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AN EXAMINATION OF HOW WRISTBAND WEARABLE TECHNOLOGIES CAN BE USED AS AN AID IN RECOVERY AMONGST COLLEGE STUDENTS RECOVERING FROM ALCOHOL AND DRUG ADDICTION

JOHN HATZELL
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Reviewed and approved* by the following:

H. Harrington Clevelend
Associate Professor of Human Development and Family Studies
Thesis Supervisor

Edward J. Glantz
Senior Lecturer of Information Sciences and Technology
Honors Adviser

* Signatures are on file in the Schreyer Honors College.

ABSTRACT

Millions of people are affected by alcoholism and drug addiction each and every day. Many college students are constantly exposed to drugs and alcohol because of the environment that they live in. Students with drug addiction problems have found help through Collegiate Recovery Programs and other support groups. Even with the help that is available, new ways can always be found to help this population.

With the development of different technologies, there may be ways to utilize new devices to help the large population of students in recovery from drug addiction. Wristband wearable devices are just some of the technologies that could help this population. By tracking physiological data, there may be a way to predict cravings for alcohol and drugs and prevent relapse.

This study uses Empatica E4 wristband wearable devices to track temperature, electrodermal activity, and heart rate amongst a population of College Students in recovery from drug addiction. By combining this physiological data with survey data delivered from an iPhone application, this thesis looks to find times where participants are feeling a craving or responding to mood questions in a negative way. The research hopes to find spikes or other trends in physiological data during these time periods so that future research can trace these patterns to prevent relapse and promote well-being.

To do this, three participants wore Empatica devices that measured electrodermal activity, heart rate, and temperature for a span of 21 days. During this span, participants responded to 5 surveys a day that were delivered to their phones via an iPhone application. These surveys asked a number of mood and cravings questions.

At the end of this 21-day span, the physiological data was grouped with the survey data to see if any of the physiological data could predict mood changes or changes in cravings levels. Based on this particular study, these physiological measures could not accurately predict negative mood or cravings amongst the participants of the study.

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Chapter 1

Introduction

Opening

In today's society, we are beginning to see new wearable technologies utilized each day by a wide variety of users. Amongst these wearable technologies, the most commonly used wearable is worn on the wrist. Today it is very common to see someone wearing a Fitbit, an Apple Watch, or some other sort of wearable technology. These wearables are typically used for fitness purposes such as tracking steps, measuring heart rate, and tracking running or walking times. The hope is that these technologies can lead to a healthier society, promoting fitness and exercise. Obviously, there is nothing wrong with that, but why should we limit these wearable technologies to their current purpose? What if wristband and other wearable technologies could be used for purposes that have not yet been explored?

Significance

The disease of alcoholism has affected so many lives and will continue to affect the lives of many. Recovering from alcoholism and staying sober is a constant fight for those in recovery, and despite the success of the 12-steps and other recovery methods, relapse is all too common amongst those in recovery. This is common with those whose drug of first choice is a drug other than alcohol as well. Previous research has shown that these relapses are related to cravings and negative mood states. Individuals who have higher levels of cravings and negative mood are at a higher risk of relapse. When someone's subjective well-being is low, and craving levels are high, there is a much greater chance of relapse. A similar concept is seen with those who suffer from diabetes. When glucose levels are low, this leads to Hypoglycemia, the dangerous condition that occurs from low blood sugar. Diabetics can monitor their blood glucose levels with various tools that help them understand how diet and exercise factor into the levels, and help them take steps to prevent complications. Recovery researchers have not yet discovered similar tools that can help recovering alcoholics and drug addicts become aware of situations that could lead to relapse. This is where new wearable technologies could come into play.

Purpose

The purpose of this research is to determine the feasibility of using a wristband wearable technology to study if measurable biological traits can be related to subjective cravings and negative mood states amongst College-aged drug addicts in recovery. The study observes how subjective cravings and well-being vary over time using self-reported survey data that gives insight into craving levels and mood state throughout each day. Overall, the goal of the research is to examine if it is possible to relate measurable biological traits to self-reported well-being surveys in an attempt to predict cravings and potentially prevent relapse amongst alcoholics and drug addicts in recovery. If cravings and well-being could be linked to certain biological markers, new tools and current technologies could be used to help this population. If we could use current wearable technology to link physiological data such as heart rate, temperature, and electrodermal activity to mood and cravings, wearable technologies could be used as a tool to mitigate relapse risk. This could provide real-time indications of heightened risk, distress, and relapse.

