Fullproof: Towards the Detection of Impostor Syndrome Using Smartphone Sensors

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ABSTRACT

Impostor syndrome is a psychological pattern characterized by doubts in one's capabilities or achievements despite evident success. In this paper, we demonstrate the potential of a smartphone-aided solution for impostor syndrome detection among high-achieving college students by presenting some initial findings from our 3-week user study. We collected GPS, Bluetooth, light, screen and app usage data along with Clance Impostor Phenomenon Scale (CIPS) survey results from 37 students. We conducted a correlation analysis between CIPS scores and features extracted from sensor data. Then we grouped the features into three categories that reflect the behavioral characteristics of individuals with impostor syndrome, namely social avoidance, sense of obligation, and restlessness. Based on these findings, we suggest further examination of the use of behavioral sensing data in detecting impostor syndrome.

CCS CONCEPTS

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

KEYWORDS

Smartphone; Impostor Syndrome; Mental Health; Students; Mobile Sensing

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1 INTRODUCTION

Impostor syndrome is a phenomenon in which individuals, despite their talents and accomplishments that tell otherwise, constantly undervalue their competence and fear being exposed as "frauds" [7]. Though causes of the phenomenon are yet to be determined, some common factors that contribute to impostor syndrome are overachieving, perfectionism, social comparisons and fear of failure. This leaves high-achieving university students at a notably higher risk of impostor syndrome, as the students are constantly put under pressure to strive for and to accomplish challenging pursuits.

While impostor syndrome may serve as a source of motivation for some, others may find it difficult to overcome the feelings of anxiety and inadequacy triggered by impostor syndrome. In fact, some well-known correlates of impostor syndrome include depression, anxiety, stress, and negative affect [16]. Moreover, students struggling from impostor syndrome often experience burnouts and impaired academic performances [4], leading to high academic attrition and dropout rates [10]. Although many universities offer counseling and mental health services, the efficacy of such services is questionable as students often fail to identify themselves as having impostor syndrome. Hence, there is a crucial need for an early detection system for impostor syndrome.

Ubiquitous computing has proven effective in the detection and monitoring of psychological disorders and mental health issues for some time now, and much research was devoted to detecting depression and anxiety, the well-known correlates of impostor syndrome. In that regard, mobile sensing systems have the potential to serve as a scalable and effective early detection tool for impostor syndrome. However, limited research has explored the behavioral characteristics of impostor syndrome (which may be easier to capture using smartphone sensors than affective or cognitive characteristics), or the use of technology in detecting impostor syndrome. To address this gap, we propose a smartphone-aided solution for impostor syndrome detection amongst high-achieving college students and present some work-in-progress findings derived from the system.

We conducted a user study with 37 undergraduate students from Seoul National University, a prestigious university in Korea, over 22 days. From the sensor data collected using our Android application, we extracted 368 features we believed best reflect the behavioral characteristics of impostor syndrome. Also, to quantify the extent of impostor syndrome in a psychologically valid manner, we asked the participants to answer the Clance Impostor Phenomenon Scale (CIPS) [8], a widely used scale in measuring impostor syndrome. We performed correlation analysis between the sensor data features and the CIPS scores to identify meaningful correlates. Then, based on prior knowledge, we categorized the correlates into three major categories of behaviors that indicate impostor syndrome, specifically social avoidance, sense of obligation, and restlessness.

Our contributions are twofold:

(1) We extracted, analyzed, and categorized smartphone sensor-based features correlated with the likelihood of impostor syndrome. Highly correlated features captured with smartphone sensors reflect the behavioral characteristics of impostor syndrome.
(2) We deployed and evaluated, in a pilot study with 37 participants, a passive sensing-based early detection system for impostor syndrome in high-achieving college students.

We hope our paper lay the groundwork for additional research on finding the "full proof" that smartphone sensors may in fact serve in identifying people with impostor syndrome, the individuals in constant search for proofs that they themselves are fools.

