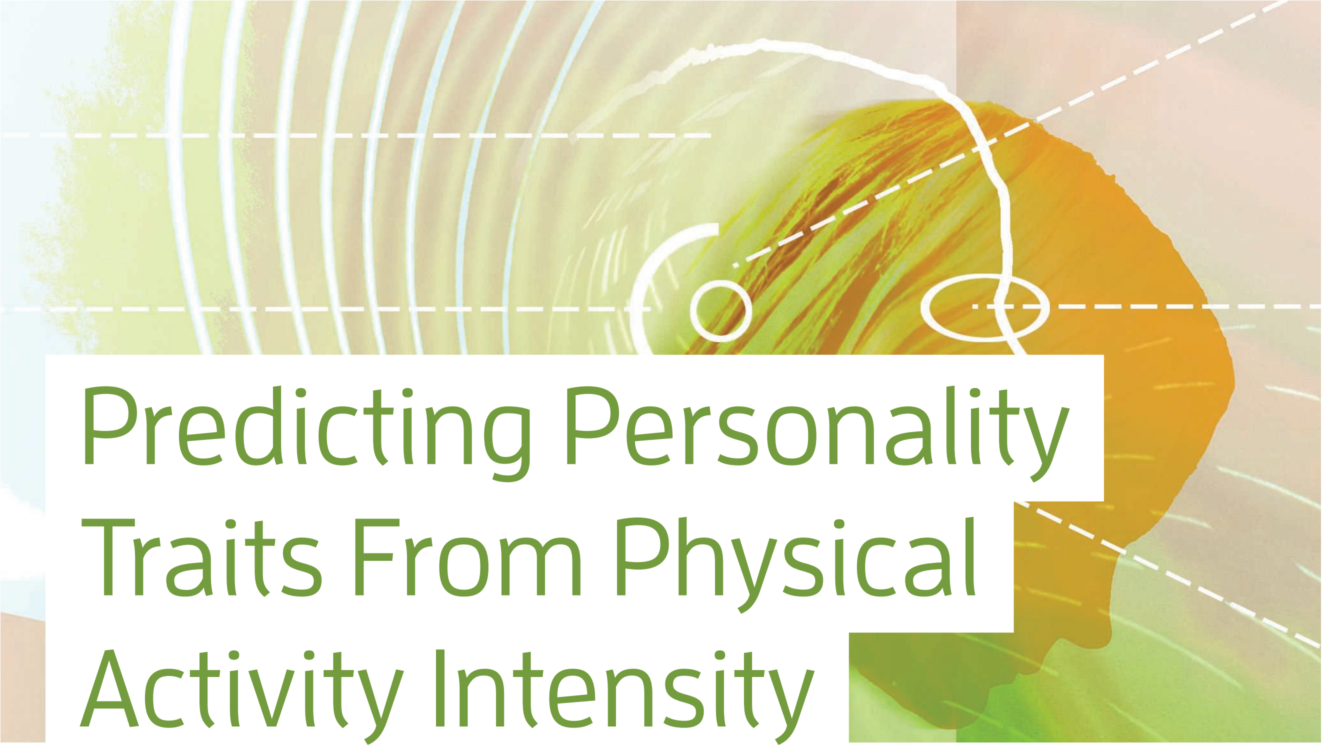

Predicting Personality Traits From Physical Activity Intensity

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Call and messaging logs from mobile devices have successfully been used to predict personality traits. Yet accelerometer data have not been applied for this purpose. Here we used accelerometer data, along with data from call and messaging logs, to predict five key personality traits.

Traditional self-reported personality predictions have many limitations and rely too much on answers from participants, making the process time-consuming and the results unreliable. Past research has shown that it is possible to predict a human's personality through historical records of mobile data, such as those collected from calls, messages, app usage, and location logs.[1–3]

Studies have indicated a strong correlation between the intensity of physical activity with human personality.[4] Accelerometers have been widely applied in various devices, such as mobile phones and fitness wristbands, to measure the intensity of physical activity.[1] To predict personality traits through mobile phones, researchers have focused on exploring phone activities or app usage.

