Intelligent Task Recognition: Towards Enabling Productivity Assistance in Daily Life

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ABSTRACT

We introduce the novel research problem of task recognition in daily life. We recognize tasks such as project management, planning, meal-breaks, communication, documentation, and family care. We capture Cyber, Physical, and Social (CPS) activities of 17 participants over four weeks using device-based sensing, app activity logging, and an experience sampling methodology. Our cohort includes students, casual workers, and professionals, forming the first real-world context-rich task behaviour dataset. We model CPS activities across different task categories, results highlight the importance of considering the CPS feature sets in modelling, especially work-related tasks.

CCS CONCEPTS

• **Human-centered computing → Empirical studies in ubiquitous and mobile computing**.

KEYWORDS

Task recognition, mobile sensing, pervasive computing, intelligent assistant, productivity

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1 INTRODUCTION

Imagine a future personal digital assistant that can identify and track our tasks ubiquitously, whenever and wherever it is required based on our context. Such intelligent applications would be beneficial not only to track human tasks in daily life but also to improve work productivity and overall well-being.

If tasks can be recognised and tracked, support systems, such as digital assistants, recommender systems, or search engines can be adapted to better help humans complete their tasks. An intelligent assistant could monitor the progress and completion of a task, even encourage someone to switch from their current task to one that is critical. Supporting task progression and completion is the last mile in search interaction [30], and more generally in supporting digital assistant applications. Characterising and modelling tasks are the first steps to enable this support.

Recognising human tasks in daily life is non-trivial. The main challenges lie in the noisy environment and dynamics of human activities as well as the wide range of tasks human undertake across different professions.

A task can be characterized by many factors, such as human activities, actions, mobility, social encounters, and online behaviors. We, therefore, approach task recognition with a Cyber-Physical-Social (CPS) modelling paradigm [22–24]. We hypothesize that tasks can be recognised from modelling the underlying signals of app and online (cyber), mobility [21] and locomotion (physical) and interaction with others (social).

To study our hypothesis, we have generated a task behaviour dataset of logs captured over a four-week period from participants including professionals and non-professionals. We capture smartphone sensor and app foreground and background data, laptop/desktop logs of apps running, along with participant annotations of performed tasks based on two recall mechanisms: *in-situ*, recalling tasks in the past hour; and *retrospective*, recalling at the end of the day tasks which were performed that day.

To the best of our knowledge, this is the first work aimed at recognizing daily tasks, utilizing CPS signals. Our research contributions are as follows:

- A new problem formulation, and a novel framework to capture and perform task recognition.
- Modeling of CPS activity to derive characteristics of a wide range of tasks.
- Analysis of underlying CPS activity signals in modelling task behaviours across different cohorts of participants.

2 RELATED WORK

The prediction of user tasks using human-computer interaction and machine learning was described in 2005 [27]. The authors identified a task by observing an activity sequence (e.g., opening a file, saving a file, sending an email, cutting and pasting information). Task goals can be achieved through the support of human activities, in order to progress and complete a task [3, 4, 12]. People can complete tasks more easily when they have well-defined action plans, which is difficult to achieve [1, 8, 13, 16, 18]. To provide automatic action plans, a Genies workflow is presented in [11] that combines the power of crowd with collaborative refinement and automation.

More recently, sensors and behavioral data have been used to address the modeling and prediction of time-based reminders [9], the estimation of the duration of tasks [31], and the modeling of context and user intent for context-aware recommender systems [28]. The discovery of contextual information from daily routines has been previously addressed by [19]. Task phase recognition and progress estimation by modeling highly mobile workers in a large hospital complex was proposed [26]. Here, approximation of localizations from WiFi access points and smartphone accelerometer sensors were used. A machine-learning-based approach to task boundary identification was presented by [10].

Others focused on mining behavioral rules from smartphones in order to manage incoming calls [25]. Sensor data and machine learning have been exploited to construct attention management systems [2] so as to predict when a notification should be sent and to which device [17] in order to improve the user experience. Recently, Ren et al. investigated how to predict users' demographics by considering their CPS behaviors [23].

However, the CPS aspects which could further describe a user task were not considered. To the best of our knowledge, task recognition through ubiquitous sensing is yet untapped, especially by incorporating CPS contexts in behavior modeling of mobile users. Therefore, the contributions of this paper will enable future intelligent and assistive applications to support daily human tasks.

