

# Deliverable

## [D5.6 The Potential of Crowdsourced EEWS]

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## Summary

This report synthesises the results obtained from our study of crowdsourced Earthquake Early Warning (EEW).

Since 2016, the smartphone app EQN has been turning user's phones into sensors and providing earthquake warnings. We have demonstrated that EQN is successfully providing an operational earthquake early warning system.

## **1. Aim of this report**

The aim of this deliverable is to present how citizen science and crowdsourced data can potentially contribute to earthquake early warning. This objective was ambitious but was achieved. The results are presented in 3 papers (Bondar et al., 2020, Bossu et al., 2021, Fallou et al., 2021 accepted) as well as another complementary manuscript currently under preparation (Finazzi et al., 2021 in preparation).

Rather than repeating the content of our 3 accepted/published peer reviewed articles, this report contains an overview of this work and describes the perspectives opened.

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## 2. Synthesis

Two different strategies have been explored for crowdsourced earthquake early warning (EEW). The first one is based on the combined analysis of crowdsourced and seismic data, and the second one is based on the dedicated earthquake early warning smartphone app named EQN.

### 2.1 CsLoc - the combined analysis of crowdsourced and seismic data

- The principle of this combined analysis is simple. Felt earthquakes can be detected through the digital footprint generated by eyewitnesses seeking information about the shaking that they have just felt. These footprints are linked to publications on Twitter, visits to earthquake related websites or opening of earthquake apps. The detections are called crowdsourced detections and happen within 15 to 90 s of the earthquake and often precede seismic location. The location of the crowdsourced detection defines a geographical area where seismic stations have likely detected this earthquake and the crowdsourced detection time defines a time window within which seismic signals have likely reached each station. Based on this data, automatic arrival times are automatically retrieved from these stations, outliers are filtered out and a seismic location performed. These seismic locations have been shown to be fast and robust (Bondar et al., 2020). This approach is called CsLoc (CrowdSeeded seismic Locations)
- CsLoc does significantly speed up earthquake location at no cost and without any modification to the monitoring network, however it is not sufficient for an EEW: Locations are typically available within one minute while they must be available within a few to a dozen seconds for an EEW. The main advantage of this approach is to provide rapid earthquake information (Bondar et al., 2020).

### 2.2 EQN smartphone app

- The EQN app, a popular earthquake app turns users' charging smartphones into earthquake detectors. Following the detection of a cluster of concomitant triggers (i.e. different smartphones detecting shaking at approximately the same time and location), a notification is sent to all users in a pre-defined distance of the triggers. Notifications contain a countdown to the theoretical arrival time of S-waves at a user's location.
- A detailed analysis of EQN performance over a 26-month period shows that it does deliver early warning in multiple countries, at a typical rate of twice a month. For the damaging 2019 Albania earthquake, it was shown that users affected by an intensity 6 (slightly damaging) benefited of at least 8s of warning (Bossu et al., 2021). EQN was the first operational smartphone based public EEW system and has been giving warnings since 2016-2017. Google has announced in 2021 that it is also deploying such a system but although it has published a few warnings, no information is available on its actual performance.
- Beyond this technical analysis, we also evaluated how the service is perceived and how users react to the warnings (Bossu et al., Fallou et al., 2021) There are only a couple of such studies in the literature. What has been shown is that users appreciate and understand the service and what a warning is. However only a fraction (25%) takes actual protective actions. In other words, the assumption from seismologists that a technically efficient EEW will lead to individual risk reduction is only partially valid. This does not mean that EEW are not useful as they are praised by users notably as a way to limit the psychological impact of earthquakes.

### 3. Conclusion and perspective

Due to EQN, crowdsourced EEW has been a reality since 2016? and its EEW service is regularly in action in multiple countries. Its cost is many order of magnitude lower than the cost of EEW based on scientific grade instruments and it covers several countries. More studies are needed to understand why so few users actually take protective actions and what could be envisaged to nudge users towards self-protection.

While CsLoc is not an EEW, synergies are being tested with EQN. EQN detections are shared with EMSC which employs them to engage with eyewitnesses and crowdsource their felt experiences. EQN detections also trigger CsLoc, leading to fast earthquake locations which can then be forwarded to EQN users for rapid earthquake information.

## 4. References

Bondár, I., Steed, R., Roch, J., Bossu, R., Heinloo, A., Saul, J., & Strollo, A. (2020). Accurate locations of felt earthquakes using crowdsourced detections. *Frontiers in Earth Science*, 8, 272.

Bossu, R., Finazzi, F., Steed, R., Fallou, L., & Bondár, I. (2021). "Shaking in 5 Seconds!"—Performance and User Appreciation Assessment of the Earthquake Network Smartphone-Based Public Earthquake Early Warning System. *Seismological Research Letters*.

Fallou, L., Finazzi, F. & R. Bossu (2021) Efficacy and usefulness of an independent Public Earthquake Early Warning system. A case study: The Earthquake Network initiative in Peru. Accepted for publication in *Seismological Research Letters*

## **5. ANNEXE 1: Bondar et al. 2020**



# Accurate Locations of Felt Earthquakes Using Crowdsourced Detections

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We present a methodology that uses crowdsourced detections as an initial location to obtain fast and reliable hypocenter parameters for felt earthquakes using arrival-time data from the GEOFON Program. We derive selection criteria for issuing an alert message using a 3-year-long training set from the trial runs at the European-Mediterranean Seismological Centre (EMSC) to identify accurate event locations at a high confidence level. Since an event may have several crowdsourced detections, we also develop a methodology dealing with multiple triggers. We validate the selection criteria using real-time processing of recent data and demonstrate that 95% of the selected events are within 50 km distance from the traditional seismic location published by the EMSC. Since CsLoc remains essentially a seismic location algorithm, the selection criteria measure the quality of the seismological network coverage used in the location, not the method itself. We show that our methodology provides accurate locations much faster than those published by conventional seismic methods. On average, the EMSC CsLoc service can provide rapid and accurate locations within a minute after the occurrence of a felt earthquake, thus it can provide timely and accurate information on a felt earthquake to the civil protection services and the general public.

**Keywords:** crowdsourced detection, earthquake location, earthquake alert, real time seismology, citizen seismology

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## INTRODUCTION

Earthquake crowdsourced detections are based on following eyewitnesses' immediate reactions to felt earthquakes on various social media platforms, such as Twitter (Earle et al., 2011), traffic on the EMSC website (Bossu et al., 2014), and the number of launches of the EMSC smartphone app, *LastQuake* (Bossu et al., 2018). While other crowdsourced approaches in seismology (e.g., Cochran et al., 2009; Minson et al., 2015; Finazzi, 2016; Kong et al., 2016; Cochran, 2018) have focused on using accelerometers in smartphones or dedicated sensors that are maintained by the public, our approach exploits the public's search for information and their online reactions (Steed et al., 2019). In other words, a crowdsourced earthquake detection reflects a public desire for information. Offering a very fast earthquake location is a way to answer this desire. It is also instrumental for rapid engagement of eyewitnesses and to ensure efficient felt report collection from eyewitnesses which are in turn essential for rapid impact assessment (Bossu et al., 2015). It can also be exploited

as a “heads-up” for civil protection services which might save lives in a period where every minute counts and this is why seismic networks around the world have been constantly pushing for always faster earthquake information (Kanamori, 2005).

Crowdsourced detections typically appear very fast in social media, almost immediately after the earthquake occurrence in densely populated areas. Hence, they can be used as an initial estimate of the earthquake location. This initial guess triggers our seismic data analysis to obtain a reliable earthquake location with a state-of-the-art event location algorithm. Steed et al. (2019) demonstrated that the crowdseeded location (*CsLoc*) approach produces quicker results than traditional earthquake alert algorithms, and that it can provide reliable locations even with a limited number of seismic phase arrivals.

This paper focuses on the conditions that would allow our method to enter into routine operational service, providing fast, reliable locations of felt earthquakes. This information can then be provided to the civil protection services and disseminated to the public. The public's appreciation for high accuracy is much less than it's dislike of false alarms, so one of the crucial aspects of our effort is to minimize the number of events with inaccurate locations whilst providing accurate locations on average. Hence, our objective is to achieve 50 and 80 km location accuracy (measured as the distance from the traditional seismic network location) at the 95 and 98% confidence levels, respectively, while maximizing the number of events that pass the publication criteria. To derive the selection criteria, we use a training set of 3-year data, and validate the results on 4-month data from current real-time processing.

## DATA AND METHODS

### Crowdsourced Detection

We rely on three different crowdsourced detection methodologies to start a *CsLoc* analysis. Note that they may trigger *CsLoc* independently, therefore several triggers may exist for the same earthquake. *CsLoc* is initiated by the detection of increased traffic at the EMSC website, [www.emsc-csem.org](http://www.emsc-csem.org) (Bossu et al., 2014); the detection of increased number of launches of the EMSC LastQuake smartphone application (Bossu et al., 2018); and the detection from the Twitter Earthquake Detection (TED, Earle et al., 2011) system that follows the keyword “earthquake” in 59 languages in tweets of less than seven words because people tend to react to stressful events such as earthquakes in just a few words. The TED system was developed by the United States Geological Survey National Earthquake Information Center (NEIC), and it is currently used in the EMSC crowdsourced detection system.

To detect an event, the number of app launches or website visits are monitored as counts/minute at 5 s intervals and a short-term average/long-term average (STA/LTA) algorithm is applied to these curves to detect peaks in the traffic (Bossu et al., 2019). The latest count/minute is compared to a baseline created from an average of the last half an hour of traffic and if the difference reaches a preset threshold then a peak is declared. Various procedures are used to increase signal to noise and to

eliminate false detections (such as those caused by automated scans of IP addresses or the website). For instance, only visitors that have not been seen within 30 min are included in the analysis, as this helps to remove frequent users from the data such as researchers from institutes. We also bin our users by country of origin so that the background noise level is reduced. As the EMSC becomes more known by the public, we will probably need to adjust our triggering system to take account of greater levels of traffic but the current system has worked well for since 2014.

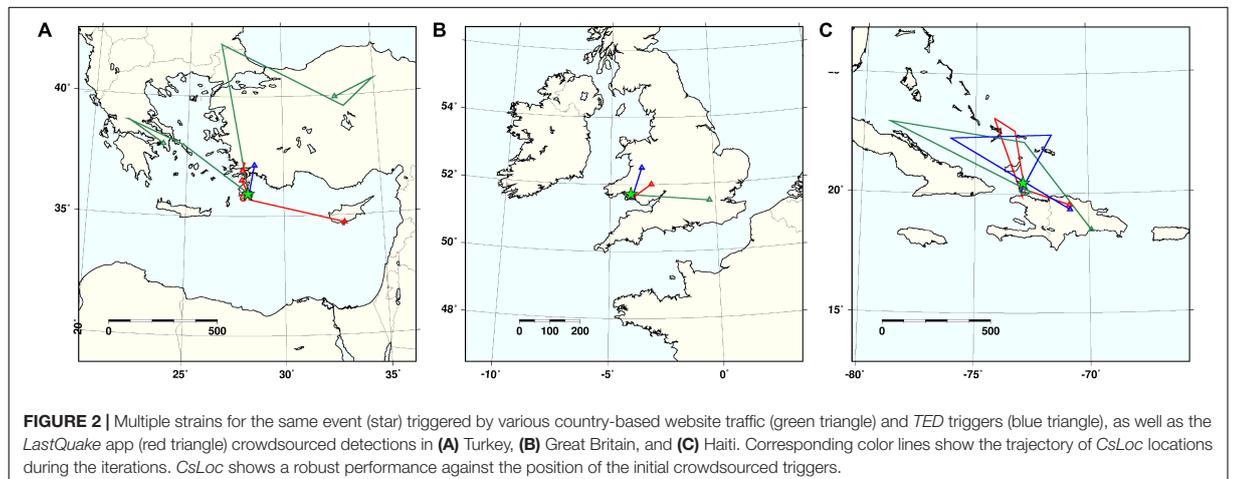
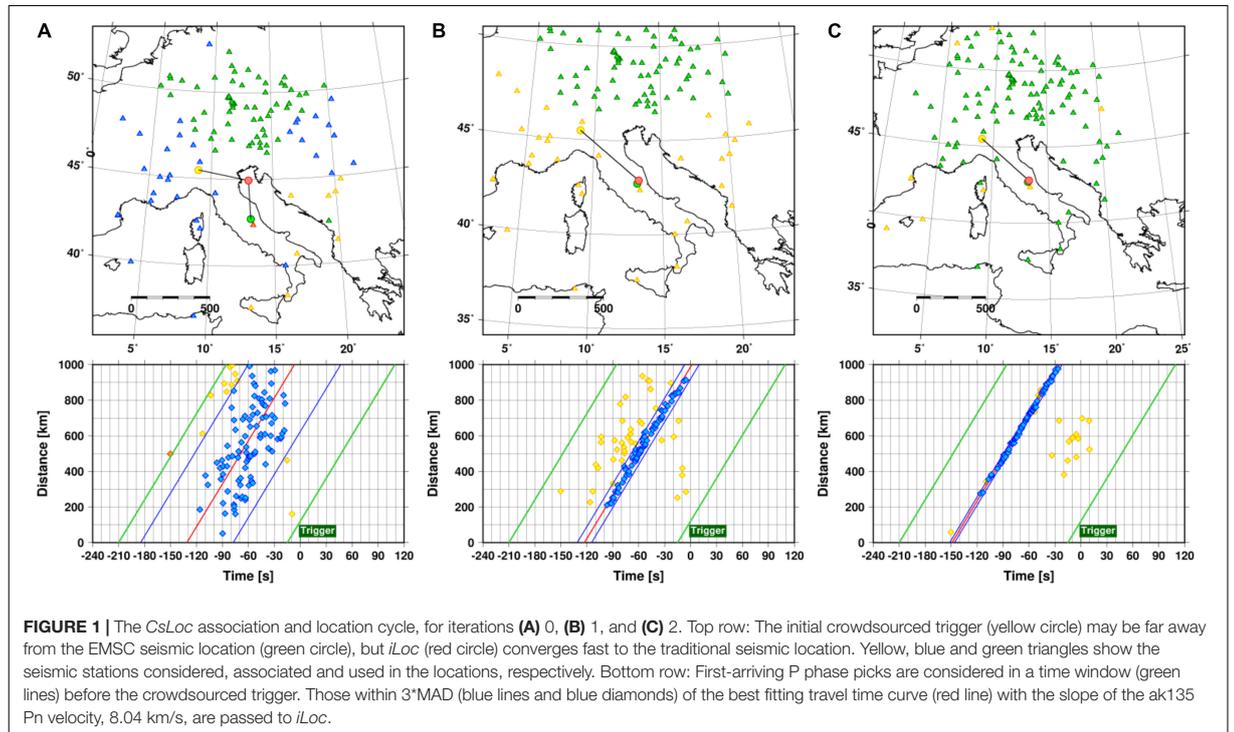
Crowdsourced detections are typically obtained before the first seismic location is made, therefore the *CsLoc* procedure starts without having a location provided by local or regional seismic networks. Once a crowdsourced detection is made, the centroid of the largest cluster of geolocations of the users within 120 s before the detection time and within the country where the detection was made is passed to the *CsLoc* association module (Steed et al., 2019). The cluster centroid and the crowdsourced detection time serves as an initial guess for the earthquake location, and as noted above, several *CsLoc* processes could be initiated for the same event. The system collects arrival picks within 1000 km (for regions with sparse networks up to 2000 km) distance of the crowdsourced initial location from the global GEOFON Program (73 FDSN networks as used in GEOFON Data Centre, 2019; Steed et al., 2019) that includes some 800 stations. The P-wave arrival picks are received in real time from 210 s before until 120 s after the crowdsourced detection time using the GEOFON HTTP Message Bus (Heinloo, 2016).

### CsLoc Association and Location

The *CsLoc* association process is optimized for speed and it uses the crowdsourced initial guess as the event hypothesis for finding corroborating arrivals. Hence, *CsLoc* is a seismic location algorithm that exploits the fact that we already know from crowdsourcing that an earthquake occurred, and we have a rough idea where and when the earthquake has struck. We assume that for our spatial range of interest the first P wave arrival is a Pn phase and we search for first-arriving P-phases that given the hypocenter origin hypothesis, providing a reasonably good fit to the *ak135* (Kennett et al., 1995) Pn travel-time curve. Only those arrivals that are within three times the median absolute deviation (MAD) of the Pn travel time curve are passed to the locator.

Using the selected arrivals, we apply the *iLoc* (Bondár and Storchak, 2011; Bondár et al., 2018) location algorithm to locate the event. *iLoc* accounts for correlated travel time prediction errors due to unmodeled 3D velocity structures (Bondár and McLaughlin, 2009) and thus provides robust location estimates even for unfavorable network geometries. It is an iterative linearized inversion method that obtains an improved hypocenter estimate using a neighborhood algorithm (Sambridge, 1999).

