Anxiety Detection Leveraging Mobile Passive Sensing

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Abstract. Anxiety disorders are the most common class of psychiatric problems affecting both children and adults. However, tools to effectively monitor and manage anxiety are lacking, and comparatively limited research has been applied to addressing the unique challenges around anxiety. Leveraging passive and unobtrusive data collection from smartphones could be a viable alternative to classical methods, allowing for real-time mental health surveillance and disease management. This paper presents eWellness, an experimental mobile application designed to track a full-suite of sensor and user-log data off an individual's device in a continuous and passive manner. We report on an initial pilot study tracking ten people over the course of a month that showed a nearly 76% success rate at predicting daily anxiety and depression levels based solely on the passively monitored features.

Keywords: Mobile application · Anxiety · Remote mental health monitoring · Passive sensing · Machine learning

1 Background and Introduction

Within the spectrum of mental health disorders, Anxiety disorders are the most common class of psychiatric problems affecting both children and adults [7,9,17], with up to one in three people in the US meeting full diagnostic criteria by early adulthood [13,25]. This manifests in the form of roughly to 7 to 9% of the population in the US suffering from a specific phobia, 7% from social anxiety disorder, and 2 to 3% each from panic disorder, agoraphobia, generalized anxiety disorder, and separation anxiety disorder [4]. Individuals with anxiety disorders contend with substantial distress and impairment. They are at heightened risk for a host of negative long-term outcomes including depression, substance abuse, educational underachievement, and poor physical health [5,19,27].

The optimal method for the prevention or care of mental illness is early identification, diagnosis, and proactive treatment [26]. Time-sensitive intervention is

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therefore crucial for preventing conditions from becoming chronic and debilitating. However, traditional methods of psychiatric assessment, including clinical interviews and self-reports, are limited in their ability to provide just-in-time interventions as well as early identification. They depend heavily on retrospective summaries collected in clinical settings, conditions that often result in reporting biases, inaccurate recall, or late and ineffectual treatment.

Additionally, anxiety disorders are, for the most part, vastly overlooked and under-treated in the community; only 15–30% of anxious individuals in the community receive treatment of any kind. Recent research has found strikingly high levels of anxiety among college-age youth. Indeed, 58.4% of college-aged youth report feeling “overwhelmed by anxiety” [3]. Several other recent studies document the high proportion of college students meeting full diagnostic criteria for an anxiety disorder [8]. At the same time, young adults are particularly overlooked within the health care system, with rates of screening, identification, and referral falling below those of either children or adults [27]. Given this landscape, there remains a pressing need for tools that improve early identification of anxiety symptoms, provide users with the platforms to monitor their activities, raise awareness of factors impacting on their wellbeing, and provide a mechanism for intervention should an anxiety episode escalate.

The growing ubiquity of consumer devices, among them smartphones, smartwatches, and in-home sensors, all equipped with an array of sensors and user-logs, have resulted in an unprecedented opportunity to catalog and quantify the daily aspects of an individual’s life, creating repositories of personalized information [23].

While much has been noted about the insidious aspects of such surveillance capabilities, there is also significant potential for such monitoring, if harnessed and utilized by the individuals themselves, to dramatically improve their healthcare outcomes. Such tools could potentially allow the user to accurately track their behaviors and habits, compare personal activities with population-level baselines, establish outlier behaviors with their peers, and even motivate behavioral change and the promotion of healthy habits.

There is significant potential for such monitoring, if harnessed and utilized by the individuals themselves, to improve their healthcare outcomes dramatically. This potential has long been recognized with physical behavior and physiological health, as both are extensively tracked. In contrast, mental health is largely overlooked.

The notable exception to this trend has been the success in remote stress monitoring that has been achieved with physiological stress monitoring of features like heart-rate variability and Galvanic Skin Response that is accomplished by wearable sensing devices like smartwatches to determine stress level [10]. While such approaches have demonstrated efficacy, they are limited in their potential applicability by requiring the wearing of a physical sensing device, and provide little contextual awareness as to the causes of stress that are encountered. More recent advances have attempted to compensate for the restrictions in activity detection leveraging novel sensing modalities including wireless signal fluctuations around the body, but such efforts are still in their infancy [24].