3 PROBLEM FORMULATION

We formulate the problem of recognizing daily tasks based on CPS activities of human participants. Signals can be sourced from smart devices (e.g., phones, tablets, wearables, desktop computers, and the Internet of Things). Ground truth labels of daily tasks performed by the participants are captured through in-situ annotations. Our aim is to recognise tasks by characterizing the following signals.

Cyber: Capture of a user's online activities, composed of the cyber content and a timestamp. In our research, we investigate *Social Networking, Utilities, Communication & Scheduling, News & Opinion, Entertainment, Design & Composition, Business, Reference & Learning, Software Development*, and *Shopping*. We define each activity as a binary variable f_c to represent whether users are involved in the corresponding activity at a certain time. Thus, a user's cyber activity is defined as a set of records: $< u, F_c, t_i >$, where u is the user, t_i is the timestamp, and F_c is the set of cyber features, denoting the user's involvement in the above mentioned cyber activities.

Physical: These include a user's physical activities in the spatio-temporal domain. In our research, we investigate *accelerometers, gyroscopes, magnetometers* as well as derived data such a *transport mode*, and semantic labels of *visited locations* (e.g., home, office, and train stations). Thus, a user's physical activity is defined as a set of records: $< u, F_p, t_i >$, where F_p is the set of physical features, denoting the users' physical activities as mentioned. The details of each feature $f_p \in F_P$ are presented in Section 5.

Social: These include information about a user's *social interactions*, including direct interactions with other people. In our research, interactions are captured through *WiFi/Bluetooth access points, and audio noise levels* In addition, *in-situ annotations*, which characterize the degree of environment and social encounters with others. A user's social activity is defined as a set of records: $< u, F_s, t_i >$, where F_s is the set of social features, denoting the users' social environment as mentioned above. Again, details of the social features used in this study are presented in Section 5.

Tasks: These are the *daily tasks* performed by users. There are existing categories of tasks [29] including travel, physical, education, meals/breaks, communication, planning, project, documentation, low-level, admin and management, finance, IT (software or hardware-related tasks), customer care and problem solving. All tasks under each task category are obtained via an Experience Sampling Method (ESM) [6, 7, 14].

Task Boundary Construction: Since task descriptions (including their CPS activities) are unique to each user, the boundary of a task and granularity of contextual information can be different for the same experienced task when a mobile user is providing a corresponding annotation. The annotation that the user provides can be associated with its relative perception upon answering a short questionnaire.

Task Recognition: Given a user CPS activity u at time t, the recognition of the task a currently being undertaken is defined as:

$$g(F_c, F_p, F_s) \rightarrow a \tag{1}$$

where $g(\cdot)$ is a function that establishes a mapping between a task and its CPS activities denoted as F_c, F_p and F_s, respectively.

4 PROPOSED FRAMEWORK

In this section, we propose an end-to-end framework (see Figure 1) to recognize daily tasks for mobile users based on their CPS activities. Specifically, our framework provides a detailed solution for intelligent task recognition leveraging the CPS signals collected through smart devices used in our daily lives. These signals are then processed in different modules of our framework to learn and recognize daily tasks. The key components of our framework include *task capture, task boundary construction, CPS feature construction, CPS-based task modeling and learning*, which are discussed in the subsections 4.1 - 4.4.

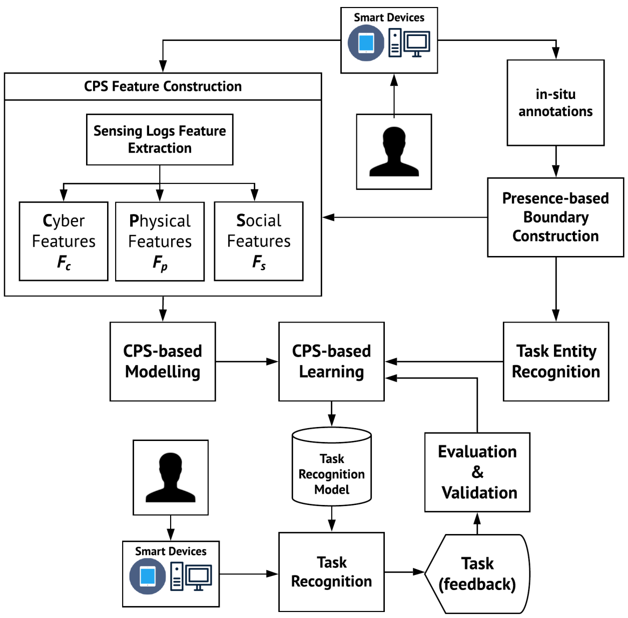

Figure 1: Conceptual framework for task recognition.

