

Finally, the features described above, and the overall "Técnico Go!" mobile app, were developed using the Dart programming language² and the Flutter toolkit³ for easier deployment across Android and iOS platforms. The back-end runs on MongoDB⁴ and is responsible for (Figure 1):

- **Gathering** event data from monitored access points;
- **Storing** access point meta and event data, as well as user-provided information (i.e., occupancy feedback and intent);
- **Training** machine learning models that predict occupancy information based on the number of connected devices;
- **Exposing** the metrics computed and user reports via an API.

2.1 Occupancy Visualization

The core aspect of our work is a room occupancy visualization that allows students to quickly check which rooms and spaces of the University are less crowded, and thus potentially offer a safer and more relaxed choice for study or group work. To enable this we first compiled a list of access points (APs) across the two campuses, their geographic coordinates, and which room(s) or space(s) they covered. To narrow down this search we focused solely on APs that covered: (i) the rooms accessible to Computer Science students (as this AP data was readily available); (ii) the larger study spaces (e.g., libraries); and (iii) the rooms and spaces that were accessible to students around the clock. This search wielded a list of 14 APs and 31 rooms and spaces. Data on the latter also included their coordinates, location (building and floor), capacity, and type (class or study room, laboratory, or library).

After several iterations we settled on two complementary visualizations. The first is built on user occupancy feedback reports, and allows students to inspect room-level occupancy information. The second is built on sensed data – predicted occupancy based on connected devices – and provides a coarser overview centered around the APs. Taken together, these visualizations allow students to get a sense of which areas of the campus are busy at a glance, and to narrow down their search to a particular room once they have found a less crowded area. They also complement their shortcomings; e.g., a student can easily avoid a room with no occupancy feedback information if a nearby AP predicts a high number of users nearby. Finally, we purposefully avoided using any terms related to the COVID-19 pandemic when designing these visualizations. This way, we argue this feature can be of use to students when simply looking for a quiet place to study or to manage their group work post-COVID-19 pandemic.

2.1.1 Occupancy Feedback (Room-level). Our occupancy feedback visualization displays room-level occupancy and is built around two elements. The first displays these rooms and spaces as icons on a 2d map (Figure 2 – left). Using the metaphor of a rising tide in yellow, these icons fill up in response to user feedback reports on room occupancy over the last hour (mean). This allows students to quickly pan around the map of the campus and identify which are its quieter spots. For more details, and upon tapping one of these room icons, users access the second element of the visualization: a pop-up with two tabs and the room's type and location. The first

²<https://dart.dev/>

³<https://flutter.dev/>

⁴<https://www.mongodb.com/>

Figure 3: Users provide occupancy feedback via a single-screen UI. This requires room information, the time of day this feedback refers to, and the number of people in the room. To invite participation, users can access this form from multiple points in the interface, and the system pre-fills these input fields to expedite submission.

tab displays the room occupancy and capacity numbers (Figure 2 – middle); a button that shares the intent of the user of heading to that particular room (*Study here*); and a button for feedback on occupancy (*Give feedback*). The second tab displays a plot with hourly information on: (i) the reported number of users in the room in the last hour (mean, yellow bar); (ii) historical mean reports (green bars); and (iii) intents received from other users (grey line), displayed as (unenforced) bookings (Figure 2 – right). While in this tab the user can also navigate backwards for a view of historical data, or forwards for future bookings.

2.1.2 Occupancy Prediction (AP-level). In addition to the visualizations centered exclusively around (anonymous) user reports, an additional visualization was provided and centered around the APs. This mimicked the behavior described above – icons on a 2d map and plots – but used a different color scheme and reported on the expected number of people in the area surrounding the AP. This was predicted using a regression neural network that relies on the number of connected devices – no information was recorded about

Figure 4: Users can let the system know of their intent of traveling to campus via a room booking UI. If they access this via a room occupancy visualization they see the two screens on the left, where they can inform the system of the time, duration, and number of people traveling together (e.g., a study group). If a student has no preference for a room and accesses the booking UI via the tabular menu, the system recommends a room based on other bookings and historical occupancy feedback (right).

these devices – and temporal data to understand the people’s behavior in different places and time. The results of this model present an RMSE of 1.7, which means that the approximation fails on average by 2 people in each AP. An autoencoder network was also created to understand the normal occupancy for each area of the campus and detect abnormal situations. User occupancy feedback at room level improves this prediction by providing ground truth values to continuously train the regression network, and users transition between AP and room visualizations zooming in (rooms) and out (APs) of the map, or via a button on the map UI. This allows users to quickly transition from coarser to finer visualizations.