As new data arrives and the location changes, it is necessary to repeat the association and location procedures several times until an acceptable solution is reached. **Figure 1** illustrates the iterative association-location steps for the 2016-08-24, magnitude 6.2 Central Italy event. The crowdseeded location triggered by the EMSC website traffic is some 450 km away from the earthquake epicenter. The association algorithm considers P picks arriving

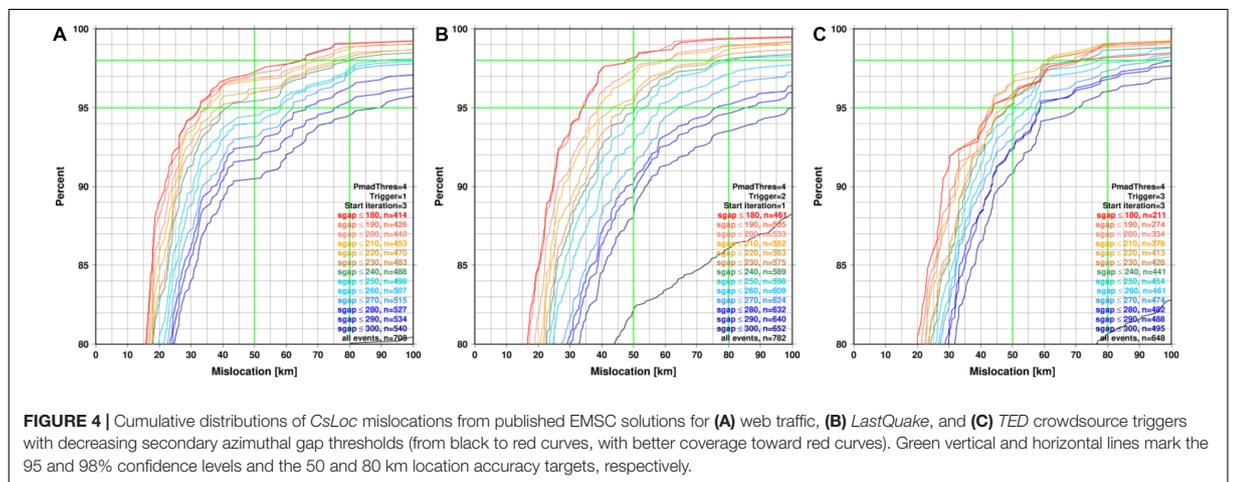
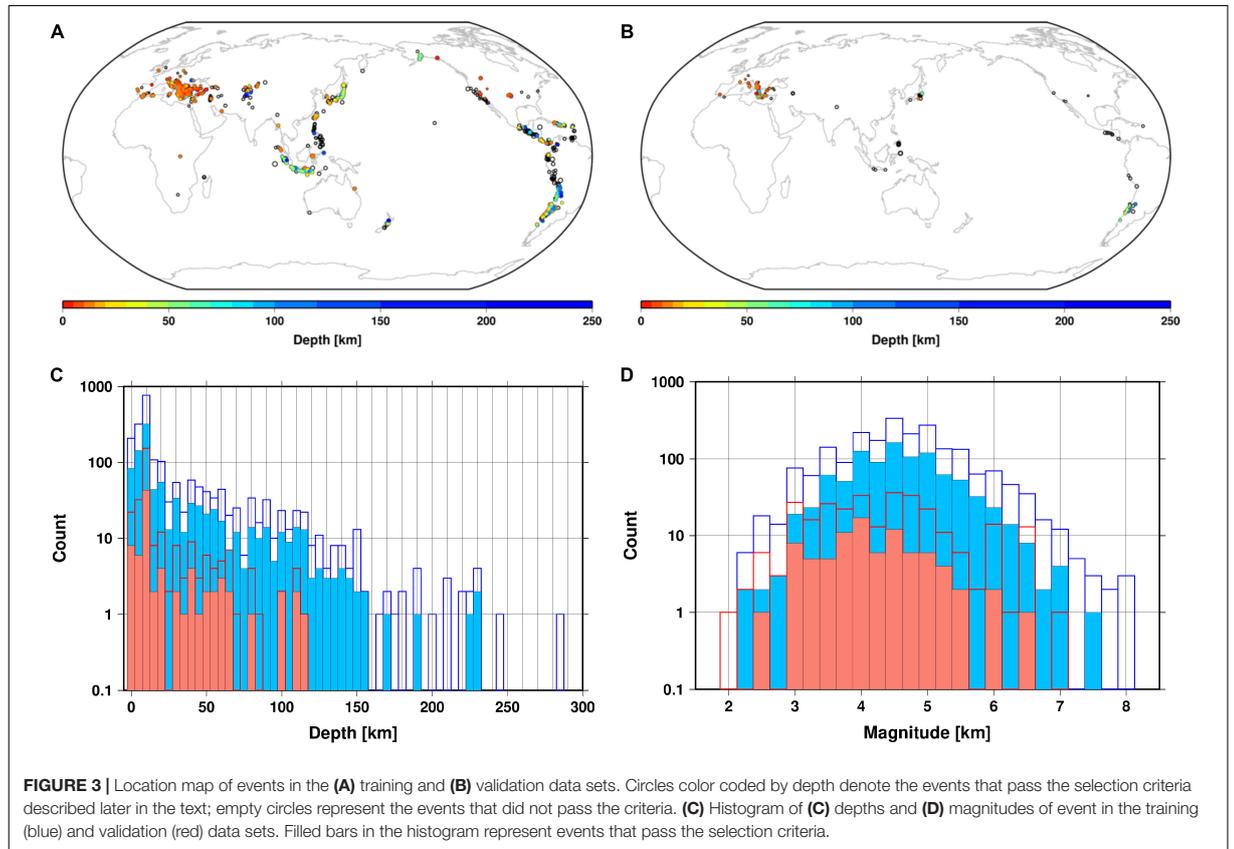


in the time interval shown in green lines, and selects those that are within the  $3 \cdot \text{MAD}$  of the best fitting line with a slope of 8.04 km/s, the ak135 Pn velocity. On the map, green triangles show the seismic stations that *iLoc* used in the location and the *iLoc* solution is shown as a red circle. In the two next iterations, as the *iLoc* solution improves, the  $3 \cdot \text{MAD}$  interval for the candidate associations shrinks drastically and even after the first iteration the *iLoc* solution is very close to the final EMSC seismic location.

Steed et al. (2019) executed 10 iterations of the association and location cycle with 15-s delays between each step. In this paper

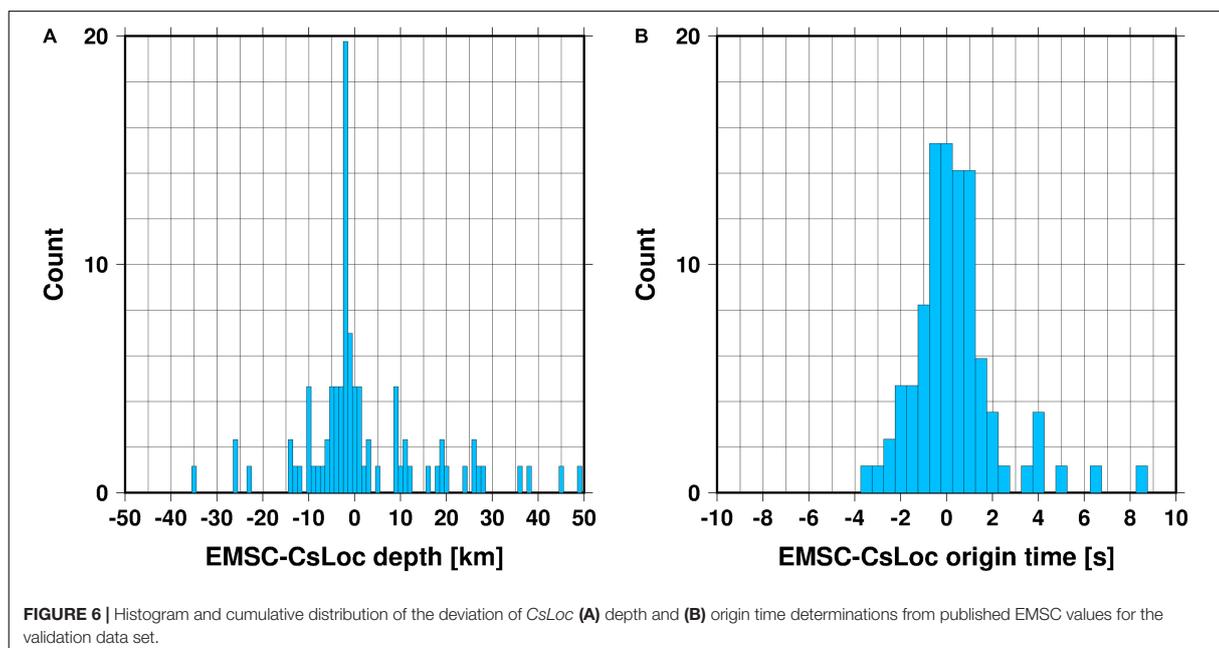
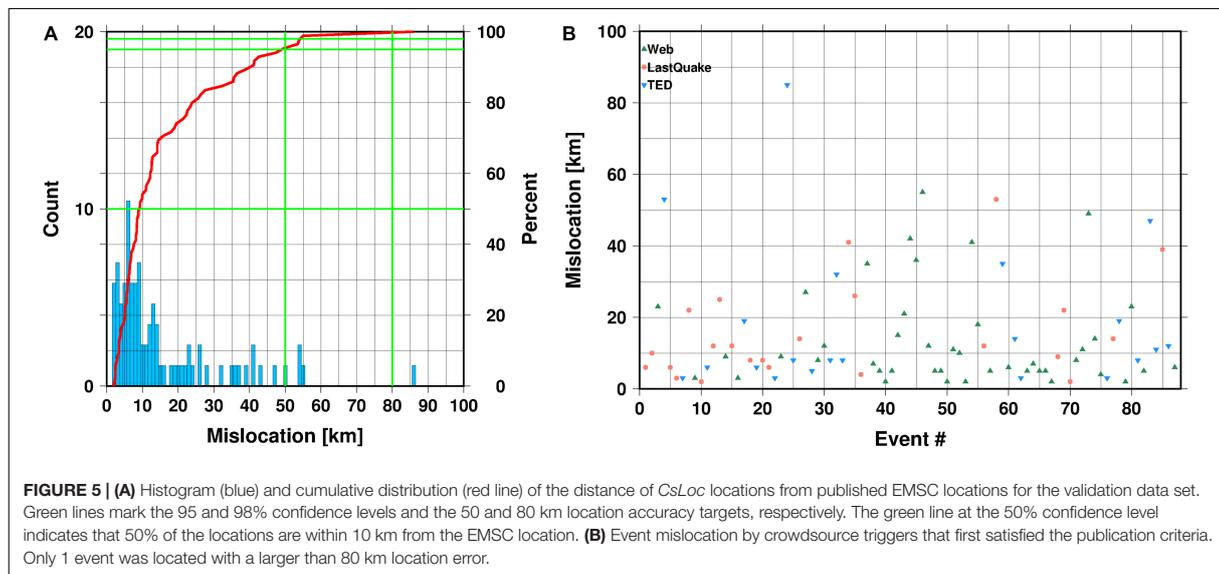
we focus on the determination of the set of conditions that will allow us to stop as soon as some quality assurance criteria are met. The selection criteria will also allow us to fully automate the *CsLoc* procedures.

The three types of crowdsourced detections (web traffic, *LastQuake* app, and *TED*) can each trigger the *CsLoc* procedure. For the web triggers the geolocation is based on the user's IP address that varies from country to country and it is often accurate to the city level or less. If the website is accessed via a mobile phone, the geolocation often gives the location where the



mobile network is connected to the internet. Thus, as **Figures 1, 2** illustrate, the physical location of the users can be quite inaccurate and often biased by large cities and therefore the centroid of the crowdsourced detections often coincides with a large city, such as Istanbul, Athens, Milan, etc. This is always true for IP locations and tweets.

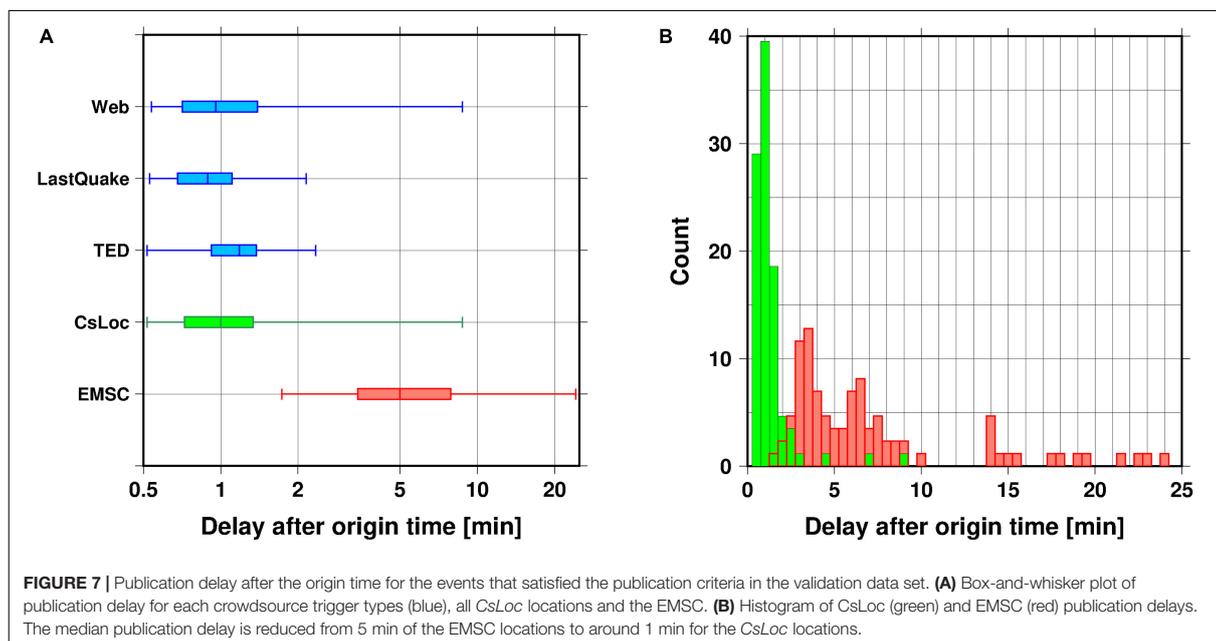
The LastQuake app asks for the user’s permission to access their mobile phone’s location, otherwise it determines the user’s location using triangulation or wifi. Some 80% of users allow the use of location services, therefore the app triggers are considered the most accurate. Furthermore, the website and app detection systems are monitored in each country separately. The Twitter



detection system determines the location of the user from the profile of the author found in each tweet. It also tries to divine the user's location based on the language used in the tweet. Therefore, the accuracy of *TED* triggers may also exhibit a large scatter.

Because of the various triggers, it is not uncommon that there are several crowdsource detections for the same event. *CsLoc* is robust enough to reach accurate locations, even if the initial location is far off. However, it helps to identify these multiple strains early on. We analyzed our data set to find reasonable criteria to decide if two crowdsourced detections

are generated by the same event. We found that events with a large number of seismic arrivals and those with just a few seismic arrivals require separate logic. We rely on the assumption that if two solutions share a fair amount of common seismic arrival picks then the events are likely to be the same. For candidate events for multiple triggers we check the number of common seismic arrivals for each event pair. If the number of common seismic arrival picks is larger than 20, we declare the two events common. For events with just a few picks, we require at least three common seismic arrival picks and that



20% of the seismic phases be shared between the events to declare them the same.

**Figure 2** shows examples for *CsLoc* event location trajectories starting from several different crowdsourced detection. Recall that the crowdsourced detection is the barycenter of the eyewitness locations. Green trajectories denote web-based triggers, red lines *LastQuake* app triggers and blue trajectories *TED* triggers. One of the major strengths of our method is that regardless of the trigger type and the initial mislocation, *CsLoc* is capable to obtain a final solution that is very compatible to the final EMSC solution of the event.

## RESULTS

Steed et al. (2019) executed 10 iterations of the association and location cycle with 15-s delays between each step and developed publication criteria based on the combination of acceptance thresholds of six different parameters. Exploiting the accumulated wealth of data, we aim to simplify the original publication criteria and focus on the determination of the set of conditions that will allow us to stop as soon as some quality assurance criteria are met.

To determine the new selection criteria, we use a training set of crowdsourced detections between January 2016 and May 2019 including 708 events triggered by the EMSC web-site traffic, 782 events triggered by the *LastQuake* app, and 648 events triggered by *TED*. Note that the same earthquake may initiate several triggers and the data set represents 2,138 unique events. To validate the selection criteria, we use the data set between 10 October 2019 and 12 December 2019 that were not used in the creation of the training data set. We

consider only those events that produced a location at the last, 10th iteration. The validation data set contains 288 events of which 123 events triggered by the EMSC web-site traffic, 97 events triggered by the *LastQuake* app, and 68 events triggered by *TED*.

