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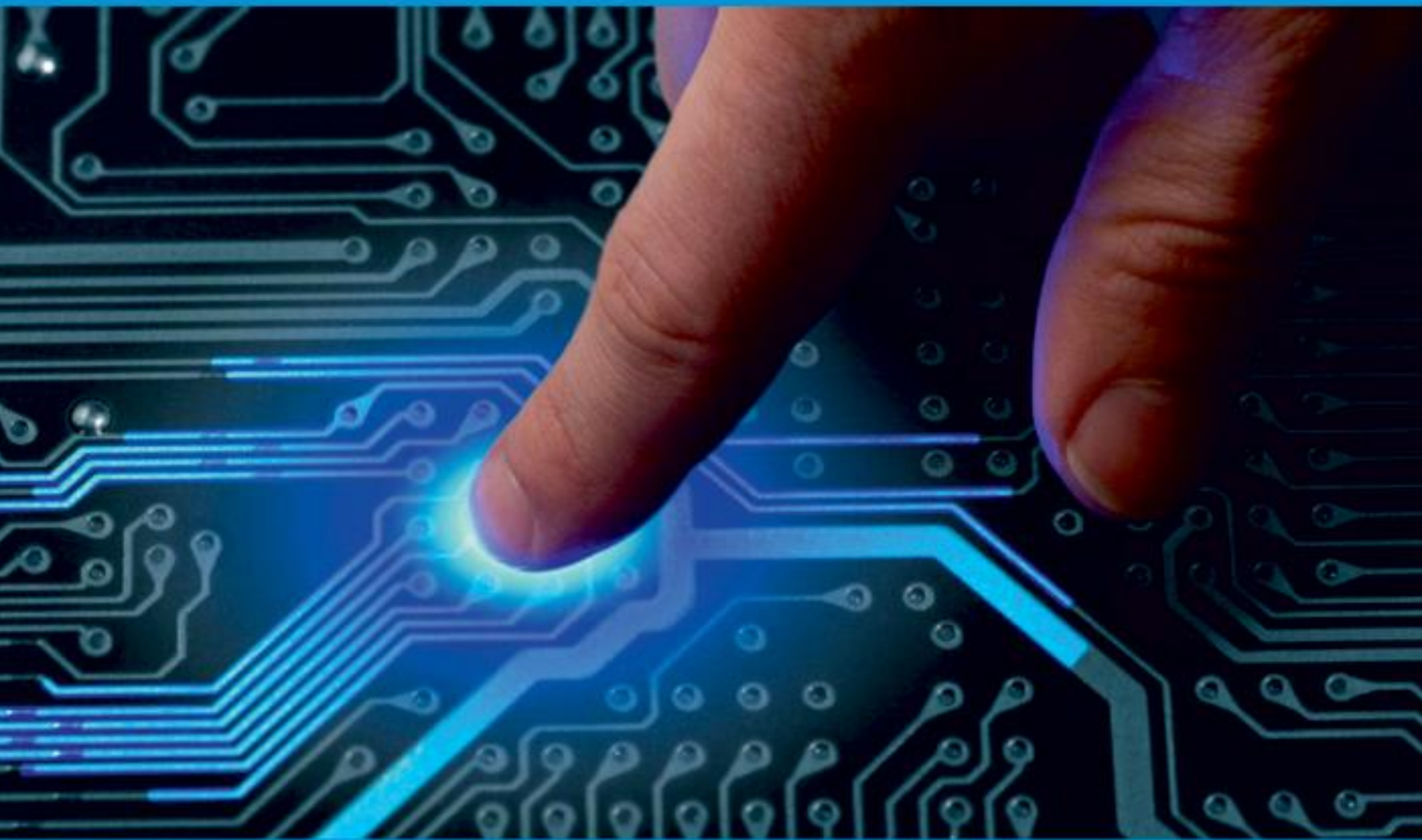

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An Adaptable and Extensible Mobile Sensing Framework for Patient Monitoring

Tushar Malpekar

Assistant Professor, Department of Electronics and Telecommunication Engineering, Metropolitan Institute of Technology and Management, Sukalwad, Sindhudurg, Maharashtra, India