Specifically, The capability to track behavioral metrics and associate them to mental health, although intimately linked, has not been definitively established. This owes to the significant difficulty in correlating monitorable behaviors and corresponding mental health. Behavioral patterns both within (e.g., the transition from weekday to weekend) and across individuals (e.g., simple differences in how many men and women carry their phones) are simply too diverse and too subject to confounding factors beyond mental health to allow for easy correlations. Nevertheless, the growing challenges around mental health, necessitate exploring the possibility further.

Recent efforts have explored whether pervasive mental health monitoring could be feasible through a smartphone and the embedded sensors, such as motion sensors, ambient light, microphone, camera, Global Positioning System (GPS), proximity, and touch screen [6,10,18,20]. These efforts have shown the promise of this approach in successfully tying behavioral monitoring to mental health; however, such approaches have not translated into fully mature frameworks, and have focused almost exclusively on depression-related conditions, which while often spoken in conjunction with anxiety, manifest in distinct ways [12].

The advantages of leveraging a smartphone-based platform are that the continuous collection of quantitative data potentially provides a more reliable indicator of an individual's risk at any given time, as well as offering a mechanism for just-in-time intervention should a mental health episode occur [6]. Conversely, smartphone-derived data present several challenges, some of which have already been noted, which can result in limited accuracy owing to differences in behavioral patterns across users, and the indirect manner of detection [12].

We present a system for the remote monitoring of mental health symptoms, their fluctuation, and their attendant disruption to personal functioning, called eWellness. The eWellness framework is designed to capture a broad spectrum of remote monitoring, survey data acquisition, secure data transmission and management, data analytics, and visualization.

The primary component of eWellness is a mobile application that facilitates data collection and transmission harvested from an array of sensors and usage logs from a user's smartphone. The data is collected passively, pre-processed, and transmitted through a secure gateway to the cloud, where it is securely stored, and indexed using a scalable database.

Concurrently the eWellness application includes an active querying component where users can be prompted with Ecological Momentary Assessments (EMA) of their mental health status. This architecture is complemented by a back-end analytic engine, capable of mapping observed metrics and exogenous data sources to a user's mental health state, based on adaptive statistical models, and advanced machine learning algorithms. The system is designed to monitor overall mental health as well as acute crisis events in both a retrospective and predictive capacity.

2 Framework

2.1 Server

Data from the study, both sensor feeds and usage-logs, along with user-generated EMA responses, are first encrypted, cached locally on the user's device, and then transmitted to a secure remote server, where it is stored in an encrypted scalable MySQL database.