**Figure 3** shows the location map of the training and validation sets, as well as their depth and magnitude distributions. The training set represents a fairly good representation of global seismicity of felt earthquakes, while the validation data set, owing to its much shorter time window, have events mostly from Europe and South America. Nevertheless, the depth and magnitude distribution of the events in the training and validation sets are quite similar. Note that both sets have subcrustal and intermediate depth events, and the magnitudes span from small to large events.

We consider the secondary azimuthal gap in the network used in the location, and the MAD of the residuals after the *iLoc* location in each iteration. The secondary azimuthal gap is obtained by calculating the largest azimuthal gap when removing one station from the network and it is a good indicator of reliable, accurate locations (Bondár et al., 2004). The MAD of the residuals helps removing outliers due to noisy data or associations from other events, typically aftershocks. We use the distance between the published EMSC location and the *CsLoc* location as the metric to measure the performance of *CsLoc*. These parameters measure of the seismic network coverage that ultimately controls the location accuracy.

Our design goal is to achieve 50 km location accuracy at the 95% confidence level and less than 80 km mislocation at the 98% confidence level while maximizing the number of events that pass the criteria and stop the iterations as soon as possible to facilitate quick but reliable earthquake alert

information. This means that only 5 and 2% of the events would have a location error larger than 50 km and 80 km, respectively, all the rest will be much more accurately located. We calculate the metric for a series of secondary azimuthal gap thresholds between 180 and 300 degrees (the smaller the secondary azimuthal gap, the more favorable the network geometry to produce accurate locations) and a MAD residual threshold of 3, 4, 5, and 100 (the latter being no constraint on MAD). We found that setting the MAD threshold to 4 s is a reasonable choice, that excludes obvious outliers while keeping most events.

As noted previously and illustrated on **Figure 2**, the different triggers represent different levels of reliability, therefore we develop the selection criteria for each trigger type separately. The web traffic and *TED* crowdseeded initial locations can be far away from the final solution, and they may need a few iterations for *CsLoc* to close on the right location. On the other hand, the *LastQuake* app crowdseeded location can be quite accurate, therefore the final *CsLoc* solution might be obtained in just one iteration. Thus, we also set thresholds for the minimum number of iterations *CsLoc* has to perform before we apply the selection criteria.

**Figure 4** summarizes our results. The figure shows the cumulative distributions of the distance of the *CsLoc* location from the published EMSC solution for each trigger type for the series of secondary azimuthal gap thresholds for MAD *leq* 4. Note that **Figure 4** shows only the upper 20% percentiles, from 80 to 100%, as we focus on location errors in the top 10 percentiles. We found that for the web traffic and *TED* triggers we should execute at least two iterations to allow for the warm-in period for *CsLoc* before testing for the criteria; for the *LastQuake* triggers we can apply the selection criteria right away.

We list our final publication criteria for each trigger types below. Note that these criteria measure the seismic network performance, not the quality of the crowdsource detection. That is only used as the initial guess for the location using observations from seismological stations. Once the selection criteria are met at any iteration after the prescribed number of iterations, the *CsLoc* association – location iteration cycle stops and an earthquake alert can be issued.

- For website traffic triggers after the 3rd iteration accept an event for publication if the secondary azimuthal gap *leq* 240° and the MAD of residuals *leq* 4 s.
- For *LastQuake* triggers after the 1st iteration accept an event for publication if the secondary azimuthal gap *leq* 230° and the MAD of residuals *leq* 4 s.
- For *TED* triggers after the 3rd iteration accept an event for publication if the secondary azimuthal gap *leq* 240° and the MAD of residuals *leq* 4 s.

The selection criteria for the web traffic triggers select 69% (488 out of 708) of the events with a median mislocation of 9.2 km from the EMSC solution and with a location accuracy of 41 and 77 km at the 95 and 98% confidence levels, respectively. For the *LastQuake* app triggers, they select 73.5% (575 out of 782) of events with a location

accuracy of 10.4, 47, and 74 km at the median, 95 and 98% percentiles, respectively. For the *TED* triggers, the criteria select 68% (441 out of 648) of events with a mislocation of 13.2, 48, and 65 km at the median, 95 and 98% confidence levels, respectively.

Applied to the validation data set, the publication criteria for web traffic triggers selected 60.2% (74 out of 123) of events with a mislocation of 7.5, 42, and 52 km at the median, 95 and 98% confidence levels, respectively. The publication criteria for the *LastQuake* triggers select 56% (54 out of 97) of events with 8.7, 38, and 40 km mislocation at the median, 95 and 98% confidence levels, respectively. For the *TED* triggers, the publication criteria select 37% (25 out of 68) of events with a location accuracy of 8.5, 51, and 71 km at the median, 95 and 98% percentiles, respectively.

We indicated those events that passed our selection criteria in **Figure 3** as the events color coded by depth. The events that did not pass the selection criteria are shown as empty circles, and concentrate in regions with somewhat poorer station coverage. The depth and magnitude distributions do not show any particular bias for events passing (colored bars) or failing the selection criteria (empty bars) either.

**Figure 5** shows the distribution of the *CsLoc* location differences from the published EMSC locations as well as the mislocations by the trigger types that first reached the publication criteria. The green lines show our target design criteria of 50 and 80 km location accuracy at the 95 and 98% confidence level, respectively. They indicate that the validation data set confirms that our publication criteria are indeed able to identify accurate locations for all trigger types that satisfy our design goals of minimizing the number of poorly located events and maximizing the number of accurately located events when issuing an earthquake alert to the public. The selection criteria will also allow us to fully automate the *CsLoc* procedures and the automatic publication of fast and reliable locations even using very limited data sets.

## DISCUSSION

Aiming at fast and accurate locations for an operational centre such as the EMSC, the first issue to address is the identification of the single event to trigger among the various triggers for the same event. Thus, we check at each iteration if the event has already satisfied the publication criteria from another trigger, by applying the test for common events. If the event proves to be a common event by an earlier trigger and is already published, we simply abandon the trigger and stop processing the event. While other triggers may later result in slightly more accurate locations, our objective is to issue an alert at the earliest possible time with the stated location accuracy at high, 95 and 98% confidence levels.

Our crowdsourced detections carry no information on event depth, yet with the *CsLoc* procedures we are able to determine the depth with reasonable accuracy. Recall that *CsLoc* employs the *iLoc* location algorithm (Bondár and Storchak, 2011; Bondár et al., 2018) that provides robust depth estimates. In the *CsLoc* procedures the local networks typically provide sufficient resolution for depth determination. **Figure 6** shows the

histograms of the deviation of the *CsLoc* depth and origin time from the published EMSC values for the validation data set. The vast majority of *CsLoc* event depths are within 10 km of the EMSC depth, and the origin times are within 2 s from the published EMSC origin time.

In principle, *CsLoc* can also provide magnitude estimates. We plan to publish magnitudes alongside the hypocenters as that would be a fairly trivial task; all we need to do is to get the automatic amplitude measurements along with the first-P arrival picks and calculate the magnitude. Since we collect phase picks up to 1,000 km (for sparse networks up to 2,000 km) this would allow us to calculate local magnitude, ML. However, ML starts saturating relatively early at medium moment magnitudes, therefore for some cases ML would underestimate the magnitude. For these events we will not publish ML at all. Attenuation along the ray path and possible interference with Lg phase poses further problems that might bias the ML estimate. Obviously, we will have to rely on generic attenuation relations the same way as the most popular programs, such as Antelope, SeisComp3 do. Nevertheless, we believe that besides producing rapid, accurate locations for felt earthquakes it is also important to publish magnitudes for small events that may not be recorded at teleseismic distances.

## CONCLUSION

We successfully developed a methodology that can be used to identify accurately located events at a high confidence level. The selection criteria are quite robust against the various crowdsourced triggers and facilitate the handling of multiple triggers for the same event. The location accuracy is better than 10 km for 50% of the events, which is comparable to the average location error of 9.4 km in the EHB bulletin (Engdahl et al., 1998). The EHB bulletin is the groomed ISC bulletin and it is considered amongst the highest quality global bulletins and thus the preferred source for doing global and regional tomography. The location error is larger than 50 and 80 km or only for 5 and 2% of the events, respectively. Similarly, the *CsLoc* depth and origin time estimates are on average within 5 km and 1 s of the EMSC solution for 50% of the events, and larger than 25 km and 3 s for only 10% of the events.

Our selection criteria for publication allows us to significantly reduce the publication latency times compared to those cited in Steed et al. (2019) as the majority of events can be published right after the third iteration and notably it was never necessary to wait for the full ten iterations. **Figure 7** shows the publication delay after the origin time for the EMSC published hypocenter and the *CsLoc* locations that satisfy the publication criteria. The median delay time for the EMSC is 5.6 min, while the median delay in publication time is reduced to 55, 53, and 72 s for the web traffic, *LastQuake* and *TED* triggers, respectively. Overall, the median delay in publication time for the *CsLoc* locations is reduced to 60 s, hence providing a significant improvement over the 103 s median delay reported by Steed et al. (2019).

The selection criteria allow us to reduce the EMSC publication delay after the event origin time by as much as 4 min on

average and publish 75% of the events within 2 min after their occurrence. The performance of the *CsLoc* services depends on both population and station density as well as information timeliness. To further improve the *CsLoc* services we plan to improve the network coverage by complementing the actual real time seismic phases obtained from the GEOFON Program with more openly accessible stations, without significantly increasing the data latency.

## DATA AVAILABILITY STATEMENT

All datasets generated for this study are included in the article/**Supplementary Material**.

## AUTHOR CONTRIBUTIONS

IB developed the phase association algorithm and its code, developed the event acceptance criteria, and also the author of the *iLoc* location algorithm, available for download at <https://seiscode.iris.washington.edu/projects/iloc>. RS and JR developed the *CsLoc* implementation, and created both the training and the validation data sets. RB formulated the overarching research goals, led and supervised the project, and acquired funding. AH developed the HMB messaging bus. AS and JS provided the feedback during the discussions as well as phase and seismic detection from the GEOFON program both historically and in real time using the HTTP Message Bus (HMB). All authors contributed to the article and approved the submitted version.

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## SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: <https://www.frontiersin.org/articles/10.3389/feart.2020.00272/full#supplementary-material>

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**Conflict of Interest:** The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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## **6. ANNEXE 2: Bossu et al., 2021**

# **"Shaking in 5 seconds!" - Performance and user appreciation assessment of the Earthquake Network smartphone-based public earthquake early warning system**

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## **Abstract**

Public earthquake early warning systems have the potential to reduce individual risk by warning people of approaching tremors, but their development has been hampered by costly infrastructure. Furthermore, both users' understanding of such a service and their reactions to actual warnings have been the topic of only a few surveys. The smartphone app of the Earthquake Network initiative utilizes users' smartphones as motion detectors and provides the first example of a purely smartphone-based earthquake early warning system, without the need for dedicated seismic station infrastructure and operating in multiple countries. We demonstrate that this system has issued early warnings in multiple countries including for damaging shaking levels and hence that this offers an alternative in the many regions unlikely to be covered by conventional early warning systems in the foreseeable future. We also show that although warnings are understood and appreciated by users, notably to get psychologically prepared, only a fraction take protective actions such as "drop, cover and hold".

## Introduction

Earthquake early warning systems aim to warn people or infrastructure of imminent shaking through the rapid detection of earthquakes. Public earthquake early warning (PEEW) systems specifically target people rather than infrastructure and strive to reduce an individual's risk by allowing them to take protective actions (such as “drop, cover and hold”) in the seconds or tens of seconds separating the warning from ground shaking at the user’s location. They were deployed first in 1991 in Mexico City (Suárez et al. 2009) and then in Japan in 2007 (Nakayachi et al. 2019). Despite this desirable goal and the existence of a number of other implementations - such as ShakeAlert in the Western USA (Kohler et al., 2018; Given et al., 2018), Taiwan (Hsiao et al. 2009; Xu et al. 2017) and some private initiatives in Mexico and Chile - so far PEEW systems have not been put into service more widely, even in regions of high earthquake hazard, because they require dense, real time, and robust seismic and communication networks (Cremen and Galasso 2020). Furthermore, PEEW evaluations have mainly focused on technical performance (e.g., rapidity, false/missed alert rates) with only a few studies carried out from users’ perspectives that assess how the service is valued and whether users react or not after receiving a warning (Suarez et al. 2009; Nakayachi et al. 2019), or how they anticipate reacting for a future service (Beker et al. 2020). This situation has led to a lack of actual assessment of PEEW in terms of individual risk reduction so that key parameters such as the public’s tolerance to false and missed alerts remain unknown, making it difficult to develop informed and efficient warning strategies (Allen and Melgar 2019; Cochran and Husker 2019).

Smartphones, due to their internal accelerometers, communication capabilities and their ubiquity were rapidly identified for their low-cost potential for earthquake early warning (Minson et al. 2015; Kong et al. 2016). The Earthquake Network (EQN) initiative (Finazzi 2016; Finazzi and Fassò 2017; Finazzi 2020b) implemented the first smartphone-based PEEW system that both detects earthquakes in real time and also publishes the earthquake warnings that the network generates. The feasibility of building a monitoring network from participants’ smartphones has been further demonstrated by Kong et al. (2020ab) and the results of a 6-month study was re-

cently published on creating a seismic network using fixed dedicated smartphones in Costa Rica (Brooks et al. 2021) but these systems did not issue their own early warnings. Also, Google announced in April 2021 that it has started a project to use Android smartphones to detect earthquakes and publish PEEW (Voosen 2021). Google's system was initially tested in New Zealand and Greece and is gradually being expanded to more regions. It appears to operate similarly to EQN, however at the current time, no details are available on its implementation and there are no published analyses of its efficacy.

The smartphone app of the EQN initiative turns participants' smartphones into real time seismic detectors by monitoring their internal accelerometers while their phones are charging. The resulting monitoring network is fully dynamic, with new users often joining after feeling earthquakes and users often slowly leaving during calm periods. Since its inception in 2012, EQN has grown its userbase with 8 million app downloads and 1.2 million active users in July 2021, but this work is the first evaluation of its ability to provide early warnings.

When an active (i.e. charging) smartphone senses an acceleration above a noise-dependent threshold a smartphone trigger is sent to the EQN servers and time stamped upon reception. No attempt is made to analyze waveforms from the phones' accelerometers; instead, a detection occurs when the number of triggers within 30 km of each other and within a 10 s time frame exceeds a dynamic acceleration amplitude threshold that is a function of the actual number of active smartphones and of the desired false alarm probability, a level currently set to one per year per country (Finazzi and Fassò 2017). Hereafter, a trigger will describe the motion detection performed by a single smartphone while detection will refer to the EQN system detecting an earthquake through a statistical analysis of the collected individual triggers. A geo-located alert is issued at detection time to all users within 300 km of the detection location. This location is the centroid of the triggered smartphones, and it is taken as a proxy for the epicentral location. The alert is a smartphone notification with an easily recognizable sound and an automatic display of the epicentral location proxy, as well as a countdown in seconds to the estimated S-wave arrival time at the user location (Figure 1). Large earthquakes can cause several detections. To

avoid multiple alerts for the same earthquake only detections at least 300 km and 120 s apart are released. EQN does not estimate the magnitude or intensity of events, which may not be appropriate for critical infrastructure stakeholders such as train operators or nuclear power plants. Instead, EQN is designed to provide value for the general public by focusing exclusively on disseminating information and issuing early earthquake warnings to the population.

The objectives of this work are to 1) evaluate EQN's detection performance, 2) demonstrate that it is capable of providing public earthquake early warning in multiple countries, and 3) assess the potential of EQN's contribution to individual risk reduction by studying EQN users' reactions after an actual early warning. One of the purposes of this paper is to ascertain whether the service is still appreciated without the presence of intensity predictions. Performance has been evaluated over a 26-month period (from December 15<sup>th</sup>, 2017 to January 31<sup>st</sup>, 2020) during which the EQN data processing methodology was not modified. In addition, reaction to and understanding of early warning by EQN users has been inferred from an online survey of local EQN users in the felt area of the M8 2019 Peru earthquake.

## **Results**

### *EQN detection performance*

EQN's detection performance in terms of latency, false detection rate and missed earthquake detections has been evaluated using 550 detections from Chile, USA, and Italy. These are the three countries that had at least 10 detections and had national catalogues that possessed both good location accuracy and coverage of low magnitude earthquakes, and additionally had accelerometric data available. Accurate locations are required in order to make proper estimates of the system's latency and catalogues including low magnitude earthquakes are essential for both network sensitivity and false detection rate estimates as smartphone detections are possible down at least to M2 (Kong et al. 2020a). Finally, accelerometric data was sought out from avail-

able scientific-grade stations close to each detection location for a final consistency check against waveform data.