ABSTRACT: Smartphone apps with self-monitoring and sensingcapabilities can help in disease prevention; however, suchcontext-aware applications are difficult to develop, due to thecomplexities of sensor data acquisition, context modeling, anddata management. To ease the development of mHealth andTelemedicine apps, we developed the Mobile Sensing Framework(MSF), which dynamically installs device appropriate contextsensing plug-ins that provide a wealth of information aboutusers' mental and physical states. The MSF automatically collectsinformation about incoming/outgoing/missed calls; apps usage;sound pressure levels; light sensor values; movement data (e.g.,step count); location; heart rate; etc. The MSF also includes asearchable object-based persistence layer, which is capable ofrapidly serializing and de-serializing detected context data.Collected data are stored securely in the phone's database, wherethey can be retrieved by applications for local analysis, remotemonitoring, and alert generation. We developed a fullyoperational prototype of the MSF platform that was validatedusing several Android-based devices. This paper presents anoverview of our approach along with a description of theexperiments conducted using the MSF prototype.

KEYWORDS:***m***Health; Telemedicine; Mobile Sensing; Contextawareness;Ambient Dynamix; Android

I. INTRODUCTION

Smartphones represent powerful platforms for diseaseprevention and health interventions. Disease risk conditions can be mapped to data collected via phone sensors and selfreports,providing users and doctors access to rich health dataor broadcasting alerts to caregivers. In this article we introduceour rapid prototyping, mobile sensing platform for mHealthand Telemedicine applications that can dynamically adapt tothe device's capabilities while automatically monitoring andreporting user behavior using the device's inbuilt sensors,connected external sensors, and virtual sensors.

As mobile technologies advance, developers areincreasingly interested in creating applications that are able tofluidly adapt to the needs and circumstances of their users.Contextual information extracted from the user's environmentcan be used to enable an app to adapt its runtime behavior andcapabilities to better fit a user's changing situation andrequirements [1]. Due to the complexity of context sensing andacting, middleware is often used to orchestrate context-awareadaptation in mobile applications [2]. Unfortunately, existingappropriate security features, support few context types, andare unable to integrate new (or updated) capabilities at runtime[3]. The lack of context framework support is particularlyevident in the mHealth and telemedicine domains, whichrequire advanced sensing capabilities.

II. THE MOBILE SENSING FRAMEWORK

To address these challenges, we developed an extensibleMobile Sensing Framework (MSF), which dynamically installsdevice appropriate context sensing plug-ins into commoditymobile devices that provide a wealth of information aboutusers' mental and physical states. The MSF automaticallycollects information about phone usage patterns such asincoming/outgoing/missed calls; apps usage; sound pressure;light sensor value; movement (e.g., step count); location; etc.The MSF also contains the necessary mechanisms to manageand persist data from the different sensor sources, providesadditional functions, such as location based notification system,self-reporting capabilities and includes flexible querymechanism that allows applications to query current andhistorical context data using simple interfaces. The MSFleverages the Ambient Dynamix plug-and-play contextframework for Android [4], which enables mobile apps andwebsites to fluidly interact with the physical world throughsensing and actuation plug-ins that can be installed on-demand.
An overview of the Dynamix framework is shown in Fig. 1.

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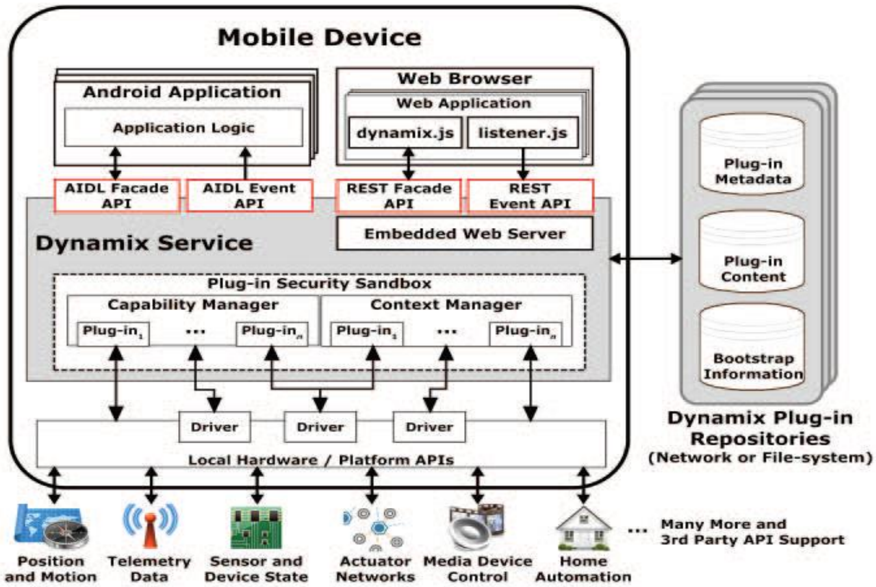

