# Understanding Social Context from Smartphone Sensing: Generalization Across Countries and Daily Life Moments

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Understanding and longitudinally tracking the social context of people help in understanding their behavior and mental well-being better. Hence, instead of burdensome questionnaires, some studies used passive smartphone sensors to infer social context with machine learning models. However, the few studies that have been done up to date have focused on unique, situated contexts (i.e., when eating or drinking) in one or two countries, hence limiting the understanding of the inference in terms of generalization to (*i*) everyday life occasions and (*ii*) different countries. In this paper, we used a novel, large-scale, and multimodal smartphone sensing dataset with over 216K self-reports collected from over 580 participants in five countries (Mongolia, Italy, Denmark, UK, Paraguay), first to understand whether social context inference (i.e., alone or not) is feasible with sensor data, and then, to know how behavioral and country-level diversity affects the inference. We found that (*i*) sensor features from modalities such as activity, location, app usage, Bluetooth, and WiFi could be informative of social context; (*iii*) partially personalized multi-country models (trained and tested with data from all countries) and country-specific models (trained and tested within countries) achieved similar accuracies in the range of 80%-90%; and (*iii*) models do not generalize well to unseen countries regardless of geographic similarity.

Additional Key Words and Phrases: ubiquitous computing, mobile sensing, social context, alone or not, smartphone sensors, machine learning, context-awareness, context inference

# 1 INTRODUCTION

Human beings have a fundamental need for social interactions, community, and interpersonal relationships [8]. A well-embedded social life has been found to be especially important for the mental well-being of young adults [11, 27, 64]. Studies show that being with others (i.e., not alone – being with friends, family, or colleagues) frequently in adolescence has long-term effects on mental and physical well-being. Being in social isolation, on the other hand (i.e., living alone, being alone for long time periods [30]) increases the probability of depression and other mental and physical illnesses [8, 11, 30, 39, 60]. Hence, understanding the social context of people longitudinally has benefits in mobile health applications to provide interventions in receptive moments [42, 43]. Moreover, according to Dey [23], "a system is context-aware if it uses context to provide relevant information and/or services to the user, where relevancy depends on the user's task". The social context is an attribute that could allow mobile health applications, and other mobile apps to be context-aware [18, 24, 35, 51].

Even though there is no single definition for the concept of social context, whether a person is alone or not at a given moment has been used in prior studies as a fundamental construct for social context [42, 43]. Traditionally, the social context, similar to other behavioral and contextual factors such as mood, semantic location, and food consumption, has been tracked longitudinally through the use of surveys and ecological momentary assessments [42]. However, the reliance on surveys can impose a burden on users and result in sparse data. An alternative approach to understanding the behavior, context, and overall well-being of individuals involves utilizing mobile and wearable sensors, along with self-reports [41]. These efforts are part of the larger field of ubiquitous computing, which explores the potential of passively sensing the holistic context of individuals

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Table 1. Terminology & definitions used in this paper

Term	Description
Social Context	If a person is Alone or Not (i.e., with friends, family, or others). We borrow this definition from prior studies in ubiquitous computing domain [42, 43].
Country-specific approach	Machine learning models are trained and tested only on data from one specific country.
Country-agnostic approach	Machine learning models are trained on one country or a set of countries and tested on another country or another set of countries. Such models are usually trained with the assumption that the model could be deployed to other countries, hence the term agnostic.
Multi-country approach	Machine learning models are trained on a set of countries and tested again on the same set of countries. This is the generic way of training models when data from multiple countries are available.
Population-Level Model (PLM)	Training and Testing splits have a disjoint set of users. Represents a case where a machine learning model trained with a population is deployed to a mobile app that a new user uses. Hence, end-user data are not used in model training leading to non-personalized and generic one-size-fits-all models.
Hybrid Model (HM)	Training and testing splits do not have a disjoint set of users. Represent a case when a mobile app user uses a machine learning model for some time, and data from the user is used in re-training (or fine-tuning in the case of neural networks) models. Hence, this approach leads to partially personalized models.

[2, 22, 68]. In contrast to questionnaires and surveys, mobile sensing-based inferences are less prone to bias and less burdensome for users [9]. However, accurately inferring whether a person is alone or in the company of others using mobile sensing data remains a challenging task [3, 14, 41, 43, 67, 68]. Previous studies are often limited in scope, only exploring the inference of social context in specific contexts such as eating events [43], alcohol consumption events [41], or among a population diagnosed with depression [14]. Hence first, there remains a lack of knowledge regarding the interaction between social context and other behavioral/contextual features, such as self-reported mood, semantic location, time of day, and concurrent activities, as well as passive sensor data (including activity, step counts, app usage, Bluetooth, and WiFi), across a wide range of daily life moments beyond eating or drinking. Furthermore, the effectiveness of smartphone sensing-based social context inference models for complex daily life moments across countries, remains unknown.

The concept of data diversification involves expanding the sample of data used for training machine learning models in order to enhance representation and improve the model's ability to generalize to a range of populations [29]. The consideration of data diversity has been applied to a variety of domains, including computer vision [13, 56] and natural language processing [12, 62], with the country of origin of the data serving as a key factor. These efforts not only improve the performance of the models but also guarantee fairness in the results produced by the machine learning models, benefiting diverse users across countries [25, 70]. Despite the importance of data diversification, the application of this concept to mobile sensing has been hindered by the lack of large-scale datasets collected from various countries using a consistent protocol [4, 40]. The cost and time-intensive nature of collecting in-the-wild data across multiple countries present a significant challenge. As a result, even smartphone sensing studies focusing on specific contexts such as eating and drinking events have only used data from one or two countries [42, 43]. To date, only a few studies have explored the impact of geographical diversity on mobile sensing-based inference models [31, 40], while none have focused on social context inference [47]. Hence, this study represents one of the first endeavors to examine social context inference across daily life moments, using multimodal sensing data collected from multiple countries. Therefore, we ask the following research questions:

• **RQ1:** Which situational and behavioral aspects are associated with different social contexts in a large dataset consisting of over 216K self-reports and passive smartphone sensing data?

• **RQ2:** Can the social context of daily life moments be inferred using smartphone sensing with population-level models (non-personalized), with a generic one-size-fits-all multi-country approach? Does the separation of sensing data by its origin countries aid the inference performance?

- **RQ3:** What is the effect of training hybrid models (partially personalized) on model performance?
- RQ4: Do social context inference models generalize well to unseen countries?

In answering the above research questions, this study provides the following contributions:

• **Contribution 1:** We examined a large smartphone sensing dataset collected in-the-wild from 581 college students in five countries: UK, Denmark, Italy, Paraguay, and Mongolia. This dataset contains passive sensing data from continuous sensing modalities such as activity type, step count, bluetooth, wifi, location, cellular, and proximity; and interaction sensing modalities such as app usage, touch events, screen on/off episodes, notification, etc. In addition, the dataset contains over 216K social context self-reports captured from users over four weeks. In a statistical analysis, we found that individual features from modalities such as app usage (type and amount of app categories being used – tools, communication, productivity, social), activity types (in a vehicle, on foot, walking), location (altitude), Bluetooth, WiFi, proximity, and screen episodes were among the top five features in terms of statistical significance in discriminating alone or not events. Further, we also found that the statistically significant features in discriminating social contexts, are not common across countries. This shows the diversity of behaviors of individuals across countries and the related contextual features around different social contexts.