4.1 Task Capture: In-situ Annotations

The ESM-based acquisition of task annotations was achieved through in-situ surveys, triggered by a brief questionnaire through a mobile app. The in-situ survey is at t; the annotation is conducted at time t_δ, corresponding to the task and its contextual information within the boundary of t_β and t; β is the estimated boundary of a performed task that can be inferred from the ESM annotation process, see Figure 2. The approach was chosen in order to minimize interruption of daily activities, and hopefully reduce reliance on participants' ability to accurately recall earlier experiences [5].

4.2 Task Boundary Construction

A participant can elect to answer a questionnaire later when they have more free time (before or after the next hourly mobile app notification for ESM survey). Our framework applies a rule-based function. Any timestamped in-situ annotations correspond to the previous hour time segment. Note, this rule is robust towards any temporal shift (i.e., changing timezones), which occurred with a number of our participants.

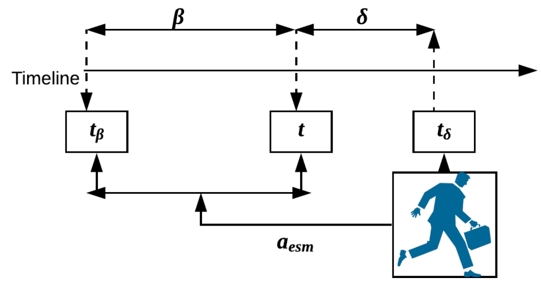

Figure 2: Task annotation acquisition through ESM.

4.3 CPS Feature Construction

This module utilizes sensing logs from participants' smart devices to construct CPS features associated with a task. Since raw sensing signals are timestamped and can be streamed from these smart devices, we define the following general process for CPS feature construction. All features can be constructed based on the alignment of tasks and the time segments defined within the scope of annotation fusion. Several functions can be applied to these raw signals to construct three feature sets:

- F_c**:** consisting of the features that are related to a participant's cyber activities, such as smartphone app usage patterns and categories of visited web domains.
- F_p**:** consisting of the features that are related to a participant's physical movement, locations (including their semantics), mobility (e.g. accelerometer, gyroscope and magnetometer signals), transportation mode, change of location clusters, and transportation hot-spots.
- F_s**:** consisting of the features that are related to a participant's social environment; social profiles and interactions with other individuals on the tasks (e.g. relative noise level around a participant), indication of proximity to other individuals or sensing devices, direct interaction with an individual, or the number of people involved in completing a task.

Table 1: CPS feature sets used in modelling.

Feature Set	Features
Cyber	Binary features of uncategorized, social networking, utilities, communication & Scheduling, news & opinion, entertainment, design & composition, business, reference & learning, software development, shopping within the scope of one hour before the task and during the task.
Physical	Statistical features from sliding window model on magnitudes of accelerometer, gyroscope, and magnetometer readings.
Social	The count of unique ID of wireless access points (i.e., BSSID) and statistical features from sliding window model on noise level.
Task Labels [29]	Travel, physical, education, meals and breaks, communication, planning, project, documentation, low-level, admin and management, finance, IT (software or hardware-related tasks), customer care, or problem-solving.

Note that the statistical features about CPS activities (see Table 1) correspond to the following temporal features extracted from a sliding window of size $\delta = 300$ seconds and 50% overlap: *mean, median, maximum, minimum, standard deviation, interquartile range (IQR)*, and *root mean square (RMS)*. Specifically, in each window for F_p construction, the magnitudes of accelerometer, gyroscope, and magnetic field are computed as $\sqrt{x_{sensor}^2 + y_{sensor}^2 + z_{sensor}^2}$. Moreover, the noise level and magnitude values from accelerometer, gyroscope, and magnetometer readings are normalized using min-max normalization.

4.4 CPS-based Task Modeling and Learning

The three feature sets are integrated to build a CPS-based task model. To build the model, the temporal dependency of feature sets *before*, and *during* the task were considered in our experiment. CPS-based modeling can be applied to any of the sets (i.e., F_c, F_p, F_s). As shown in the previous section, we expanded F_c to include the cyber features one hour before, and during a task is performed, while a sliding window model is applied to extract statistical features from smartphone sensors for F_p and F_s. The combination of F_c, F_p and F_s produces the final CPS feature set.

The CPS feature set is then used to build a set of classifiers. The learning process includes training, testing, and an internal evaluation processes to select the best classifier, based on certain metrics, such as accuracy and F_1-score.