Fig. 1 Overview of the Dynamix Architecture

Dynamix runs as lightweight background service on the user's mobile device, leveraging the device itself as a sensing, processing and communications platform. Dynamix automatically discovers, downloads and installs the plug-ins needed for a given context sensing or acting task. When the user changes environments, new or updated plug-ins can be deployed to the device at runtime, without the need to restartthe application or framework. Dynamix comes with a growing collection of ready-made plug-ins and provides open software developments kits (SDKs) and a scalable repositoryarchitecture, which enable 3rd party developers to quickly create and share new plug-in types with the community.The MSF builds upon Dynamix, which enables the MSF to benefit from the rich contextual information provided byvarious plug-ins. Depending on the types of data sources and sensors available on the user's device, the MSF utilizes Dynamix to download and install appropriate context sensing plug-ins at runtime. Dynamix plug-ins can run exclusively onthe device or in tandem with additional processing and storagefacilities in the cloud. The MSF can utilize existing Dynamixplug-ins or deploy custom Dynamix plug-ins from which eitherfrom private, network-based repositories or from the device's file-system. In addition, we created plug-in specific persistenceclasses that handle data serialization into the MSF's object based database. The developer can access the data from thedatabase any time via object-based queries. The relationship
between the MSF and Dynamix is shown in Fig. 2.

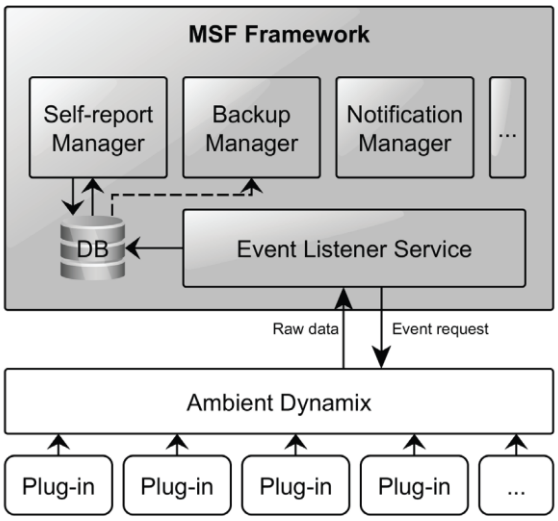

Fig. 2 Overview of the MSF and Dynamix

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mechanism to manage context sensing, plug-in installation, anddata gathering. Therefore, both run in the background on thedevice and use memory. Although the memory utilized duringruntime varies depending on the number of installed plug-ins,Dynamix used about 15 MB and the MSF used about 22 MBmemory for the scenarios described in this paper. This memoryrequirement is fulfilled by most modern Android devices. Boththe MSF and Dynamix can be used on devices runningAndroid version 2.2 or higher. An example of the variouscontext data currently available from the MSF is shown inTABLE I

Context Data	Description
Application log	The name of running application and their run duration.
Battery level	The current battery charge level.
Browser history	Visited Websites (identified by a unique hash for privacy).
Heart rate	Heart rate data from a connected Zephyr HxM HRM device.
Calls	Incoming, outgoing, and missed calls (identified by a unique hash for privacy) with call duration.
Location	The device's geo-location.
Light Level	Lux values from the device's photodetector sensor.
SMS Data	SMS data (identified by a unique hash for privacy) that includes the number of words.
Sound pressure level	The calculated decibel value of the user's ambient environment.
Pedometer	Calculated step information from the gyroscope and accelerometer.
Wireless devices	Nearby Bluetooth devices and WiFi hotspots.
Weather information	Local weather information.
Real life event	Labeled data (e.g., the user drinks a cup of coffee).