2.2 eWellness Data Collection

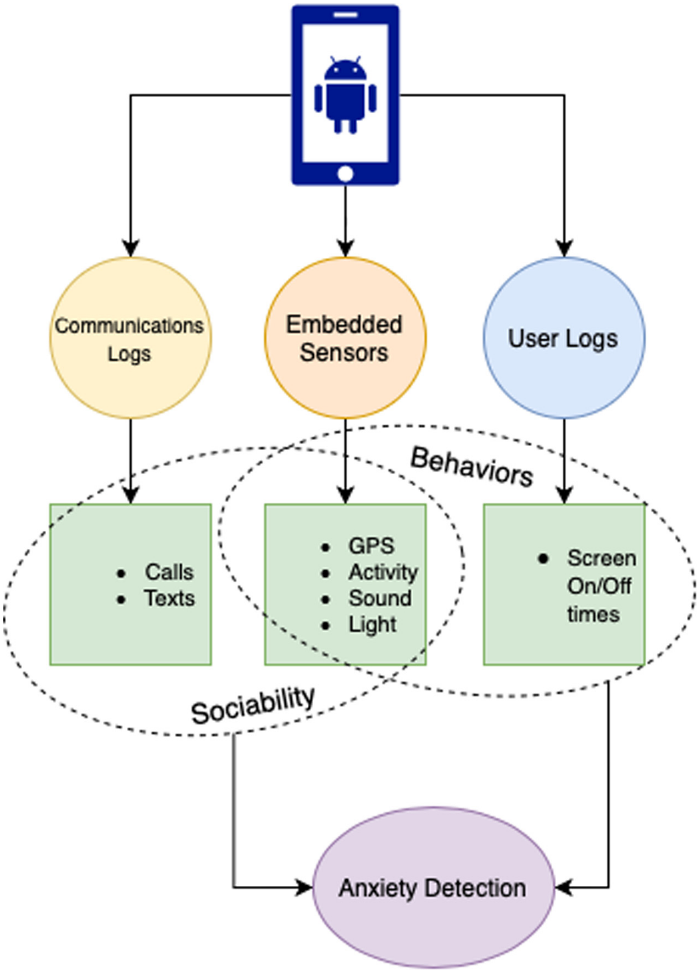


Fig. 1. eWellness data collection hierarchy

The eWellness mobile application, developed for android devices, collects passive behavioral data derived from communications logs, embedded sensors, and user-logs capturing (Fig. 1) the following metrics:

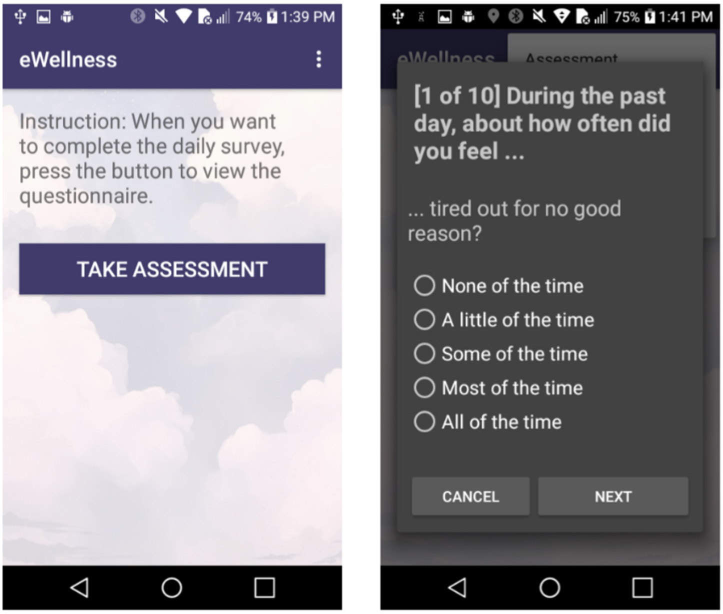
- **Communication**: monitors incoming and outgoing phone calls and text messages, including the duration of phone calls, the number of texts and phone calls, and unique individuals contacted. This does not assess the content of communications or the recipient of the communication, beyond establishing a unique contact.
- **Location**: is periodically sampled using GPS, network, and Wi-Fi detection. Prompts for a new location after moving 5 m, up to once a minute. This metric leverages the Google Fused Location API. The application does not track specific locations; instead, it keeps a total distance traveled using the vectorized haversine distance function.
- **Ambient Sound**: is a numeric measure, designed to detect speech and communication above 50 decibels using the phone's microphone. It samples every 5 min for 5 s. This metric does not capture the audio files of communications and merely documents the sound frequency and decibel level as numeric values.
- **Activity and Movements**: leverage the device's accelerometer, gyroscope, and GPS tracking. Activity is sampled every 60 s. In order to determine stationary and moving activity-type, the application leverages Google's Activity Recognition API.
- **Light**: detects light level associated with possibly being in an outdoor or indoor location. This sensor is sampled every 6 s.
- **Phone Use**: is user-log monitoring the device's screen on-time.

From these raw values, we derived daily aggregated features from these metrics to infer both a user's sociability, and behavioral patterns. These were then used to learn a model for prediction of anxiety symptom severity. We obtained statistical characteristics, such as minimum, maximum, mean, standard deviation, the 25th, 50th, and 75th percentiles, of the numeric values of noise exposure and the ambient luminescence. The number of activity transitions and duration of each physical activity per day also became a significant metric of identifying mentally distressed days.

2.3 Limiting Personally Identifiable Data Collection

Recognizing the potentially invasive nature of applications like this, data collection was carefully scoped to avoid the collection of Personally Identifiable Information (PII) that could link a particular user to a particular dataset. For example, when attempting to gauge sociability, the application logs the total number of phone calls made, total time on the phone, and the number of unique contacts called; the identities of specific callers were not tracked. This has the consequence of introducing a degree of obscurity into an observed finding (e.g., as the application is unable to differentiate between calls to friends and calls to a customer-service hotline). At the same time, in the interest of both respecting privacy and ensuring the acceptability of the app, these efforts were felt to be necessary constraints on data collection.