However, nobody has examined the idea of combining phone activity data with data about physical activity intensity collected from accelerometer sensors. For this article, we assumed that we can predict human personality by studying participants' phone activity and physical activity intensity. Because men and women usually have different activity patterns, we ran the experiments separately for each gender.

The Big-Five personality framework, one of the most important tools for measuring personality traits,[5,6] consists of five dimensions: extraversion, agreeableness, conscientiousness, neuroticism, and openness to experience (openness). *Extraversion* reflects the degree of being energetic, sociable, and talkative. *Openness* is the tendency to be curious and inventive. *Agreeableness* usually means

Digital Object Identifier 10.1109/MC.2019.2913751
Date of publication: 2 July 2019

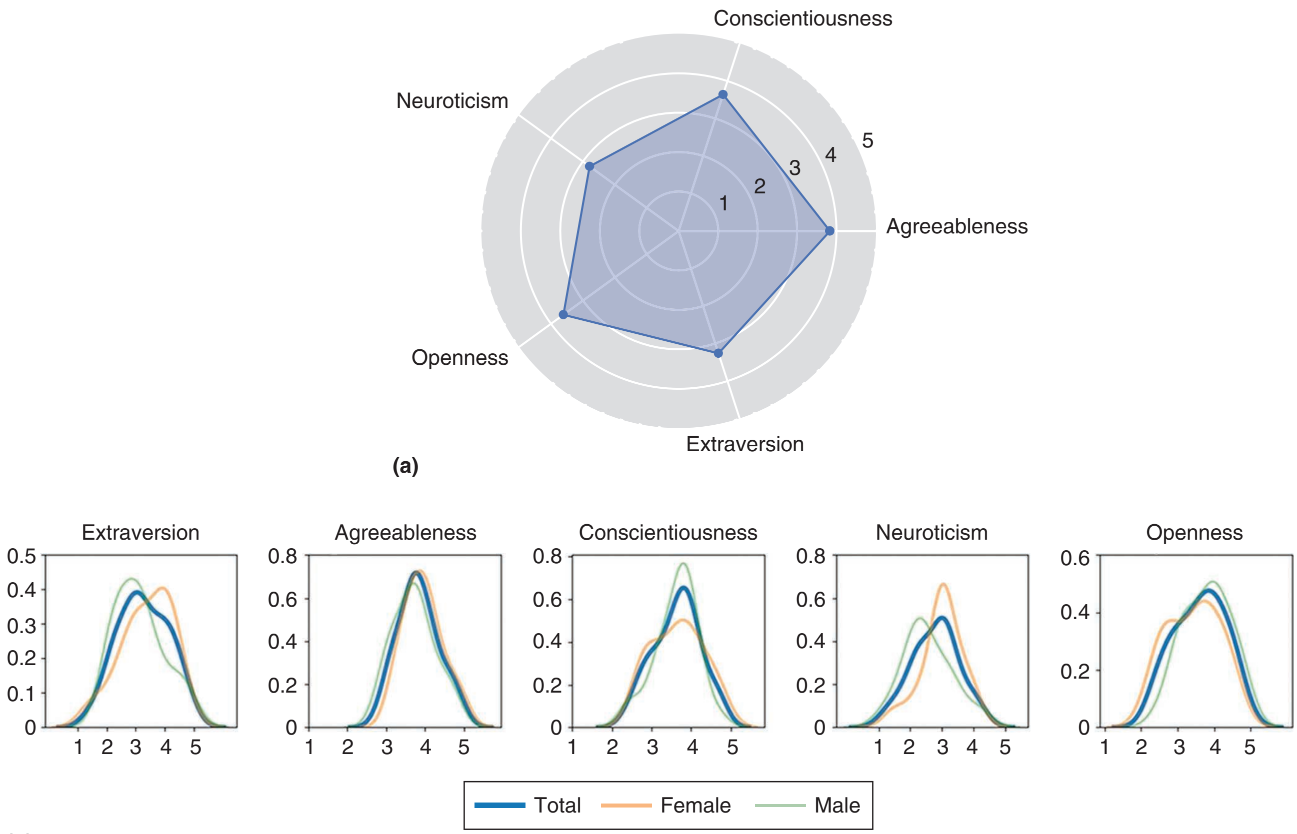

FIGURE 1. (a) The average score for the five personality traits. (b) The kernel density distribution of five personality traits based on gender differences.