TABLE I. MSF CONTEXT DATA

The connection between the MSF and Dynamix is twoway,because there are two kinds of events in the MSF: *request type* events and *auto triggered* events. Auto triggered events,such as a phone call or received SMS data, happen without userinteraction. When these events occur, Dynamix automaticallysends the raw data to the MSF. For request type events, such assound pressure level or light level, the MSF frameworkperiodically sends context scan requests to Dynamix, whichresponds with the requested data. For request type events, thedeveloper can configure the time interval between two eventrequests.
The MSF is able to handle new context sources withminimal programming effort. For example, heart-rate information is currently provided by the Dynamix Zephyr HxMheart rate device plug-in. Additional heart-rate sensors can beeasily introduced into the MSF by utilizing new Dynamixheart-rate plug-ins as they become available. If a new Dynamixheart-rate plug-in supports the original context data type, noadditional programming effort is required to persist the datawithin the MSF. However, if a new Dynamix heart-rate plug-inexposes different data types, complementary MSF persistenceclasses must be created to describe the data. Further, the MSFand Dynamix can be extended with additional biosignal sensorsthat can persist arbitrary data types, including support for rawdata gathering.
The MSF is configured through an XML file that defineswhich events should be collected. There are also options to define the data collection details for each event type, such ashow often to collect data based on the device's battery level(e.g., collect less location data when the battery level is low toconserve power). The MSF logging mechanism is alsoconfigured by this configuration file.

ADDITIONAL MSF FUNCTIONALITIES

A. Loading data with queries

In the MSF, the developer does not have to manage individual sensors (e.g., register for Android's built-in`SensorEventListener`class) or provide sophisticatedimplementations of sensor types not directly available in Android (e.g., wireless bio-telemetry sensors). Rather, the MSFregisters for context data streams using Dynamix plug-ins, andwhen corresponding events arrive, the MSF automaticallypersists the context data in the phone's database using a customObject-relational mapping (ORM) framework. Context eventstorage is fully automatic, meaning that

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applications can loadthe collected data from the phone's database as needed.Towards this end, we developed persistence wrapper classesfor Dynamix context data. These classes are designed toserialize and de-serialize context data. Every context data classis inherited from an abstract super class, which lets the MSF tohandle different event instances in a unified manner. Forloading the stored context data the developer can use theMSF's query class, which provides an object oriented, SQLbased query mechanism for the data gathering. Every databasequery is requested through the main MSF DAO object instance.

B. Location based notifications

The developer uses the MSF framework to collect datafrom the sensors, but sometimes the developer also wants tocollect additional data entered by the user. Since users mayforget to enter the user inputs in a timely fashion, the MSF'sbuilt-in location based notification system can be used to alertthe user during specific time intervals and locations. The userreceives location based notifications when the preconfiguredtarget location is nearby, and the the current time is within aspecified time interval. The MSF allows the developer tospecify the exact condition when the notification should betriggered. The MSF will send a broadcast intent with a specificaction string. The developer has to register an Android`IntentReceiver`for this action and define the notification.To create a location based notification, the developer can usethe MSF's main notification manager class instance. Thedeveloper can set up a notification with a start and an end time,a location that can be entered as an address string, and amaximum distance from the location. The developer also candefine a time delay in the notification, which will delay thealert

C. Managing backups

We also created a backup system within the MSF foroffline data analysis. The backup system is able to export the stored data into standard CSV files, which are stored on thephone's SD card. The framework provides functionality to create an archive file from the saved data and send it to aserver. The developer can configure this mechanism in the MSF's XML configuration file. In the near future we wouldlike to include popular cloud storage mechanisms, such as Google Cloud Storage or Dropbox

D. Visualisation

The MSF also provides mechanisms for creating anddisplaying chart-based visualizations [17] of the collected data using the achartengine library1. The MSF provides bar, pie anddotted charts to show data to the user. The charts can be used tocreate user awareness applications. The MSF can generatecharts, based on context data types. It also provides options tocreate a new chart, based on other data. There is a built-infunction for a pie chart that shows the dispersion of theapplication log, and bar charts that visualize the average soundpressure level and the light level values. The developer cancreate new charts based on different information. Fig. 3 showsan example of the inbuilt visualization mechanisms providedby the MSF. In this example, social events (total number ofphone calls and SMSs per day) are plotted against the derivedmood information. This chart show only the user's local datafor self-awareness.

