Contextual Analysis to Understand Compliance with Smartphone-based Ecological Momentary Assessment

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ABSTRACT

Mobile device-based ecological momentary assessment (mobile EMA) is increasingly utilized to capture *in situ* information about a person's physical and mental health states. Mobile EMA has methodological advantages over traditional survey methods (e.g., decreased recall bias); however, these advantages are reduced by participant noncompliance with EMA protocols. There is a dearth of information about how different participant contexts predict compliance. We examine how different spatiotemporal contexts and participant-phone interactions predict EMA response rate and response latency. Utilizing data from 65 participants during a two-week study, we first extract features from smartphone sensors that characterize participant context (location, social context, activity). We then build and evaluate a classifier to predict participant response rate and response latency for EMA-delivered prompts based on the context features, achieving 78% accuracy. We discuss the implications of our results for improving participant compliance in future health studies that deploy mobile EMAs.

CCS CONCEPTS

• **Human-centered computing** → *Empirical studies in ubiquitous and mobile computing*; *Ubiquitous and mobile computing design and evaluation methods*;

KEYWORDS

Ecological Momentary Assessment, Mobile Sensing, Spatiotemporal Patterns, Context-awareness, Phone Motion, Phone Usage.

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1 INTRODUCTION

There is a growing interest in studying the dynamic relationship between individuals' experiences, social and physical environments, mental states, and behaviors. The assessment of these dynamic relationships is enabled by the development of momentary data collection strategies, such as experience sampling methods (ESM) and ecological momentary assessment (EMA) [14]. EMA has been used in research studies since the 1940s, emerging from the accuracy limitations of retrospective questionnaires that suffer from recall bias [14]. EMA includes various data collection methods and strategies, such as diaries and questionnaires. It offers a method for capturing time-varying subjective experiences close to when they happen, thereby reducing concerns about memory distortions. With the rise in smartphone adoption, EMA now manifests as device-prompted questions that appear on participants' mobile phones, often multiple times per day (e.g., "How negative do you feel at this moment?"). In this way, EMA increases the ecological validity of measurements, allowing researchers and clinicians to better capture the dynamics of behavioral and emotional processes in everyday life.

Technology innovations have transformed and enhanced momentary data collection in natural settings during the past decade. As mobile electronic technologies advance, EMA methods have been used extensively to study human behaviors, states, and contexts. Within the last few years alone, mobile EMAs have been used in a wide variety of studies, focusing on topics such as substance abuse [14], psychopathology [12], levels of pain [4], levels of physical activity, emotional states, and anxiety [2, 6, 7].

Although collecting momentary data using mobile technologies offers many advantages in health-related studies, these advantages are dependent on both the participant response rate and the quality of the collected data [16]. EMA provides an opportunity to understand behavior on a more granular level, but systematically missing data (e.g., correlations between participant noncompliance and outcomes of interest) threaten validity. Since EMA study protocols usually involve participants being repeatedly interrupted and asked to provide self-reported information, these demands on study participants can lead to high perceived participant burden and to noncompliance [16]. Indeed, EMA depends on participants' motivation and adherence, which may vary during the study period. For instance, EMA compliance rates have been shown to erode significantly after two weeks of data collection [8, 15]. Moreover, participants are often unable to respond to EMA prompts because of their context (e.g., a student during a class). These concerns could limit the utility of EMA applications in clinical practice and research if they are not addressed.

Consequently, when and where to schedule EMAs is an important question that plays a role in keeping participants' motivation and engagement high, thereby ensuring measurement quality. Despite the growing number of studies using EMA, evidence on how well participants comply with mobile EMA protocols and how contextual factors are associated with participant compliance are still limited. The majority of research in user compliance has been limited to describing response rates and their relationships with time (e.g. end of the study), without studying relationships with contextual features. Thus, to the best of our knowledge, this work is among the first to leverage passive sensing capabilities to understand contextual states of users and their impacts on how participants are interacting with EMA requests.

This paper investigates the relationship between participants' contexts of use and compliance with EMA requests during a two-week study. We hypothesize that participants' engagement with EMA (as indicated by compliance, response latency, and time taken to complete an EMA request) will be affected by time (e.g., time of day) and location (e.g., home vs. work) of prompt, phone motion (phone movement patterns) before prompts, and phone usage (calling or texting) right before the prompt. Our contribution also includes a predictive model that uses the extracted contextual features to estimate EMA compliance in a given situation. We believe that this model will help researchers and clinicians to design EMA protocols that enhance compliance and improve data quality.