2 RELATED WORK

Digital phenotyping and monitoring of mental illnesses based on sensing technology have proven effective in many contexts [1, 20]. Correlates or behavioral characteristics of impostor syndrome such as depression [22], and stress [25] have also been explored. As such, findings from previous studies on sensor-based psychiatric disorder detection offer valuable insight into developing a smartphone-based detection system for impostor syndrome.

Though it is not a psychiatric disorder, impostor syndrome is a psychological phenomenon that affects individuals' affective states and cognitive processes in a non-trivial manner. Prior work has shown that impostor syndrome leads to self-perception issues such as low self-esteem, low self confidence and low self-acceptance [17, 23]. Moreover, considerable research has shown that impostor syndrome is related to mood problems [18] such as stress, dysphoria, and particularly, anxiety.

Several works have investigated the predictability of social anxiety using mobile sensor data. A majority of the studies employed location data; high levels of social anxiety were associated with less diversity of visited places [3], more time spent at home [2, 6], and less time spent at religious locations [15]. Gao et al [11] discovered a number of significant correlations between social anxiety and smartphone usage data including call, text message, and app usage logs. Recent studies also leveraged location, call, and text messaging data to conduct correlation analysis [12, 21] on social anxiety. Although these works offer valuable insight into inferring the likelihood of impostor syndrome, this work is the first to explore sensor-based detection of impostor syndrome in isolation.

3 METHODOLOGY

3.1 Data Collection

3.1.1 Participants. In this work, we used data collected from 37 undergraduate students (F=19, M=18) with an average age of 21.5. Participants were undergraduate students of different majors recruited from Seoul National University. The study was conducted for 22 days, including the last week of a vacation and the first two weeks of a semester. The study was approved by the IRB and participants were granted up to $50 as an incentive.

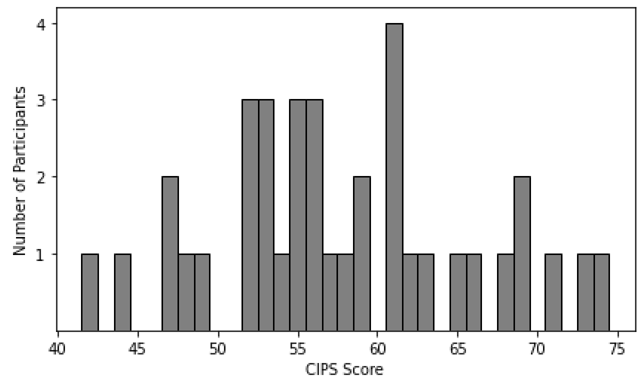

Figure 1: The distribution of CIPS scores

3.1.2 Smartphone Sensing. We acquire phone usage and daily activity data by utilizing an Android app designed to unobtrusively collect everyday behavior using smartphone sensors. Specifically, the following data were collected and uploaded to the server under sufficient battery and network conditions:

- **App usage**: app package name, total duration in foreground, and start/end timestamp were logged on a daily basis
- **GPS**: latitude, longitude, altitude, and timestamp were logged every 5 minutes
- **Bluetooth**: Bluetooth MAC ID, device type, signal strength in dBm, and timestamp were logged every 5 minutes
- **Light**: light value in lx, accuracy, and timestamp were logged whenever ambient light value changes
- **Screen**: event (i.e., screen on/unlock/off), and timestamp were logged whenever a screen event is triggered

3.1.3 Survey Instrument. To understand the frequency and intensity of experienced impostor feelings among participants, we used the Clance Impostor Phenomenon Scale (CIPS) [8], the most commonly used tool to measure impostor syndrome. The scale assesses impostor syndrome from various facets, including self-perceived competency, fear of failure, and reluctance to accept praises.

The CIPS is a 20-item 5-point Likert scale questionnaire with minimum score of 20 and maximum of 100. The items were translated into Korean and the translation was cross-checked by two researchers. CIPS scores in the range of 20-40 denotes no impostorism, 40-59 mild, 60–79 moderate, and 80-100 severe impostor feelings [8]. When using the score of 62 as a cutoff [14], 10 out of 37 participants from our study were identified as having impostor syndrome. The overall distribution of CIPS scores is illustrated in Figure 1.