Fig. 3 Chart show correlation between mood and social events

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III. EXPERIMENTS AND APPLICATIONS

We are planning experimental studies using the MSF tofacilitate the rapid development of medical mobile applications with context sensing capabilities. One such study aims atinferring the user's mood from data collected by the MSF. Emotions have much to do with our health, and monitoringmood changes of patients and patient performance in life

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situations is important for the effective treatment of manymedical conditions. Knowing the patient's mood changes helpsthe doctor judge the efficacy of prescribed interventions. Weare working together with therapists from the PsychologicalMedicine Department at the National University of Singapore(NUS) to provide mobile support for Cognitive BehavioralTherapy (CBT). Interventions to be completed by patients inbetweentherapy sessions (i.e., Homework) is a central conceptin CBT. We are creating a CBT Assistant app that conductsCBT Homework assignments using the user's mobile device.When the CBT Assistant is equipped with mood sensingcapability, it will be able to trigger interventions that arecustomized to the patient's situation, and assess the efficacy ofCBT interventions in the short- and long-term, providinginvaluable input to both the patient and the doctor.
For the mood inferring study, we implemented a self-reporting app called Emotion Tracker and integrated it with the[16] that allows the user to log mood, and input data such asproductivity at work, socializing, sleep quality, diet, exercise,and hobbies. The self-reported data is managed by the MSFwith the same mechanism that manages storing sensor data.Self-reported data annotates the context data collected by theMSF, which enables us to analyze all the collected data to findstatistically significant correlations among mood and useractivities recorded by the MSF. Understanding recurringpatterns of data correlations leads to the formulation of moodmodels capable of predicting the user's mood based onautomatically collected sensor data. Building and validatingmood models is a prime goal of our mood inferring study
There are a number of validated scales for self-assessmentof emotions, mood and well-being. Among mood scales that have been widely researched and published in literature, wechose SAM [24], AffectButton [12], PANAS [20][13], SPANE[23], and PAM [21]. As these scales have different strengthsand weaknesses, we decided to design mobile versions of all ofthem within the Emotion Tracker to facilitate comparativestudies among the scales, and to provide researchers with aflexible toolbox of emotion, mood and general well-being self-reporting scales that might be useful in a wide range ofexperiments and surveys.

SAM and AffectButton are based on Mehrabian's PAD(pleasure-arousal-dominance) emotion model [13]. PAD modelrepresents emotion or mood on three scales corresponding tothree PAD values, namely valence (pleasure-displeasure),arousal (the energy level), and dominance (the sense of controlover the situation or lack of control). PAD model has been usedin many studies on mood inferring and emotion sensing,therefore for the sake of comparison, we use it as a primarymode for mood self-reporting.

Despite much validation and demonstrated usefulness ofPAD in categorizing emotions, it is not easy for people todecompose their own feeling into three dimensions and ratethem separately on numeric scales. This makes it difficult touse PAD directly as a mood self-reporting scale. To overcomethis problem, SAM provides a pictorial illustration for moodaspects that are to be rated on each PAD scale. Rather thanrating mood dimensions on a numeric scale, the user picks oneof the five manikin icons placed on the scale. Still, the usermust understand the meaning of each mood dimension scale

Affect Button is a computer or smartphone-based scale that removes this difficulty. AffectButton displays an image of ahuman face. As the user moves her finger around the icon, the expression of the face changes. The user selects the facialexpression that best matches her current mood. Each face expression of an AffectButton is mapped to a specific combination of three PAD values of pleasure, arousal anddominance. The validity of these mappings have beenconfirmed in empirical studies.