the potential to be friendly and compassionate to others, instead of suspicious and hostile. *Conscientiousness* shows the tendency to be organized, efficient, and careful. *Neuroticism* is the tendency to be nervous and sensitive instead of confident and secure. Figure 1(a) shows the average score for five different personality traits in our data set (see the section "Big-Five Personality Ground Truth" for more details).

In this article, we describe how we combined physical activity intensity data and phone activity data to predict human personality. We propose several important metrics based on diversity, dispersion, and regularity. Then we categorize these features based on different temporal factors and gender. We applied support vector regression (SVR) to build a prediction model of human personality traits. Experiment results showed that using features from human physical intensity through accelerometer data can improve prediction accuracy. In addition, the prediction performance improvement for males differed from that for females when activity intensity was considered.

This article makes the following contributions:

- We predict human personality traits for the first time by combining physical activity intensity data with traditional phone activity data.
- We propose novel metrics based on different categories—diversity, dispersion, and regularity—and identify some significant associations between human physical activity intensity and self-reported personality traits.
- We found that the features describing physical activity intensity can improve the performance

of personality prediction, with observable reduction of errors across male and female groups.

To the best of our knowledge, this is the first attempt to combine human physical activity intensity data with traditional phone activity data for predicting personality traits. Our results establish a foundation for the future study of this topic.

RELATED WORK

Machine-learning techniques have been applied successfully using sensor data for predicting human mobility,[7] identity,[8] activities, transportation modes, and complex behavior.[9] Various media applications can be used to predict users' personality traits. Facebook profiles[10] and messages[11] are examples of online social networking sites that can be used to detect a user's personality. Nhi et al. proposed a personality-mining framework to exploit information from videos (e.g., YouTube clips), which includes visual, auditory, and textural perspectives.[12] Xin et al. demonstrated the relationships between active users' microblogging behaviors and personality traits.[13] Other research has shown that it is possible to estimate the personality traits of users by exploring the use of mobile devices as inferred from mobile data, such as call, application, Bluetooth, and message logs.[14]

Through the use of accelerometers and proximity sensors embedded in wearable devices alone, Cabrera-Quiros et al.[15] recognized personality self-assessments in the context of people mingling in a crowded scenario. Although they considered the physical activity of each person, their research required people to wear the same wristband in the specified scenarios, which is not normal for typical daily life. Recently, Weichen et al.[3] predicted personality traits through mobile sensing of, for example, ambient voices and other sounds, physical activity, and phone activity. However, they only computed the sedentary duration within every hour to represent the pattern of physical activity, which is simple and naïve since they did not consider the whole physical activity intensity distribution. For phone activity, they used the number of phone lock/unlock events and unlock duration to estimate the phone usage. They did not consider the diversity, regularity, and dispersion of phone contacts.

Mobile logs (phone and message activity) are easily accessible and have been used for efficient personality prediction.[2] To the best of our knowledge, there has been no application to infer personality by combining traditional mobile activity with physical activity intensity, which has proven to have a strong association with human personality.[4] Physical activity intensity can be estimated through data from accelerometers,[16] which have been widely deployed in various devices, such as mobile phones and fitness wristbands.