EQN detections were first associated in time and space with hypocenters from national catalogues, then among the potential candidates, an earthquake was considered as the source of the detection if the theoretical arrival time of the P-wave at the detection location was between 90 s before to 10 s after the detection time. The 90 s lead time was primarily to allow the association of detections triggered by the S-phase as well as location and velocity model uncertainties. This led to an initial association of 535 out of 550 detections. For this analysis, whenever an accelerometer station was available within 20 km of the detection location (410 out of 550 detections), the existence and time consistency of ground motion was visually checked. This inspection enabled association with earthquakes for 4 additional detections. One was associated to a M3.8 earthquake at an unusually large distance of 350 km, and two to small magnitude earthquakes (M1.4 and M1.5 located 2 and 8 km from the detection) located through additional investigation by the Seismological Centre of the University of Chile. The fourth was found to be a secondary detection 800 km from epicenter of the March 1<sup>st</sup>, 2019, Peru M7.0 earthquake. A number of detections cannot be associated to any known earthquake leading to a false detection rate of ~2%.

The 539 associated detections are consistent with previous detectability study of smartphone sensors (Kong et al. 2019). With half related to earthquakes below M4 (Figure 2), there are many events that are unlikely to have generated strong shaking and therefore for which an early warning may not have been necessary. However, comparison with independent data (Figure 2) indicates that nearly all of the EQN detections are likely to have also been felt, which make them relevant for rapid public information, even the few that were very low magnitude.

Assessment of EQN's rate of missed earthquakes is more complex than for traditional seismic monitoring networks as the network geometry is governed by spatiotemporal variations in population distribution - higher in cities, lower in low population areas - and it constantly changes with app installations and deletions, and the number of active smartphones. Hence, EQN detect-

ability generally increases at night when more phones are charging. The rate of EQN earthquake detections was 3.1 times higher at night than during the day (Table 1). Despite this variability, in Italy where the number of app users (about 45,000) remained stable during the studied period the two largest earthquakes (M5.1 and M4.9) were both detected, as well as 4 out of 6 earthquakes between M4.5-4.9.

### *Latency of earthquake detections from a dynamic monitoring network*

The shortest earthquake detection latencies, i.e., the time difference between earthquake origin time and alert issuance, are achieved when the hypocenter is close to regions where the EQN app is popular. This explains why the median detection time was around 7-8 s in Italy and USA, where all detected earthquakes were onshore and at crustal depth (<40 km) compared to 17 s in Chile where a significant proportion of detected earthquakes were offshore and/or at intermediate depth (Table 1).

A limited comparison of earthquake detection times can be performed with ShakeAlert, the operational EEW system which aims to cover the West Coast of the USA with 1,700 seismic stations (Kohler et al. 2018; Given et al. 2018). Four earthquakes, the M7.1 Ridgecrest mainshock and 3 of its aftershocks ranging in magnitude from 3.8 to 4.5 were detected by both systems. Excluding the case of the mainshock (discussed below), EQN latencies are larger by an average 1.6 s (7.6 s versus 6.0 s averages for EQN and ShakeAlert respectively) which is rather small considering the difference in technology levels. The Ridgecrest sequence exemplifies how EQN performance can rapidly change due to sudden app adoption. This sequence started with a M6.4 foreshock 36 hours before the mainshock. The foreshock was not detected due to a lack of EQN users in California at the time. However, this foreshock led to EQN installations in sufficient number in the Los Angeles (LA) area (but not in the epicentral region) so that the mainshock was detected in LA, 200 km to the south of its epicenter. Seismic wave propagation times from epicenter to LA where it was detected explains the unusually large detection latency of 40 s (see

Table 2). In turn, the mainshock led to new EQN installations at shorter epicentral distances leading to a drop of EQN detection latency to 8 s (median times) for the 27 subsequent detected M2.7 to M4.6 aftershocks (see Table 2).

To evaluate EQN's intrinsic latency, the wave propagation time from the epicenter to the EQN's detection location is subtracted from alert issuance latency, using the most probable causative seismic phase. This gives an estimation of cumulative processing and transmission delays but is an overestimate as it implicitly assumes that acceleration (i.e., the monitored parameter) is large at seismic phase onset when in fact it usually occurs later. Therefore, the minimum and median latencies (0.5 s and 4.3 s respectively, Table 1) characterize the best detection latencies that the EQN system can offer; such fast detection is an achievement considering EQN's low investment cost.

In summary, in regions with a significant app audience, EQN detection latency with respect to origin times for crustal earthquakes is comparable (5-8 s) to latencies observed in systems such as ShakeAlert (Table 2) and, in the best-case scenario, it could be as low as a couple of seconds.

### *EQN warning times*

Warning time is defined for a given target intensity as the time delay between the publication of the alert and the S-wave arriving at the locations of the users who experience that target intensity. Hence, the larger warning time, the more time the user has to prepare for the incoming shaking. It is computed for the slower and stronger S-wave and assumes that the P-wave is imperceptible and that, from a user point of view, this is the delay between the alert issuance and the perceived tremor. It also assumes that the maximum intensity begins with the onset of S-wave.

Warning times have been computed for target intensities 4 (largely observed), 5 (strong) or 6 (slightly damaging) for all detected earthquakes worldwide greater than M4.5 in Italy and USA and greater than M5 in the rest of the world. Intensities with respect to radial distance were estimated using intensity predictive equations (IPE) according to the validity domain of the con-

sidered IPE. Region-specific IPE were used in the Western USA (Atkinson et al. 2014), and Italy (Tosi et al. 2015) for crustal earthquakes (focal depth between 0 and 40 km). For all other regions, including deeper earthquakes, the same IPE (Allen et al. 2012) was used. Since this earthquake dataset is global, for the sake of homogeneity earthquake parameters were all taken from the US Geological Survey (USGS).

According to these estimations, within the 72 detected earthquakes greater than M4.5 or M5, EQN issued early warnings for target intensity 4 for 53 (74%) earthquakes (i.e., on average twice a month) that were located in 11 countries in North, Central and South America, Europe, and Asia (Figures 3 and 4). Among these, 18 events also benefited from a warning for target intensity 5 and for two earthquakes there was a warning for target intensity 6: M6.4 November 26<sup>th</sup>, 2019, Albania and M6.2 July 26<sup>th</sup>, 2019, Panama. As expected, for a given target intensity, warning times increased with increasing magnitude and for a given earthquake, they decreased with increasing target intensities. For earthquakes greater than M6, estimated warning times were typically more than 10 s for target intensity 4 and more than 5 s for target intensity 5 (see Figure 3), long enough for the user to take protective measures.

The warning time for target intensity 6 for the Panama earthquake was too short for individual protective action. However, for the Albania earthquake, which struck at night and killed 51 people, a warning time of 6.9 s for intensity 6 has been estimated through the IPE, for a detection delay of 5.1 s after its occurrence, and the location of the detection 20 km from its epicenter. According to the IPE, the isoseismal for intensity 6 was 34 km from the epicenter compared to 45 km from the empirical intensity-distance curve derived from about 4,000 eyewitnesses' reports crowdsourced for this event (Bossu et al. 2020). This implies that the warning times derived from the IPE is likely underestimated by about 2 s for intensity 6 leading to a warning time for “slightly damaging” shaking exceeding 8 s. Based on the spatial distribution of EQN users at the time of the earthquake, assuming 100% delivery success, and neglecting the transmission delay of the alert, we estimate that 1,005 of them received the early warning for intensity 6, 231 for intensity 5 and 632 for intensity 4. With approximately 800,000 inhabitants within 40 km of

the epicenter, the proportion of warned individuals remains small in this case. Still, it proves that EQN can offer significant warning time for damaging shaking levels and so has the potential to lower individual seismic risk for its users.

*Do EQN users take protective actions after a warning?*

The reaction to, and understanding of, early warning has been assessed by an online survey of EQN users in the felt area of the M8 26<sup>th</sup> May 2019 Peru earthquake in order to evaluate EQN's efficiency at individual risk reduction. This earthquake had a focal depth of 120 km and generated two EQN detections, one in Peru and one in Ecuador. Alerts were issued for 599 users for intensity 5 and 54,228 for intensity 4, respectively.

There were 61,863 users within 1,500 km of the epicenter, a distance where USGS and EMSC estimate the intensity felt was between 3 and 4. 2,625 self-selected over 18 years old participants responded to the questionnaire; over  $\frac{2}{3}$  of them declared to be between 500 to 1,000 km from the epicenter at the time of the earthquake, a range containing the capital cities of Quito and Lima. Most respondents (82%) declared previous earthquake experiences and 25% answered that they had experienced an EQN earthquake early warning before. 72% were convinced or strongly convinced of the usefulness of the app which confirms previous studies about public expectations for EEWs (e.g., Becker et al. 2021). Among these 2,625 self-selected respondents, 1,663 had the app at the time of the earthquake, while the others installed it following the earthquake. Those who already had the app described various experiences: 34% received EQN notification before feeling the shaking as expected from a PEEW system, 35% received it after having felt the shaking, 11% received the notification but did not feel the quake, 14% did not receive the notification while feeling the shaking, and 6% neither received the notification nor felt the quake.

Importantly, among the users who received the notification before feeling the shaking, 79% understood that a tremor was about to hit. This means they had a good comprehension of what an early warning is but when asked about their reaction (Table 3), only 25% performed “drop, cover and hold”. A major concern was to warn relatives nearby (55%) or for the ones not in imme-

diate proximity through social media (22%). Additionally, 35% waited for the shaking. These results are consistent with findings from Nakayachi et al. 2019, who showed that following an EEW in Japan, people mentally prepared rather than took actual safety actions.

This single study based on self-selected participants and on a single case confirms that a low-cost smartphone based PEEW system can offer an actual early warning to some users even if the alert dissemination delay is unknown and may differ from one user to the next. Despite the lack of information about the magnitude and some users experiencing what they perceived as false alerts (namely alerts for real earthquakes which, however, are not felt at the user location), levels of satisfaction and trust are still high. In fact, the survey showed that 82% of users would appreciate being informed about an incoming earthquake, even if it did not reach damaging levels of intensity. However, in its current setting, and although the meaning of the notification is often understood, it only leads to adequate protective actions in a minority of cases, possibly because it does not answer an expressed priority need, which is to inform loved ones who may not have the app. The fact that EQN is appreciated by most of its users suggests that, despite EQN's inability to systematically guarantee an early warning or estimate an event's magnitude, such a service combining early warning and rapid detection of felt earthquakes is valued by its users and constitutes a progress in public earthquake information.

## **Discussion**

The EQN initiative exploits smartphone ubiquity to create an operational network that provides an early warning service to its users. This service differs from conventional services as EQN's alerting strategy is not based on predicted intensity, which in some ways simplifies the service behavior. Indeed, even when earthquake source parameters (magnitude and location) are accurately determined, ground motion variability means that a conventional service sometimes has users receive an undue alert because the predicted intensity is overestimated or, more commonly, has users not receive the expected alert because of underestimation of the intensity (Minson

et al. 2019). Instead, EQN provides both PEEW and rapid information (preliminary epicenter and time of the event) for small magnitude felt earthquakes for which no early warning is possible, which, as shown by user survey, is valued by users. It is noteworthy that following the Ridgecrest earthquake, ShakeAlert users' complaints of not having received an alert for felt shaking led to a lowering of the target intensity to 3. Considering above mentioned limitations, this leads to an actual ShakeAlert service not far from the one offered by EQN (Cochran and Husker 2019). In Mexico, extending early warning services to also offer rapid public information for felt earthquakes seems to be an appreciated feature, with an alert being considered as false only if an earthquake did not actually occur (Allen et al. 2018). In addition, following feedback from Mexico's users, it was proposed that PEEW messages do not include intensity because it is often confused with magnitude and may create difficulties with interpretation and hamper decisions to take protective actions (Allen et al. 2018). The EQN users' survey, which also took place in Latin America, presents further support for these findings, though EQN, like any app, is based on self-selective participation and its users' feedback may not be a representative sample of the opinion of a global audience. As the evidence implies that the lack of intensity prediction is not a major impediment, it can be concluded that EQN's early warning and rapid information services are a significant improvement from existing rapid public information systems for seismically active regions of the globe not yet covered by conventional PEEWs.

## **Data and Resources**

Datasets analyzed in this article are available through GFZ Data Services at the following links.

Steed, R., R. Bossu, F. Finazzi, I. Bondár and L. Fallou (2021). Analysis of Detections by the Earthquake Network App between 2017-12-15 and 2020-01-31. V. 0.9. GFZ Data Services.

<https://doi.org/10.5880/fidgeo.2021.007>

Steed, R., R. Bossu, F. Finazzi, I. Bondár and L. Fallou. Analysis of Strong Motion Waveforms Near the Locations of Detections by the Earthquake Network App in Chile, the USA and Italy. V. 0.9. GFZ Data Services (2021). <https://doi.org/10.5880/fidgeo.2021.002>

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### **Declaration of Competing Interests**

The authors declare no competing interests.

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## Tables

**Table 1.** Summary statistics of earthquake detections. Associated detections are the number of EQN detections for which it was possible to identify the causative earthquake. The accelerometric record column gives the number of detections for which accelerometric data is available within 20 km of the detection location. Detection delays of the EQN system were computed with respect to the earthquake origin time and the theoretical arrival time of the most likely causative seismic phase. False detection rate is the ratio between the number of false detections and the total number of detections while the nighttime/daytime ratio is computed considering that day (7:00 a.m. - 10:59 p.m.) lasts twice the night. CSN: Centro Sismologico Nacional, Chile. INGV: Istituto Nazionale Geologia e Vulcanologia, Italy. USGS: United States Geological Survey.

Country	Chile	USA	Italy	Total
<b>Detections</b>	458	70	22	550
<b>Detections associated with known earthquakes</b>	449	70	20	539
<b>Available accelerometric records</b>	328	69	13	410
<b>Magnitude (min; max)</b>	1.4; 7.1	2.2; 7.1	2.4; 5.1	1.4; 7.1
<b>System detection delay w.r.t. origin time (min; median; max in s)</b>	4.8; 17.2; 209.0	4.3; 8.1; 42.5	3.4; 7.3; 11.0	3.4; 15.4; 209.0
<b>System detection delay w.r.t. passing of triggering seismic wave (min; median; max in s)</b>	0.5; 4.3; 12.1	2.0; 4.6; 10.2	1.8; 4.5; 5.9	0.5; 4.3; 12.1

<b>False detection rate (%)</b>	2.0	0.0	9.1	2.0
<b>Nighttime/daytime ratio</b>	2.7	11.3	8.0	3.1
<b>Source of catalogue</b>	CSN	USGS	INGV	

**Table 2.** Detection latencies for the 4 earthquakes detected by both ShakeAlert and EQN. These 4 earthquakes were detected in California and they followed the M7.1 Ridgecrest mainshock. ShakeAlert detection times were retrieved from Chung et al. (2020) for the M7.1 Ridgecrest earthquake in California and from <http://earthquake.usgs.gov> for the others.

<b>Magnitude</b>	<b>Origin time</b>	<b>ShakeAlert detection delay (s)</b>	<b>EQN detection delay (s)</b>	<b>EQN detection distance (km)</b>
7.1	July 6 <sup>th</sup> , 2019 03:19:53.04	6.9	40.0	188
4.5	October 15 <sup>th</sup> , 2019 05:33:42.81	5.6	7.2	3
3.8	December 5 <sup>th</sup> , 2019 08:55:31.65	5.7	5.4	10
3.9	December 12 <sup>th</sup> , 2019 08:24:32.6	6.8	10.4	20

**Table 3.** The summary of responses to question 16 in the online survey of EQN users that was carried out in Peru following the May 26<sup>th</sup>, 2019, M8 Peruvian earthquake. Participants were allowed to give multiple answers.

<b>Q16. What did you do when you received the notification?</b>	
I warned my relatives physically present with me	54.6%
I waited for the first vibrations of the earthquake	35.4%
I went to a safe place in my house (under a table, etc.) dropped, covered and hold on	25.0%
I warned my relatives through social media, SMS, etc.	22.1%

I ran outside	9.6%
Nothing	2.8%
Other	2.8%
Base: users who received the notification and felt the earthquake afterwards (n=571). Several answers possible.	

