Measuring Self-Esteem with Passive Sensing

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ABSTRACT

Self-esteem encompasses how individuals evaluate themselves and is an important contributor to their success. Self-esteem has been traditionally measured using survey-based methodologies. However, surveys suffer from limitations such as retrospective recall and reporting biases, leading to a need for proactive measurement approaches. Our work uses smartphone sensors to predict self-esteem and is situated in a multimodal sensing study on college students for five weeks. We use theory-driven features, such as phone communications and physical activity to predict three dimensions, performance, social, and appearance self-esteem. We conduct statistical modeling including linear, ensemble, and neural network regression to measure self-esteem. Our best model predicts self-esteem with a high correlation (r) of 0.60 and low SMAPE of 7.26% indicating high predictive accuracy. We inspect the top features finding theoretical alignment; for example, social interaction significantly contributes to performance and appearance-based self-esteem, whereas, and physical activity is the most significant contributor towards social self-esteem. Our work reveals the efficacy of passive sensors for predicting self-esteem, and we situate our observations with literature and discuss the implications of our work for tailored interventions and improving wellbeing.

CCS CONCEPTS

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

KEYWORDS

self-esteem, passive sensing, college students, wellbeing, campuslife

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1 INTRODUCTION AND BACKGROUND

> A musician must make music, an artist must paint, a poet must write, if he is to be ultimately at peace with himself. What a man can be, he must be. This need we may call self-actualization —Maslow 1981

Psychologist Abraham Harold Maslow in his seminal book, *Motivation and Personality*, identified various human needs that range from survival to intellectual growth [22]. Such needs, often referred to as Maslow's hierarchy of needs can be clustered into five categories—Physiological, Safety, Love or Belonging, Self-Esteem, and Self-Actualization (Figure 1).

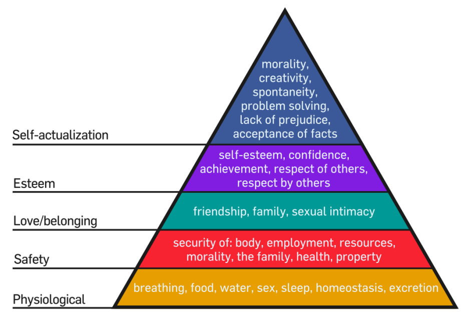

Figure 1: Maslow's Hierarchy of Needs as per Maslow [21]

Self-esteem is considered to be a form of a concept that encompasses how an individual evaluates themselves on a scale ranging from positive (or self-affirming) to negative (or self-denigrating) [18]. In other words, self-esteem corresponds to someone evaluating themselves in the form of how much they like or dislike themselves [3]. This process of self-evaluation continues throughout the lifetime of an individual, and it is aided by a variety of social, cultural, and environmental constraints. Self-esteem is one of the basic human needs, and it is known to significantly contribute to one's motivation and success [21]. Low self-esteem can affect performance at school or work, and high self-esteem can help an individual navigate life by positive attitude and belief in achieving their goals. Individuals with damaged and lower self-esteem are at a greater risk of psychosocial distress, and maybe vulnerable to the demanding circumstances of day-to-day life [19]. An early assessment of one's self-esteem can not only facilitate one to reflect on their capabilities, but also can guide tailored interventions towards uplifting their self-esteem, motivation, desire to perform, and in turn their wellbeing. Understanding self-esteem can foster adopting preemptive steps to facilitate the psychological and cognitive needs of individuals.

Over the years, researchers from the domain of psychology, sociology, cognitive sciences, etc., have come up with different methodologies to estimate one's self-esteem [3]. Heatherton and Polivy proposed self-esteem to consist of three primary dimensions: performance, social, and physical appearance [17]. Rosenberg's scale is a popular way to measure self-esteem among a variety of targets, and it measures the self-esteem of individuals in absolute terms [28]. Miyamoto and Dornbush proposed an alternate self-esteem measurement scale that focuses on more individual aspects (e.g., intelligence, physical attractiveness, etc.) [24], and Ziller

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Table 1: Descriptive statistics of the DASS-21 data. Levels inferred as per Gomez [14].