METHODOLOGY

Participants and procedure

In the research, which was conducted from March 2010 to July 2011, we exploited a data set made up of 55 participants living in a residential community for young families adjacent to a major research university in North America.[17] Each participant was equipped with an Android OS-based mobile phone running with Funf, a sensing software designed for periodically collecting mobile data.[17] The software operates in a passive way and thus does not influence users' normal habits involving the mobile phone. At the initial stage of data collection, each participant needed to complete a personality survey. Big-Five scores can be calculated using methods described by John and Srivastava.[6] After removing participants who did not respond completely to the Big-Five survey, we created a final sample of 52 participants (27 female; 25 male).

For this data set, we focused on users' activity data, which included phone activity and physical activity. Phone activity data, such as call and text messages received and sent, have been widely used for personality prediction.[2] Physical activity data inferred from accelerometers have proven to be strongly associated with an individual's personality.[4] In this research, we limited the scope of the study to the participants' call, text-message, and accelerometer logs, which are easily accessible for future mobile data collection.

For accelerometer logs, raw three-axis measurements were sampled at a rate of 5 Hz over 15 s every 2 min. Participants had no constraints on how they carried the phone. For call logs and message logs, the human-readable texts were captured as hashed identifiers. For more details about the data set, see Aharony et al.[17]

Activity behavior metrics

As stated previously, the human personality can be evaluated through the Big-Five model, which consists of five major dimensions: openness, extraversion, agreeableness, conscientiousness, and neuroticism. To better understand the patterns of daily human activity, we computed several metrics that could meaningfully reflect differences in personality traits. The metrics are divided into three categories: dispersion, diversity, and regularity. We used these metrics to evaluate the participants' phone activity and physical activity.

Phone activity includes call and message interactions, which were computed separately based on the metrics. For physical activity, we first partitioned each day's raw accelerometer data into 24-h periods and processed it hourly. Then we used the mean amplitude deviation (MAD)[18,19] across each hour to assess the intensity of physical activity:

$$\mathrm{MAD} = \frac{1}{n}\sum\left|r_i - \overline{r}\right|, \tag{1}$$

where n is the number of accelerometer data samples in each time period, r_i means the resultant acceleration at the ith time stamp, and $\overline{r}$ represents the mean resultant value across the time period. r_i can be calculated through

$$r_i = \sqrt{x_i^{\,2} + y_i^{\,2} + z_i^{\,2}}, \tag{2}$$

where x_i, y_i, z_i represents the x, y, z direction of the raw acceleration signal. Next, for assessing activity behavior, we computed the following metrics: dispersion, diversity, and regularity of activity behavior.

Dispersion has to do with how sporadic activity behavior is. In our research, standard deviation (SD) is used to evaluate the dispersion of people's phone activity and physical activity intensity. Since people tend to have different activity patterns at different times (i.e., more physical activity on weekends or fewer phone calls in the night), we computed the SD for three time stages (daytime, evening, and night) across weekdays and weekends during the data-collection period.

Diversity is the state of being diverse for users' activity. Shannon entropy measures the amount of disorder in a system, which can be used to measure the diversity of users' contacts:

$$S = -\sum_{i=1}^{n} F_i \log F_i, \tag{3}$$

where F_i means the frequency that user s interacts with i of all contacts n. Higher entropy means user s interacts equally with many contacts and lower entropy happens when the user mostly interacts with specified contacts. Shannon entropy is used to evaluate the diversity of phone activity in this study.

Regularity is the state of regular patterns. We propose the regularity index (RI) based on the work of Wang et al.[3] to calculate the difference between specified time periods T in two different days. First, we rescaled the data for each participant to [–1], where –1 corresponds to the minimum value in the original data and 1 corresponds to the maximum value. The RI is positive if the values are close and negative if they are not similar. Then we define the RI of the time period t between day i and day j as

$$\forall (i,j) \in S,\ \mathrm{RI}_{i,j}^{T} = \frac{1}{T}\sum_{t=1}^{T} x_t^i x_t^j, \tag{4}$$

where S is the set of two time-period pairs, x_t^i and x_t^j means the rescaled value at hour t in the time period T. We computed the average RI values from every possible pair within the following sets: 1) all days, 2) weekdays, 3) weekends, 4) daytimes on weekdays, 5) nighttimes on weekdays, 6) weekday evenings, 7) daytimes on weekends, 8) weekend evenings, and 9) weekend nights. RI is used to evaluate the regularity of phone activity and physical activity in this study.