3 Pilot Study Methodology



(a) Landing page. (b) Daily EMA questionnaire.

Fig. 2. Screenshots of eWellness

An IRB-approved pilot study was conducted on a dozen individuals who are use smartphone devices with Android version 5.0 and above. Participants were recruited from the university community, and included both students and staff. Study participants did not have a reported history of mental illness. Participants were asked to download and install the eWellness application (Fig. 2), and then run it on their phone for a month. Passive data was collected continuously by the application throughout the month. Participants were asked to answer EMA daily through the eWellness app, but did not provide any other personal information, such as name, gender, age, during participation.

The Kessler Psychological Distress Scale (K10) [2] is a validated measure of psychological distress over the past 30 d, which is used for clinical and epidemiological purposes. It has a notable success in measuring feelings of anxiety along with depression. For this pilot, the K10 was modified to assess criteria over the previous 24 h period. The modified K10 prompted the users as daily EMA to measure their feelings of anxiety and depression. The K10 is composed of ten questions, structured on the following standardized template, "Over the past 24 h, how often have you...", to which users can provide one of five standardized responses: All of the time, Most of the time, Some of the time, A little of the time, and None of the time). These responses are scored on a range from five (All of the time) through one (None of the time). The minimum possible score of K10 is 10, and the maximum possible score is 50. K10 results are categorized into four levels of psychological distress: low distress, moderate distress, high distress, and very high distress. Table 1 details the stress threshold scores. These results were leveraged as a label for the classification of supervised learning.

Table 1. Categorization of K10 Scores [1].

K10 Score	Level	Samples (N = 146)
10–15	Low distress	91
16–21	Moderate distress	29
22–29	High distress	21
30–50	Very high distress	5

4 Results

Only 10 participants answered at least seven days of EMAs and provided successful passive sensing data throughout the month. Our analysis focused on a fully supervised learning approach, and only labeled samples were included. For this pilot study, we used 146 daily samples to identify daily anxiety and depression levels. The Z-Score normalization was applied to the features to reach normalized values from different participants.

We selected 25 features that have a relatively higher correlation with the raw K10 score. Table 2 provides a detailed list of feature labels and associated descriptions.

For the 4-class classification, we used 5-fold Cross-Validation (CV) with four models: K-Nearest Neighbors (KNN), Extra-Trees (ET), Support Vector Machine (SVM), and Multilayer Perceptron (MLP). The class weight was automatically applied to the models inversely proportional to the class frequencies to train the imbalanced dataset. The highest classification accuracy achieved was around 76% with the extra-trees model. We also applied the under-sampling technique to improve the performance of an imbalanced dataset. Samples from the low distress class were removed randomly to make uniformly distributed class labels. Samples from the very high distress class were also ignored. A confusion-matrix (Fig. 3) demonstrates that the average score of classifying three classes is 0.65.

Table 2. 25 features most highly correlated to K10 scores

Feature name	Description
total-messages	Total # of text messages-received
is-silent-count	Number of instances no noise was detected
freq-std	Standard deviation for noise frequency
freq-25%	Noise frequency 25th percentile value
deci-std	Standard deviation for noise decibel
deci-50%	Noise decibel 50th percentile value
deci-75%	Noise decibel 75th percentile value
rms-max	Root mean squared measure of audio over time
act-transition	Activity tracking count when in transition
still-cnt	Total count of time user was still
tilting-cnt	Total count of instances the user was tilting
on-foot-cnt	Total count of the instances the user was still
on-bicycle-cnt	Total count of time user was riding a bike
on-foot-dur	Duration of time on foot
on-bicycle-dur	The duration the user spent on a bike
elapsed-device-on	Count of time the phone was active
elapsed-device-off	Count of time the phone was inactive
light-std	Standard deviation for luminescence value
light-25%	Luminescence 25th percentile value
light-50%	Luminescence 50th percentile value
loc-speed-mean	Average speed traveled in a day
loc-alt-mean	Mean Altitude Location
loc-alt-std	Standard deviation od the altitude
loc-alt-75%	Altitude 75th percentile value
loc-alt-max	Altitude max value

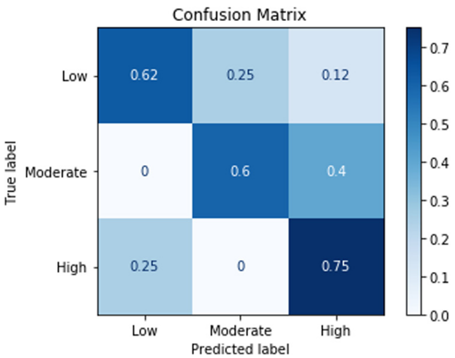


Fig. 3. 3-class (Low, Moderate, and High distress) classification confusion matrix.