5 EXPERIMENTS AND EVALUATION

We now discuss our experimental setup and evaluate our task recognition framework.

5.1 Mobile Data Collection and Task Capture

To evaluate our task recognition framework, participants committed to provide annotations during a month-long data collection period over a course of 20 week days (6 am to 7 pm).[1] Our cohort consisted of ten male and seven female participants. Fourteen participants were engaged in a job while three participants had no job commitments. Twelve of the participants were non-professionals (e.g., full-time or part-time students) and five were professionals.

The data collection was performed using Android smartphone apps (RescueTime[2] and our sensor data collection app denoted as sensing-app) and a desktop app (i.e., RescueTime[3], to collect cyber data, i.e., visited Web domains and their categorizations). Our sensing-app recorded sensor data with the following reading frequency settings: 50 Hz for accelerometer, magnetometer, and gyroscope, and 1 Hz for noise level.

To minimize the battery usage of the data collection Android app, we collected these sensor data within a 30 second time frame, and a 1-minute gap between frames for no data collection mode. The collection of sensor data was scheduled from 06:00 AM to 07:00 PM. The participants reported their timestamped tasks through the ESM (triggered through hourly app notifications, from 10:00 AM to 07:00 PM). A task entity recognition process can be used on the in-situ annotations after their boundaries are constructed (refer to Section 4.2) to assign each reported task to one of the following task categories (compact categorization derived from American Time Use Survey (ATUS)[4]) which includes work-related tasks, personal tasks, social-exercise-entertainment tasks, caring tasks, and civil obligations.

[1]Data collection protocol reviewed and approved by the Human Research Ethics Committee at *RMIT University*, ref "SEHAPP 09-18 SALIM-LIONO".
[2]https://play.google.com/store/apps/details?id=com.rescuetime.android
[3]https://www.rescuetime.com/download

5.2 Collected Mobile Sensing Data and Task Annotations

In our data collection campaign, the protocol for logging mobile sensing data and its task-capture survey design are reproduced (and adjusted) from [15] on task intelligence to collect rich pervasive sensing data. Hence, utilising the data that we collect (including personal lifestyles, movement behaviors, and progress of tasks according to user perception) from real participants will expand the task understanding beyond this study.

We conducted the task annotations surveys based on an ESM method since the idea of ESM is to minimize human cognitive bias while reducing the reliance on participants' ability to accurately recall earlier experiences. Specifically, a short questionnaire is sent through a push notification in an hourly basis aiming to minimize the interruption to daily activities and tasks. In this study, the annotations acquired from the ESM process are defined as in-situ annotations.

5.3 Task Annotations: Non-professionals and professionals

We perform an exploratory analysis of in-situ task annotations collected from the ESM hourly surveys. We further expand each task category into more granular tasks based on a recent study [29] on work-tasks. Specifically, we assign task annotations given by the users to one of the following tasks: travel, physical, education, meals and breaks, communication, planning, project, documentation, low-level, admin and management, finance, IT (software- or hardware-related tasks), customer care, and problem solving. Any task annotations that do not belong to any of these task categories are relabelled as "other". The distribution of these tasks are shown in Figure 3 for both non-professionals and professionals.

After data pre-processing and feature extraction the CPS feature sets contain a total of 7,653 instances for non-professionals (on all reported 1,121 in-situ annotations) and 5,271 instances for professionals (on all reported 721 in-situ annotations), respectively. Consequently, 62 features are extracted corresponding to each task label of the instances, consisting of 22 features of F_c, 21 features of F_p and 8 features of F_s.

5.4 Experimental Setup

In order to signify our contributions for CPS activity modeling, we conduct our study over three different experiment sets:

(1) **Work-related tasks:** The annotations categorized as "work-related" are included to perform task recognition (i.e., tasks associated with main roles/occupations of corresponding users).