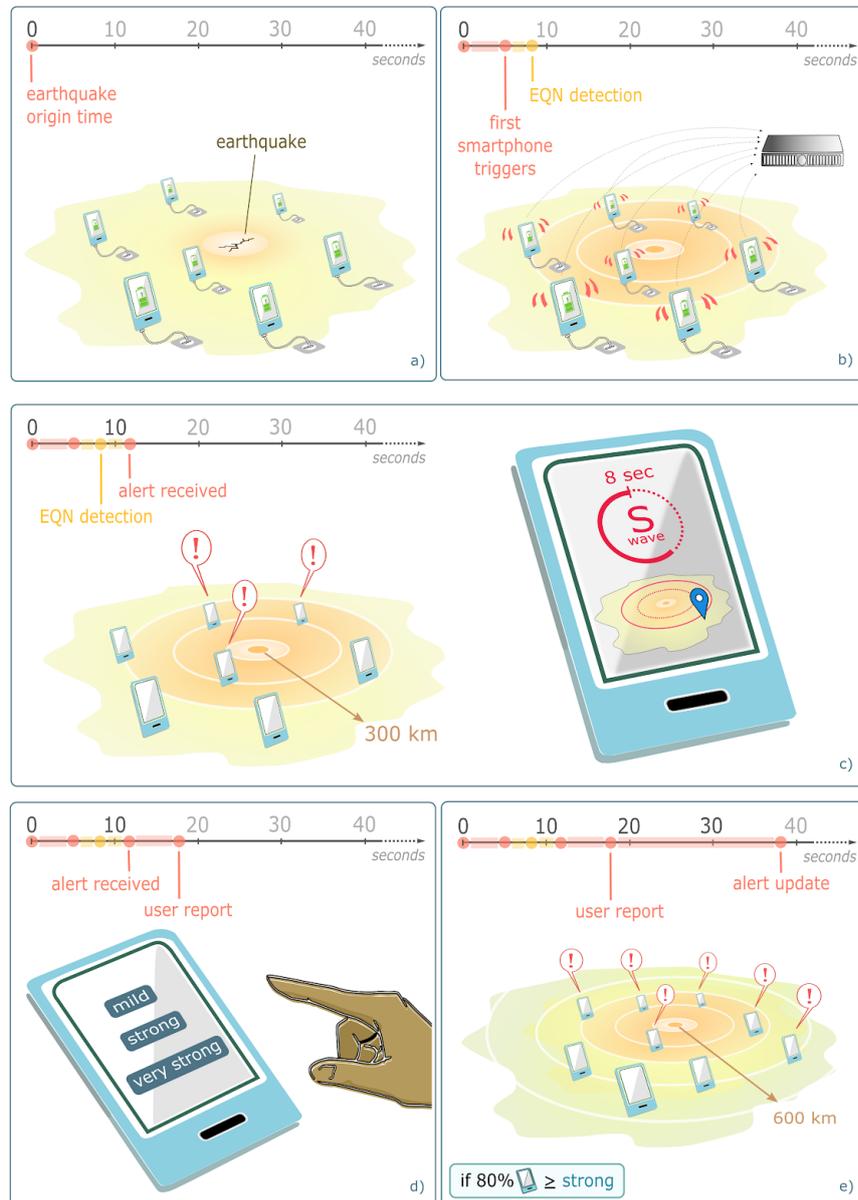
### List of figure captions

**Figure 1.** The EQN app turns a charging smartphone into a ground motion detector. Earthquakes are detected through a cluster of smartphone triggers. Once detected, an alert is issued to all users within a default distance of the detection and a countdown of the estimated S-wave arrival time is displayed at the user’s location. Users can qualitatively report the level of shaking if they choose to, with 3 levels (Finazzi 2020a). This is intended to identify larger earthquakes as EQN does not provide magnitude estimates. If at least 10% of the users in the area of detection submit reports and 80% of these reports are “strong” or “very strong”, a second alert is issued –typically 30 s after the first one– to users in an enlarged region (600 km by default). Users can opt in or out of the two alerts and customize alerting distances.

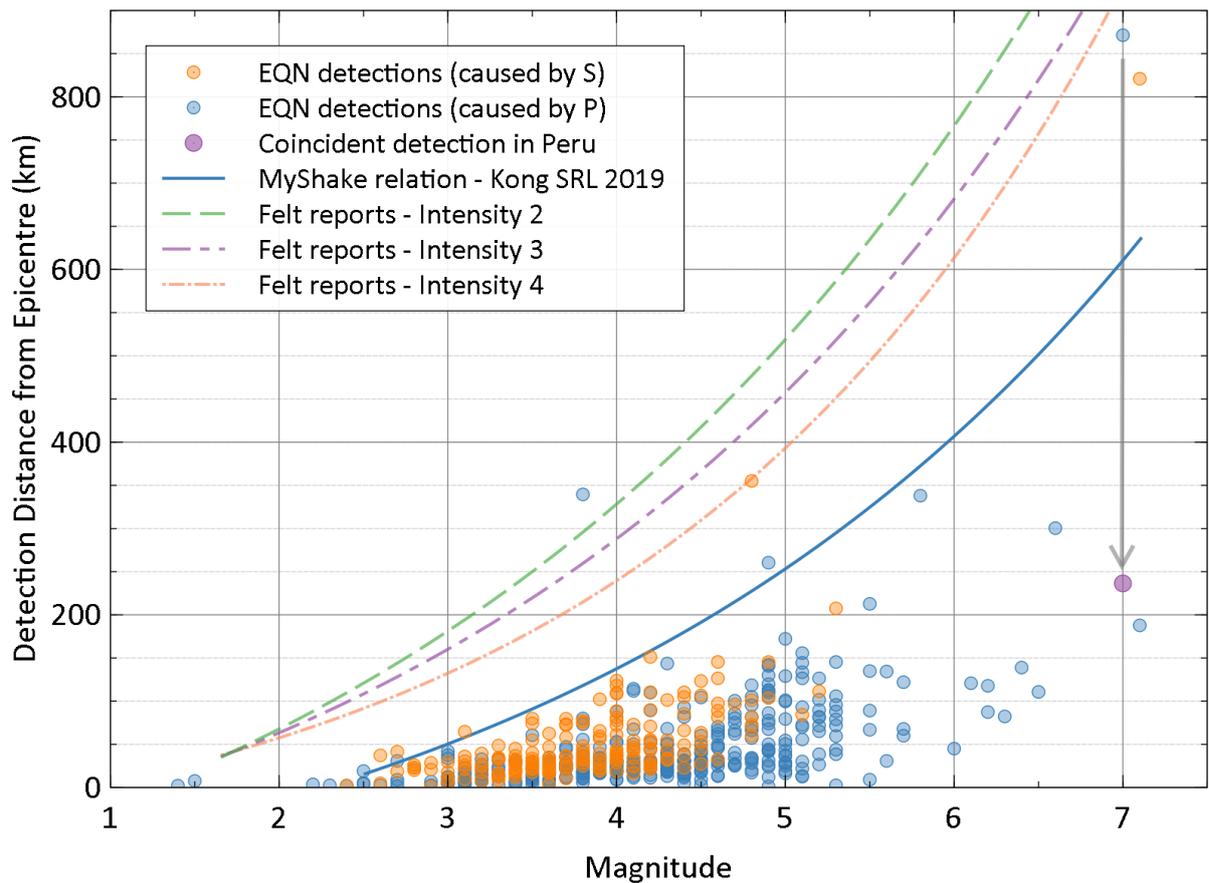
**Figure 2.** Distance between the location of the detection and the epicenter for 539 EQN associated detections as a function of magnitude. Blue and orange dots represent detections likely caused by P and S waves, respectively (although the causative seismic phase is uncertain for epicentral distances below about 50 km). One M7 earthquake detected at more than 800 km epicentral distance was also detected in Peru at about 250 km epicentral distance (arrow and purple dot); a rare example of a duplicate detection. For comparison, the blue curve approximates the maximum distance to which smartphones operating MyShake app can detect earthquakes (Kong et al. 2019) while the 3 dashed lines approximate the 90% radial distance quantile of user-assigned intensities 2 (scarcely felt), 3 (weak) and 4 (largely observed) (based on the 1,528 global earthquakes between 2011 and end of October 2020 with at least 100 felt reports collected by the European-Mediterranean Seismological Center (EMSC)).

**Figure 3.** Estimated warning times for the 53 earthquakes detected worldwide with magnitude equal or greater than 4.5 with positive warning time. Blue, green, and yellow triangles depict warning times for target intensities 4, 5, and 6, respectively. Crustal and deep earthquakes are shown by triangles and inverted triangles, respectively. Warning times related to the same event are connected by red lines. For sake of clarity, magnitude is altered by a random shift of +/- (0.03, 0.06) for earthquakes sharing the same magnitude.

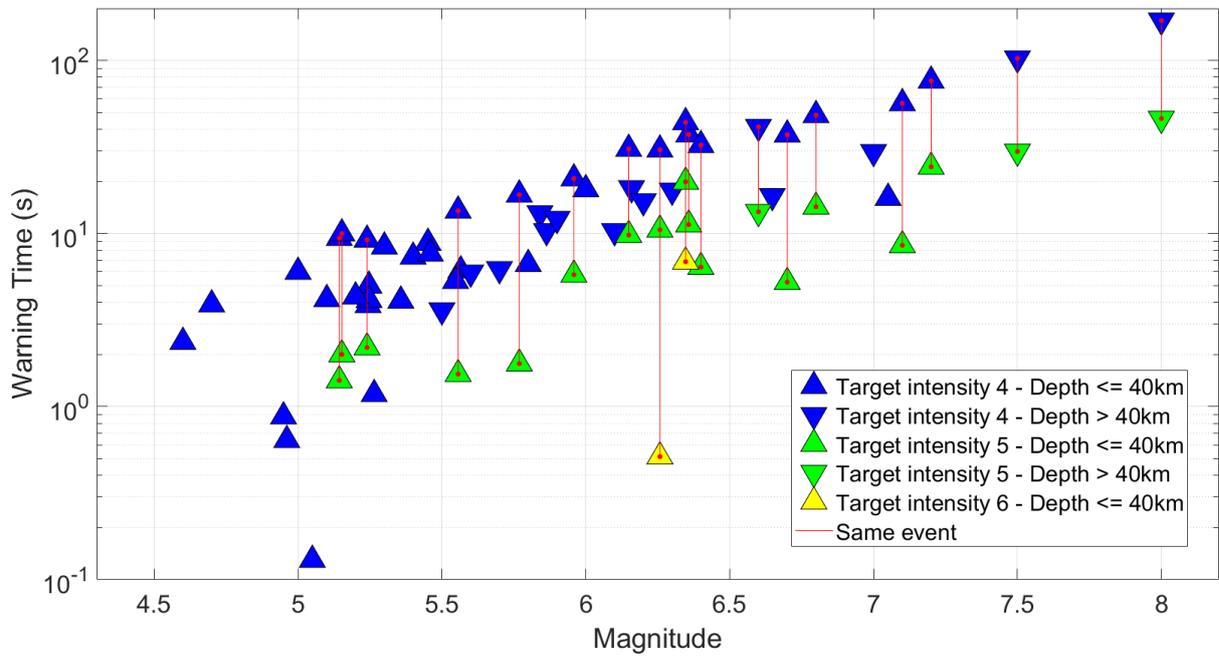
**Figure 4.** Geographical distribution of the 53 earthquakes for which a positive warning time is determined, shown as triangles (see Figure 3 for legend). All other EQN detected earthquakes of magnitude M4.5 or above are represented by circles - in red when the maximum onshore intensity reached or exceeded intensity 4 (for which an EEW is theoretically possible) and in grey otherwise. The number of EEW in the legends indicates the number of positive warning times at intensity 4.



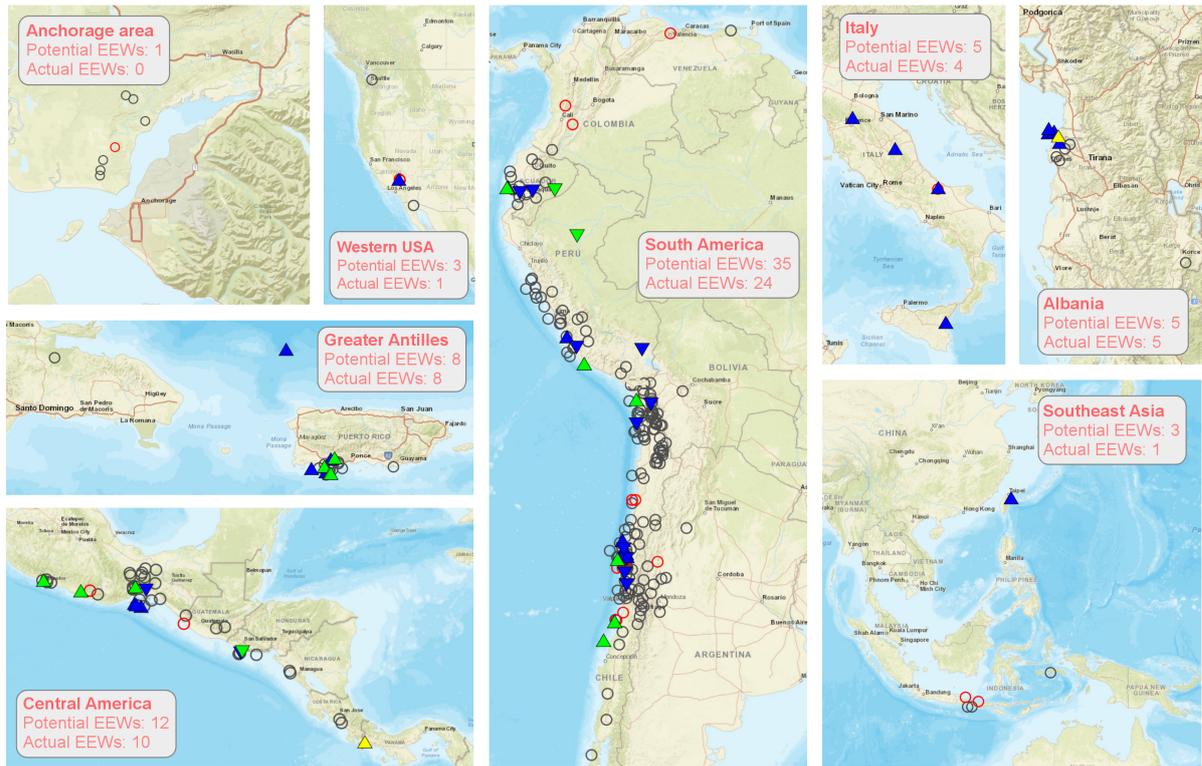
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## Appendices

### *Datasets used in analysis*

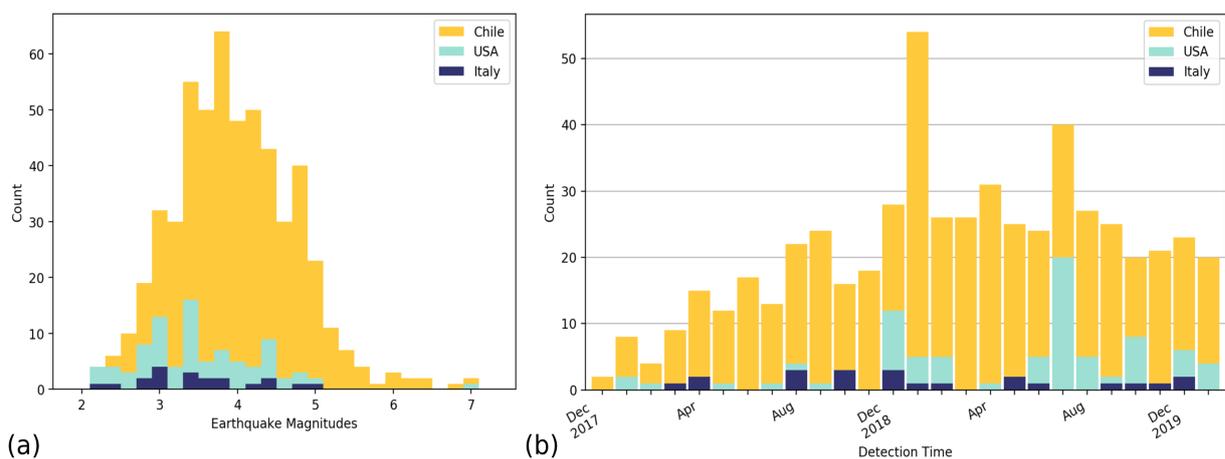
Datasets were constructed from the events detected by the Earthquake Network (EQN) app between December 15<sup>th</sup>, 2017, and January 31<sup>st</sup>, 2020. This time range was chosen so that EQN's detection procedures would be stable during the entire period. There were 1,792 detections during this period in 19 countries. In order to perform quantitative analysis, 2 sub-datasets were extracted from this global dataset. These datasets are available as externally hosted supplementary material as Data S1 and Data S2 (see Steed et al. 2021a in Data and Resources section).

Data S1 is composed of 550 detections for examining the speed and location accuracy of EQN. Among the countries with a strong user base for the app, we chose to analyze the events in Chile, USA, and Italy due to the accuracy and completeness of their catalogues. Importantly, all three regions operate dense seismological station networks that are able to produce accurate event locations and magnitude estimates. An epicentral location inaccuracy of 15 km translates to a seismic phase arrival time change of 2-3 s which can become important in the case of EQN due to its rapid response times. All 3 regions also have dense accelerometer networks whose records were used to validate the EQN triggers. The USGS (USA) and INGV (Italy) catalogues of earthquake parameters were searched via FDSN requests while the CSN (Chile) catalogue was provided upon request. Calculations of the P and S seismic phases used the ak135 model and were carried out by the obspy Python library (see following sections for other calculation of other fields). The distributions of Data S1 with respect to magnitude and detection date are depicted in Figure A1.