5 Discussion

5.1 Relevant Features

There are some notable and counter-intuitive findings regarding what data elements proved to be most-highly correlated to mental health. It is not surprising to note the presence of features closely related to physical activities (e.g., Duration of time spent biking or walking) as such activities have been definitively linked to mental health [22].

What is somewhat less intuitive is the presence of multiple audio and light sensing features. Audio sensing was included in the protocol under the hypothesis that a moderate level of sound could be indicative of pro-social activities like being outdoors or in group settings. Conversely, overly loud or quiet noise profiles could be indicative of stressful environments or isolated conditions that could be deleterious to mental health. But while interesting in theory, there are many confounding causes of noise that, by limiting ourselves to solely capturing the frequency and decibel levels of the sound, we would fail to distinguish. (intuitively, someone watching TV at home alone could register the same noise profile as someone out to dinner with friends).

Similarly, it was hypothesized that light sensing could be indicative of an individual being outside, which has been shown to positively correlate to mental health [16], however here too, many confounding factors would impact light readings, foremost among them, that the user would actually have to have their phones out and exposed when outside for the light sensor to register it.

The authors note that Sound and Light sensing is notable in that both were the most frequently sampled of all features. It is possible that the high degree of granularity of readings afforded to these particular sensing modalities explains their relevance. Regardless, the authors suggest additional work is needed to understand whether or not these features are indeed more universally indicative of mental health, and explore why that is potentially the case.

5.2 Limitations of the Study

While 10 subjects completing one-months worth of continuous data represents a critical validation of the technology and its potential utility, the dataset is too small to achieve statistically significant results. Additionally, this pilot was scoped to only include individuals without a clinical diagnosis of Anxiety. Consequently, there were insufficient cases of user-reported mental distress, particularly moderate or severe cases, in order to classify them effectively. Additional studies are planned to enlarge our dataset and include a cohort of individuals with diagnosed mental health conditions.

5.3 Accuracy of Labeling

The authors feel there is significant concern about the veracity of user self-reported labeling of mental health that was leveraged in this study. When constructing the experimental design, focus was placed on maximizing user participation in the study. At the time, the primary concern the authors had was that participants would fail to submit a sufficient number of survey responses. Therefore the protocol was designed to combat this, by prompting users to fill out a daily EMA in the application via push-notification, with manual outreach to users who failed to complete an EMA within 48 h, as well as designing the K10 to be a simple to complete multiple-choice assessment. This combination resulted in successfully encouraging active participation in the study; however, there was no mechanism designed to confirm or validate that the resulting inputs were an accurate reflection of a user's actual wellbeing.

It is highly likely, therefore, that at least some users were motivated to respond quickly, and not necessarily accurately. This would result in users simply selecting the default answer of no reported anxiety to each question.

Furthermore, there may have been a reluctance among users to accurately report out mental health issues given perceived embarrassment or stigma associated with poor mental health. Under-reporting of mental health issues is a persistent issue that plagues the domain more generally, and isn't limited to this study [11], however failing to account for under-reporting is a notable issue.

Finally, even well-meaning participants may have failed to accurately represent their mental health state due to their either overlooking, or mischaracterizing, stresses they encountered. This is particularly true when comparing responses across users, where baseline expectations of stress may vary wildly among participants, with prior work for instance demonstrating a clear association between gender and reported wellbeing [21], the result being that one participant's perception of a 'normal' day, might easily be classified as a low or moderately-stressed day by another.

Solving this challenge is essential for ultimately achieving the intended goal of accurate classification of mental illness, for unlike alternative labeling exercises, where quantifiable metrics are possible, here the labeling of an objective state, mental illness, particularly when physiological monitoring is not available, is entirely reliant on subjective inputs, ones that are difficult to accurately capture, and even more difficult to standardize across users.