[4]https://www.bls.gov/news.release/pdf/atus.pdf

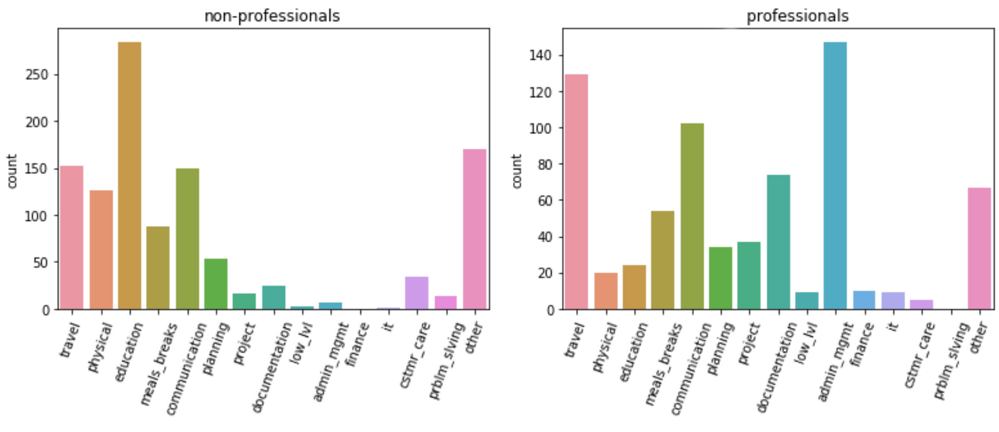

Figure 3: Frequency of tasks in all categories, for non-professionals and professionals.

(2) **Social/exercise/entertainment tasks:** The annotations that belong to tasks related to social events, exercise and relaxation are included for identifying the associated tasks.
(3) **Personal/caring/civil tasks:** The annotations of "caring" and "civil obligation" related tasks are sparse. Therefore, these two task categories are grouped with personal tasks due to the similar nature of these tasks.

For each experiment, we conduct an empirical performance evaluation of intelligent task recognition using four settings on both cohorts of non-professionals and professionals including task recognition based on F_c, F_p, F_s, and task recognition using F_c, F_p, and F_s combined.

Task recognition using the CPS feature sets separately are defined as the baselines in our experiment. In our implementation of intelligent task recognition, we deployed a set of classifiers including: Support Vector Machine (SVM), Naïve Bayes, k-Nearest Neighbor (k-NN), Logistic Regression Classifier with Restricted Boltzmann Machine feature extractor (LRC (RBM)), Decision Trees, and Random Forests. These classifiers are instantiated using scikit-learn [20].

5.5 Evaluation

To evaluate and validate the performance of task recognition, we applied stratified five-fold cross-validation. The model for intelligent task recognition was built based on a person-independent approach. In other words, our proposed intelligent task recognition framework aimed to discover and distinguish the general tasks of different categories (i.e. work-related, social/exercise/entertainment, personal/caring/civil) for all mobile users, based on CPS contexts. In our framework, the internal evaluation process was based on F_1-score which refers to the harmonic mean of precision and recall of task recognition.

5.5.1 Work-related tasks. For work-related tasks, our experiment result is validated on the recognition of the following tasks:

- **Non-professionals:** all task labels [18] except finance, IT and problem-solving as highlighted in Table 1.
- **Professionals:** all task labels [18] except customer care and problem-solving as highlighted in Table 1.

The result in Figure 4 (F_1-score) show the imperative performance on work-related task recognition when our application is trained using all CPS features. From the outcome of our empirical evaluation on the three experiment sets, it is evident that incorporating all CPS feature sets together in the process of building a classifier, will provide better overall predictive performance.

In our experiments, random forests model for non-professionals cohort achieves the best classifier performance (with F_1-score of 52.06%). On the other hand, the model is also suggested as the best classifier (with F_1-score of 39.13%) for task recognition. The best models for both cohorts are attained when they are trained on CPS feature set.

5.5.2 Social/exercise/entertainment tasks. Our experiment result is validated on the recognition of the following tasks:

- **Non-professionals:** Travel, physical, education, meals and breaks, communication, and planning.
- **Professionals:** Travel, physical, education, meals and breaks, communication, and IT.

We found that random forest model shows the best performance with F_1-score of 36.99% for professionals. However, the decision tree model is suggested for professionals since it achieves overall F_1-score of 56.44%, which outperforms the random forest by 4.2%. The highest performance can still be achieved by these models based on the CPS feature set. This result suggests that social/exercise/entertainment tasks could be more predictable to work-related tasks for professionals, and vice-versa for non-professionals.

5.5.3 Recognition of personal/caring/civil tasks. For personal/caring/civil tasks, the our experiment result is validated on the recognition of the following tasks:

- **Non-professionals:** Travel, physical, education, meals and breaks, communication, planning, documentation, admin and management, IT, and problem solving.
- **Professionals:** Travel, physical, education, meals and breaks, communication, planning, documentation, admin and management, and finance.