In the following section, we introduce the design of our study and data collection procedures. We then study the dynamic relationships between context and compliance with EMA by highlighting four dimensions: time, space, phone motion, and phone usage. Finally, we introduce a predictive model that predicts response compliance in a given situation.

2 STUDY DESIGN

After receiving approval from the Institutional Review Board at our university, N=65 undergraduate students ($M_{age} = 19.8 years, SD = 2.4, 52\%$ female) were recruited for a two-week study period to understand dynamics of emotional, cognitive, and interpersonal processes associated with depression and social anxiety symptoms. Participants were recruited from undergraduate psychology classes that offer course credit and monetary compensation as study participation incentives. Students were recruited through email advertisements as well as through an undergraduate study participant pool. The sample reported their race/ethnicity as 42% White, 38% Asian, 5% Black, 5% Latino, and 10% multiracial.

We explained the study to participants, and following consent we installed a custom mobile app (Sensus [17]) on their personal smartphone (Android devices). The study contained an EMA phase that requests self-report data on psychological affect (negativity and positivity) throughout the day. Sensus was programmed to deliver 6 Random Time (RT) surveys throughout the day (each survey contained 12 questions), randomly in each two-hour block between 9 a.m.-9 p.m. (i.e., once between 9 a.m.-11 a.m., once between 11 a.m.-1 p.m., etc.). Sensus was also programmed to deliver an End of Day (EOD) survey (containing 15 questions) at 10 p.m. each day. During the study, Sensus was preset to give students the freedom to answer the surveys or skip them. Furthermore, when a survey was fired, participants had the choice to complete it anytime between the prompt signal and the next EMA prompt. Thus, the response latency (i.e., time from prompt signal to prompt answering), the survey duration (time spent responding to questions), and if the survey was responded to or not were also recorded by Sensus.

In addition to these active assessments, Sensus also passively collected Global Positioning System (GPS) coordinates every 150 seconds and accelerometer data at 1 Hz, in addition to call and text logs. All data were transmitted wirelessly to a secure Amazon Web Services server, where data were stored for further analysis.

3,756 EMA surveys were deployed by Sensus, of which 2,719 were responded to (compliance rate of 72%). The average response latency (i.e., the average amount of time from prompt signal to prompt answering) was 906 sec (SD=1,468), While the overall average of EMA duration was 82 sec (SD=195).

3 ANALYSIS OF EMA RESPONSES

Interruptions steer users from an ongoing task to secondary tasks [5]. As suggested by Clark [9], users can respond to an interruption in four possible ways: (i) handle it immediately; (ii) acknowledge it and agree to handle it later; (iii) decline it (explicitly refusing to handle it); (iv) withdraw it (implicitly refusing to handle it). As such, we propose in the following analysis to investigate if these four behaviors are impacted by the users' current context. Specifically, we investigate if the compliance rate, response latency, and duration of EMA responses relate to the participants' context: location, time, phone motion, and phone usage. Location is important because researchers need to understand whether they are systematically missing data (due to low compliance rates) when participants are in certain locations, which could mean that measurements in particular social or work environments are not being taken. Similarly, routine activities vary by time of day, so knowing whether there are critical gaps in responding (e.g., routinely missing mealtimes) could bias the data, especially given that mood can also vary in part based on time of day and activity. Similar concerns arise tied to ways participants are otherwise interacting with their phones (e.g., engaged in texting, which implies a type of social interaction). Researchers want to know not only whether or not a response is provided, but also how close in time to the prompt the participant responds (response latency), and to assess whether real-time affect and other cognitive states are being captured. It is also meaningful to understand how long people spend replying to obtain a proxy for engagement with the questions being asked, which may speak to data quality.

3.1 Temporal Analysis

This step investigates whether participants' compliance is influenced by time of day and day of study. We present in Figure 1 the average survey latency, average duration, and number of answered surveys on an hourly and daily basis. On an hourly basis,