Level	Dep.	Anx.	Str.
Normal	26	27	26
Mild	5	6	9
Moderate	8	10	8
Severe	3	0	1
Extremely Severe	3	2	1

Table 2: Descriptive statistics of the EMA data.

Metric	Value
# Participants	51
# Responses	1,606
Mean Responses	31.49
Median Responses	28.00
StDev. Responses	21.13

et al. proposed a social self-esteem scale where individuals evaluate themselves in their social circle [48].

Traditionally, interviews and surveys have been the primary instruments to quantify psychological constructs [9]. These approaches are highly reliant on a respondent's retrospective recall and subjective assessments [13]. Aggregating multiple events over the past leads to difficulty in recollection, leading to poor quality of recorded data. Some of the confounds of static self-reported data can be mitigated by using in-situ data collection approaches [34]. One popular approach is using ecological momentary assessments (EMAs), also known as experience sampling [10, 35]. EMAs have many advantages over traditional research designs for characterizing complex psychological processes [39, 40], and has been a promising approach in longitudinal studies facilitating actively sensed behaviors and moods [36, 43]. This approach works by prompting participants to respond to survey items in-the-moment and within their natural context.

With the advances in mobile active-sensing (e.g, through smartphones), EMAs can now be conducted at scale. Accordingly, EMAs are now extensively used in large-scale multimodal sensing studies in ubiquitous computing research [23, 27, 45]. Within the StudentLife Project, Wang et al. used mobile EMAs to capture groundtruth information about student activity, emotions, contexts, etc [45].

Although better than static survey instruments on many fronts, active sensing comes with limitations of scale, access, and affordance [35]. EMAs often disseminated through prompts induce a response burden on participants through disruptions [41]. This leads to a tradeoff between balancing the construct validity of participant responses and their compliance [7]. Also, towards a more proactive and holistic understanding of individual wellbeing, researchers have recently valued passive sensing modalities [4, 45]. The unobtrusive and low burden nature of passively sensed data complement actively sensed data. With the ubiquity and widespread use of smartphones and wearables, passive sensing modalities enable a cheap and easier mechanism to capture longitudinal and dense human behavior at scale [44–46].

This paper asks, *Can we automatically and scalably predict self-esteem using passive sensing modalities available on commodity devices?* Our study conducts an EMA-based survey of self-esteem drawing on Heatherton's State Self-Esteem Scale [17]. We build statistical models to predict self-esteem using passively sensed data such as physical activity, conversation patterns, and digital communication patterns. We conduct a deeper dive into the predictive features and adopt a theory-driven approach to understand the importance of the significant features in the context of self-esteem.

2 STUDY AND DATA

This paper leverages data collected in the CampusLife project at Georgia Tech [7, 31]. The data collection was conducted for five weeks during Spring 2016 (March-April) by enrolling several students at Georgia Tech, a large public university in the U.S., and the study was approved by the Institutional Review Board at Georgia Tech. This study enrolled 51 students, consisting of 40% females and 60% males, and 46% undergraduate and 54% graduate students. The mean age of participants was 22 years.

The CampusLife study provided the participants with smartphones that were instrumented to collect a variety of actively and passively sensed data. For active sensing, the smartphones used the Quedget platform that sent ecological momentary assessments in the form of daily state-based survey constructs including affect states, self-esteem, stress, etc. For passive sensing, smartphone-based sensor data was collected in the form of physical activity, frequency of incoming and outgoing calls, frequency of messages, conversation inferences of individuals, WiFi access points, etc. In addition, the participants also answered one-time surveys on their individual differences (e.g., demographics) and wellbeing-trait based measures (Perceived Stress Scale (PSS) [8], Flourishing Scale, and Depression Anxiety and Stress Scale (DASS-21) [1]). For the ease of exposition, we provide a brief summary of the student mental wellbeing in terms of DASS-21 based mental health assessment in Table 1. Given that roughly half the study population shows above-normal levels of mental health, this dataset can be assumed to contain a variety of representation in terms of mental well-being. For self-esteem, we adopted the Heatherton's State Self-Esteem Scale as a Self-Esteem EMA employed on Quedget. These EMAs asked the participants to reflect on their academic performance (scholastic ability), social (e.g., feeling good, feeling self-conscious), and physical appearance based self-esteem.