To prove the advantages of extracted physical activity features and make the comparison fair, we also obtained some traditional phone activity features based on previous literature,[2] including average of interevent time, variance of interevent time, response rate, response latency, percentage during the night, and percentage initiated. Table 1 summarizes the features used in our study.

Big-Five personality ground truth

We used the self-reported Big-Five results from the participants as the ground truth for different personality traits. The scores were computed from 52 questions related to different personality traits,[20] and the score is from one to five, where one is the lowest score and five indicates the highest score of the personality trait. Figure 1(b) shows the distribution of five personality traits based on gender differences.

The descriptive statistical results (mean value, SD, median value, minimum value, and maximum value) for the entire population and different gender groups are given in Table 2. For the entire population, the average score of different personality traits is close to three. It can be observed that the average score of agreeableness is around four, followed by conscientiousness, openness, extraversion, and neuroticism. The agreeableness trait has the lowest SD, which means that the agreeableness scores of most participants are very close.

Interestingly, we found that females and males had different distribution patterns in the five personality traits. This is especially the case with the neuroticism score. Females usually scored higher than males in that category (t-test p value, 0.03). This leads us to believe

TABLE 1. A description of the extracted features.

Feature	Features computed	Data
Dispersion	SD on the number of interactions for all days	Call, message, or call and message
	SD on physical activity intensity for all days: daytime, evening, and nighttime	Accelerometer
	SD on physical activity intensity for weekdays: daytime, evening, and nighttime	Accelerometer
	SD on physical activity intensity for weekends: daytime, evening, and nighttime	Accelerometer
	SD on physical activity magnitude for all days	Accelerometer
Diversity	Entropy of total contacts for all days	Call, message, or call and message
	Entropy of total contacts for weekdays	Call, message, or call and message
	Entropy of contacts in sent box for all days	Call, message, or call and message
	Entropy of contacts in sent box for weekdays	Call, message, or call and message
Regularity	Average RI of number of interactions for all days	Call, message, or call and message
	Average RI of physical activity intensity	Accelerometer
	Variance of RI for the number of interactions: daytime, evening, and nighttime	Call, message, or call and message
	Variance of RI for physical activity intensity: daytime, evening, and nighttime	Accelerometer
Basic	Total number of interactions for all days and for all weekdays	Call, message, or call and message
	Average physical activity intensity for all days: daytime, evening, and nighttime	Accelerometer
	Average physical activity intensity for weekdays: daytime, evening, nighttime	Accelerometer
	Average physical activity intensity for weekends: daytime, evening, nighttime	Accelerometer
	Average interevent time for all days	Call, message, or call and message
	SD on interevent time for all days	Call, message, or call and message
	Contacts-to-interactions ratio for all days	Call, message, or call and message
	Response rate for all days	Call, message
	Response latency for all days	Call, message
	Percentage during the night for all days	Call
	Percentage initiated for all days	Call, message, or call and message

that females in our population sample are more sensitive and emotional than males. Furthermore, the males seem to have higher openness scores than females, which indicates that most males are likely to be curious while the females tend to be cautious.

ASSESSING PERSONALITY USING ACTIVITY PATTERNS

Feature analysis

We extracted features based on the introduced metrics and different time spans in the section "Activity Behavior Metrics" (see Table 1). We define the daytime period as 9:00 a.m. to 6:00 p.m., the evening period as 6:00 p.m. to midnight, and the night as midnight to 9:00 a.m.

Since most features, except for entropy metrics, were strongly skewed positive, we applied log transformation for them

TABLE 2. An overview of the Big-Five scores for participants.