We found that the random forest model for professionals achieves the highest classifier performance (with F_1-score of 51.19%) and is

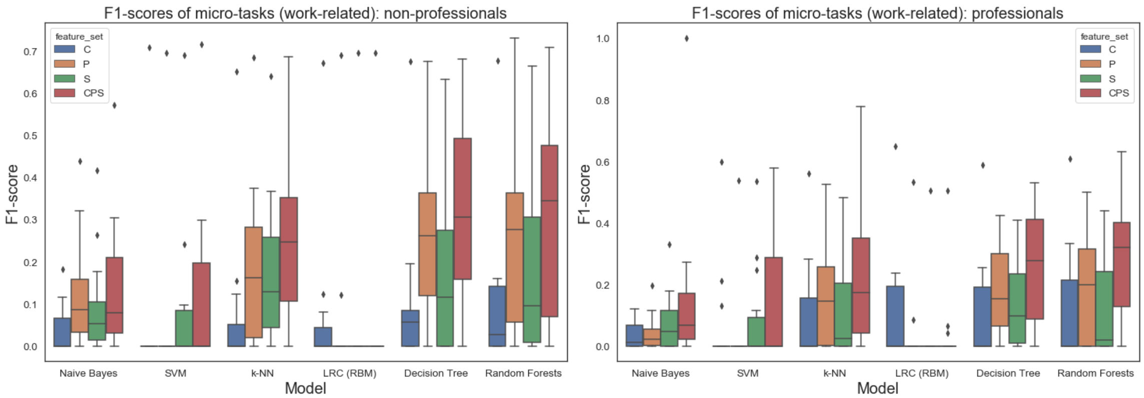

Figure 4: Boxplots of F_1-scores on work-related task recognition: non-professionals and professionals.

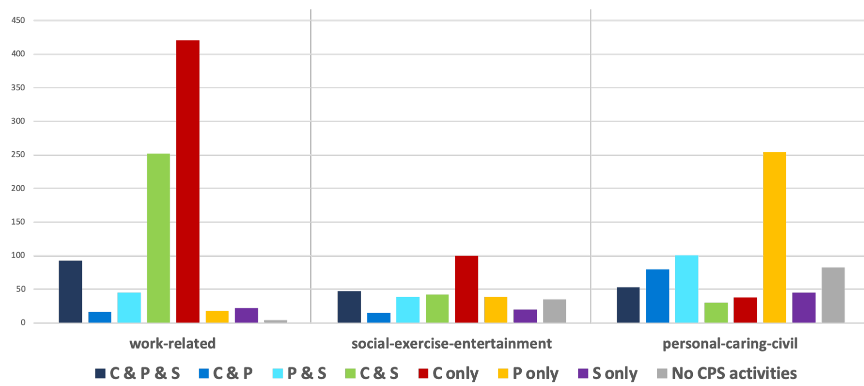

Figure 5: Overall participant perception of CPS activities on their tasks.

also selected as the best model for non-professionals (with F_1-score of 30.43%). Although such models provide lower overall performance for non-professionals, a substantial improvement is still noticeable when the model is trained using all CPS features.

Furthermore, a general overview of participant perception about CPS activities on their engaged tasks is reported in Figure 5. From the survey answers, it is evident that the majority of work-related tasks (up to 673 tasks) require either cyber activities only or both cyber and social activities. At least 93 such tasks were reported requiring all CPS activities in order to progress or complete. For social/exercise/entertainment related tasks, the many tasks require only cyber activities. Examples for this set of tasks would be "watching/browsing youtube videos" or "read online news". For personal/caring/civil tasks, a total of 254 tasks were commonly reported as tasks that require physical activities. However, the lowest count of 30 tasks was reported to require both cyber and social activities, followed by 38 tasks reported to only requiring cyber activities.

6 CONCLUSIONS AND FUTURE WORK

In this paper, we developed an end-to-end framework to recognize user tasks based on sensing logs of CPS activities. We presented the results and analysis of our conducted experiments and showed that we can recognize tasks by leveraging a range of CPS features. Specifically, we showed that by incorporating CPS features together can improve task recognition performance. Task recognition using our framework can promote the development of future digital assistants, productivity applications, and other intelligent/assistive technologies which may include interruption support, task management, and generating task-relevant recommendations to help users make progress on their tasks.

Future research may include experimenting with richer feature sets, performing additional user studies (with more users, a broader portfolio of tasks, and different user cohorts), and integrating our task recognition methods into technologies to help boost users' task efficiency and effectiveness, among other goals. Since privacy could be an issue for real-world deployment, future research also must include the ethical and privacy considerations of such in-the-wild data collection.

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