2.2 Room Occupancy Feedback

Both the visualizations described earlier require room occupancy feedback information in some capacity. This data was also crucial in establishing a ground truth for our machine learning models. In order to promote participation, in addition to not storing any user data, our primary design objective was to make the feedback process as simple as possible, by: (i) minimizing the number of steps required to submit a feedback form; and (ii) providing multiple ways to access this form. This single-screen UI can be seen in Figure 3.

2.2.1 Minimizing Input on Feedback Forms. In order to expedite form completion, this describes solely three input fields that are often pre-filled and require only the user to press *Submit*:

- **Room.** Pre-filled with a room if the feedback form was accessed after the user tapped a room in the 2d map or had a booking for this time. This room is displayed as part of a short list of rooms that were currently in view in the map (for quick corrections), but a *Show All Rooms* button allows the user to access a list of all rooms.
- **Time.** Pre-filled with the current time. A standard calendar UI allows the user to select any hour or day so they are able to provide room occupancy feedback at their own leisure (e.g., at the end of the day).
- **Number of people in the room.** A slider is pre-filled with the mean value from user feedback reports over the last hour. This allows the report about to be submitted to confirm or tweak existing occupancy data.

2.2.2 Accessing Feedback Forms. In order to invite form completion, users can access this in two ways: (i) an always available

feedback button on the top of the map (Figure 2); and (ii) *Give feedback* buttons after the user accesses the detailed visualizations on occupancy feedback (Figure 2 – middle) or occupancy prediction.

2.3 Intent and Booking

The last element of our crowdsensing approach relies on users sharing their room usage intents. This information can be visualized to support a better decision-making process (Figure 2 – right), and as input to our machine learning models. This intent or (unenforced) booking functionality has two components that can be accessed via the tabular menu at the bottom of the screen (Figure 2): make and view/edit a booking(s). The former can also be assessed via the *Study here* buttons on the detailed visualizations on occupancy feedback (Figure 2 – middle) or occupancy prediction screens; and only one active booking for a given day and time is allowed per user. As before, we pre-fill our booking completion form when possible:

- **Room.** Pre-filled with a room if the booking form was accessed after the user tapped a room in the 2d map or had a booking for this time (Figure 4 – left). If the booking form was accessed via the tabular menu, and in likely scenarios where a student has no preference for a room and is just looking for a quiet and safe place to study, the system can also pre-fill this field with two recommendations based on other booking information available and historical feedback reports (Figure 4 – right).
- **Start time.** Pre-filled with the current time. Users can edit this start time via a standard calendar UI and provide the estimated duration of their stay (pre-filled as one hour).
- **Number of people.** The third input field allows the user to indicate approximately how many other people will be using the room as part of this booking, e.g., as part of a study group (pre-filled with one person).

3 FUTURE WORK AND CONCLUSION

In this paper we describe the work behind a privacy-preserving, crowdsensing approach to room occupancy at Instituto Superior Técnico in Portugal. This feature-set was part of "Técnico Go!", a mobile application that was deployed to enable the safe return of University students to campus. After the release of the app in 2021, several other Universities expressed interest in adapting our app to their facilities, particularly in regards to features that can outlast the pandemic. One example is the intent and booking functionality, which could easily be expanded to include a topic or goal for the study group when carrying out a booking (e.g., "Algebra I study group"). When distancing guidelines are no longer relevant, such visualization of student activity could support a better integration of new students, and better promote campus culture. Likewise, if we continue to move the app away from the context of COVID-19, and thus students lessen their concerns about contact tracing and privacy, further approaches could be explored to promote participation – including gamification strategies that award users for occupancy or intent reports, and positive reinforcement.

With that said, the pressing work following the app's deployment is to continue to improve our machine learning models based on the increasing amounts of incoming data. This data will also allow us to build better forecasting models that leverage historical data.

Beyond this, future models can also benefit from a hyperparameter tuning process that could include modifying the architecture of the network, the number of layers, the number of nodes per layer, or the activation functions. Finally, we aim to continue to iterate over the app's design via user studies as our students finally return to campus. We are particularly interested in assessing the success of the occupancy visualizations and students' engagement with the occupancy and intent feedback. Ultimately, we hope our students take ownership over the work and make use of these features well beyond the COVID-19 pandemic.