3.2 Feature Extraction

We aim to extract features that reflect the behavioral tendencies of impostor syndrome. We chose our features based on previous works on impostor syndrome and studies that investigated sensor data correlations with depression and anxiety, the well-known correlates of impostor syndrome. The list of features for each sensor is shown in Table 1.

Table 1: Extracted features

Subgroup	Description	Sensor
all	duration of app usage	App Usage
entertainment		
productivity		
total distance	total distance traveled	Location
radius of gyration	coverage area[1]	
places visited	freq. of unique places visited	
frequency of interaction	freq. of interactions with encountered devices	Bluetooth
devices within proximity	ratio of close devices[2] to total devices	
dark count	freq. of dark ambient light[3]	Light
dark duration	duration of dark ambient light	
count	freq. of screen on events	Screen
duration ≤ 1 sec count	freq. of screen on events with duration ≤ 1 sec	
duration	duration of screen on events	
unlock count	freq. of screen unlock events	

[1] computed based on [5]
[2] RSSI signal ≤ -60 dBm
[3] lux value ≤ 50 lx

Movement and mobility. As prior work has shown that mobility data reflect mood disorders and/or feelings of anxiety, we extracted features such as the total distance traveled, radius of gyration, and the number of places visited. To extract such features, we computed the movement trajectories of each participant using the GPS sensor data. A trajectory in a time interval is defined by the sequence of places visited during the time interval [24]. We used a time-based clustering algorithm to determine significant places and extract a trajectory. We employed a distance threshold of 30 meters and time threshold of 5 minutes. Identical geographic locations assigned with different coordinates or IDs were merged appropriately, using an algorithm from the literature [5].

Social Interaction. We leveraged data from Bluetooth sensors to infer social interactions. The quality and quantity of social interactions were explored through features such as frequency of encounters with known devices and ratio of devices within proximity, respectively. As Liu et al. [19] stated that two phones that are 2 to 4 meters apart from each other cover a Received Signal Strength Indicator (RSSI) value of -60dBm to -50dBm under ideal indoor circumstances, we consider a device is *within proximity* when the RSSI signal strength is less than or equal to -60dBm.

Smartphone Usage Pattern. To analyze app usage patterns, we examined apps that appear in our app usage data and assigned two category labels for relevant apps: *entertainment* and *productivity*. In respect to the app categorization shown in Google Play, we considered apps in categories such as 'Music & Audio', 'Entertainment', and 'Sports' as entertainment apps. Apps in categories like 'Education', 'Productivity', and 'Business' were labeled as productivity apps. The duration of app usage for each category as well as the overall duration of app usage were computed.

Data from screen sensors were used to extract features related to phone usage: frequency and duration of screen on events and frequency of screen unlock events. Note that screen on and screen unlock events differ in that the latter indicates users unlocking the lock screen for further use. We aim to capture the behavior of frequently checking the screen without further use by computing the frequency of screen on events with a duration less than or equal to 1 second.

Light. We extracted features related to ambient light levels using data collected from light sensors. We consider that the captured environment is dark when the light value is less than or equal to 50lx. The frequency and duration of dark ambient light conditions were computed. One thing to note is that low lux values do not necessarily indicate users being present in dark surroundings; a low lux value may be recorded in various cases, such as when a phone is put face down or inside a pocket.

Other Variations. Each of the features were computed separately for weekdays and weekends. In addition, we divided a day into 3 epochs (i.e., day 9am–6pm, evening 6pm–12am, night 12am–9am) and extracted features accordingly. Statistics such as mean and standard deviation were used to extract variations of each feature. A total of 368 features were extracted as a result.

4 RESULTS AND DISCUSSION

4.1 Correlation Analysis

We performed correlation analysis between sensor-based features and the CIPS scores to explore the use of sensing systems to predict impostor syndrome. Highly correlated features identified in the analysis may shed light not only on how each sensor can be used in predicting impostor syndrome, but also on how each sensor-based behavioral feature reflects behaviors associated with the latent variable (i.e., impostor syndrome).