The authors recommend that future studies will have to address these concerns by better anticipating and correcting for challenges with accurate labeling of mental health.

There are a number of possible remedies to this. In the questionnaire itself, careful structuring of the questions can engage users to provide more thought-out results [14]. Cross-validating questions designed to ensure internal consistency are also an effective means of ensuring user accuracy [15].

Consideration should also be given to alternative methods for collecting labels. Interviewing subjects to determine their mental health, for instance, would likely produce more accurate results, although would have attendant tradeoffs of its own, such as reducing the number of labels that could effectively be captured.

Educating participants on the presentations of Anxiety could also be key towards a more accurate and consistent recall of symptoms. Finally, developing the trust of participants through engagement and transparency, could help to solicit more honest engagement.

5.4 Subject Heterogeneity

The activities tracked by the eWellness app showcase significant heterogeneity across subjects in-terms of usage-patterns. Variables like distance-traveled, number of texts and calls, and physical activity levels, are all far more likely to be impacted by the individual's lifestyle, than their mental health on any given day.

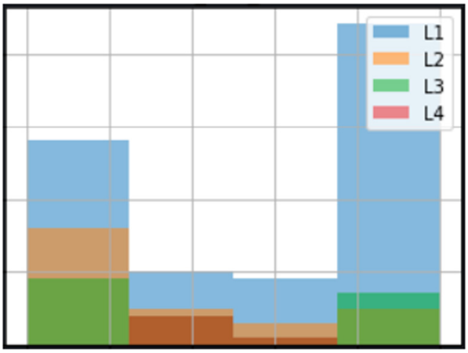


Fig. 4. Histogram of normalized values of Duration on Foot for the 4 labels of stress

Figure 4 showcases a fairly typical distribution, in this case the duration spent on foot in a given day, bucketed into quartiles, with the 4 labels of interest (with L1 or Level-1 corresponding to Low-distress, L2 to Moderate Distress, L3 to High-Distress, and L4 to Very high Distress), in this classification superimposed. While intuitively more time spent on foot may be associated with better mental health, here we observe no clear pattern.

It was therefore assumed that primary-success would be achieved by classifying mental health within users across time, once their baselines for normative behavior were established, rather than across users. The limitations of this initial dataset did not allow for adequate classifying by individual; however, the fact that classification success was achieved by bundling samples across all subjects is remarkable in its indication that cross-subject learning in this domain could be possible. The authors suspect that part of this result likely stems from normalization performed on the data to account for habitual differences in subject usage. By normalizing the data in this manner, the absolute number is rendered largely moot, and instead variances in user patterns are highlighted, as it is likely the day-to-day variations that are more reflective of shifts in mental health. Additional data collection is necessary to validate this finding.

5.5 Usability

Attempting to gauge the viability of the concept, participants in the pilot were asked to submit a voluntary anonymized post-study questionnaire regarding their perceptions about the application and its data collection practices. All participants responded. A significant majority described the application as somewhat (40%) or mostly (40%) useful. Likewise, all users endorsed feeling comfortable with the application, and only one user expressed reservations about the data being collected.

All participants obtained detailed accounting of the data that was collected as part of their onboarding process to the study. No individual declined to participate after learning the precise nature of what was being tracked. This sampling suggests that, particularly among the young adults who are more accustomed to digitized lives, there is less concern about data collection through their mobile devices. Limiting the collection of PII could be sufficient to assuage most privacy concerns.

The primary issue users had with the application was its battery consumption resulting from heavy over-sampling of the sensors. Future iterations of the application will seek to optimize battery usage by minimizing the sampling frequency.

6 Conclusion

Remote health monitoring of mental health, when done so leveraging passive and unobtrusive data collection, could be a useful alternative for conducting real-time mental health surveillance. This paper presents eWellness, an experimental mobile application designed to track a full-suite of sensor and log data off a user's device continuously and passively. An initial pilot study tracking ten people over a month showed a nearly 76% success rate at predicting daily anxiety levels based solely on the passively monitored features. Our current approach may prove useful at tracking longitudinal trends in an individual's mental health, as well as providing a platform for just-in-time interventions to mental health crises. Additional work is needed to refine both the technology and analytics.

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