3 METHODS AND RESULTS

3.1 Measuring Self-Esteem from EMAs

First, we compile our groundtruth dataset of measuring self-esteem from ecological momentary assessment (EMA) responses from participants. The EMAs correspond to daily state-based self-esteem measurement, along three dimensions — 1) Performance, 2) Social, and 3) Appearance [17]. Based on these three dimensions, we measure daily self-esteem per individual as a state-measure. Additionally, we aggregate the self-esteem assessments per individual throughout the duration of the study.

We draw upon the literature to evaluate the convergent validity of our self-esteem measurement. Prior work reports self-esteem to show a correlation with mood in a range of 0.40 and 0.60 [6, 17], and the average correlation in our dataset is 0.52 with statistical significance (see Table 3). This provides reliability in our groundtruth assessment of self-esteem. Figure 2 shows a distribution of state self-esteem within our dataset, we find that it averages at 2.41 (std. = 0.97) for performance, 2.84 (std. = 0.55) for social, 2.17 (std. = 1.07) for appearance per participant.

3.2 Measuring Self-Esteem with Passively Sensed Data

We aim at scalably inferring the self-esteem using passive sensing data. Adopting a theory-driven approach, we build machine learning classifiers of self-esteem. As any other classification methodology, our approach involves tuning both machine learning algorithm (and corresponding parameters) and the sensing features.

Table 3: Pearson's r betwen EMA-based self-esteem and DASS-21 scores.

DASS	Performance	Social	Appearance
Depression	0.60***	0.51***	0.57***
Anxiety	0.38**	0.51***	0.65***
Stress	0.40*	0.40***	0.60***

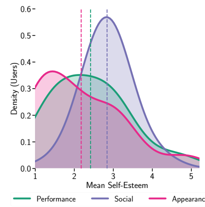


Figure 2: Distribution of self-esteem in EMA data.

3.2.1 *Passive Sensing Features.*

This paper uses a variety of passively sensed features captured by sensors on smartphones. We adopt a theory-driven approach to consider a feature space that is situated in prior literature on psychological contructs, wellbeing, and self-esteem [3]. We describe our features below.

Physical Activity. We consider physical activity based features drawing on two streams of prior research — 1) theoretically, self-esteem is known to be associated with physical movement and activity [33, 42], and 2) ubiquitous computing research has revealed the potential of passively sensed physical activity to understand wellbeing and human dynamics [11, 12, 25]. We use state-of-the-art google activity recognition API that records activity in various states such as *walking*, *biking*, *sitting*, etc [2].

Conversational Setting. Because social and environmental context of an individual bears a potential link to one's self-esteem [37], we use microphone-captured conversation signals as one of our features. This datastream infers if at a given point of time, an individual is situated in a social setting. Our approach does not include storing or using any sensitive voice data, rather the inference of social conversation events.

Communication Pattern. Because social and environmental context of an individual bears a potential link to one's self-esteem [37], we use communication signals as one of our features. Specifically, we use the total number of calls and frequency of messages per day.

3.2.2 *Prediction Model.*

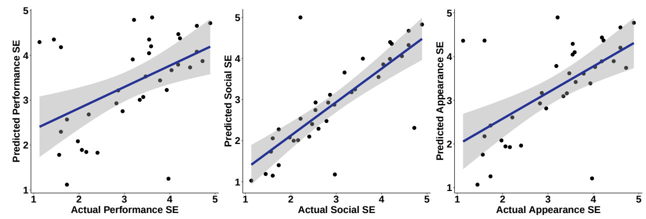
To predict self-esteem from passively sensed features scalably, we adopt regression models. We use individual-wise mean, median, and standard deviation per sensing modality as independent variables to predict corresponding self-esteem measures. We build three separate models for three self-esteem components, academic performance, social, and appearance. We try a variety of algorithms, particularly, linear regression (LR), gradient boosted regression (GBR), and deep learning based multilayer perceptron (MLP). These algorithm choices are motivated by the notion that these cover a broad spectrum of algorithm families spread across linear and non-linear regression, decision trees and ensemble learning, and deep neural networks. We tune model parameters and evaluate our models using a leave-one-out cross-validation approach and measure goodness of fit as R^2. To evaluate our models, we consider a pooled correlation (r) and pooled symmetric mean absolute percentage error (SMAPE), which is computed as the mean percentage relative difference between predicted and actual values over a mean of the two values [20, 29]. SMAPE values range at 0-100%, and lower values of error indicate better predictive ability.