• **Contribution 2:** We operationalized three approaches to examine the inference of social context (Table 1). They are country-specific, country-agnostic, and multi-country. Without considering the country-level diversity of data sources, we found that the generic multi-country approach provides a moderate accuracy of 62.21% without feature selection and 62.35% with feature selection, using population-level models. With the country-specific approach, we found that models perform similarly to the multi-country approach, where in most countries, the margins were less than 2% for both with and without feature selection. However, except for Italy, which yielded an accuracy of 62.03% compared to the multi-country accuracy of 62.35%, all other countries achieved slightly higher accuracies above multi-country performance. This finding contradicts prior studies that used similar multi-country datasets for health-related inferences, which suggested that country-specific models are generally superior by large margins. Hence, we found that it might not always be the case for social context inference.

• **Contribution 3:** With hybrid models, the multi-country approach provided an accuracy of 83.45%, whereas, except the UK, which provided an accuracy of 82.08%, all other countries performed better. However, these differences are marginal in Italy (84.20%) and Paraguay (83.76%), whereas for Denmark (88.72%) and Mongolia (87.47%), the differences were around 5%. However, across ten iterations of testing each setup, the performance difference between multi-country models and country-specific models was not statistically significant (p-value  $\approx$  0.18). Hence, these results suggest that regardless of the level of personalization, having a generic multi-country model could be sufficient for social context inference, while country-specific models would provide minor gains in certain cases. This finding, too, is contrary to prior studies that used smartphone sensor data for health-related inferences that suggested using country-specific models for better performance, even after personalization.

• **Contribution 4:** In the specific case of mood inference, even though prior work found that models might generalize well to geographically closer countries in Europe, we did not find such associations when examining social context inference performance. In fact, in all cases, models did not generalize well to unseen countries. Hence, similar to previous studies, we also found that models lack generalization when deployed to unseen countries, compared to country-specific or multi-country performance.

This paper is organized as follows: In section 2, the related literature is presented and summarized. In section 3, the dataset, its collection methodology, the chosen feature aggregation, and data pre-processing steps are

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discussed. In section 4, the experimental setup to answer RQ1-RQ4 is discussed. In section 5, the results are presented. In section 6, the results are interpreted and discussed. A conclusion follows in section 7.

# 2 BACKGROUND AND RELATED WORK

Next, we surveyed various lines of research that our work draws upon, and grouped them into three main areas: (*i*) context recognition and health sensing; (*ii*) social context inference; and (*iii*) leveraging diversity-awareness.

# 2.1 Context Recognition and Health Sensing

In the mobile sensing literature, Alone-or-Not inference, or in general, the social context inference, amounts to a context recognition task. According to ideas regarding pillars of data that categorize mobile sensing-based inferences into three categories: behavior, person, and context, the social context inference falls into the third pillar [41]. Context awareness promises great potential for the optimization and personalization of devices. For instance, the battery life can be optimized by considering the context of a device and its associated battery usage profile [68]. Thus, in low battery usage contexts (e.g., sleeping, sociable events, etc.), sampling rates of certain sensors (GPS, cellular sensors) can be decreased [68]. Context-aware applications may also customize the behavior of the device in a given situation. For instance, the device might disable incoming calls or put the phone in silent mode if the user is in a meeting (not alone) [38]. Another category of context-aware applications uses mobile sensing to determine the health and well-being of users. There is a large body of literature around mobile sensing studies that attempt to detect a diverse set of health-related contexts such as stress [15], mood [36, 55], depression [14], eating and drinking behavior [10, 53], and related social context [42, 43].

The main aim of such studies lies in the detection, analysis, and intervention of health and well-being-related contexts. Accurate detection of such a context is the prerequisite for the analysis or intervention [9]. Given the complexity of many health-related activity recognition tasks, the construction of an appropriate detection pipeline and the correct modeling of the mobile sensing data is non-trivial. After the correct detection of a health context, one might explore factors and characteristics which might be associated with negative health outcomes (e.g., social context). For instance, heavy drinking episodes of young college students might be associated with peer pressure from colleagues [42], or one is experiencing a depressive mood after being alone for a long time period [39]. At last, assuming episodes of adverse well-being-related contexts can be correctly identified, applications can be developed with the aim of directly improving the well-being of users or intervening in a needed situation. Such applications have already been developed for depression intervention [14, 63] or mood tracing [55]. Social context recognition can be classified as one instance of health sensing given its direct relation to mental and physical well-being [30, 39].

#### 2.2 Social Context Recognition

The social context of people involves complicated phenomena operating on several different dimensions [2]. Two dimensions that are of particular importance are (*i*) the number of people the user interacts with; and (*ii*) the relationship which is associated with the current social context of the user (e.g., family, colleagues, partner, etc.) [2]. Considering the number of people a user interacts with, the trivial case describes if a user is alone or not. Thus, this variable is often explored in mobile sensing studies, which discuss depression, mood, eating behavior, drinking behavior, and general mental well-being [9, 14, 42, 43, 55].

Prior studies which consider the task of social context sensing often discuss ethical and technical considerations [3] or try to contextualize the task in the broader sense of social networks and behavior of users [2]. One rather paradoxical effect of the internet, which one has to consider in such an analysis, is that mobile phones function as platforms to emulate and partially even supplant social context. This applies especially to young adults who substitute in-person relationships with interactions over mobile phones [59]. One could therefore claim that

"the 'connection technology' of the Internet [...] has in many cases increased social disconnection" [2]. However, in this study, the task of social context inference only considers actual in-person people being present and not virtual connections over mobile phones or social networks.

Several studies attempted the inference of in-person social context, alone or not, with sensing data. In [14] for instance, the authors collected sensor data for eight weeks from eight people with 38 different sensors. They trained regression trees to predict if a user is alone or not and predicted on data of the same user (fully personalized models), thereby reaching mean accuracies of 80% across users. However, the eight participants they recruited were diagnosed with depressive symptoms. Hence, the sample size was very small, and the data did not capture the social context of individuals who were not diagnosed with mental health-related aspects. Other studies consider the task of social context inference in a specific situated context. In [43], the authors consider the social context of university students during eating episodes. The authors argued that inferring whether an individual is alone or not has immense value in providing timely interventions and feedback in mobile food diaries. By using population-level models, they archive accuracy rates of 70%-75% by only using sensor data across Switzerland and Mexico separately. However, the authors mention that the results of countries can not be directly compared because data collection was done with different sensors, in different time periods, and with different protocols. In addition, the sample sizes are much smaller compared to our study. [42] examined the social context of young adults during alcohol drinking episodes. With population-level models, they reached accuracies in the range 80%-87% in several two-class social context inferences, including alone or not, and also alone or with friends/family/partners. However, their study was done using a dataset collected in a single European country and only contains the social context around drinking events. In addition, even though both these studies had healthy participants (i.e., no eating, drinking, and mental well-being-related disorders), both studies focused on specific situated contexts such as eating and drinking. Hence, the social context of young adults in daily life moments has not been studied in prior work with smartphone sensing data. In addition, a deeper analysis of country-level diversity and model personalization approaches has not been provided in prior work.