If links between these variables (mood, cravings levels, and biological measures) are discovered, there is potential to predict when a recovering alcoholic is in acute distress or is on a trajectory that increases chance of relapse. Further studies can attempt to predict and prevent relapse by intervening with an encouraging message, contacting a sponsor, or helping in some other way. If relapse can be prevented and this community is made better aware of their emotions and mood, not only does this benefit the individual, but it also benefits his or her family, friends, and society as a whole. Relapse can cause huge emotional distress to so many people and can lead to negative consequences that do not typically occur when an individual maintains long-term recovery. Addiction is a disease that affects an enormous amount of people across the world, and any study that can help aid recovery has the potential to help society as a whole.

Research Questions

Because this is an exploratory study, it is difficult to predict what the outcome will conclude. By combining physiological data from the wearable and subjective mood surveys that are collected from a smartphone application installed on each participant's phones, the goal is to investigate whether variation in cravings and mood can be mapped to variation in measurable physiological data. The two main goals of the study are to

(1) Determine if there are meaningful within-person changes in cravings and aspects of well-being (i.e., aspects of mood), as opposed to measurement noise.

(2) Determine how physiological data relate to within person dynamics in cravings and well-being.

Based on these study endpoints, the main research questions and hypotheses of the study goes as follows:

Q1: Can wristband wearables that track heart rate, temperature, and electrodermal activity predict to some extent when a participant in this population is experiencing cravings?

H1: Yes, to some extent, the wristband wearables can predict when a participant is facing a moment of experiencing cravings.

Q2: Can wristband wearables that track heart rate, temperature, and electrodermal activity predict to some extent when a participant in this population is experiencing a negative mood state?

H1: Yes, to some extent, the wristband wearables can predict when a participant is experiencing a negative mood state.

Chapter 2

Literature Review

Alcoholism and drug addiction is a major problem in society that causes damage to a variety of populations each day. This issue is especially difficult at the College level, where drugs and alcohol are widespread. According to the Substance Abuse and Mental Health Services Administration, (SAMSHA) in 2013, “the rate of substance dependence or abuse among adults aged 18 to 25 was 17.3 percent” (Substance Abuse and Mental Health Services Administration, 2014). Furthermore, SAMSHA reported that an estimated 21.6 million people 12 years or older were classified with substance dependence or abuse in the past year. The fact that drugs are being abused at this heavy of a rate is a problem in its own, but these drugs take over the lives of many users who need to seek treatment to stay clean. In 2013 alone, 18 million people aged 12 or older sought treatment for these problems (Substance Abuse and Mental Health Services Administration, 2014). The issue is that treatment is not always effective and relapse is all too common. In a study conducted by J.R. Cornelius, 66% of the participants who had just completed outpatient treatment relapsed to drug use within 6 months (Cornelius et al., 2003). While drug abuse and relapse cause a large amount of damage to drug users and the family and friends of these users, it also causes a large amount of damage to society as a whole. According to the National Institute of Drug Abuse, “substance abuse costs our nation over $600 billion annually.” These costs are due to crime, health care costs, and lost productivity amongst employees (NIDA, 2012). The key to bringing these numbers down for recovering alcoholics and drug addicts is to have a strong support group. One way that many Universities have increased support for youths coming out of treatment is through Collegiate Recovery Programs.

The population of this study is made up of members of a Collegiate Recovery Program at Penn State University. College towns have a very large population of alcohol and drug abuse, and recovering alcoholics and drug addicts at these Universities may face many situations that could be a trigger for relapse. Depute and Hagerdorn stress the importance of counselors and communities to facilitate recovery. They go on to state that Collegiate Recovery Programs use social support and 12-step meetings to stop students from feeling the need to use substances. These programs have shown a large amount of success, but are not utilized at every University because of lack of funding, lack of awareness, and lack of research (Depute, Hagerdon, 2015). Aside from this, because of the successful track-record of Collegiate Recovery Programs, these types of programs continue to expand. In this particular study, we do not expect a high likelihood of relapse amongst participants because of the support of this community, but fighting alcoholism and drug addiction is an ongoing effort and this means that high stress situations and potential triggers can occur on a daily basis.