Table 2 summarizes a portion of results from our correlation analysis between smartphone sensor features and CIPS scores. According to the convention [9], correlation coefficients with absolute values in the range of .1 to .3 and .3 to .5 indicate weak and moderate associations, respectively. All features included in the table have shown moderate correlations ($r \geq .3$) with the CIPS scores. The list includes features extracted using all five sensor data, and all three categories of behavior, which we will explain in the following section.

Figure 2 illustrates sensor-based features (x-axis) and CIPS scores (y-axis) of three of the strongest correlates from our analysis. The three features belong to each of the three categories of sensing-inferred behavioral characteristics of impostor syndrome that we identified.

4.2 Analyzing Correlated Features

To further analyze the correlated features, we tried to categorize features into broader categories. We first filtered out features with

Table 2: Significant Features

Feature	Category	*r*	Sensor Data
std. of daily dark (lux value ≤50) ambient light count	restlessness	0.424**	Light
std. of max. screen on event count by day of the week in an hour	restlessness	0.412*	Screen
mean of daily dark (lux value ≤50) ambient light count	social avoidance	0.381*	Light
max. of daily duration of productivity app usage	sense of obligation	0.375*	App Usage
places visited count during evening	social avoidance	-0.343*	Location
mean of daily duration of productivity app usage on weekends	sense of obligation	0.333*	App Usage
std. of daily screen on event count with duration ≤ 1 sec	restlessness	0.332*	Screen
ratio of phones in proximity to all phones during night	social avoidance	0.328	Bluetooth
mean of daily duration of productivity app usage	sense of obligation	0.321	App Usage

Note. The category column denotes the category of the feature as defined in Section 4.2. We selected features with correlation coefficients of sizes greater than or equal to 0.3, which is the widely used convention for determining a significant effect size [9]. One, two, and three asterisks indicate significant levels at $p<.05$, $p<.01$, and $p<.001$, respectively.

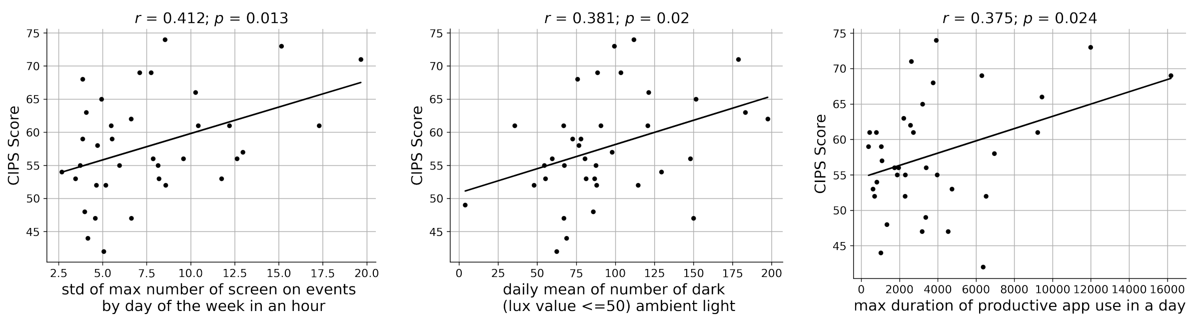

Figure 2: Scatter plots for top features versus CIPS scores. The correlation coefficient between each feature and CIPS scores and its corresponding p-value is shown on top of each plot. Solid lines show the fitted regression model.

an effect size ($r \geq .2$). Though an effect size between .1 and .3 indicate weak associations, .2 from empirical data is sufficient for interpretation of correlation analysis [13]. Then, based on prior research and the outcomes of our study, we identified three categories - social avoidance, sense of obligation, and restlessness- as the sensor-inferred behavioral correlates of impostor syndrome.

The key characteristics of individuals with impostor syndrome that we took into consideration were that they (1) constantly compare themselves with other people, (2) suffer from strong feelings of anxiety, and (3) have (overly) high expectations of themselves. The presented categories are neither conclusive nor exclusive of each other, and should be carefully examined in future works. Nevertheless, we hope these categories provide ideas and overall insights into how each of the features may be interpreted in the context of impostor syndrome.