4 ACKNOWLEDGMENTS

This research was supported by LARSyS (Projeto – UIDB/50009/2020) and FCT (RESEARCH 4 COVID-19 2nd Edition – 344).

REFERENCES

- [1] Nadeem Ahmed, Regio A Michelin, Wanli Xue, Sushmita Ruj, Robert Malaney, Salil S Kanhere, Aruna Seneviratne, Wen Hu, Helge Janicke, and Sanjay K Jha. 2020. A survey of covid-19 contact tracing apps. *IEEE Access* 8 (2020), 134577–134601.
- [2] Andrea Capponi, Claudio Fiandrino, Burak Kantarci, Luca Foschini, Dmitriy Kliazovich, and Pascal Bouvry. 2019. A survey on mobile crowdsensing systems: Challenges, solutions, and opportunities. *IEEE communications surveys & tutorials* 21, 3 (2019), 2419–2465.
- [3] José M Cecilia, Juan-Carlos Cano, Enrique Hernández-Orallo, Carlos T Calafate, and Pietro Manzoni. 2020. Mobile crowdsensing approaches to address the COVID-19 pandemic in Spain. *IET Smart Cities* 2, 2 (2020), 58–63.
- [4] Eugene Y Chan and Najam U Saqib. 2021. Privacy concerns can explain unwillingness to download and use contact tracing apps when COVID-19 concerns are high. *Computers in Human Behavior* 119 (2021), 106718.
- [5] Delphine Christin, Andreas Reinhardt, Salil S Kanhere, and Matthias Hollick. 2011. A survey on privacy in mobile participatory sensing applications. *Journal of systems and software* 84, 11 (2011), 1928–1946.
- [6] John Daniel. 2020. Education and the COVID-19 pandemic. *Prospects* 49, 1 (2020), 91–96.
- [7] Organisation for Economic Cooperation and Development (OECD). 2020. Flattening the COVID-19 peak: containment and mitigation policies. (2020).
- [8] Francisco José García-Peñalvo, Alfredo Corell, Víctor Abella-García, and Mario Grande-de Prado. 2021. Recommendations for Mandatory Online Assessment in Higher Education During the COVID-19 Pandemic. In *Radical Solutions for Education in a Crisis Context*. Springer, 85–98.
- [9] Juho Hamari, Jonna Koivisto, and Harri Sarsa. 2014. Does gamification work?—a literature review of empirical studies on gamification. In *2014 47th Hawaii international conference on system sciences*. Ieee, 3025–3034.
- [10] Ali Imran, Iryna Posokhova, Haney N Qureshi, Usama Masood, Muhammad Sajid Riaz, Kamran Ali, Charles N John, MD Iftikhar Hussain, and Muhammad Nabeel. 2020. AI4COVID-19: AI enabled preliminary diagnosis for COVID-19 from cough samples via an app. *Informatics in Medicine Unlocked* 20 (2020), 100378.
- [11] Sedevizo Kielienyu, Burak Kantarci, Damla Turgut, and Shahzad Khan. 2020. Bridging Predictive Analytics and Mobile Crowdsensing for Future Risk Maps of Communities Against COVID-19. In *Proceedings of the 18th ACM Symposium on Mobility Management and Wireless Access*. 37–45.
- [12] Cristina Menni, Ana M Valdes, Maxim B Freidin, Carole H Sudre, Long H Nguyen, David A Drew, Sajaysurya Ganesh, Thomas Varsavsky, M Jorge Cardoso, Julia S El-Sayed Moustafa, et al. 2020. Real-time tracking of self-reported symptoms to predict potential COVID-19. *Nature medicine* 26, 7 (2020), 1037–1040.
- [13] Sirat Samyoun, Sudipta Saha Shubha, Md Abu Sayeed Mondol, and John A Stankovic. 2021. iWash: A smartwatch handwashing quality assessment and reminder system with real-time feedback in the context of infectious disease. *Smart Health (Amsterdam, Netherlands)* 19 (2021), 100171.
- [14] Andreas Schleicher. 2020. The impact of covid-19 on education insights from education at a glance 2020. Retrieved from <https://www.oecd.org/education/the-impact-of-covid-19-on-education-insights-education-at-a-glance-2020.pdf> (2020).
- [15] Adam E Wyse, Eric M Stickney, David Butz, Amanda Beckler, and Catherine N Close. 2020. The Potential Impact of COVID-19 on Student Learning and How Schools Can Respond. *Educational Measurement: Issues and Practice* 39, 3 (2020), 60–64.