## 2.3 Leveraging Diversity Awareness

Systems that are fundamentally based on learning patterns from data (e.g., classification, regression, etc.) might be drawn to represent the internal biases present in the training data [70]. This may lead to biased predictions depending on the gender, race, socio-economic, or psychological profile of new users of the given pre-trained model. In computer vision research, the effect of biased learning data has already been widely discussed. One study evaluated gender classification models with respect to different subgroups of genders and races [13]. The authors found that dark-skinned women were classified worse with error rates up to 34.7% while the classification error rate of light-skinned men amounted only to around 0.8%. The origin of such biases often lies in the lack of representation in datasets used for training models.

In both ImageNet [20] and Open Images [33], which are the two most commonly used image datasets for classification, only 1% of all images originate from China, and only 2% of images come from India [56]. This has been shown to bias model predictions when deployed in these countries [56]. Similar biases can also be found in natural language processing, where racial and gender biases might not be as obvious and apparent as in computer vision. Here researchers found that gender stereotypes are often encoded into word embeddings and thus reinforce biases in text generation or text correction [12]. Other research suggests that Google Translate, a widely popular machine translation software, consistently translates gender-neutral job descriptions to male job descriptions in English [49]. Being aware of representation and imbalances in machine learning datasets and outcomes improves the out-of-sample performance of machine learning systems and, more importantly, makes them more 'fair' [70]. In the mobile sensing literature, the assessment of diversity across datasets is challenging because data biases are not as clearly visible as in computer vision or natural language processing. Some existing

country	# of participants	# of participants with sufficient data	# of reports	alone percentage
UK	72	53	26,687	69.05%
Denmark	25	17	10,058	49.63%
Italy	238	221	151,335	64.78%
Paraguay	29	24	9,745	54.52%
Mongolia	217	138	94,249	24.52%
All	581	453	292,074	51.31%

Table 2. Data summary statistics of the used dataset

approaches suggest that splitting large, diverse datasets into smaller, more homogeneous datasets improves computational time complexity and might even improve accuracy [1]. Going along this line of work, in the sensing domain, even though aspects such as wearing diversity (location of wearing) of wearable sensor data has been discussed [16], prior work has not extensively discussed the effect of geographical diversity on sensor-based inference tasks [47].

One obvious approach to maximize the diversity within a dataset is to collect the mobile sensing data from several vastly different geographic locations and thereby try to increase cultural, socio-economic, and racial diversity [54]. This has been examined in only a few prior mobile sensing studies. Khwaja et al. [31] collected and explored mobile sensing datasets from users from five countries (UK, Spain, Colombia, Peru, and Chile) and inferred the personality traits. They found that country-specific models outperformed multi-country models by 3%-7% for Extraversion, Agreeableness, and Conscientiousness. Two recent studies also showed that training models for individual countries would perform better than training generic one-size-fits-all models for all countries in mood inference [40] and complex daily activity recognition tasks [4]. However, whether such findings hold true for social context inference needs further investigation.

In light of these lines of related work, this study has novelty in the following aspects: (*i*) we identify smartphone sensing features and other behavioral and contextual aspects from self-reports that help discriminate the social context, including a comparison across different countries. This was done using a novel, large-scale, and multimodal smartphone sensing dataset, compared to studies discussed in the literature; (*ii*) we examine the feasibility of inferring social context using a generic multi-country approach, with both population-level and hybrid models – making this one of the first studies to attempt social context inference with smartphone sensing data collected from a large sample of users; and (*iii*) we compare country-specific, country-agnostic and multi-country approaches, showing that multi-country models work fine for social context inference, while generalization issues persist when models are deployed to unseen countries.

## 3 DATASET

We used a novel smartphone sensing dataset from our previous work, that was collected in a study conducted simultaneously in five countries [4, 28]. The data were collected for four weeks from college students of the following five universities: Aalborg University (Denmark), London School of Economics and Political Science (the United Kingdom), the National University of Mongolia (Mongolia), the Universidad Católica "Nuestra Señora de la Asunción" (Paraguay), and the University of Trento (Italy). The study participants contributed three different kinds of data: *(i)* closed-ended questionnaires, *(ii)* hourly self-reports throughout the day, and *(iii)* sensor data.

(*i*) The closed-ended questionnaires consisted of three separate questionnaires, which were administered to the study participants before the start of the study, before the start of the sensor data collection, and after two weeks of sensor data collection. This design allowed the collection of a large amount of information from participants

without overburdening them. The questionnaires were designed to capture surface diversity information (age, sex, country, etc.) and deep diversity information (personality, values, intelligence, etc.— with validated scales).

(*ii*) During the data collection, a mobile app was deployed. Using the app sensor data were captured passively, and participants also self-reported details about their behavior and context. These hourly self-reports were meant to capture how people spend their time. A notification was sent to participants once every hour, and they were asked to report their current activities (studying, cooking, etc.), semantic location (home, library, etc.), mood (valence— in a five-point scale from very negative to very position), and social context (alone, friends, relatives, classmates, roommates, colleagues, partner, other). Hence, the dependent variable for the discussed alone-or-not inference is based on the answers from the social context self-report.

*(iii)* The sensor data originally consisted of 34 different sensors, which are divided into continuous and interaction sensing. Continuous sensing modalities (captures sensor data regardless of user activities) included activity type, step count, Bluetooth, WiFi, location, cellular, and proximity; and interaction sensing modalities (measures the interactions users have with the phone) included app usage, touch events, the screen on/off episodes, notification, etc.

In total, four weeks of sensor and self-report data were collected from study participants. However, the completeness and the number of responses to time diaries and questionnaires vary greatly between different countries (Table 2) and different users (Figure 2). Furthermore, the quality and quantity of sensor data also vary between different users. This is also observable in the amount of missing sensor data (Nan) for certain sensors or study participants (Figure 1). A more detailed discussion about the dataset and feature extraction can be found in papers that presented the dataset [4, 40].

The final analysis of this study consists of inferring the social context of a user. Given the large size of the original dataset, which amounts to approximately 30GB of data in different data formats, the sensor data were processed and aggregated to sensible features at the self-report level. To do this, we used an approach similar to prior mobile sensing studies where sensor data are aggregated around a time of an in-situ self-report [5, 10, 42, 43, 55]. More specifically, all sensor data corresponding to five minutes before and five minutes after each social context self-report was aggregated to features as summarized in Table 3. Thus the aggregation time frame corresponds to a ten minutes window around the answering time of a self-report which captures the user's current activity, semantic location, mood, and finally, the social context. In total, 117 distinct sensor features were created, including 48 features that correspond to app usage time period based on app categories in Google Playstore (e.g., action, dating, music, puzzle, social, etc.) similar to [36, 53]. Additionally, time and day features were also included in the analysis, where the day of the week corresponds to a categorical variable, weekday or weekend, while the time was noted with the hour of the corresponding time dairy event (a numeric value between 0 and 23). Furthermore, missing data markers were introduced, which indicate when data is missing for certain sensor groups [37]. In summary, the features of the final dataset used for inference are detailed in Table 3.