4.2.1 Social Avoidance. First, we conjectured that features that imply immobility and fewer social interactions show higher likelihood of impostor syndrome. One reasoning behind this claim is that impostor syndrome is related to feelings of anxiety and anxiety causes people to tire more easily. Also, people with severe impostor feelings - those who frequently compare themselves to others and experience feelings of self-doubt and inadequacy - are more likely to avoid social situations.

As exemplified in Table 3, our correlation analysis moderately supports our hypothesis. Mobility features such as the number of places visited during the evening epoch and social interaction features such as the frequency of interactions with devices within proximity were negatively correlated with the CIPS scores. Though open to interpretations, we also presumed the mean daily frequency of dark ambient light indicates immobility and fatigue. The feature was positively correlated with CIPS scores.

4.2.2 Sense of Obligation. One of the key differences between general anxiety and impostor syndrome is that for people with impostor syndrome, their main concern and the source of discomfort are their abilities and achievements. Though the tendency to overachieve does not invoke impostor feelings in and of itself, it is very common that these people have high expectations of themselves. Due to stress and pressure from such expectations coupled with low self-worth and a sense of incompetence, people with impostor syndrome struggle from the gap between their ideal and/or ought selves and their self-perceived selves. We expected that such "sense of obligation" be reflected in the use of productivity apps.

Table 4 illustrates the features related to sense of obligation, extracted from app usage, ambient light, and screen unlock patterns. The results were in line with our hypothesis, as more frequent use of productivity apps correlated with higher likelihood of impostor

Table 3: Features related to social avoidance

Feature	*r*	Sensor Data
places visited count during evening	-0.343*	Location
std. of daily max. distance between two visited places during night	-0.290	Location
mean of daily max. distance between two visited places during day	-0.288	Location
std. of daily radius of gyration during night	-0.285	Location
std. of daily total distance traveled during night	-0.280	Location
mean of daily radius of gyration during day	-0.263	Location
std. of daily max. distance between two visited places during day	-0.259	Location
std. of daily total distance traveled during day	-0.246	Location
std. of daily radius of gyration during day	-0.228	Location
freq. of interaction with close devices	-0.227	Bluetooth

Note. List of social avoidance features with absolute value of $r \geq 0.2$. One, two, and three asterisks indicate significant levels at $p<.05$, $p<.01$, and $p<.001$, respectively.

Table 4: Features related to the sense of obligation

Feature	*r*	Sensor Data
std. of daily freq. of dark (lux value ≤ 50) ambient light	0.424**	Light
mean of daily freq. of dark (lux value ≤ 50) ambient light	0.381*	Light
max. of daily duration of productivity app usage	0.375*	App Usage
mean of daily duration of productivity app usage on weekends	0.333*	App Usage
mean of daily duration of productivity app usage	0.321	App Usage
mean of daily duration of productivity app usage on weekdays	0.280	App Usage
mean of daily duration of dark(lux value ≤ 50) ambient light	0.254	Light
mean of daily duration of entertainment app usage on weekends	-0.230	App Usage
total duration of productivity app usage	0.229	App Usage
std. of freq. of daily screen unlock event during night on weekdays	-0.217	Screen
std. of freq. of daily screen unlock event during night	-0.216	Screen

Note. List of sense of obligation features with absolute value of $r \geq 0.2$. One, two, and three asterisks indicate significant levels at $p<.05$, $p<.01$, and $p<.001$, respectively.

syndrome, while less frequent use of entertainment apps during the weekends was negatively correlated. Furthermore, the duration and frequency of dark ambient light had positive associations with the CIPS scores and features related to the standard deviation of screen unlock event had negative associations. As mentioned before, dark ambient light conditions indicate not only that the user is present in dark surroundings, but also the possibility that the phone is put face down or inside a pocket. Also, events of screen unlock indicate the actual use of the phone, as opposed to the mere act of turning the screen on. These results reveal that people with impostor syndrome are strongly urged towards productivity, and suggest features that could help differentiate impostor syndrome from general anxiety.