Data S2 was used for an analysis of EQN's early warning performance and consists of moderate to large magnitude earthquakes from around the world that were detected by EQN. This analysis employed intensity predictive equations (IPE) to estimate the intensities felt in regions that were warned of imminent shaking by the EQN app. The IPE equations' validities limited the analysis to earthquakes  $\geq M5$  in most of the world and  $\geq M4.5$  in Italy and USA (the equations are pre-

sented in the section *Calculation of Shaking Intensities*). The dataset is composed of 168 earthquakes and has 68 detections in common with Data S1. The main results from analysis of Data S2 can be seen in Figures 3 and 4. All of the earthquake parameters were obtained from the USGS catalogue for consistency.

There were also 3 earthquakes that were detected twice by EQN, normally such duplicate detections are suppressed automatically but all 3 earthquakes were large magnitude events (M7.0, M7.5 and M8.0) that led to EQN making detections at distances far from the epicenters. These 3 duplicate detections have been removed from the dataset for clarity.

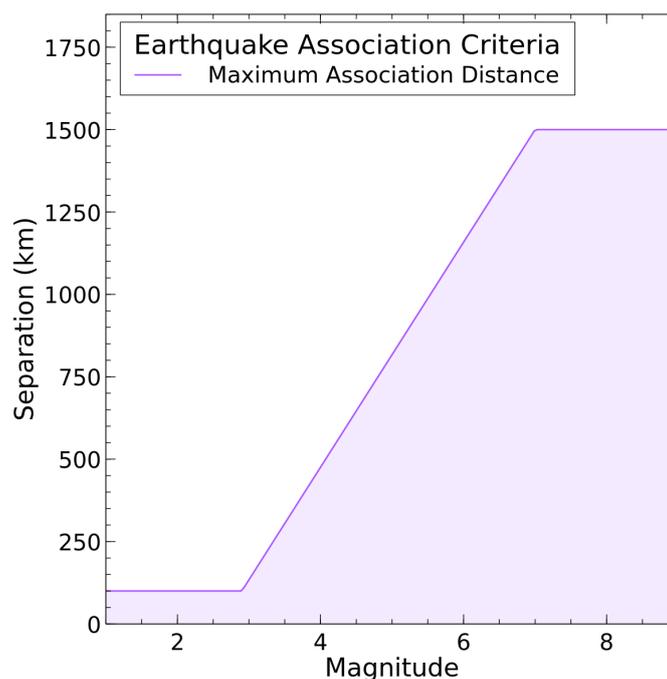


**Figure A1.** (a) This stacked histogram shows that EQN detected earthquakes over a range of magnitudes in Chile, USA, and Italy. 539 out of the 550 EQN detections studied were associated with earthquakes with published parameters. (b) A stacked histogram of the number of EQN detections per month in Chile, USA, and Italy. A growth in the number of detections can be seen for Chile and the USA over this period.

#### *Association of Detections with Earthquakes*

For the purposes of the analysis, it is important to associate each EQN detection with earthquakes parameters held in an institute’s catalogues of events. The following procedure was used for association:

1. Earthquakes were selected from the catalogue from 250 s before the time of the detection until 4 s afterwards.
2. Earthquakes were selected that are also within the association distance defined by each earthquake's magnitude (see Figure A2).
3. For each earthquake, the arrival time of the P waves at the EQN detection location was estimated using the ak135 model's speed of 8.04 km/s. The events whose P waves arrive within 90 s before the EQN detection and 10 s after the detection were chosen.
4. If multiple earthquakes remained in the selection, then the earthquake of the largest magnitude was chosen as the associated earthquake.



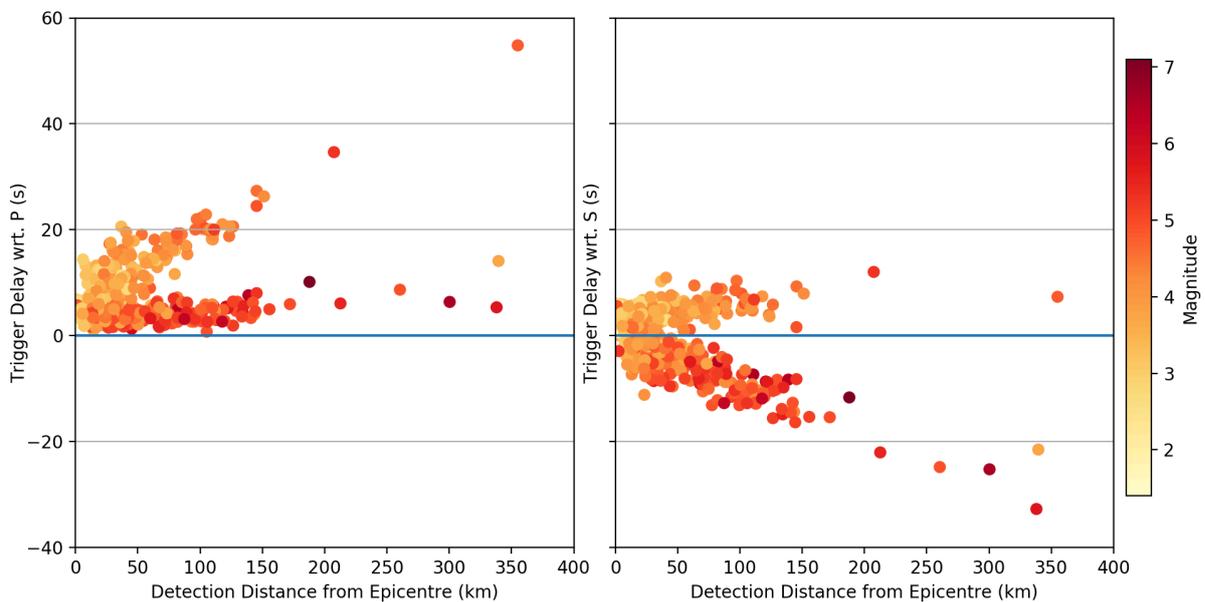
**Figure A2.** Association between an earthquake and EQN detection is allowed only if the separation between the epicenter and the EQN detection location is less than a threshold distance dependent upon the earthquake's magnitude as shown above.

### *Causal Seismic Phase of EQN detections*

It has been found that EQN detections can be triggered by either P or S seismic phases (see Figure 7). The EQN detections were split heuristically into being caused by P or S phases using the criteria:

*Caused by S if: (detection delay w.r.t. S > 0 s) & (detection delay w.r.t. P > 6 s). (A1)*

Note that distinguishing between P and S phases is less clear within 50 km of the epicenter since both arrive within a short interval of time. In addition, the EQN detections are triggered by strong motion due to the relative insensitivity of the smartphone accelerometers and the P/S phase arrival does not exactly coincide with the onset of motion strong enough to cause a detection.



**Figure A3.** Determination of whether EQN detections follow the P or S seismic phase using Data S1. The arrival of the P and S phases at the detection location were calculated using the ak135 model and the latency between each phase arrival and the detection time is plotted against separation between the detection location and the epicenter. It can be seen that detections closely

follow the passing of either the P or S phases and that EQN tends to detect larger magnitude earthquakes using the P wave.

### *Calculation of Shaking Intensities*

Intensity predictive equations (IPE) were used to create the columns in the datasets (Data S1 and S2) and for the analysis of early warning times presented in the article. An IPE predicts the total felt intensity of shaking with respect to hypocentral distance for a given magnitude of earthquake. For a given delay from the origin time of an earthquake, the distance of the S phase from the epicenter can be calculated using the ak135 model and the intensity of shaking for this distance can then be calculated using the IPE. Alternatively, the distance at which the intensity reaches a certain value can be found and then the time at which the S phase passes this distance can be calculated in order to estimate whether there would be time for a warning to be given to people at this intensity.

To convert between epicentral and hypocentral distance the following equation was adopted:

$$r^2 = d^2 + 4R(R - d)\sin^2\left(\frac{s}{2R}\right), \quad (A2)$$

where  $r$  is the hypocentral distance,  $d$  is the hypocentral depth,  $R$  is the Earth's radius and  $s$  is the epicentral distance.

For most earthquakes, the IPE from Allen et al. (2012) were used, this formula is only valid for magnitudes  $>M5$  and so we restricted the analysis accordingly:

$$Intensity = \begin{cases} 2.085 + 1.428M + 1.402\ln\sqrt{r^2 + R_m^2}, & r < 50 \text{ km} \\ 2.085 + 1.428M + 1.402\ln\sqrt{r^2 + R_m^2} + 0.078\ln\frac{r}{50}, & r \geq 50 \text{ km} \end{cases} \quad (A3)$$

where  $M$  is the earthquake magnitude and:

$$R_m = -0.209 + 2.042 \exp(M - 5). \quad (\text{A4})$$

For the Italian earthquakes, the IPE from Tosi et al. (2015) was employed for crustal earthquakes (focal depth between 0 and 40 km):

$$\text{Intensity} = -2.15 \log_{10} r + 1.03M + 2.31. \quad (\text{A5})$$

For the western USA, the IPE from Atkinson et al. (2014) was used:

$$\begin{aligned} \text{Intensity} = & 0.309 + 1.864M - 1.672 \log_{10} \sqrt{r^2 + 14^2} - 0.00219 \sqrt{r^2 + 14^2} + \\ & 1.77 \max\left(0, \log_{10} \frac{r}{50}\right) - 0.383M \log_{10} \sqrt{r^2 + 14^2}. \quad (\text{A6}) \end{aligned}$$

### *Comparisons with Strong Motion Waveforms*

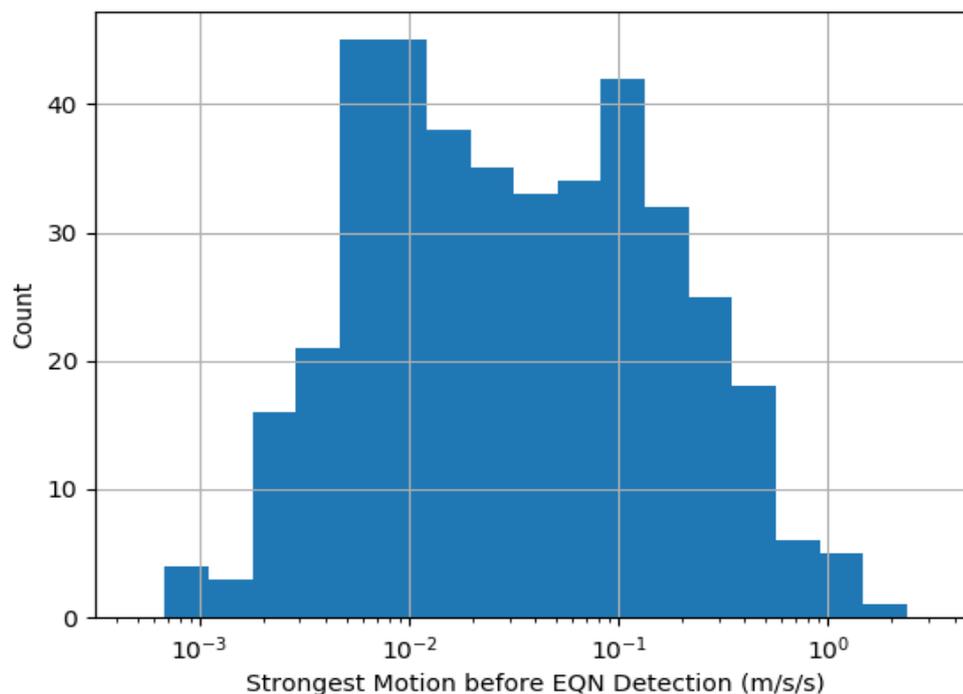
For Data S1 (detections in Chile, USA, and Italy), a search was made using the FDSN protocol for accelerometer station waveforms within 20 km of each EQN detection. The waveforms were detrended, calibrated as acceleration measurements and bandpass filtered between 0.5-12 Hz. The waveform was also shifted in time to account for the difference in radial distance for the EQN detection location and the strong motion station with respect to the epicenter of the earthquake. The shift crudely assumed a P-wave velocity of 8 km/s and the time shift was less than 1s in the majority of cases. The correction ensured that there was no confusion in causality for the analysis whereby the EQN detection occurred before the strong motion arrived.

Accelerometric data was found for 410 of the 550 detections in Data S1. The analysis demonstrated a strong correlation between strong motion and the EQN detections as would be expected and that it was also found that even small accelerations were able to cause EQN triggers (see Figure A4). The analysis also corroborated that the detections can be triggered by both P and S seismic phases (see also Figure A3 which shows this through a timing analysis) although it

should be remembered that the strong motion necessary to cause triggers might follow a few seconds after the passing wavefront.

### *Survey of Peruvian EQN users following the M8 earthquake in Peru on 26<sup>th</sup> May 2019*

The survey was carried out from July 23<sup>rd</sup> to August 19<sup>th</sup>, 2019. It was initiated through a message sent for technical reasons to all Spanish language users of the EQN app, linking to an online questionnaire in Spanish (using google forms). The questionnaire was designed based on the existing literature (Lindell and Perry 2021; Wood et al. 2018; Nakayachi et al. 2019) and two preliminary interviews with Peruvian EQN users. The questions aimed to assess expectations for EEW, understanding of the EQN warnings, and reactions to the warnings and to false or late alerts. It included both open-ended questions and Likert scales and took about 8 minutes to complete. In compliance with the European GDPR, no private data was collected, and explicit consent was obtained for data collection from participants. The original version and an English translation of the questionnaire can be found in an external electronic supplement along with the results of the survey. In addition, this survey will be discussed in more depth in a separate article.



**Figure A4.** Histogram of the strongest acceleration found in the closest strong motion recording for each EQN detection in the 30 s period before detection. The results are only approximate since the level of shaking can significantly vary even over a distance of 10-20 km (Ancheta et al. 2011).

## **7. Annexe 3: Fallou et al. 2021**

# **Efficacy and usefulness of an independent Public Earthquake Early Warning system. A case study: The Earthquake Network initiative in Peru**

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## **Declaration of Competing Interests**

The authors declare no competing interests.

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**Abstract:**

Public Earthquake Early Warning (PEEW) systems are intended to reduce individual risk by warning people ahead of shaking and allowing them to take protective action. Yet very few studies have assessed their actual efficacy from a risk reduction perspective. Moreover, according to these studies a majority of people do not undertake safety actions when receiving the warning. The spectrum of PEEW systems has expanded, with a greater diversity of actors (from citizens to private companies), increased independence from national authorities, and greater internationality. Beyond differences in warning and messaging strategies, systems' characteristics may impact the way the public perceive, trust, understand and respond to these warnings, which in turn will influence PEEW systems' efficacy and perceived usefulness, enhancing the need for additional research.

We take the example of Earthquake Network (EQN), an independent, voluntary, community-based and free system that offers a PEEW service. Through a quantitative survey (n=2,625) we studied users' perception and reaction to a warning sent related to a M8.0 earthquake in Peru (where no national system existed). We observed that even though only a minority of users actually took protective action, the system was appreciated and perceived as useful by the majority, as it enabled mental preparation before the shaking. We found evidence for a tolerance for perceived late, missed and false alerts. However, because it is a voluntary and independent system, the social dimension of the warning was incomplete as only a fringe of the population benefited from the warning. Therefore, many users' first reaction was to warn their relatives. We discuss the need for partnerships between PEEW operators and national authorities to guarantee universal access to the service and maximize PEEW efficacy.

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## Introduction

Public Earthquake Early Warning (PEEW) systems aim at rapidly detecting earthquakes and informing the public of incoming S-waves' shaking that they are about to feel. The hope is to reduce seismic risk by giving the public a valuable window (from few to dozens of seconds) to get to safety. PEEW could reduce the number of injuries from earthquakes by more than 50% if everyone received warnings and took protective action (Strauss and Allen, 2016).

Over the last decade, PEEW systems have notably been set up at local or national levels in Japan, Taiwan, Mexico, South Korea and the USA (Cremen and Galasso, 2020). PEEW have become a public expectation in many regions where earthquake risk is significant (Becker et al., 2020; Dallo and Marti, 2021). Yet, their development is hampered by the implementation and operating costs of such systems (Strauss and Allen, 2016).

From a risk management perspective, PEEWS are considered effective if they contribute to risk reduction and prevent casualties. The technical performance and current limitations of PEEW systems have been extensively assessed (Allen and Melgar, 2019; Minson et al., 2019; Cremen and Galasso, 2020). However, their efficacy in terms of individual risk reduction also depends on social and cultural components. People need to receive, understand, trust and act upon the warnings (Reddy, 2016; Wald and Eeri, 2020). Therefore, a burgeoning series of theoretical and prospective works have explored the importance of both alerting and messaging strategies. Previous literature focuses on alert thresholds, tolerance for missed and false alerts and how systems should be explained beforehand to manage expectations (Cochran et al., 2018; Allen and Melgar, 2019; Becker et al., 2020). When it comes to messaging, the format, design and content of the message matter (Allen and Melgar, 2019; Sutton et al., 2020). Warnings should be user-centered, considering *inter alia* cultural context, technology access, spoken languages, literacy and preparedness level (Basher, 2006). In the end, beyond technical performances, the primary criterion to assess PEEWS efficacy, remains whether people take protective action or not.