## 4 EXPERIMENTAL SETUP

### 4.1 RQ1: Situational and Contextual Aspects Around Social Contexts

The aim of this analysis was to examine various situational and behavioral cues around social context (alone or not), that can be captured from self-reports and sensor data. This allows us to gain a holistic understanding of the dataset and positions our work in comparison to prior work. First, the original dataset contained fine-grained social contexts such as alone, with classmates, with colleagues, with partner, with relatives, with roommates, and with others. Using these labels, we examined how fine-grained social context patterns differ in countries (Figure 3). Then, by considering all countries together, we examined how social context across those fine-grained categories differ through the hour of the day (Figure 4). Next, since prior work has linked social context with mood (discussed in Section 2), we did an analysis around the binary social context (i.e., alone or not) across

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Table 3. Summary tables of sensors and extracted sensor features. The sensor features are computed by aggregating ten minutes of sensor data before and after a diary entry. In total, one sensor feature corresponds to 10 minutes of sensor data.

Sensor	# of Features	Features and Description Radius of gyration the sum of distance covered altitude
Location (gyroscope)	5	Radius of gyration, the sum of distance covered, attitude
Bluetooth low energy	5	Number of devices connected, mean rssi (received signal strength indicator), max rssi, min rssi, std rssi
Bluetooth (Normal)	5	Number of devices connected, mean rssi (received signal strength indicator), max rssi, min rssi, std rssi
Wifi	6	Number of devices connected to the device wifi hotspot, if the device is con- nected to a wifi, wifi mean rssi (received signal strength indicator), max rssi, min rssi, std rssi
Cellular gsm (2G network)	4	Strength of the mobile signal as defined by mean, max, min, std
Cellular wcdma (3G network)	4	Strength of the mobile signal as defined by mean, max, min, std
Cellular lte (4G network)	4	Strength of the mobile signal as defined by mean, max, min, std
Notifications	4	notifications posted, notifications removed, notifications posted without duplicates, notifications removed without duplicates
Proximity sensor	4	Measures of the proximity sensor as mean, max, min, std
Activity (accelerometer)	8	Activities as classified from the accelerometer data by the Google Activity Recognition API [21]; activity still, activity tilting, activity invehicle, activity onbicycle, activity onfoot, activity walking, activity running, activity unknown
Step counter	2	step counted, steps detected
Touch sensor	1	Number of touch events
Screen sensor	7	User presence time, screen number of episodes, screen time total, screen time per episode, screen time max episode, screen time min episode, screen time std episode
Apps categories	48	App categories as classified by the google play tore [53]. E.g.: Action apps, dating apps, music apps, puzzle apps, etc.
Time	2	Hour of the day, day of the week

different levels of mood, captured as valence, in a five-point Likert scale (very positive, positive, neutral, negative, very negative). Then, we examined how the social context differs across different locations and while performing various activities (5).

To assess which sensor features (including the hour of the day, and day of the week) are most indicative of determining if someone is alone or not, independent student t-tests [32] have been performed (see Table 4). The t-tests have been performed with the data distribution of the sensing features while a participant is alone and while he is not alone for all five countries, separately. The p-values have been adjusted with the Bonferroni correction [61]. As an additional measure, the effect size is estimated with Cohen's-d estimates and the 95% confidence intervals [34].





Fig. 2. Boxplot of the number of self-reports per user, grouped by country. The boxes extend till the upper and lower quartiles, the median is indicated by an orange line, and whiskers extend till 1.5x IQR

Fig. 1. Ratio of missing data (Nan values) in percentage aggregated to sensor group

# 4.2 RQ2, RQ3 & RQ4: Social Context Inference

To better understand the significance of geographical diversity in social context inference, the central idea is to divide the dataset into several subsets [1] according to the origin of the data [31, 43]. Countries can have different cultural and socio-economic norms, and one can assume that this influences the behavior of people, their smartphone usage, and their social behavior [31]. Thus our basic assumption states that data generated by a specific country is more adequately suited to train and construct a model for that specific country. To evaluate this assumption, we need to compare the results of models trained on different data splits. Hence, motivated by previous literature that considered multi-country data [4, 31, 40], we used several experimental approaches:

- Multi-country: training and testing with all available countries.
- Country-specific: training and testing within the same country.
- Country-agnostic: training on one or more countries and testing on an unseen country.

In fact, these scenarios represent how models are trained and deployed in practice, where sometimes companies attempt to gather representative smartphone/wearable sensor data from multiple countries to train models. However, in cases, where such multi-country data collection is infeasible, a model would be trained within a country (or with data from a few countries) and deployed to other countries that were not part of training the model.

Moreover, we trained different machine learning models such as logistic regression, random forest classifiers, XGBoost, AdaBoost, and multilayer perceptron neural networks. First, all models were run with all available sensor features. Then, sequential forward feature selection (FS) [50] was used to select the most predictive features for training in both country-specific and multi-country approaches. Further, motivated by prior work [40, 44], we trained two types of models with different levels of personalization:

- Population-level models (non-personalized): Similar to leave-k-users-out strategy—that is, data in training and testing splits are not from the same users, ≈ 80:20 training and testing split.
- Hybrid models (partially personalized): First, data in training and testing splits are not from the same users, ≈ 60:40 split. Then, add 50% of data from testing users into the training set to achieve partial personalization for users in the testing set, leading to ≈ 80:20 training and testing split.

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In summary, to examine **RQ2**, that is (*i*) whether a generic non-personalized model could be used to infer social context with multimodal smartphone sensor data, and (*ii*) whether separating data based on countries leads to better performance, we used multi-country and country-specific approaches with population-level models. Then, to examine **RQ3**, which is how partial personalization affects model performance, we used multi-country and country-specific approaches with hybrid models. Finally, to examine **RQ4**, that is on how models trained in one or more countries generalize to data in an unseen country, we used the country-agnostic approach with population-level models under two setups: Setup 1—training with data available in a single country, and testing on all other countries, separately; Setup 2—training with data available in four countries, and testing on the remaining country).

In all cases, data were randomly sampled ten times to obtain results for each setup, and results were averaged to obtain the mean and standard deviation of accuracies. To deal with the class imbalance, Synthetic Minority Over-sampling (SMOTE) [17] was used in training, while under-sampling of the majority class was done in testing to obtain balanced testing sets. Thus, all experiments are to be evaluated against a baseline of 50%. Given run time restrictions, GPU implementations of the models were used. All models were run in python with commonly used libraries such as scikit-learn [46] for logistic regression and Ada Boost, cuml [52] as it implements a random forest model on the GPU, and lastly, a python XGBoost implementation [19]. Finally, in all cases, the hyper-parameter search was done using Grid Search (e.g., random forest: number of trees, max depth, min sample split; XGboost: learning rate, min split loss, max depth, reg lambda, etc.). For neural networks, four layers were used, with 256, 256, and 128 in hidden layers. Further, we used the *relu* activation function in hidden layers and the *sigmoid* activation function in the output layer. Moreover, we used *adam* as the optimizer and dropout for regularization (keep prob of 50%, 50%, and 70% respectively) to avoid over-fitting. Models were trained with 100 epochs.