PANAS is based on 20 affect items such as excited, upsetor inspired. The user rates each item and the scores for 10 positive emotions. The ratings are combined into a PositiveAffect score. Similarly, the score of 10 negative emotions are combined into a Negative Affect score. PANAS can be used toself-assess momentary emotional experience, longer-term mood or even more lasting personality traits. However,PANAS affect items cover only high-arousal positive and negative emotions. Low-arousal affective states such assadness or serenity cannot be distinguished using the PANASscale

SPANE attempts to capture full range of emotional experience with 12 affective items. PAM uses a simple scale with 16 photos representing variety of emotions laid out in agrid. The user selects a photo that best matches the experiencedemotion.
Among the mood scales discussed, many are paper-based, although AffectButton and PAM have been implemented on mobile phones, and SAM has also been implemented on acomputer. The limitations of paper-based surveys and studiesbased on artificially triggering emotions in a laboratory setting(e.g., by showing pictures or videos) are widely reported inliterature. An appeal of mood self-reporting via smartphones isthat it allows for frequent, in-situ capturing of mood reportsover longer period. Mobile self-reporting is low cost and scalesto many participants. It creates a

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possibility of collectinggenuine data about emotions and the context in which emotionsoccur. This opens the door for new kinds of studies that havenot been possible with other approaches, including novelfindings related to health issues in large populations andinsights into emotion mechanisms

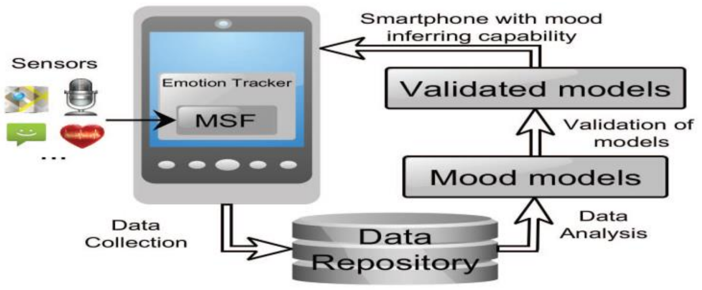
However, adapting paper-based mood scales forsmartphones is not easy. Central challenges include fitting therequired information into the small screens common to mobiledevices and devising mechanisms that allow users to input selfreportin real life, without assistance from experts who usuallyare around during lab experiments to provide proper explanations of the scales. Furthermore, using mobile moodself-reporting scales repeatedly during a longer study may leadto boredom and the lack of user engagement. Boredom andlack of engagement are likely to negatively affect the accuracyof self-reported data that requires participants to connect toheir own emotions and mood. It may also lead to diminishingcompliance with the reporting routine required in a givenstudy, which has been reported in many studies.

We counter the risk of boredom and the lack of engagementwith "gamification" strategies and by using smartphone technology to make mobile mood scales intuitive andengaging, as a way of promoting a sense of satisfaction, achievement and pleasure. Towards this end, we consider usingmultiple sensory modalities to enrich the user's experience ofusing mood scales as a way of promoting their repeated use.For example, we use photos/pictures sound, music, touch(vibrations) rather than the text and number scales, as iscommon in paper-based mood reports. We think that emotionrating on smartphones may be much more intuitive andaccurate than the classical paper-based scales if we engagemultiple sensory modalities.

To enable researchers to experiment with multiple moodscales, the Emotion Tracker is designed to be flexible in termsof including/excluding the above-described modalities as a wayof optimizing the mood scales for a given experiment andparticipant profile. The MSF provides predefined classes forvarious types of self-reports, and the developers can easily addnew types to extend MSF's self-reporting capability. Thedefault self-reports contain classes, based on PAD. The MSFprovides an extended, PAD-based self-report class, whichcontains fields for notes regarding each PAD value. This selfreportgives option to store a secondary PAD model value,based on other sources. The developer can use this to findcorrelation, or chose the most accurate one between differentdata entering methods. In the Emotion Tracker application weuse this secondary option to store PAD values from an AffectButton. There are self-reports for collecting discrete emotions[5] and labeled values. The labeled value self-report contains a`Map<String,Integer>`field. In our prototype we use thisself-report to store day related values, such as last night's sleepquality, productivity at work, etc. Every value is entered by theuser's own admission. To create own self-report the developerneeds to create a new self-report class, which extends the`BaseSelfReport`class. The new self-report class also hasto be annotated with ORM framework's `@Entity` annotation,and the developer has to register it in the configuration XMLfile. The self-reports are stored in the phone's database like theevent's context data. The developer can load the data with thesame `MsfQuery`class through the `MsfDao`instance.