3.2.3 *Prediction Performance.*

Table 4 reports the performance metrics of the above models. We find that the GBR model outperforms

Table 4: Pooled performance metrics as leave-one-out cross-validation. (*p<0.0001, **p<0.001)**

	Performance			Social			Appearance		
Model	R^2	r	SMAPE	R^2	r	SMAPE	R^2	r	SMAPE
LR	0.29	0.36***	18.57	0.61	0.54***	14.32	0.49	0.38***	15.32
GBR	0.46	0.42**	8.61	0.83	0.77***	5.64	0.79	0.59***	7.53
MLP	0.35	0.41***	13.62	0.68***	0.63***	10.23***	0.62	0.43**	10.37



(a) Performance **(b) Social** **(c) Appearance**

Figure 3: Scatter plots of actual and predicted values of the three kinds of self-esteem.

Table 5: Relative feature importance in the GBR model.

Features	Performance	Social	Appearance
Calls	0.29***	0.28***	0.26***
Texts	0.27***	0.11***	0.31***
Conversations	0.21***	0.25***	0.15***
Phy. Activity	0.23***	0.37***	0.28***

all both in terms of low SMAPE and high correlation with statistical significance. GBR performs at an SMAPE=8.61% and r=0.42 for performance, SMAPE=5.64% and r=0.77 for social, and SMAPE=7.53% and r=0.59 for appearance based self-esteem (ref: Figure 3).

3.2.4 *Feature-Model Relevance Interpretation.*

For the best performing (GBR) model, we use K-best univariate statistical scoring model using mutual information to obtain the relative importance among features and establish their statistical significance using ANOVA to obtain the top features, which are reported in Table 5. We find that many digital behavioral categories are significant, which also aligns with prior literature on a self-esteem [38, 47].

For example, calls, texts, and conversations are proxies for social interaction. For predicting social self-esteem, we can see that features from calls, conversations, and physical activities are the strongest predictors. Several studies suggest that low social self-esteem often leads to isolation and a lack of communication [5]. In the case of predicting appearance, we can see that calls, messages, and physical activities are most predictive. Hayes et al. found that self-esteem related to physical appearance was strongly correlated with physical activities undertaken by the individual [16].

4 DISCUSSION AND CONCLUSION

This paper adopted a statistical modeling-based approach to predict three kinds of self-esteem (academic, social, and appearance) to find that passive sensing modalities can reliably predict self-esteem. These approaches that rely on passively sensed data can help not only address challenges associated with traditional modes of data collection but also help us make assessments with a continual and longitudinal fashion. When enacted on a situated community such as college campuses and student populations, these approaches can help student-wellbeing-stakeholders understand how student psychological constructs change (both at the individual- and community-level) over time in both normalcy and crisis [15].

Limitations and Future Directions Our work has limitations, many of which open up opportunities for future research. Our study concerns college students, and our results may not generalize to other populations, and we refrain from making generalized claims within and beyond college campuses because of self-selection and population biases. In one way, we conduct a feasibility study that reveals the potential of passive sensing in predicting self-esteem. Future work can conduct similar studies with a larger participation pool and over a longer duration of time, taking advantage of more newly available commercial smart devices and sensing modalities, e.g., health tracker, smartwatches [23, 30]. While we considered physical passive sensors, prior work has also shown the potential of unobtrusively obtained social media and online digital footprints in measuring self-esteem [26, 47] and psychological constructs in situated communities like college campuses [32]. It would be interesting to examine how all of these modalities may complementarily function together towards measuring psychological constructs.

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