Moreover, behavioral sensor data are often extremely sparse and tend to have high amounts of missing data [66]. Missing data in this dataset can correspond to several distinct cases: (*i*) a sensor malfunction, (*ii*) the sensor is broken or none existent, and (*iii*) the intentional disabling of the sensor by the user (e.g., disabling Bluetooth/WiFi, setting the phone to flight mode, etc.). However, those cases are hard to distinguish solely with the available sensor data and are thus all treated equally, similar to previous studies [48, 57]. The proportion of missing data also depended on the sensor (see Figure 1) and on the country in which the experiment was conducted (60% of Mongolian sensor data is missing). To deal with missing data, first, all sensor groups with more than 90% of missing data have been dropped, similar to prior work [53]. This only corresponds to the 'cellular\_gsm' features (see Figure 1). The rest of the missing observations were estimated with the k-nearest-neighbor (kNN) algorithm [66, 69], with k experimentally determined to be optimal at two. As discussed in prior work [4, 66, 69], the estimation was done for the training set, and the learned model was used to fill in missing data in the testing sets. To preserve the information which might be encoded in the missing entry of a given sensor group, binary markers were used to indicate that the data has been interpolated [37].

#### 5 RESULTS

## 5.1 RQ1: Situational and Contextual Aspects Around Social Contexts

As shown in Table 2, the number of study participants and self-reports varied according to where the pilot study was conducted. Overall 581 participants of the study provided 'social context' self-reports and also provided usable sensor data. The number of self-reports per participant varied greatly depending on the individual participant and the country. As can be seen in Figure 2, the median number of self-reports per participant varied between 200 (Denmark) and 800 (Italy). On average, participants provided around 300 to 400 self-reports. Some users provided well above 1000 self-reports, while some users provided close to zero self-reports, even after providing sensor data for many days. To make sure there is enough data for model personalization, users with less than 100



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Fig. 3. Distribution of social context across countries, as a ratio of the total number of self-reports.



Fig. 4. Social context distribution according to the hour of the day, across all participants.

self-reports or less than six observations of the minority class were excluded from the analysis, resulting in 453 participants for the analysis (see Table 2).

The distribution of the social context depends heavily on the respective country, as can be observed in Figure 3. For most countries, besides the curious exception of Mongolia, people were predominately alone. However, in Mongolia, people were with their families in over 60% cases. This indicates different cultural practices concerning living arrangements or family contact. What we can state with certainty is that in the dataset, the country of a participant highly influenced the distribution of the social context types (i.e., alone, with family/friends/partner, etc.). In Denmark and the UK, for instance, participants seemed to have spent more time with their partner (even more than with their families). Country-specific differences in the frequencies, quality, and kind of social context are also supported by literature from the life sciences [58]. However, it is also important to mention that there seems to be quite some variability between individual study participants as indicated by the 95% intervals in Figure 3.

Besides the country-specific effect on the frequency and kind of social context of participants, a time-specific effect was also observed. Figure 4 shows the distribution of social context depending on the hour of the day. Participants seemed to be mostly alone or with their romantic partner during the morning hours. During lunch and dinner, people tend to spend time (i.e., eating) with their family. Further, in Figure 5, we show the co-occurrences of specific moods (positive and negative valence), activities, and semantic locations, with the social context (alone-or-not). There does not seem to be an obvious relation between the valence of participants and their social





📕 Alone 📒 Not alone



(c) Concurrent Activity

Fig. 5. Alone or not alone depending on a) Valence, b) Semantic Location, and c) Concurrent Activity of the participants.

context. This is surprising as prior research suggests a strong link between valence and social context, especially between valence and being alone or in a group [45].

In terms of concurrent activities and being alone or not, activities such as studying, listening to lectures, sleeping, and personal care were done predominantly alone, whereas obvious social activities such as family care, eating, and fostering one social life were done with other people. Lastly, participants spent most of their time alone at home. This, again, might be heavily influenced by the pandemic and remote work and study environments [26]. In terms of gender-specific differences, there were no huge divergences between men and women. Men were alone more, with 54.6% of all self-reports, while women reported of being slightly less alone, with 49.1% of all self-reports. Women also spent more time with their family, with an average of 31.6%, which is approximately 5% more than men. All other differences between women and men were minor (see Table ?? in Appendix). This is

Table 4. Top ten t-statistics of sensing features to infer the alone-or-not social context depending on country with: t-value, p-value with Bonferroni correction ( $\leq 10^{-4}$  : \*\*\*\*), Cohen's d and 95% confidence intervals of Cohen's d.

	feature	t-statistic	Cohen's-d	[95% CI]		feature	t-statistic	Cohen's-d	[95% CI]
UK	app_tools	16.88****	0.239	[0.212, 0.264]		activity_invehicle	12.71****	0.363	[0.323, 0.403]
	cellular_wcdma_nan_marker	13.93****	0.180	[0.154, 0.206]	ıy	wifi_num_of_devices	10.82****	0.254	[0.214, 0.294]
	app_nan_marker	12.63****	0.189	[0.163, 0.215]		location_altitude	10.58****	0.260	[0.220, 0.301]
	screen_num_of_episodes	11.87****	0.159	[0.133, 0.185]		bluetooth_le_min_rssi	10.18****	0.231	[0.192, 0.272]
	time	11.19****	0.153	[0.127, 0.179]	gü	bluetooth_nor_min_rssi	9.93****	0.181	[0.162, 0.242]
	cellular_lte_max	10.08****	0.153	[0.127, 0.179]	la	day	8.82****	0.181	[0.141, 0.221]
	cellular_lte_mean	9.46****	0.153	[0.127, 0.179]	Pa	activity_onfoot	7.62****	0.168	[0.128, 0.208]
	proximity_std	8.29****	0.134	[0.108, 0.160]		activity_walking	7.61****	0.167	[0.127, 0.207]
	day	8.21****	0.109	[0.083, 0.135]		activity_running	5.75****	0.122	[0.082, 0.162]
	wifi_nan_marker	7.54****	0.103	[0.077, 0.128]		activity_onbicycle	5.75****	0.122	[0.082, 0.162]
	app_tools	24.44****	0.530	[0.490, 0.570]	ongolia	app_productivity	32.40****	0.272	[0.258, 0.288]
	proximity_max	14.78****	0.368	[0.329, 0.408]		location_altitude	19.95****	0.151	[0.136, 0.166]
	location_altitude	14.70****	0.503	[0.464, 0.543]		app_social	18.80****	0.142	[0.127, 0.157]
ž	proximity_std	14.20****	0.355	[0.315, 0.394]		activity_onfoot	16.33****	0.123	[0.108, 0.138]
uai	app_communication	13.94****	0.290	[0.251, 0.329]		activity_walking	16.22****	0.122	[0.108, 0.138]
nu	wifi_max_rssi	13.80****	0.283	[0.244, 0.323]		activity_walking	16.22****	0.123	[0.108, 0.138]
Ď	proximity_mean	13.61****	0.323	[0.284, 0.362]	ž	activity_still	14.65****	0.111	[0.096, 0.126]
	wifi_mean_rssi	10.93****	0.227	[0.188, 0.266]		touch_events	12.65****	0.096	[0.081, 0.111]
	day	10.16****	0.203	[0.164, 0.242]		user_presence_time	11.53****	0.087	[0.072, 0.102]
	bluetooth_le_num_of_devices	10.15****	0.252	[0.212,0.291]		bluetooth_nor_min_rssi	11.07****	0.084	[0.069, 0.099]
	time	51.39****	0.282	[0.270, 0.292]		screen_nan_marker	80.95****	0.309	[0.302, 0.316]
	app_tools	29.12****	0.165	[0.154, 0.175]	All	proximity_nan_marker	70.89****	0.268	[0.260, 0.275]
	bluetooth_nor_max_rssi	28.10****	0.155	[0.145, 0.166]		location_altitude	67.45****	0.293	[0.286, 0.300]
	day	27.68****	0.150	[0.139, 0.161]		bluetooth_le_nan_marker	56.68****	0.201	[0.194, 0.209]
Italy	bluetooth_le_num_of_devices	22.69****	0.141	[0.131, 0.152]		steps_counter_nan_marker	55.86****	0.204	[0.197, 0.212]
	bluetooth_le_num_of_devices	22.69****	0.142	[0.131, 0.152]		bluetooth_nor_nan_marker	55.58****	0.198	[ 0.191, 0.205]
	bluetooth_nor_mean_rssi	20.34****	0.112	[0.102, 0.123]		wifi_nan_marker	52.92****	0.197	[0.190, 0.204]
	bluetooth_nor_num_of_devices	18.44****	0.110	[0.099, 0.120]		location_nan_marker	52.07****	0.194	[0.187,0.201]
	bluetooth_le_max_rssi	17.06****	0.094	[0.083, 0.104]		time	49.58****	0.185	[0.178, 0.192]
	location_altitude	14.72****	0.086	[0.075, 0.096]		app_nan_marker	48.58	0.188	[0.181, 0.195]