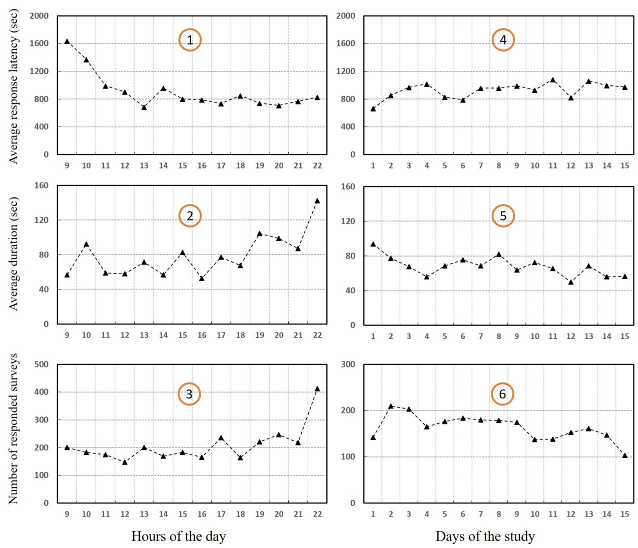

Figure 1: Hourly and daily analysis of EMA compliance, duration and response latency.

response latency and compliance rate seem to be affected by time. Results show how response latency decreases and how number of answered surveys increases during the evening (see graph 1 and 3 in Figure 1). This finding indicates that the participants preferred to answer surveys late in the day more than in the morning, perhaps because students' routines involve morning classes or sleeping late, which interfere with responding to prompts. The spike at the end of the day in graph 3 is due to the "End of day (EOD)" surveys being delivered at a fixed time (10pm) each day. This suggests either that participants tend to be more compliant with surveys happening at a predefined vs. random time, or that 10pm is a particularly convenient time for many people to respond.

The fact that participants adherence is higher in the evening than in the morning can also be demonstrated by the survey duration. Indeed, the survey duration is also affected by the time of day given participants appeared to spend more time answering questions during the evening surveys than during the morning ones (see graph 2 in Figure 1). Brief durations responding to surveys may reflect disengagement in that participants are not investing time to describe their current state (maybe because they are doing something else), potentially reducing quality of the data. The spike at 10pm is due to EOD because it contained more questions than did random time surveys.

On a daily basis, we noticed that participants' compliance dropped as the study progressed. In the three right graphs of Figure 1 (graphs: 4,5, and 6), we can observe an increase in response latency and a drop in both number of answered surveys and survey duration by the end of the study. This confirms what has been reported in the prior literature concerning the relationship between compliance and length of study. Most studies [3, 8, 15] reported a progressive decrease in compliance as the studies progressed.

3.2 Spatial Analysis

The main goal of spatial analysis is to investigate if the locations where EMA requests happened affected the compliance rate. We first parsed participants' raw GPS data by semantic locations (e.g., restaurant, university, and home), by combining a spatiotemporal clustering algorithm [10] and OpenStreetMap (OSM) geodatabase [13]. Our label taxonomy includes the following types: Education (e.g., university and libraries), Leisure (e.g., cinemas), Food (e.g., restaurants), Health (e.g., hospital), Supermarket, Religious, Service (e.g., bank), Out of town, In transition (going from one place to another), Home, and Other houses. Our algorithm has been trained to recognize Home as the place having a house OSM-tag (e.g., apartment, dormitory, house, etc. See [13] for more details about OSM tags) where a participant stayed the most between 10 p.m. and 9 a.m. We determined the locations where EMAs were prompted by comparing the semantic locations and the EMA's prompt time.

We present in Table 1 the spatial distribution of the compliance rate, the average response latency, and average duration of all 3756 EMAs. Note that we added a new location type "Back-home" which is a transition from x place to Home, because during the analysis process we noticed that these kind of transitions have a different compliance and response latency, so we decided to distinguish it from the other transitions.

Table 1: Analyzing the EMA compliance rate (CR), average response latency (RL) and average duration in different locations. RL and duration are calculated only for answered surveys. Bold CR/RL represent very low or very high values.

Location	Occurrence	CR	RL	Duration
Supermarket	124	**77%**	**188s**	70s
Food	151	**88%**	**219s**	89s
Health	33	**93%**	**360s**	75s
Back-home	80	**83%**	**586s**	60s
Other house	124	70%	860s	89s
Transition	400	60%	868s	80s
Home	949	73%	874s	72s
Leisure	451	68%	908s	107s
Out of town	287	67%	934s	69s
Education	1108	74%	989s	81s
Religious	14	**42%**	**1134s**	184s
Service	35	**43%**	**1627s**	290s

In Table 1 we can distinguish three groups of locations formed based on compliance: locations with high, average, and low compliance. The first group includes Supermarket, Food, Health and Back-home transitions that have a high compliance and a low response latency, which means that in these kind of locations participants tend to be more accessible to answer the EMA requests. The second group contains Home, Other houses, Transitions, Leisure, Out of town, and Education. In this group, the compliance and response latency are relatively average; i.e., participants answered the EMAs in around 70% of the cases but they took a considerable time to start answering the questions (around 900 sec of response latency). The third group contains Religious and Service places where the compliance rate is relatively low (less than 50%) and the response latency is high (more than 1000 sec). These rates suggest relatively low adherence in these places.