A. Data collection and mood model validation

The mood inferring study includes data collection, dataanalysis (building mood prediction models), and validation of mood models (see Fig. 4). Participants carry smartphones withthe Emotion Tracker installed and the MSF collects sensordata. Participants self-report their mood three times daily andactivities once, at the end of the day. Sensor data annotatedwith self-reported data is stored on the phone and thenuploaded to our server.



Collected data is analyzed to find statistically significantcorrelations between a person's mood and data collected via mobile phone sensors. *Mood prediction models* built based onthese correlations can infer user's mood from new data collected by sensors. Mood models infer user's mood fromsensor data collected in real life. Inferred mood is compared

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with self-reported mood.
In addition to mobile support for CBT, we plan to investigate the application of MSF in data in risk prevention.
Risk conditions for a given disease can be mapped to datacollected via sensors and information self-reported by phone users. Having detected risk conditions, smartphones can alertusers or their doctors about the situation. In this context, physiological information about the patient becomes highlyrelevant.

B. Privacy controls
Related to data collection, the following privacy measures arebeing implemented:
1) No sensitive data is collected; e.g., we collect the time ofphone conversations and the length of text messages, but we do not collect the contents.
2) Privacy-aware hashing mechanisms are utilized toanonymize identifiers such as phone numbers and visitedWebsite addresses.
3) Participants in the study will know exactly which data weare going to collect, and they can decide which data they want to share with us.
4) Participants can inspect the collected data before it isuploaded (anonymously) to our server for analysis.

IV. RELATED WORK

There are several context sensing frameworks related to ourwork. The MyExperience [19] project also investigated in-situdata capture on mobile computing activities. My Experience'sself-reports are contex-triggered user experience samplings,unlike mood and daily activity reports of our Emotion Tracker. My Expereince is extensible in terms of context triggers andrelated actions. MyExperience is compatible with devices running the Windows Mobile 2006 operating system; however,nowadays, these devices are rare. Our MSF framwork is asedon the widely adopted Android mobile operating system.Related, the Fünf Open Sensing framework [6], the Emotionsense [7] framework and Purple Robot2 also collectcontextual data using phone sensors and provide several datastorae options, including the file-system, remote servers andcloud-services such as Dropbox. Most existing projects utilizethe notion of sensing plug-ins, which are discrete units of codethat are statically compiled into the hosting application,although some aspects of these frameworks (notably customizable triggers and actions in MyExperience) can beconfigured.

Although these projects are similar in spirit to ourapproach, there are several notable differences. First, since the MSF utilizes Dynamix, it supports the discovery andinstallation of new or updated context sensing plug-ins *durin runtime* (enabling dynamic adaptation of sensing capabilities tothe device, user and the user's environment). The MSF alsoprovides a flexible query interface that enables applications tosearch for historical context information derived from theseplug-ins both online (i.e., during runtime) and offline (e.g., fordata mining support). Finally, the MSF provides a rich set ofself-reporting capabilities and data visualization support on theAndroid platform.

V. CONCLUSION AND FUTURE WORK

In this paper, we presented an overview of the Mobile Sensing Framework (MSF), which enables the rapid creation of M Health and Telemedicine applications that can dynamically adapt to a mobile device's capabilities. Our approach leveragest he Dynamix Framework, which enables the MSF to request the dynamic installation of context sensing plug-ins that are best suited to the user's environment and application scenario. Collected data are stored securely in the phone's database, where they can be retrieved by applications for local analysis, remote monitoring, and alert generation. We developed a fully operational prototype of the MSF platform that was validated using several Android-based devices. We also implemented various MSF plug-ins that provide a wealth of information about users' mental and physical states.
In terms of future work, we are planning to extend ourapproach to support additional wearable sensor's [9] [15], such as Electrocardiography (ECG) [10] and Galvanic skin response(GSR) [11]. We are also considering privacy-centric methodsof extracting sound features [14] from incoming and outgoingcalls [8] as a mechanism of determining emotional states.These data will be used to augment our ongoing mood inferringstudy, which will be presented in an upcoming paper.

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