in line with research, which suggests that young men tend to be more alone [7]. The authors, however, underline that being alone is correlated with a wide range of factors like culture, geography, age, and many other covariants [7].

Considering the statistical analysis, as presented in Table 4, the top ten indicative sensor features in terms of statistical significance per country can be quite different. For example, while time and day seemed to be quite indicative in Italy for the social context, it is hardly indicative in Paraguay or Mongolia. Similarly, activity (accelerometer) features were highly indicative for Paraguay (in a vehicle) and Mongolia (moving) but not so much for other countries. In Italy, Bluetooth usage seems to be highly predictive of social context, which is in line with a previous study that only relied on Bluetooth sensors to predict social context (co-location) [67]. Considering the data from all countries combined into a multi-country data pool, especially the Nan markers seem to have a high relevance in determining if someone is alone or not. Of the top ten most indicative features for the world data (see Table 4), eight are Nan markers. However, this high relevancy of Nan markers in the multi-country data is difficult to interpret given the multiple reasons for the missing sensor data [48, 57]. In general, we could assume that the great heterogeneity of features across different countries may reflect the large geographical diversity in behavior and phone usage [31] (reflected in sensor data) as well as the target variable [7] (reflected in the social context).

# 5.2 RQ2: Social Context Inference Without Personalization

This section examines whether social context can be inferred with smartphone sensing data (**RQ2**). A comparison of the obtained results can be seen in Table 5. Overall, in the generic multi-country setup, the random forest

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	$\frac{\text{Logistic (L2)}}{\overline{A} (A_{\sigma})}$	<b>Random Forest</b> $\overline{A}(A_{\sigma})$	<b>XG Boost</b> $\overline{A}(A_{\sigma})$	$\frac{\text{Ada Boost}}{\overline{A} (A_{\sigma})}$	Neural Network $\overline{A}(A_{\sigma})$
Baseline	50	50	50	50	50
Multi-Country	56.96 (10.8)	62.21 (2.73)	61.89 (3.20)	60.24 (4.63)	61.65 (3.27)
UK	54.44 (4.44)	58.35 (3.74)	58.04 (4.31)	57.52 (5.00)	58.31 (4.61)
Denmark	56.45 (6.37)	59.05 (8.11)	55.83 (7.57)	59.31 (8.40)	60.21 (5.19)
Italy	56.89 (4.08)	60.99 (1.65)	60.55 (1.85)	60.02 (2.11)	60.13 (1.98)
Paraguay	58.22 (8.00)	64.07 (9.71)	62.74 (8.81)	61.36 (9.59)	63.03 (6.21)
Mongolia	55.89 (3.96)	65.32 (4.21)	65.56 (4.29)	59.48 (3.96)	63.62 (5.17)

Table 5. Different machine learning models and their inference accuracies with standard deviations in brackets according to different countries.





Fig. 6. Comparison between Random Forest with feature selection and without feature selection with accuracy and standard deviation of accuracy according to different countries and the total data distribution (world model).

models performed the best, while having one of the smallest standard deviations. This performance is around 0.5% higher than XGBoost and Neural Networks. Thus all subsequent experiments were reported for random forest models, for brevity. The test accuracy of the random forest lies, depending on the country, between 58% and 65%. However, given the small dataset size for some countries (e.g., Only 17 participants in Denmark, and 24 participants in Paraguay) and a large number of features, we used feature selection to examine whether the performance could be improved.

In Figure 6, the accuracies of different country-specific models are compared with and without feature selection. The accuracies are improved depending on the country and thus depending on the number of participants, by between 1% (Italy) and 4.5% (Paraguay). This lower performance increase can be explained given that random forest classifiers already use embedded feature selection within models during the training phase. Hence, using explicit feature selection before training has little effect [40]. However, even for other model types we examined, we did not observe better performance bumps. Further, the optimal number of features depended on the country,

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Fig. 7. Comparison between country-specific and multi-country approaches with leave-k-user-out (population-level) and personalized (hybrid) models.

but seems to lie a little bit above 30. In fact, the final feature counts used in training were 31 in the UK, 32 in Denmark, 36 in Italy, 30 in Paraguay, 36 in Mongolia, and 90 in Multi-Country. Interestingly, compared to country-specific models with lower feature counts, feature selection in the multi-country approach retained over 90 features, showing that when data from diverse countries are used to train a single model, more features are required for better representation. In a way, the analysis in Table 4 showed that features with the highest statistical significance among countries are not the same. This could be why many features are retained when training the multi-country model. In fact, this again reinforces the idea that different cultural and social practices in different countries affect the performance of social context inference models.

## 5.3 RQ3: Effect of Partial Personalization on Model Performance

Next, we set out to examine how model personalization affects performance. In Figure 7, population-level and hybrid models are compared for all countries separately, with the multi-country model. In all cases, we compare the performance after feature selection. First, results show that personalization leads to improved performance across all countries and the multi-country approach. The increase in performance is  $\approx 20\%$  in all cases. Prior work in areas such as mood inference and eating behavior prediction too has shown that smartphone sensing-based models could perform well after personalization [6, 36, 40]. Hence, not surprisingly, we found a similar result for social context inference as well. The drastic increase in model performance of the personalized models indicates, that social interactions seem to be an extremely personal behavior with high variability from user to user. This observation motivates further investigation into the conceptualization and modeling of human diversity within sensing models. By more precisely modeling human diversity in a leave-k-user-out model and with some basic diversity information of a new user, one could possibly create a quasi-personalized model without having any sensing data of a new user.