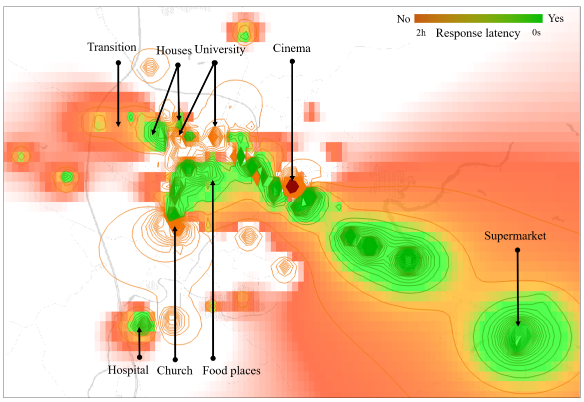

Figure 2: Spatial analysis of EMA responses. Green indicates higher likelihood of EMA response. Orange indicates lower likelihood of EMA response. To protect privacy, the background map has been blurred to reduce the identifiability of the locations.

While these results show high variance in the spatial distribution of compliance rate and response latency, the duration of EMAs did not follow the same pattern. We notice from Table 1 that the duration did not seem to be highly affected by location, except for Service and Religious places where we recorded a very high duration. This may be explained by the fact that participants were busy in these two types of locations so they tended to take breaks when completing the EMAs.

To further understand the impact of location on the participants' compliance with EMAs, in Figure 2 we present a distribution of response latency over space. We first retrieved the GPS location where each EMA was prompted, than we interpolated the response latency using the inverse distance weighted interpolation [18]. In Figure 2 we can observe how different areas of the city (where the study was conducted) impacted the response latency. For instance, when EMA requests happened in green areas, such as food places and supermarkets, participants tended to answer more quickly than when requests happened in orange areas, such as cinemas and during transitions. These disparities indicate that the spatial dimension has an important impact on the compliance rates.

3.3 Phone Motion Analysis

Next, we examine the effect of phone motion on compliance with mobile EMAs. We propose to analyze the Accelerometer (Acc) data before the EMA prompts and to study its relationship with compliance. We are aware that a common scenario would be that the phone is moving heavily because someone is walking, which is why we added GPS locations to add more information about the source of generated Acc data. For instance, high Acc detected during transitions (moving from one place to another) means that the Acc data are more likely to be generated by the body movement, while high Acc in locations where people are more likely to be in a stationary state (e.g., restaurants) suggests users are hand-handling their phones.

We passively collected the accelerometer data using the built-in acceleration sensor in the participants' smartphones with a frequency of 1Hz. Then we used different statistic measures to extract several features of phones' motion in several epochs before an EMA. These features aim to represent how much the phone is moving before an EMA happens. Next, we examined the correlation between the response latency of the EMAs and the extracted features.

When an EMA event happens, we take the accelerometer data collected in several observation periods before the EMA (10min, 30min, and 60min before the EMA). For each observation period, we extract accelerometer features using one-minute sliding windows. Our accelerometer features are extracted from the magnitude of acceleration ($a_t = \sqrt{x_t^2 + y_t^2 + z_t^2}$) to make them orientation-free. For each observation period, we then extracted the following statistical measures of a_t: mean, median, standard deviation (std), variance (var), skewness and kurtosis.

Figure 3 shows the Pearson correlation results between the different motion features we described earlier and the EMAs' response latency, and illustrates this in different locations and different time periods prior to EMA prompts: 10min, 30min, and 60min. Generally, the results show an obvious negative correlation between the average response latency and the phone's motion given the correlations are almost all negative across all locations and time epochs. However, when comparing the time epochs prior to EMA prompts, we notice that the closer the observation window is to the EMA prompt, the stronger the correlations, which means that Acc features extracted 10min before the prompt are more predictive of response latency than features extracted 30min, and 60min before the prompt.

Furthermore, motion features show a stronger negative correlation between EMA response latency and motions at locations like Food, Health, Home, Other houses, Education, Religious, and Service places (see top of Figure 3), which means that when the phone is moving in these locations, participants tend to have a short response latency. This is justified by the fact that all of these locations are places where participants are more likely to be in a stationary state (e.g., restaurant, home, friends' houses). So when the phone is moving in these locations, it is more likely that participants are hand-handling their phones, which suggests they are already doing something on their phones (e.g., using apps) when the EMA is requested. Intuitively, when users are more engaged with their phones (resulting in higher motion features), it takes less time for them to start replying to an EMA prompt.