Still, there are only a handful of studies on how people actually react to PEEW. Empirical studies were conducted after earthquakes in Mexico and Japan (Hoshiba, 2014; Allen et al., 2018; Nakayachi et al., 2019) and in all cases, most of the respondents had not taken a protective action following the warning. However, in the Japanese case, citizens still perceived the service useful, as they were able to mentally prepare for the shaking (Nakayachi et al., 2019).

Three salient points emerge from the existing research. First, warning response behaviors are not always rational and depend on social and psychological factors (Mileti, 1999; Wood, 2018). Risk culture, preparedness level, training (Paton, 2008) and situational parameters such as warning time and feasibility (i.e. having a table nearby, being able to move...) are at play (Allen et al., 2018; McBride et al., 2019). Secondly, PEEW systems are appreciated by users, even though they are not always effective or optimum in terms of individual risk reduction. So not only efficacy but also perceived usefulness should be taken into account. Finally, more empirical sociological studies are needed, since intended behaviors may vary from actual ones (Nakayachi et al., 2019).

Empirical studies become even more important as a diversity of actors is entering the PEEW field. Private companies such as Grillo, SASMEX and Skyalert are already operating in Mexico (Allen et al., 2018), and Google has announced a new service for Android users (Stogaitis, 2020). Citizens are also becoming a key part in the emerging PEEW system in Aotearoa New Zealand (Tan et al., 2021). They are already deeply involved with Earthquake Network (EQN), the first demonstrated, voluntary and smartphone-based PEEW system (Bossu et al., 2021). Smartphones are also used in fixed locations in the new ASTUTI PEEW network in Costa Rica (Brooks et al., 2021). Many of these initiatives are not coordinated with national authorities and can function regardless of borders. Beyond differences in warning and messaging strategies, the multiplication of independent actors and different systems' characteristics may impact the way the public perceive, consider, trust, understand and respond to these warnings, which in turn will influence PEEW systems' efficacy and perceived usefulness.

This paper intends to explore how PEEW systems' characteristics influence public perception and response to warnings. We're doing it through an empiric case study approach, focusing on one specific and independent PEEW system: EQN. By analysing the results of a questionnaire (n=2,625) sent to EQN users following a warning issued for a M8.0 earthquake that hit Peru in 2019, we assess how the system's characteristics affected users' perceptions and responses to the warning. This piece of research complements a previous paper (Bossu et al., 2021) which focused on EQN's technical performance and showed that despite a good understanding of the warning, only 25% of respondents took protective action.

We start with briefly describing the EQN PEEW system's main characteristics and the general context. After describing the methodology and main results, we discuss how the system's characteristics impacted users' perceptions of and reactions to the warning. We also debate actors'

complementary roles and how partnership with national authorities could increase the system's efficacy. Finally we suggest avenues for future research.

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## **Elements of context: EQN warnings and the M8.0 earthquake in Peru**

The EQN initiative offers a crowdsourced PEEW service based on a dynamic smartphone network and that is accessible through an app. The system uses charging smartphones' accelerometers to detect, in real-time, the shaking induced by an earthquake (Finazzi and Fassò, 2015). Once an earthquake is detected, the app issues a warning and sends it to all smartphones with the app in the area (Figure 1). If not too close to the detection point, users may then receive a warning in advance of the seismic wave that causes the shaking, and thus benefit from an earthquake early warning (EEW) (Finazzi, 2016; Bossu et al., 2021). The EQN app is free to download, available in eight languages and can be run all over the globe. EQN also enables users to manually report earthquakes that they feel and chat with others (Finazzi, 2020).

Contrarily to national PEEW systems, EQN is a voluntary, community-based and independent PEEW system. This implies that (1) users have to download the app to receive the alerts; (2) the more users there are, the more efficient the system; (3) the system is not supported by national authorities; and (4) alerts can only be sent to people who have downloaded the app. To benefit from the service, people must then own a smartphone, speak one of the eight languages of the app, have an internet access, have heard about the app and downloaded it.

The warning sent by EQN is designed to be very simple and contains only the most relevant information. It includes a countdown to the shaking, a visual representation (map), and the user's distance from the detection point (Figure1). Additionally, the warning comes with a loud alarm sound. No information on the expected intensity, earthquake magnitude or safety tips are part of the warning message. The app sends alerts for felt earthquakes that can be received by users who will not feel the earthquake, which is especially true for small magnitude earthquakes (Bossu et al., 2021). The warning is sent in the language chosen by the user. They can modify warning distance and generate test warnings to be better prepared.

We analyzed users' reaction to a warning sent by EQN on May 26<sup>th</sup> 2019 when a M8.0 earthquake hit Northern Peru at 02:41 a.m. local time, with a focal depth of 120km. It was largely felt 1,000km from the epicenter and more sporadically up to 2,000 km from the epicenter, a felt area that covers several nearby countries, including Colombia, Ecuador and Bolivia. Two people

died and about 30 were injured. The warning was sent to more than 54,000 EQN users over the felt area. At the time, EQN was already very popular (33k users) in Peru, where no official PEEW system existed. After the M8 earthquake, EQN's PEEW system benefited from media and social media coverage in Peru.

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## Methodology

This paper is based on a quantitative survey; the questionnaire was designed after a literature review and two exploratory interviews. The literature included theoretical and practical research focusing on people's behavioral response to warnings (Mileti, 1999; Lindell and Perry, 2012; Wein et al., 2016; Wood et al., 2018; Nakayachi et al., 2019). Interviews were conducted with two EQN users in Peru who were both very active in the chat forum, one of them being also a popular seismology amateur. They enabled us to collect qualitative information about the local earthquake culture, EQN perception and PEEW experience in Peru.

The questionnaire aimed at: (i) assessing users' expectations for PEEW, (ii) estimating the perceived experience of successful, late, missed and false warning, (iii) assessing warning understanding, (iv) collecting reactions to the warning, (v) rating tolerance for missed and false warnings and (vi) collecting feedback and improvements. It was designed with respect to the European GDPR regarding data privacy issues (European Commission, 2016) and launched online through Google Forms, in Spanish.

The questionnaire targeted EQN users who were in the felt area region at the time of the earthquake. An invitation to fill in the questionnaire was sent to all EQN users using the app in Spanish through a pop-up message that users could see when opening the app. Explicit consent was collected for each respondent. Data was collected between 23/07/2019 and the 19/08/2019, two months after the earthquake. During the data collection period no early warning was issued in the area. The dataset was analysed with basic descriptive statistics and contingency tables made with Excel, available in the appendices A1 to A6..

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## Dataset and limitations

A total of 2,625 EQN users who were 18+ and in the felt area at the time of the earthquake responded to the questionnaire, 77% of them were in Peru, 19% in Ecuador, 3% in Columbia and the remaining others were in Venezuela or Brazil. Two-thirds of them declared to be between

500 to 1,000 km from the epicentre at the time of the earthquake. Respondents were not asked about their precise location or how intensively they felt the earthquake. However, at 1,500 km from the epicentre, USGS and EMSC estimated the intensity to have been between III and IV on the modified Mercalli scale (which measures the effects of an earthquake at a given location). Overall, 82% of the respondents had already felt an earthquake in the past and 25% had already received a PEEW. Among all respondents, 962 downloaded the app *after* the M8.0 earthquake and were only questioned on their knowledge and perception of EQN's early warning features in general.

By targeting EQN users and collecting data from the whole felt area which was international, the sample is not meant to be representative of the Peruvian population. Indeed, being an EQN user requires the possession of a smartphone, and in 2018 only 32,1% of the Peruvians owned one (Newzoo, 2018). Men and people aged between 25 and 44 years old are slightly overrepresented in our sample compared to the Peruvian population. Our sample is also more educated as 65% of respondents went to university while the average number of years of schooling in Peru is 10 (UNDP, 2019).

Other limitations include that users' perceptions and remembrance of the events may have been altered by the 2 months delay between the earthquake and the survey. Moreover, due to the dissemination method, the questionnaire could only be sent to users who still had the app at the time. Those who had deleted the app because of dissatisfaction could not be reached. Yet, we observed that the EQN user number in the region increased after the earthquake from 33K before to 150k two days after the earthquake, stabilizing around 70K in November 2019 and around 200k in July 2021 after more recent events.

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## Results

### **A strong expectation for PEEW**

The main reason (73.7%) for installing the app was the possibility to receive PEEWs, which demonstrates the strong public expectation for this service (Table 1). This was supported by one of the interviewees, who reported that some Peruvians even traded their iPhone for an Android operating smartphone in order to get the app (which was only available on Android at the time).

Among the respondents who downloaded the app *after* the earthquake, 68% did it expressly to get these warnings (Table A 1)

App users have a good understanding of the community dimension of the app and the fact that they could contribute to improving earthquake-related information for their fellow citizens by using the app (Table1). This was also mentioned under “other” responses, with a certain level of pride to be part of the network.

### **EQN Early Warning users experience**

We found that 40.7% of the respondents were notified accordingly with what they experienced. To better understand the different situations we need to consider a series of scenarios related to the relative success of the warning system (McBride et al., 2020). We established five categories depending on whether users received the warning and whether they felt the earthquake (Figure 2). These categories are based on user’s perceived experiences and do not necessarily compare to technical performance evaluated from a seismological perspective (Bossu et al., 2021). Overall, 34.3% of the users declared that they were warned before feeling the shaking, which corresponds to an accurate warning situation. In addition 6.4% experienced an accurate absence of warning as they did not feel the earthquake and did not receive the warning. Among others, we identify three cases. Late warnings concern 34.6% of respondents who were warned after they had felt the shaking. 14.1% did not receive the warning even though they felt the earthquake, which corresponds to a missed warning situation. Finally, 10.6% were warned but did not feel the earthquake, which, from their point of view, can be considered as a perceived false warning. This is to be distinguished from technical false warnings, which occurs when a warning is issued but no earthquake happened. We use these categories to analyze the results and assess users’ perceptions and reactions to the warning.

### **Users’ perception and reaction to accurate warnings**

#### **Perceived warning time**

When asked about warning time, 52.8% of the respondents who received an accurate warning estimated that they received it between 1 to 5 seconds before the quake, 26.4% between 6 to

15 seconds, 9% between 16 to 30 seconds and 5.9% around a minute before, or more. Time perception in such situations may be modified and this does not necessarily represent the reality of how long in advance they were warned. Yet, it still gives an idea of the time users had to understand the notice and get ready for the quake, given that most of them were probably sleeping (the earthquake having occurred at night).

### **Users' understanding and emotions**

Among the respondents who experienced an accurate warning, 78.9% understood the message correctly (Table 2). Understanding of the notification increased with previous earthquake experience (81.6% versus 61.8%) and with previous EEW experience (85% versus 74.1%) (Table A 2). The warning led to a state of vigilance rather than panic in those who received it. Most of the respondents felt "alerted" (77.7%) whereas the proportion who felt anxious is rather low (11.2%) (Table 3). The term "alerted" translates from the Spanish "alertado" and refers here to a state of increased vigilance, respondents being *on the qui vive*.

Those who understood the notification proportionally felt more « alerted » than others (82% versus 61%), whereas those who didn't were proportionally more « confused» (11.3% versus 5%). Having experienced an earthquake in the past also played a significant role: unexperienced users were proportionally more confused and anxious, while those who had already felt an earthquake in the past were proportionally more alerted (Table A 3).

### **Users' reaction to the warning**

Only a quarter of the respondents adopted a safety behavior after receiving the warning (Table 4). The most frequent reaction was a social one: the majority stated that they warned their relatives either physically present with them (54.6%) or through technological means (22.1%).

Others simply waited for the first shaking (35.4%) (Table 4).

Those who understood the notification were relatively more likely to warn their relatives physically present (58.9% vs. 38.3%) and to take protective action (26.2% vs. 20.8%). Those with previous earthquake experience were also more likely to take protective action (26.3% vs. 17.1%) when those who had never felt an earthquake warned their relatives through social media or SMS more than others (36.8% vs. 19.8%). However, previous early warning experience is not associated with higher likelihood to take protective action. Yet, users who had received an

early warning in the past are proportionally more waiting for the shaking than others (40.9% vs. 31.0%) (Table A 4).

Despite the small share of respondents who actually undertook a safety action, 74.8% of the respondents who received the notification before feeling the earthquake agreed or strongly agreed that it was useful and 72.8% that it was understandable.

### **Respondents' perceptions and reactions to late, false and missed warning situations**

In general, despite their experience of perceived late, false or missed warnings and the downsides that come with them, users are not categorically negative about the app and expressed a certain tolerance and benevolence toward the system.

EQN users who experienced *late* warnings declared mixed feelings. For some of them, the notification added to the anxiety as they thought another earthquake was going to hit (34.1%). An equivalent share declared, on the contrary, that they felt relieved and that information helped them decrease the anxiety level. Even though 12.7% of these users trusted the app less, nearly a quarter of them still felt confident that the system would work in the future (Table 5).

*Perceived False* warning experience didn't seem to decrease users' confidence in the system.

Half of them still declared a high level of confidence in the fact that the system would function for future earthquakes (Table 6) Among the "other" responses, many EQN users explained that they were probably too far away from the epicenter for the system to function well or that they had changed their app parameters. This demonstrated a good level of understanding of how the system works. However, these false warning situations still raised anxiety for 19% of users in this situation as they waited for the shaking.

For *missed* warnings, we also observed mixed feelings (Table 7). Respondents who declared that they would trust the system in the future were as numerous as those who declared a decrease in trust in the app (22.9% each). Many chose the "other" option to state that they were asleep and had turned off their phones so they could not be warned. Others explained again how they were probably too far away from the epicenter to receive the warning.

## **EQN improvements**

Respondents were asked to rate the importance of several types of improvements for the app (Table 8). Due to the question format, all propositions received a high rate of importance. However, distinctions can still be observed. The most popular demand expresses the need for more seismological information, especially magnitude (60.9%). The second most important feature requested was the possibility to quickly share the information with relatives who do not have the app. This is in agreement with the hypothesis of the social dimension of warnings previously mentioned which cause users to think of warning their relatives before they think about taking a protective action for themselves.

Interest in damage information (after the warning) also reached a high level of interest for more than half of the respondents. Safety tips, drills as well as information on expected damage and about the system functioning, seemed to interest respondents slightly less (around 40% for each modality).

Additionally, 81.8% declared that they would rather receive warnings for all earthquakes they could potentially feel than for damaging earthquakes only (Table A 5)

## **Perceived legitimacy and propensity to pay for the service**

When asked about who they perceive as legitimate to provide a PEEW system, EQN users were 53% in favour of governments. 26% turned to the scientific community, 18% to the civil protection, only 2% to private companies. 1% selected the "other" modality.

**Nearly half of the respondents declared that they wouldn't be willing to monthly pay for a PEEW system, while 37% would agree to pay but no more than 3 SOL (about 1\$) and 15% would agree to pay more (**

Table A 6). These results must be weighed against the fact that we were addressing users who could benefit from this service free of charge thanks to the application.

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## **Discussion**

In the case of the M8.0 earthquake in Peru, EQN succeeded in sending an understandable alert ahead of the shaking to a significant part of its users in the region. Thanks to the EQN app, a

sizeable number of users benefited from an early warning, for free, where no other PEEW system is yet implemented. With its simple alerting and messaging strategy, the EQN warning was well understood by those who received it. The app largely met users' expectations and reached high satisfaction levels. Yet, it was not fully satisfactory for those who experienced missed, false and late warning. Technical improvements are therefore required to reduce inaccurate and missed warnings and meet the needs of a larger audience.

The survey results enable us to confirm a series of findings from the literature, which seem common to many PEEW systems. Similarly to what was found in Japan and Mexico (Allen et al., 2018; Nakayachi et al., 2019), the majority of warned respondents did not take protective actions. This could be considered a major drawback for PEEW efficacy. Indeed, the Strauss and Allen (2016) estimation that PEEW could reduce injuries by 50% was only based on the hypothesis that people would take pre-emptive behavior. Yet, a series of elements suggest that behaviors could change in favor of more protective actions.. Users tend to be more reactive when they have previous earthquake experience. The chance to take protective actions also increases with notification understanding, which advocates for more testing of warning designs (Sutton et al., 2020). Even though it is a user demand, whether safety tips should be included in the warning - and in what format- is still an open debate. It is unclear if it will confuse the message or give an incentive to act, and recommendations may vary from country to country (Strauss and Allen, 2016; Fallou et al., 2019).

Despite the fact that they mostly do not act upon the warnings, users perceive the system as useful. Mental preparation for the shaking is still pointed out by participants as a benefit of PEEW, as was the case in Japan (Nakayachi et al., 2019). This finding confirms that beyond PEEW efficacy, one should also consider perceived PEEW usefulness for users.