In fact, the weighted average accuracy (weighted by the number of data points) of the country-specific models is 64.12%, above the multi-country performance of 62.35% in the population-level setting, even though by a small margin. A similar result can be seen for hybrid results as well. However, one has to consider that the standard deviations (obtained by repeating experiments for ten iterations—Explained in Section 4), and therefore,



Fig. 8. Country-agnostic: Model accuracy when using data of four countries in training to predict on the fifth unseen country.

the weighted average of country-specific models' variabilities (7.12%) is clearly larger than that of the multicountry model (4.12%). This is partially explainable given the small number of participants in some countries (e.g., Denmark, Paraguay). Moreover, hybrid model performance reached above 82% across all countries and the multi-country setup, showing the effectiveness of model personalization to obtain better performance for social context inference. In conclusion, we find that training a multi-country model works reasonably well for social context inference. This finding is different compared to prior work that examined country-specific and multi-country model performance across mood inference, personality inference, and activity recognition [4, 31, 40], where they found multi-country models to underperform by larger margins. However, it is not the same case with social context inference.

# 5.4 RQ4: Generalization of Models to Unseen Countries

The multi-country model has access to more data and at the same time, to all the country-specific characteristics. Thus, it is difficult to ascertain if the differences in accuracies between the multi-country and country-specific models are driven by the different amounts of data or by the country-specific data heterogeneity. Prior work on personality modeling and mood inference has discussed how this could be a difficult problem to provide an answer to when working with multi-country data because even if under-sampled models (using the same amount of data from each country in training country-specific models. usually, the amount of data is equal to the number of data points from the country with the lowest amount of data) are trained with each country, it could lead to a lack of expressiveness within countries [31, 40].

Hence, to get a better sense of how the data heterogeneity associated with a specific country helps to detect the behavior of its participant and what kind of effect additional data has on inference accuracies, another experiment is conducted. First, this experiment takes the data of four countries and tests it on the fifth unseen country, therefore creating a country-agnostic approach where the model has not seen any data of the country it is tested on. This mimics a situation where an application is trained and constructed for a set of countries and then enters a new market in a different country. The results of this experiment can be seen in Figure 8. The accuracies of those data-rich but country-agnostic models lie consistently below the country-specific models, even though the margins are not significant. The extent of the accuracy difference between country-agnostic and country-specific approaches is the lowest in Denmark ( $\Delta$  1.5%), the country with the least amount of data, and highest in Mongolia ( $\Delta$  8.5%), a country with a high amount of data.

Table 6. Country-agnostic: Using the countries in the left column, to predict data from the countries on the top row, with accuracies and standard deviation of accuracies. Values along the diagonal are grayed out as they came from the performance obtained in Figure 6, with feature selection under the country-specific approach.

Testing Country	UK	Denmark	Italy	Paraguay	Mongolia
Training Country					
UK	62.82 (3.18)	53.34 (7.85)	57.05 (1.86)	58.89 (6.76)	52.83 (2.83)
Denmark	51.22 (3.83)	62.92 (8.49)	53.73 (2.25)	53.78 (2.25)	51.07 (3.54)
Italy	57.10 (2.76)	58.80 (6.52)	62.03 (2.35)	52.64 (6.3)	53.14 (3.66)
Paraguay	53.77 (5.58)	51.94 (5.96)	53.11 (2.64)	68.68 (11.93)	55.88 (5.54)
Mongolia	52.14 (2.36)	53.34 (5.97)	51.70 (1.55)	58.24 (6.33)	67.33 (4.58)

At last, another experimental setting was explored, where data from one country was used to train a model, which then is tested on all the other countries separately. Results are presented in Table 6. This helps to investigate the geographical proximity between different countries and how it translates to social context inference models. In the resulting matrix, the rows represent the training countries while the columns represent the testing country (e.g., using UK data to test in Denmark yields 53.34% accuracy). Here it is interesting to note that culturally close countries seem to extrapolate better to each other in one case. For instance, it can be seen that Italian data also works comparatively well for the UK and Denmark, while it does not perform very well for Paraguay or Mongolia. However, this pattern did not generalize to models trained in Denmark and UK, when testing in other European countries. This finding contrasts prior research on mood inference and complex daily activity recognition in a multi-country setting [4, 40], where the authors found models performing reasonably well when testing in geographically similar countries in Europe. However, similar to those studies, and also another study [65], we observe a performance degradation, which could be due to distributional shifts between countries. Moreover, Mongolia seemed to be a difficult country to predict without Mongolian data in training. If we test on Mongolia with a model trained with Mongolian data, we could reach a mean accuracy of 67.33%. However, if any other countries' training data is in model training, the maximum accuracy that could be reached was 55.88%, with a model trained on data from Paraguay. This is a difference of around 12%, whereas, for all other countries, the differences were around 5%. This difference could either be due to the distributional differences in sensor data across countries or the differences in the target attribute-the social context. In fact, in Figure 3, we found that the social context distribution in Mongolia is different from all other countries, with the presence of fewer alone self-reports. Hence, this could potentially be a reason for the inference performance here.

## 6 DISCUSSION

## 6.1 Summary of Results

In summary, our results shed light on the research questions as follows:

• **RQ1**: We conducted an extensive examination of a smartphone sensing dataset collected in the natural environment from 483 college students across five distinct countries: the United Kingdom, Denmark, Italy, Paraguay, and Mongolia. The dataset encompasses passive sensing data obtained through continuous sensing modalities, including activity type, step count, Bluetooth, WiFi, location, cellular, and proximity, as well as interaction sensing modalities, such as app usage, touch events, a screen on/off episodes, and notifications. The dataset further comprises over 216K social context self-reports gathered from participants over a period of four weeks. Our statistical analysis revealed that certain individual features extracted from modalities, such as app usage type and amount (classified into categories such as tools, communication, productivity, and social), activity types (e.g., in a vehicle, on foot, walking), location altitude, Bluetooth, WiFi, proximity, and screen

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episodes, were among the top five features in terms of statistical significance in discriminating between alone and not-alone events. Furthermore, we discovered that the features with statistical significance in the discrimination of social contexts are not uniform across countries, demonstrating the diversity of behaviors within countries and contextual features related to different social contexts.

• **RQ2**: In our study, we operationalized three approaches to assess the inference of social context (as described in Table 1). These approaches are country-specific, country-agnostic, and multi-country. Without accounting for the diversity of data sources at the country level, we found that the generic multi-country approach exhibits a moderate accuracy of 62.21% without feature selection and 62.35% with feature selection when using population-level models. The country-specific approach resulted in comparable performance to the multi-country approach, with most countries displaying margins of less than 2% for both with and without feature selection. The exception was Italy, which had an accuracy of 62.03% compared to the multi-country accuracy of 62.35%. All other countries achieved slightly higher accuracies that exceeded multi-country performance. This outcome contradicts prior studies that utilized similar multi-country datasets for health-related inferences, which suggested that country-specific models were generally superior by substantial margins. As a result, we concluded that this may not always hold true for social context inference.