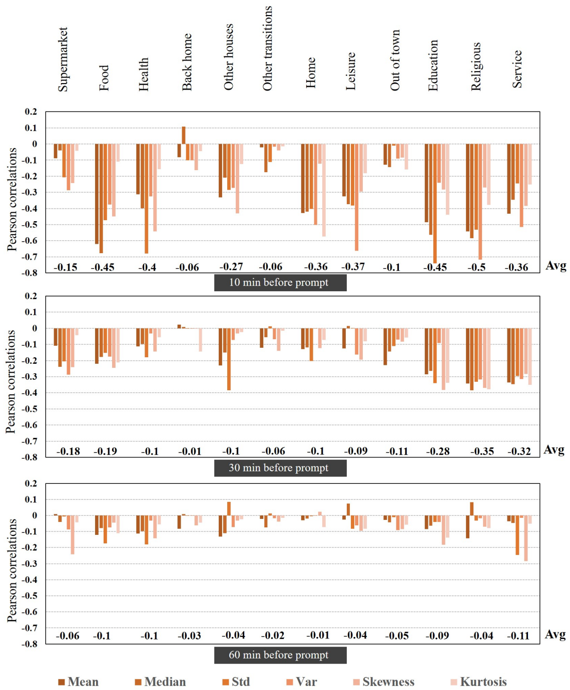

Figure 3: Phone motion analysis: multi-scale correlations between accelerometer features and response latency in different locations. accelerometer features are order from left to right as follows: mean, median, std, var, skewness, kurtosis.

On the other hand, we noticed weak correlations in locations such as Supermarket, Back Home, Other transitions, and Out of town. In these locations, participants are more likely to be moving (e.g., waking from one place to another, walking in supermarket), so the increase in motion features in these cases is justified by other reasons for a phone being in motion (e.g., tied to the participant experiencing transportation motion) besides phone use. We also observed a few positive correlations during the 30min and 60min time windows. We suspect this may simply reflect noise given the the low frequency of these observations and the weakness of the correlations. Furthermore, we studied the correlation between the Acc features and response duration. We found that there is no correlation between phone motion and duration of responses, regardless of location and observation window prior to the EMA prompt (r<0.1 for all features and for all time windows).

3.4 Phone usage analysis

Participants use their smartphones in different ways. While some participants tend to avoid spending a lot of time on smartphones, others spend extensive time on their phones texting, making phone calls, surfing the Internet, using social network apps, etc. As such, when an EMA happens, participants can be in different engagement levels with their phones (e.g., actively texting vs. the phone being in a bag). We thus investigate if phone engagement level during EMA prompts affects the compliance rate. Ideally, engagement with phones would be assessed using screen sensor (on/off) and app usage. However, these data were not available in our study. Thus, we used the communication logs as a proxy for phone usage. Communication events are a good indicator of phone usage, especially among student populations because they tend to communicate broadly using SMS texts [1]. Communication logs are time series of calls (calling or receiving call) and SMS texts (sending or receiving) events. Thus, for each EMA, we collected the number of phone calls and text messages that occurred in the 30 minutes prior to the EMA prompt, and calculated whether the number of communication events had an impact on compliance.

We also calculated the Pearson correlation between the number of communication events (texts and calls) and response latency and response duration. While we did not find any correlation between the number of texts/calls and response duration (r=0.06 and r=-0.03 respectively), we found a negative correlation between number of calls/texts and response latency (r=-0.27 and r=-0.31 for calls and texts respectively). This suggests that the more participants are using their phones to text or make calls, the more reactive they are with answering the EMA prompts.

To study the impact of communication events on compliance rate, we calculated whether the average number of communication events differed before responded and non-responded EMA prompts. Figure 4 depicts a comparison between the amount of communication events 30 minutes before responded EMAs (in orange) versus not responded EMAs (in black), and how this occurred in different places. The x-axis is the average number of communication events.

Results show that, at Home, Service places, and during transitions, the number of text messages did not substantially affect whether or not users replied to EMAs. But, at the other places (Education, Supermarket, Food, Out of town, Other houses, Leisure, Health), more text messages were linked to a higher probability of responding to EMAs. Moreover, the number of phone calls showed a more obvious difference between EMAs that were versus were not responded to. We notice that more phone calls happened before the responded versus non-responded EMAs (see Calls in Figure 4).