Participants	Personality traits	Mean	SD	Median	Minimum	Maximum
Total	Extraversion	3.26	0.86	3.13	1.50	4.88
	Agreeableness	3.83	0.52	3.78	2.78	5.00
	Conscientiousness	3.64	0.58	3.78	2.44	4.67
	Neuroticism	2.79	0.74	2.88	1.13	4.25
	Openness	3.61	0.70	3.70	2.20	4.90
Female	Extraversion	3.38	0.87	3.63	1.50	4.63
	Agreeableness	3.95	0.50	3.89	3.11	5.00
	Conscientiousness	3.65	0.64	3.67	2.67	4.67
	Neuroticism	3.00	0.65	3.00	1.38	4.13
	Openness	3.44	0.72	3.50	2.20	4.60
Male	Extraversion	3.13	0.84	3.00	2.00	4.88
	Agreeableness	3.71	0.54	3.67	2.78	4.78
	Conscientiousness	3.62	0.53	3.78	2.44	4.67
	Neuroticism	2.56	0.77	2.38	1.13	4.25
	Openness	3.80	0.64	3.90	2.50	4.90

before conducting correlation analysis. The Pearson correlation coefficient (PCC), which is widely applied to measure the correlation between variables in the psychology field, was calculated between extracted activity features and Big-Five personality traits. The PCC values range from –1 to 1, where 1 represents the total positive linear correlation, 0 means no linear correlation, and –1 indicates the total negative linear correlation. Table 3 shows the top three useful features to predict Big-Five personality scores for all participants, female participants, and male participants, where (+) represents the positive correlation and (–) means the negative correlation with the personality traits. In Table 3, we also list the PCC value for each useful feature.

- *Extraversion*. The RI of physical activity intensity for weekday evenings is negatively associated with the extraversion trait. This suggests that people who score high for extraversion usually do not follow similar patterns on weekday nights. The high entropy of contacts means that they tend to interact with different people randomly, which is consistent with our experience in daily life.
- *Agreeableness*. Similar to the extraversion trait, the people with high agreeableness usually have a low RI of physical activity for weekday evenings since they may be sociable. They also tend to be more active on weekends and on weekday evenings. It is highly likely that friendly and compassionate females have more outgoing calls.
- *Conscientiousness*. We found that both females and males with high conscientiousness scores tend to have high entropy of contacts. This tells us that people who are more organized and efficient tend to contact different people and don't usually connect to the same people. Also, organized people may have high activity intensity on weekend evenings because they have already planned it and are well prepared.
- *Neuroticism*. We found that the RI of physical activity intensity on weekday and weekend nights for females is positively correlated with neuroticism. This leads us to believe that the female who is sensitive seems to have regular physical activity at night (after midnight). Interestingly, these same features for the male group are negatively correlated with neuroticism, which displays the difference between men and women.
- *Openness*. We found that the total number of calls is negatively correlated with the openness trait. In addition, the average interevent time of calls was positively correlated with the openness score. That is to say, individuals who have fewer

phone calls and a longer period between each call tend to be more inventive and curious.

Prediction analysis

Personality prediction is commonly regarded as a regression problem. Scores range from one (lowest) to five (highest) for each personality trait. Although the personality score can be divided into several classes (e.g., high, medium, and low) using a certain threshold, researchers have proven that it is not a good practice to determine people's psychology characteristics. Most classification models showed a low prediction accuracy of around 49–63%.[2] Thus, in the study, we used the regression model to predict personality traits.

SVR with a radial basis function kernel was chosen to predict the Big-Five personality scores. SVR, which has been applied in various fields, can deal with high dimensional data and automatically models nonlinear relationships. Since there are noticeable dissimilarities for personality scores among different genders and the key features are not the same, we chose the best regressor for the female, male, and total population separately.

Baseline and evaluation

Through the literature review, we found that most researchers used the random chance or majority class selection method as the baseline for Big-Five personality predictions.[1–3] However, in our research, we aimed to improve prediction performance by combining human physical activity features with traditional phone features. Thus, it did not make much sense to compare our model with the random chance or majority class selection as the personality traits are hard predict from only one kind of data. In the experiment,

TABLE 3. The most useful features for predicting personality traits (female and male population).