• **RQ3**: In our study, the utilization of hybrid models resulted in the multi-country approach yielding an accuracy of 83.45%. The exception was the United Kingdom, which achieved an accuracy of 82.08%, while all other countries performed better, with marginal differences in Italy (84.20%) and Paraguay (83.76%) and larger differences in Denmark (88.72%) and Mongolia (87.47%) of approximately 5%. These results suggest that, regardless of the degree of personalization, a generic multi-country model is sufficient for social context inference, and country-specific models may offer minor gains in some instances. This finding also contradicts prior studies that employed smartphone sensor data for health-related inferences, which recommended the use of country-specific models for improved performance, even after personalization.

• **RQ4**: With regards to mood inference and activity recognition, despite prior research indicating that models may exhibit good generalization to geographically proximate countries in Europe, our analysis of social context inference performance did not reveal such associations. In fact, in all cases, the models performed poorly when applied to unseen countries. This finding is consistent with prior studies, which concluded that models lack generalization capabilities when deployed to previously unseen countries compared to the performance of country-specific or multi-country approaches.

### 6.2 Implications

This paper discusses the operationalization and achieved performance of a social context inference task in a multi-country setting. The presented work offers theoretical and practical implications.

Theoretical implications of the present study are manifold. Firstly, we propose an experimental framework for the implementation and comparison of social context inference experiments in a multi-country context. The experiments conducted include approaches that are country-specific, country-agnostic, and multi-country. These experiments provide insights into the extent to which country-specific social context information is encoded in multimodal sensing data and whether this information can enhance model performance. In future health sensing research that explores multi-country settings, the experimental framework used here may be adopted to ensure comparability across studies, thus facilitating cross-dataset comparisons. Secondly, our findings indicate that country-specific models outperform multi-country models by only a marginal degree. This contradicts previous research on mood inference and activity recognition, which suggested that country-specific models are superior to multi-country models. However, given the complexity of the data collected during the Covid-19 pandemic and other data limitations, the results presented here are not definitive. Consequently, future studies should examine the impact of country diversity on model performance in context-aware sensing tasks, paying attention to cultural practices that may drive differences in social behavior and that may be apparent in the multimodal data. Thirdly, our results demonstrate the importance of personalization for the social inference task. Hybrid models outperform population-level models by a large margin, suggesting that users exhibit significant differences in social behavior. Consequently, future studies should take note of the significance of collecting sufficient data from individual users to enable personalized models to be implemented.

The practical implications of this study for real-world applications are threefold. Firstly, let's consider the context of a mobile health application that includes a social context inference model. The low accuracy of mobile interventions using population-level models may be particularly problematic for new users of such applications, who may receive notifications in the wrong situations. Therefore, like many mobile health apps that do not provide insights based on inferences for several months because of the lack of personalization [?], the social context inference feature could be disabled initially and only enabled after the model is fine-tuned and personalized for a particular user. Furthermore, users may not desire interventions, as being alone do not necessarily correspond to feeling lonely. Secondly, applications should be designed to monitor social context over a long period of time. Health monitoring applications could provide users with information regarding their social context over time. This information could inform users about perceived loneliness and the actual amount of time spent alone. If necessary, users could then decide for themselves whether they would like to alter their social behavior. Thirdly, social context models could be pre-trained with a large dataset from potentially several different countries and subsequently personalized using data provided and labeled by users themselves. This approach would ensure high accuracy in inferring the social context of individual users.

## 6.3 Limitations and Future Work

Several considerations are needed to assess and contextualize the results of this study fairly. Those considerations concern the data generation process, ethical questions, experimental setup, and any implications which can be drawn from this study.

All data used for this study was generated in a time frame from November to December 2020. This coincides with a major surge of the Covid-19 pandemic in Europe but also in Paraguay and Mongolia. In all countries, social distancing measurements were mandated or at least recommended. Obviously, the COVID pandemic deeply influenced and possibly altered the behaviors, social practices, and moral norms of the pilot study participants. It is, however, highly difficult to measure or infer how those changes influenced the analyzed data. It is likely that it changed the frequency of social contexts (fewer reports being done with others), but it is impossible to say if and how it precisely changed social interactions if they occurred and how this, on the other hand, influenced the mobile sensing data produced. On the other hand, given that many universities and companies are already adhering to remote work/study settings, we expect this trend to continue for the years to come. Hence, despite the study being done during the pandemic, we expect these results to hold in the future to an extent. However, future studies could explore this further.

The underlying motivation of this study lies in detecting, analyzing, and potentially intervening in periods of the social context of mobile phone users. This is, at its core, a mental well-being concern given the straightforward connection between social isolation, loneliness, and mental health of especially young adults [59]. The presented study and preceding studies [9, 14, 42, 43], showed that mobile sensing data contains information about the social context of people. Given the sensitive nature of the user data and the sensitive nature of the discussed inference task, the ethical implications of this study are apparent and many-sided. The fact that this study discusses the social context of young people in different cultural and socio-economic environments complicates the moral implication additionally. The fact that many participants have contact with their romantic partner during the night time or early morning hours, for an instant, might be differently socially accepted depending on the cultural norms of a given study participant. The mentioned ethical considerations pose clear data safety and anonymity

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requirements to the dataset and its investigators [28]. At the same time, moral norms and data safety fears of study participants might also influence if a participant fills out a questionnaire correctly or at all.

This study considers only the two-class social context inference task of predicting if someone is alone or not. In principle, however, the used dataset differentiates between 8 different social contexts. The decision to limit this analysis to a two-class inference is mostly caused by class imbalance and page limits. First of all, the alone or not alone situation is well populated in all country data subsets, which is not necessarily given for any other two-class social context (e.g., with family, without family would not be well represented in Denmark). Thus to obtain comparable results across all countries, only this most naive social context was exhaustively investigated. Furthermore, feasibility reasons also tempered further experiments with other social context inference tasks. The accuracy of the most simple social inference task lies at minimally 62%, in the case of, for example, Italy, already quite low; thus, it can be assumed that models would perform even worse on more difficult social inference tasks. Future work could explore other constructs of social context.

The results presented in the personalization section show us that social behavior differs greatly from user to user. This indicates that even leave-k-users-out models could be greatly improved if user profiles or specific user groups could be more precisely modeled. This study tries to model different user subgroups according to their country of residence and assumes similar cultural and social behavior of people living in the same country. However, with additional diverse information about the users, for example, socio-economic background, psychological profile, and individual cultural norms, models could be potentially even more improved. This would open the possibility of constructing partially personalized models on a set of diverse information provided by a new user. Future work should try to leverage user diversity information further to improve mobile sensing models.

## 7 CONCLUSION

In this study, we examine, study, and try to predict the social behavior of close to 500 college students across 5 different countries. An in-depth analysis of different diversity concepts is conducted by comparing a multitude of models trained on different subsets of the data. The most fundamental data split compares a model trained only on one country's data to a world model trained on all available data from all countries. We find that a model which is trained only on the data of a specific country outperforms the world model by approximately 2%, despite country-specific models having significantly fewer data available than the world model. A model which is trained exclusively on data from countries other than from the test country is outperformed by country-specific models by an average of 8%. Depending on the model specification we reach accuracies ranging from 62% to 68% in predicting if a user is alone or not. Personalized models achieve accuracies ranging between 80% to 90%.

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