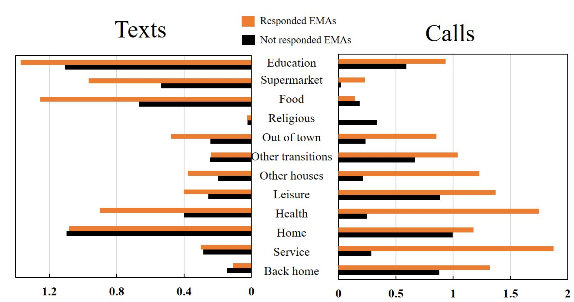

Figure 4: Analysis of number of texts and calls during the 30 minutes before EMAs that were versus were not responded to. The x-axis is the average number of communication events (texts messages and calls) 30 minutes before EMAs.

These results provide some evidence about the utility of understanding the dynamics of phone usage in EMA delivery. The results suggest it may be helpful to schedule EMAs around moments when and where participants are already engaging with their phones to increase compliance. Next, we use the full set of context dimensions that we studied earlier to highlight how context can predict compliance with EMAs.

4 PREDICTING EMA COMPLIANCE

Using the extracted temporal, spatial, phone motion, and phone usage features, we aim to investigate if the extracted context-related features can predict compliance rate and response latency. We first classified each EMA to one of the following classes: (1) not responded, (2) responded with small response latency when the latency $\in]0, 600s]$, (3) responded with moderate latency when the latency $\in]600s, 1200s]$, and (4) responded with high response latency when the latency $\in]1200s, 7200s]$ (7200s is the maximum that a response latency can be, and it represents the maximum time between two surveys). Note that we used an entropy-based discretization method [11] to create the classes 2, 3, and 4. While we recognize that this split is a somewhat simplistic and artificial way to create groups, we felt that this four-group classification was appropriate to demonstrate the feasibility of predicting the compliance rate and response latency. Indeed, we want first to predict if the EMA prompt will be answered or not, and if answered, if the EMA response will be close to the EMA prompt or not. This is motivated by the fact that researchers want to know not only whether or not a response is provided, but also how close in time to the prompt the participant responds. When EMA prompts delivery are randomized, long response latencies may remove the randomness and minimizes the diversity of situations in which we would capture data.

We then used the GPS location where the EMA request happens, locations 2 hours before the prompt (2 hours is generally the time between two prompts), time of day, day of the study, accelerometer features 10min before the prompt, and number of SMS texts and calls 30 minutes before the survey prompts to predict the EMA response group by using several algorithms: Random forest (RF), Support Vector machine (SVM), and a multilayer perceptron (MLP) by using one hidden layer with 100 nodes (we didn't perceive any increase in performance when adding more layers and more nodes).

The three models have been evaluated using leave-one participant-out cross-validation (LOOCV). In Table 2, we first calculated the accuracy of the classification by using each of the spatial, temporal, phone motion, and phone usage features separately, and then we combined them to investigate if that improved the model results. We notice, indeed, that combining the four context dimensions improved the model predictions to reach an accuracy of 78% for RF, 76% for SVM and 73% for MLP.

Table 2: Accuracy difference between combining the space, time, phone motion and phone usage features and using each of them separately.

Algorithms	**Location**	**Time**	**Motion**	**Phone usage**	**All**
RF	46%	41%	32%	42%	**78%**
SVM	50%	39%	27%	41%	**76%**
MLP	46%	41%	27%	41%	**73%**

5 CONCLUSION

Mobile EMA is increasingly used to collect participants' data in real-time and in context. Although this provides an opportunity to understand behavior on a more granular level, participant noncompliance or disengagement when completing EMAs still threatens data quality and measurement validity. In this study, we analyzed the relationships between context and EMA compliance. We proceeded by a multilevel analysis of time, locations, calls/SMS texts logs, and accelerometer data. Our findings suggest that whether a user responds to an EMA prompt is not a random event. On the contrary, user response patterns appear to be influenced by several factors, including but not limited to where they are, the social context they are embedded in, the time of day, and what they are doing. Many of these factors require different forms of passively sensed data (e.g., GPS) to approximate which points to the importance of integrating disparate sources of data. Using the active and passive sensing framework provided in the current study, there is tremendous potential to deliver EMA prompts when and where users are most open to responding. Future work will study the impact of context on compliance in a larger sample by including additional data sources such as physiological data and *in situ* mental state.

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