Personality	Population	Top three features
Extraversion	Female	(+0.55) Average physical activity intensity on weekend evenings (–0.46) Average interevent time of messages (–0.40) Response latency of messages
	Male	(+0.44) Entropy of call and messages (+0.25) Average physical activity intensity on weekday evenings (–0.25) RI of physical activity intensity on weekday evenings
	Total	(–0.30) RI of physical activity intensity on weekday evenings (+0.26) Entropy of contacts of calls and messages (–0.23) SD of physical activity intensity on weekdays during daytime
Agreeableness	Female	(+0.35) Number of outgoing calls (–0.37) Percentage of initiated calls (–0.31) RI of physical activity intensity on weekday nights
	Male	(+0.47) Average physical activity intensity on weekday evenings (–0.43) RI of physical activity intensity on weekday evenings (+0.39) Percent of initiated messages
	Total	(–0.33) RI of physical activity intensity on weekday evenings (+0.26) Average physical activity intensity on weekends (+0.23) Average physical activity intensity on weekday evenings
Conscientiousness	Female	(+0.42) RI of physical activity intensity on weekends during the daytime (+0.35) Entropy of calls and messages (+0.21) Average physical activity intensity on weekend evenings
	Male	(+0.51) Entropy of call and messages (–0.35) RI of physical activity intensity on weekend evenings (+0.34) Number of messages
	Total	(+0.44) Entropy of call and messages (+0.27) Total number of messages (+0.20) Average physical activity intensity on weekend evenings
Neuroticism	Female	(+0.44) RI of physical activity intensity on weekend nights (+0.42) Entropy of calls (+0.36) RI of physical activity intensity on weekday nights
	Male	(–0.30) RI of physical activity intensity on weekday nights (+0.21) Entropy of call and messages (–0.20) RI of physical activity intensity on weekend nights
	Total	(+0.27) Entropy of calls (+0.25) Response latency of messages (–0.24) SD of physical activity intensity on weekends during daytime
Openness	Female	(–0.27) Total number of calls (–0.22) RI of physical activity intensity on weekday evenings (–0.20) Average physical activity intensity on weekday nights
	Male	(–0.32) Total number of calls (+0.29) SD of physical activity intensity on weekday evenings (+0.19) Percent of initiated calls
	Total	(–0.32) Total number of calls (+0.26) SD of physical activity intensity on weekday evenings (+0.21) Average interevent time of calls

personality prediction with only phone activity data (call and message logs) with state-of-the-art metrics (introduced in the section "Activity Behavior Metrics") was considered as the baseline model in the experiment.

For evaluation, we adopted the leave-one-out validation method because it usually performs best when estimating the model from a small data set. Using the leave-one-out method, we calculated the average value for mean absolute error (MAE) and mean squared error (MSE) for each personality trait.

We validated our model with the MAE and MSE as follows:

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|y_{\mathrm{true}} - y_{\mathrm{pred}}\right|, \quad (5)$$

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}\left(y_{\mathrm{true}} - y_{\mathrm{pred}}\right)^2, \quad (6)$$

where n represents the number of samples, y_{true} means the true personality scores, and y_{pred} means the predictive value of personality scores. The MAE and MSE can describe the goodness of predictions compared with the ground truth of personality score. The closer the MAE and MSE are to zero, the more successful the modal forecast.

TABLE 4. The prediction performance for total/male/female participants.