4.2.3 *Restlessness.*

Table 5 lists the rest of the features with correlation coefficients of sizes greater than or equal to 0.2. We hypothesized that these features reflect behaviors caused by restlessness. We base our hypothesis on several observations; for one, all of the features were related to events of turning the screen on, and most features were standard deviation of the features. Also, the features were positively correlated with the CIPS scores, unlike the standard deviations of screen unlock events in Table 4. Further, as shown in Table 6, the mean values of the screen related features from Tables 5 and 4 were correlated in the same directions as the standard deviation values.

As previously mentioned in Section 3.2, screen on events reflect the act of pressing the power button, while screen unlock events indicate the actual use of the phone by swiping the lock screen upon turning the screen on. In other words, participants with higher CIPS scores displayed tendencies to turn their phones on many times during certain time intervals, but not actually use their phones too often.

Though there is some degree of ambiguity, we suggest the interpretation of such pattern of smartphone use in the following ways. First of all, turning a phone on often without unlocking the phone could imply that the user checks the time often or that he/she wishes not to use the phone, but is tempted to use one habitually. The mean and standard deviation of the daily frequency of screen on events with duration less than or equal to 1 second perhaps most directly reflect such behavior. Also, less frequently unlocking the phone may be due to a sense of obligation to use the phone less and to be more productive, or the use of productivity apps that lock the phones from further use. Turning the screen on often, on the other

Table 5: Features related to restlessness

Feature	r	Sensor Data
std. of freq. of hourly max. of screen on event by day of the week	0.412*	Screen
std. of freq. of daily screen on event with duration ≤ 1 sec	0.332*	Screen
std. of freq. of hourly max. of screen on event	0.237	Screen
std. of duration of daily screen on event	0.219	Screen
std. of freq. of daily screen on event	0.216	Screen
mean freq. of daily screen on event with duration ≤ 1 sec	0.215	Screen

Note. List of restlessness features with absolute value of $r \geq 0.2$. One, two, and three asterisks indicate significant levels at $p<.05$, $p<.01$, and $p<.001$, respectively.

Table 6: Representative screen event features

Feature	Category	r
std. of freq. of hourly max. of screen on event by day of the week	restlessness	0.412*
std. of freq. of daily screen on event with duration ≤ 1 sec	restlessness	0.332*
std. of freq. of hourly max. of screen on event	restlessness	0.237
std. of duration of daily screen on event	restlessness	0.219
std. of freq. of daily screen unlock event during night on weekdays	obligation	-0.217
std. of freq. of daily screen on event	restlessness	0.216
std. of freq. of daily screen unlock event during night	obligation	-0.216
mean freq. of daily screen on event with duration ≤ 1 sec	restlessness	0.215
mean freq. of hourly median of screen on event	-	0.152
mean freq. of daily screen unlock event during night on weekdays	-	-0.137
mean freq. of hourly max. of screen on event	-	0.108

Note. One, two, and three asterisks indicate significant levels at $p<.05$, $p<.01$, and $p<.001$, respectively.

hand, may reflect the state of being restless, induced by feelings of anxiety, boredom, or the lack of clear sense of purpose.

5 CONCLUSION AND FUTURE WORK

In this paper, we explored the possibility of detecting impostor syndrome using behavioral features extracted from sensing data. We collected data from 37 college students and examined linear correlations between sensor features and impostor syndrome levels. We also categorized selected features into three categories that reflect behavioral characteristics of impostor syndrome.

In future studies, findings from this study could be extended to build models that predict impostor syndrome from sensing data. We also suggest further investigations into the potential of leveraging sensing data to identify the behavioral indicators of impostor syndrome and similar psychological traits. Research thus far on predicting psychological traits using sensor data have leveraged theories and findings from social and clinical sciences. Conversely, we propose that data-driven research findings - specifically, results from exploratory studies using smartphone sensor data and data analysis methods such as the ones presented in this work - could yield valuable insights into building theoretical frameworks in the behavioral sciences.

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