Our results also confirm findings from Allen et al. (2018) where a general acceptance for the technical limitations of EEW systems and a higher tolerance of unnecessary alerts rather than missed alerts are found among users (Allen, Melgar, 2019). Technical limitations and the fact that the systems are mainly designed on the assumption that people will not feel the P-wave, make these false alarms unavoidable (Minson et al., 2019). However, it is crucial to understand reactions to false, missed and late alerts as they may decrease users' trust toward the PEEW system in the long term. Our results tend to confirm that false alerts are better understood if the risk of over-alerting the public is explained beforehand (Minson et al., 2019). Post-warning

communication is also essential to explain who was warned, who wasn't and why, as was the case for Ridgecrest earthquake for instance (Chung et al., 2020; McBride et al., 2020).

Beyond confirming previous findings, our study also enlightens some salient points, intrinsically linked to EQN's characteristics:

- **The community aspect** was revealed to be the strength of the system and was endorsed by the users who well understood this functionality. A certain pride for contributing to the provision of such a service to others emanated from several responses. This tends to advocate for an increased implication of citizens in PEEW systems through citizen science for instance (Haklay et al., 2018; Hicks et al., 2019; Becker et al., 2020). The community aspect could also explain the high tolerance for failures expressed by those who received missed and false alerts, as they understand how the system works and its potential fragilities. Additionally, it could account for the high level of confidence that the system "will work next time" among users, including those who have experienced late, false and missed warnings. Yet, it is uncertain how this benevolence will evolve in time and repeated warning experience may decrease trust in the app.
- Being a **voluntary system**, EQN is not universal. Only citizens with a functioning smartphone and an internet access can benefit from the service. Moreover, contrary to other warning systems, users need to be active (download the app) to be part of it. This may act to increase the comprehension level of how the system works and of the warnings themselves, which could result in users taking more seriously the alerts. But the flipside is that the system can alert only members of the community who already have the app, which is proving to be a an obstacle to protective behaviour as users tend to worry for their relatives who didn't get the chance to be warned before considering taking protective action. Because of this social dimension of the warning, we can assume here that the system would be more effective and efficient if it were universal. Inclusivity and integration of minority groups and vulnerable people is still a major challenge for PEEW systems (IFRC, 2018).
- Impact **of EQN's independence from national or local authorities** leads to somewhat paradoxical opinions for two reasons. On the one hand, EQN is a system that fills a need not satisfied by the state, which leads to a certain benevolence and confidence of users towards the system of which they are part of. On the other hand, citizens still con-

sider governments as the most legitimate actors to develop these systems. This is confirmed by Allen et al. (2019) who reported on a 2016 study that 88% of the sampled population was in favour of a state-wide PEEW system and that 75% were willing to pay for such systems. Moreover the involvement of national authorities may impact trust (Dallo and Marti, 2021).

Putting warning systems and their specific characteristics into perspective, the necessity of state action emerges. To increase PEEW efficacy, partnerships between authorities and independent actors, such as EQN, seem necessary where government alone cannot offer the service. Collaboration between authorities and independent actors could bring access to the service to the greatest number while contributing to educating the public on protective actions and bring substantial knowledge on local cultures. Drills, for instance, could be organized at local or national level in partnership with the system. This could make the role of experience in taking safety action more effective, as found that those who had already received an early warning were not proportionately more likely to take safety action. However, building such partnership for more effective warning systems also requires thinking of philosophic social and economic dimensions of community safety and actors' intervention. Who can and should get access to the warnings and who should pay?

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## Conclusion

Despite their limitations, PEEW systems remain a tremendous opportunity to reduce individual risk. When countries are not in a position to supply such a system to their citizens (often because of the development and operational costs), alternative systems such as EQN are an effective way to provide this service to a part of the population.

In the Peruvian case, the EQN application has effectively issued early warning to some of its users, who, even if they did not all take safety measures or receive the warning in time, seem to be generally satisfied and approve of the usefulness of the system.

However, beyond its usefulness, the system could gain in efficacy with a partnership with the State to overcome the limitations inherent in the system's characteristics. It could thus guarantee the universality of the service, while improving risk education and response behavior. Moreover, to protect citizens is one of the State's sovereign powers. The State's role as coordinator could even become essential in the years to come in order to limit the potential confusion linked

to a multiplication of systems. The question may arise, for example, in New Zealand where Google is setting up a service for its users, while at the same time a new system involving citizens is being developed (Becker et al., 2020; Tan et al., 2021).

Beyond the question of multiple warning providers, there is currently a lack of historical perspective in empirical research to study warning fatigue and the effect of these warnings (and their failures) over the long term. For that purpose, and in order to complete the present research, the questionnaire will be improved and the survey replicated. This will enable three kinds of comparisons: (1) between cultures, launching it in different countries and regions to assess the impact of risk culture, preparedness level and EQN use on perceptions and reactions to the warning; (2) between seismic scenarios, launching it in similar regions but for earthquakes causing different level of damages or different felt intensity levels; (3) between PEEW systems. If a PEEW is activated for the same earthquake by EQN and another system.

## Data and Resources :

Data used comes from the online quantitative survey described in the methodology section. The anonymized database is available as an electronic supplement

L. Fallou, R. Bossu, R. Steed, F. Finazzi, I. Bondár. A Questionnaire Survey of the Earthquake Network App's Users in Peru Following an M8 Earthquake in 2019. V. 0.9. GFZ Data Services (2021).

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**Tables, with captions above each table****Table 1 Reasons for EQN use**

<b>Q4. Why do you use the app?</b>	
To receive warnings about earthquakes that can affect me	73.7%
To get information about earthquakes around me	45.9%
To be part of a network of volunteers and citizens sensors	30.0%
To increase the quality of seismic data in my country	29.1%
To share information on earthquakes I feel	25.6%
To contribute to an innovative project	17.6%
Because a relative suggested I download it	6.3%
Other	0.8%
Base: all respondents (n=2,625).	
Note: Several answers possible	

**Table 2 Understanding of the EEW notification**

<b>Q14. What did you think when you received the information?</b>	
An earthquake is about to hit!	78.9%
An earthquake has occurred	12.1%
What is this sound?	6.1%
My alarm clock is ringing	6.0%
Someone is calling me/ sending me a message	3.2%
Other	2.8%
Note: Several answers possible.	
Base: users who received the notification before the earthquake (n=570)	

**Table 3 Emotional reaction to the EEW notification**

<b>Q15. How did the notification made you feel?</b>	
Alerted	77.7%
Surprised	15.3%
Calm	13.3%
Anxious, stressed out	11.2%
Confused	5.6%
Excited	2.5%
Other	1.0%
Note: Several answers possible.	
Base: users who received the notification before the earthquake (n=570)	

**Table 4 EQN users reactions to the EEW notification**

<b>Q16. What did you do when you received the notification?</b>	
I warned my relatives physically present with me	54.6%
I waited for the first vibrations of the earthquake	35.4%
I went to a safe place in my house (under a table...) dropped, covered and hold on	25.1%
I warned my relatives through social media, SMS...	22.1%
I ran outside	9.6%
Nothing	2.8%
Other	2.8%
Note: Several answers possible.	
Base: users who received the notification before the earthquake (n=570)	

**Table 5 Perception of EQN users to a late warning**

<b>Q21. You received an alert for an earthquake you had already felt. How did you feel about that?</b>	
Relieved, it gave me information about what had happened	34.1%
Anxious, I thought another earthquake was about to happen.	32.4%

I'm sure it'll work next time.	23.1%
I didn't expect to be warned, so that's fine.	15.1%
This reduced my confidence in the application.	12.7%
Skeptical, I don't understand how this warning works.	8.6%
Angry	2.9%
Other	3.1%
Note: Several answers possible.	
Base: users who received the notification after they had felt the earthquake (n=575)	

**Table 6 Reaction of EQN users who experienced false warning.**

<b>Q20. You received an alert for an earthquake you didn't feel. How did you feel about that?</b>	
I'm sure it will work next time.	50.0%
Anxious, I waited for the earthquake for a fairly long time.	19.0%
This reduced my confidence in the application.	8.2%
Skeptical, I don't understand how this warning works.	6.0%
Angry	1.1%
Other	20.1%
Several answers possible, Base: users who received the notification but never felt the earthquake (n=177)	

**Table 7 Reaction of EQN users who experienced missed warning**

<b>Q23. You didn't receive the earthquake warning information in advance, how do you feel about that?</b>	
This reduced my confidence in the application.	36,3%
I'm sure it'll work next time.	31,6%
I don't understand how this warning works	17,9%
I think I was in an area that could not be warned in advance about the earthquake.	17,1%
Angry	6,4%
I didn't expect to be warned, so that's fine.	6,0%
Other	7,3%
Note : Several answers possible	
Base: users who didn't receive the notification but felt the earthquake (n=234)	

**Table 8 EQN improvements assessment**

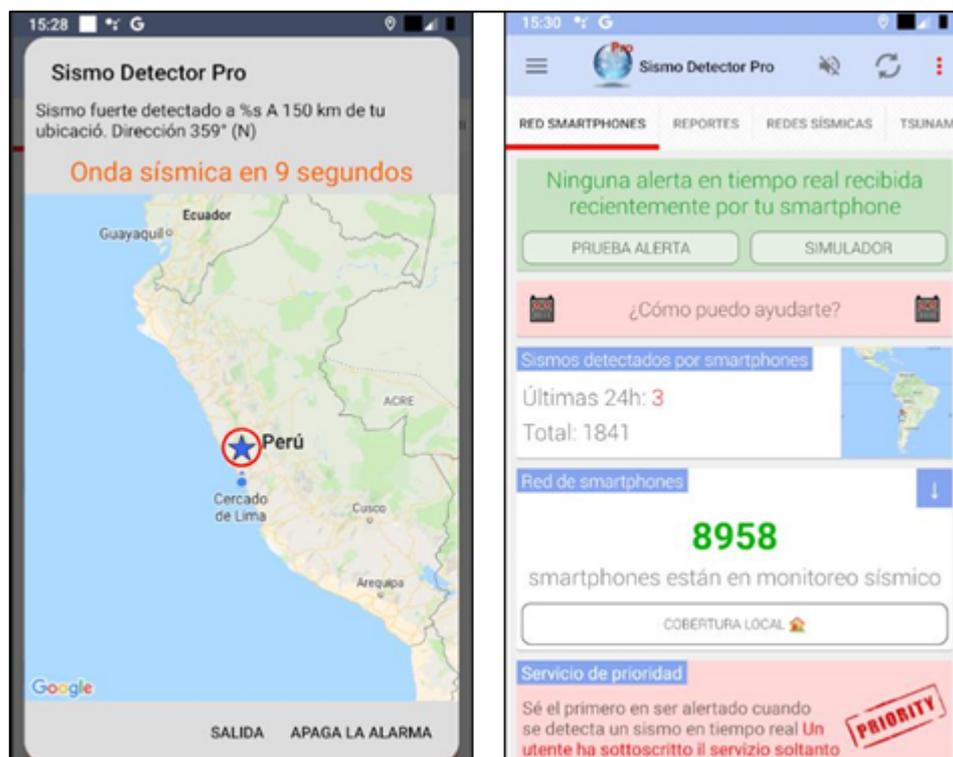
<b>“What kind of information or feature would you like to receive in the notification that warns you that an earthquake may hit your location?”</b>					
	Very im- portant	Important	Neutral	Not very important	Not im- portant at all
Include information about the magnitude	60.9%	20.2%	3.1%	4.2%	11.6%
Be able to share quickly the information with my relatives who don't have the app	55.9%	22.2%	5.3%	5.0%	11.6%
Receive information about the earthquake and the damages AFTER the earthquake	52.1%	25.1%	6.5%	4.8%	11.5%
Include information on the expected damages	43.2%	29.6%	9.1%	6.6%	11.5%
Include Safety tips on what to do in case of earthquake	41.7%	30.9%	9.6%	6.4%	11.4%
Include information on the way the system works	40.9%	30.9%	11.1%	6.1%	11.0%
Include drills and test messages to be better prepared when a real earthquake occurs	39.1%	29.3%	13.8%	6.5%	11.3%
Base: All respondents (n=2,624) on a combination of responses for question 9 and 28					

## List of Figure Captions

**Figure 1** Screenshot of the start page of theEQN app (left) and an EQN EEW notification (right). The app has not been designed by a professional web designer and is in constant evolution. Screenshots were made on May 26<sup>th</sup> 2019 and correspond to users' experience at the time of the studied earthquake.

**Figure 2** EQN users' experience of EEW for the M8.0 earthquake

**Figures, with captions below each figure**



**Figure 1** Screenshot of the start page of theEQN app (left) and an EQN EEW notification (right). The app has not been designed by a professional web designer and is in constant evolution. Screenshots were made on May 26<sup>th</sup> 2019 and correspond to users' experience at the time of the studied earthquake.

		Received the warning			Total
		Yes		No	
		Before the quake	After the quake		
Felt the earthquake	Yes	<b><u>Accurate early warning</u></b> 34.3%	<b><u>Late warning</u></b> 34.6%	<b><u>Missed warning</u></b> 14.1%	83.0%
	No	<b><u>Perceived false warning</u></b> 10.6%		<b><u>Accurate absence of warning</u></b> 6.4%	17.0%
Total		79.5%		20.5%	100%

Base: EQN users who had the app before the earthquake (n=1,662)

Figure 1 EQN users' experience of EEW for the M8.0 earthquake

Appendices

Q7. Did you know there was such a feature in the app?	
Yes and that's partly why I downloaded it	67,8%
Yes, but that's not why I downloaded it	7,0%
No, I didn't know	25,3%
Base : New users, who didn't have the app when the M8.0 earthquake occurred (n=962)	

Table A 1 Awareness of the EEW feature among new users

<b>Q14. What did you think when you received the earthquake warning?</b>	Had previous earthquake experience		Had previous EEW experience	
	Yes	No	Yes	No
An earthquake is about to hit!	81,6%	61,8%	85,0%	74,1%
An earthquake has occurred	11,5%	15,8%	10,6%	13,3%
What is this sound?	5,9%	7,9%	3,1%	8,5%
My alarm clock is ringing	4,9%	13,2%	5,9%	6,0%
Someone is calling me/ sending me a message	2,8%	2,6%	2,4%	3,2%
Other	2,4%	7,9%	4,7%	1,9%
Base : Users who experienced an accurate warning (n=570)				
Note: Several answers possible				

**Table A 2 Comparison between previous earthquake and early warning experience and notification understanding**

<b>Q15. How did the notification made you feel?</b>	Previous earthquake experience		Previous early warning experience	
	Yes	No	Yes	No
Confused	4,5%	13,2%	4,7%	6,3%
Anxious, stressed out	10,7%	14,5%	12,6%	10,1%
Alerted	79,6%	65,8%	76,4%	78,8%
Suprised	12,8%	31,6%	9,8%	19,6%
Excited	2,2%	3,9%	1,6%	3,2%
Calm	13,2%	14,5%	15,0%	12,0%
Other	1,2%	2,6%	1,6%	1,6%
Base : Users who experienced an accurate warning (n=570)				
Note: Several answers possible				

**Table A 3 Comparison between previous experience and emotions felt when receiveing the warning**

	Understood the warning		Had previous earthquake experience		Had previous early warning experience	
	Yes	No	Yes	No	Yes	No
<b>Q16. What did you do when you received the warning?</b>						
I warned my relatives physically present with me	58.9%	38.3%	55.1%	51.3%	55.1%	54.1%
I waited for the first vibrations of the earthquake	36.7%	30.8%	36.6%	27.6%	40.9%	31.0%
I went to a safe place in my house (under a table,...) dropped, covered and hold on	26.2%	20.8%	26.3%	17.1%	23.6%	26.3%
I warned my relatives through social media, SMS,...	23.6%	16.7%	19.8%	36.8%	20.1%	23.7%
I ran outside	9.6%	10.0%	8.5%	17.1%	9.1%	10.1%
Nothing	1.8%	6.7%	2.4%	5.3%	2.8%	2.8%
Other	1.8%	6.7%	2.0%	7.9%	3.9%	1.9%
Base : Users who experienced an accurate warning (n=570)						
Note: Several answers possible						

**Table A 4 Correlation between users' reaction to the warning and their (1) understanding of the warning, (2) previous earthquake experience and (3) previous early warning experience.**

<b>Q27. Would you rather?</b>	
receive warnings only in case of earthquakes with potential damage	18.2%
receive warnings of all earthquakes you may feel	81.8%
Base : All users (n=2,626)	

**Table A 5 Preference for warning threshold**

**Table A 6 Propensity to pay for PEEW**

<b>Q30. How much would you be willing to pay monthly to get an earthquake early warning system?</b>	
I wouldn't be willing to pay	48%
3 SOL or less (1\$)	37%
Between 4 and 15 SOL (2-5\$)	13%
Between 16 and 32 SOL (6-10\$)	2%
More than 32 SOL (11\$)	1%
Total	100%
Base: all users (n=2,625)	

### **Electronic Supplement (optional)**

The questionnaire translation and database are available as an electronic supplement.  
 L. Fallou, R. Bossu, R. Steed, F. Finazzi, I. Bondár. A Questionnaire Survey of the Earthquake Network App's Users in Peru Following an M8 Earthquake in 2019. V. 0.9. GFZ Data Services (2021). <https://doi.org/10.5880/fidgeo.2021.001>.