Group	Big-Five traits	MAE Baseline	MAE Proposed	MSE Baseline	MSE Proposed
Total	Extraversion	0.685	**0.655**	0.730	**0.692**
	Agreeableness	0.444	**<u>0.399</u>**	0.298	**0.262**
	Conscientiousness	0.397	**<u>0.249</u>**	0.249	**0.240**
	Neuroticism	0.618	**0.591**	0.562	**0.545**
	Openness	0.622	**0.619**	0.517	**0.515**
Female	Extraversion	0.621	**0.573**	0.729	**<u>0.601</u>**
	Agreeableness	0.393	**0.381**	0.258	**0.242**
	Conscientiousness	0.561	**<u>0.492</u>**	0.415	**<u>0.334</u>**
	Neuroticism	0.612	**<u>0.532</u>**	0.554	**<u>0.425</u>**
	Openness	0.709	0.709	0.625	0.625
Male	Extraversion	0.691	**0.661**	0.736	**0.734**
	Agreeableness	0.422	**0.415**	0.270	**0.264**
	Conscientiousness	0.407	**0.393**	0.293	**0.275**
	Neuroticism	0.571	**<u>0.525</u>**	0.536	**<u>0.463</u>**
	Openness	0.521	**0.520**	0.400	0.400

Numbers in boldface mean the proposed method has better prediction performance than the baseline in specific personality traits, whereas underlining shows the significant improvement of prediction.

DISCUSSION

Table 4 displays the performance of our prediction model based on the extracted features from call, message, and raw accelerometer logs. With the observable reduction of errors, our model performs better than the baseline model for all personality traits. The predicted Big-Five scores are highly correlated with the ground truth.

In comparing the MAE and MSE between our model and the baseline, it is interesting to note that conscientiousness, neuroticism, and extraversion were the personality traits best predicted in our model. For the entire population, the model predicting conscientiousness score achieves 0.249 of MAE, which is 0.148 (37.28%) lower than the baseline model. For the female group, the model predicting neuroticism score achieved 0.425 of MSE, which is 0.129 (23.29%) lower than the baseline model. In the meantime, the MSE of the extraversion score for the female group was 0.128 (17.56%) lower than the baseline.

We found that the performance of neuroticism prediction is better in the gender-specific model than in the entire-population model, which may be due to the different key features for males and females. According to our explanations in the section "Feature Analysis," males and females with high neuroticism scores may exhibit very different patterns of activity intensity in the night. However, if we do not consider the gender difference, the regularity of activity intensity will not become the key features in the entire population. This phenomenon addresses the importance of building the gender-specific prediction models for the neuroticism personality trait.

Our model was less effective in predicting the openness trait. The reason may be that human physical activity intensity is not strongly associated with the openness trait. In daily life, it is also hard to tell whether someone is inventive or curious by his or her activity intensity pattern.

Our research had some limitations. First, the sample size of our adopted data set (52) was relatively small, which may limit the performance of personality predictions. Further research is needed to explore larger data sets to prove the effectiveness of physical activity features. Second, the evaluation method is relatively simple, and a comprehensive evaluation method needs to be proposed for better comparison with existing work. Last, the existence of biases in the Big-Five self-report data, such as sampling and response biases (i.e., misunderstanding the measurement, social desirability bias, wanting to "look good" in the survey), may affect prediction performance. Further work needs to recognize and mitigate such biases.

In this research, we first demonstrated that it is possible to combine human physical activity intensity data with traditional phone activity data to estimate the Big-Five personality traits score. We proposed a set of important metrics based on dispersion, diversity, and regularity and found some interesting associations between human activity patterns and personality traits. SVR was used to predict participants' personality scores.

Experiment results showed that our predictive model highly correlated with the ground truth and outperforms the baseline model. We also found that the performance of our predictive model for the female group differed from the male group, with observable reduction of errors compared with the total participants' group.

This research presents a significant step toward passive human personality prediction from the measurements of smartphone activity data. In the future, larger data sets will be explored to prove the effectiveness of physical activity features in personality prediction. Different activity types will be extracted to enhance our predictive model. Also, recognizing and mitigating the biases in the Big-Five self-report data will become another important direction in our future research. C

ACKNOWLEDGMENTS

This research was supported by the Australian Government through the Australian Research Council's Linkage Projects funding scheme (Project LP150100246).

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