Sometimes even communities like these are not enough to prevent relapse because the populations of these communities are not always together and interacting. In the future, it is possible that by combining technologies such as the wearables used in the current study with the strong support groups of Collegiate Recovery Programs and other similar programs, the risk of relapse can be lowered amongst the College population in recovery and other similar groups. Before getting into how these technologies can help, it is important to understand the background on what emotions and triggers can lead to relapse.

Past research has shown how subjective mood of alcoholics and drug addicts is associated with relapse. The idea of the current study is to try to make a connection between negative mood and traceable data to discover how this mood data can be quantitatively predicted. Research has shown that negative emotional state can trigger an alcoholic's return to drinking. A study carried out by Cooney, Litt, Morse, Bauer, and Gaupp found that exposing recovering alcoholics who had reported negative moods to alcohol led to an increased desire to drink (Cooney et al., 1987). Furthermore, another factor that can lead to relapse is stress. A study presented at the 2004 Research Society of Alcoholism Meeting looked into how stress affects alcoholics in early abstinence. In the study, "alcoholics who were confronted with stressful circumstances showed increased susceptibility for relapse" (Breese at el., 2005). This was because cravings were increased during these stressful situations. Recovery.org outlines a variety of ways to cope with alcoholism and prevent relapse. On their website, they list common triggers for cravings as "bars and restaurants, sporting events, social gatherings, being around family and friends who also drink, negative emotions, and stressful life events" (Guarnatta, 2016). The daily survey questions delivered to participants' phones and qualitative survey questions in the current study look to map out times that these types of situations occurred amongst the participants in hopes of finding physiological trends that occur during these times where triggers are present. Because there is a lack of research that has discovered the variation in measures such as heart rate and electrodermal activity during these times of potential triggers, this study looks to use new technologies to touch upon a new area of research.

This study looks into a few technologically-traceable measures and a variety of self-reported data that can potentially be used to assist recovering alcoholics and drug addicts. The physiological measures examined are heart rate, temperature, and electrodermal activity. By constantly tracking these measures, the goal is to predict high stress and negative emotional situations that could lead to relapse. In reviewing changes in heart rate, a 2006 study found that heart rate variation may contain indicators of current disease, or warnings about impending cardiac diseases. Furthermore, they found that these indicators can occur at certain time periods during the day. The researchers went on to find that computer analytical tools can be very useful in studying these variations and making sense of constant heart rate monitoring (Acharya et al., 2006). By constantly monitoring heart rate levels of a population of recovering alcoholics, our study uses computer analytic tools to combine this constant flow of data with self-reported survey data to look for variations that may occur during a time of self-reported distress. Amongst a population of College Students in recovery, constantly tracking heart rate can prove to be very useful, seeing that high stress situations can lead to a risk of relapse. By combining self-reported mood data and biological measures, our analysis looks to examine the situations where stress, negative mood, and cravings were reported and map that onto the real-time data of the biological measures to see if these trends exist.

Some research has also been done to look into how mood affects body temperature. While temperature variation in humans is difficult to map to a specific emotion, some studies have linked changes in body temperature with stress, which is considered a trigger for relapse. In a study about the effect of stress on body temperature, researchers found that “stress exposure resulted in changes in skin temperature that followed a gradient-like pattern” (Vinkers et al., 2013). Although temperature measurements varied in different parts of the body during, these trends during stressful situations may be meaningful and it is something that the current study will further look into.

The other biological measurement that the wearable will be tracing, electrodermal activity (EDA), is measured through the electrical conductance of skin and can be used to indicate psychological arousal (Garbarino et al., 2014). EDA varies often and is difficult to trace to a specific emotion, but does typically indicate an emotional change of some sort. The goal of this study is to look into trends and make new discoveries, so this study looks to discover if there is a relationship between a specific mood, cravings levels, and EDA. EDA levels vary and fluctuate much more than heart rate typically does, so finding trends with this measurement may be more difficult. This is still an important measure to look into because of its link to emotions. Researchers Braithwaite, Watson, Jones, and Rowe wrote a guide on analyzing EDA for physiological experiments and stated that "the coupling between cognitive states, arousal, emotion and attention enables EDA to be used as an objective index of emotional states. EDA can also be used to examine implicit emotional responses that may occur without conscious awareness or are beyond cognitive intent (i.e., threat, anticipation, salience, novelty)" (Braithwaite et al., 2015). This is a particularly interesting measure to look into because it has been directly related to emotional responses. It is difficult to tell what particular emotion EDA links to, but this study could potentially provide a better idea of how mood maps to the EDA measurements.

There has been a wide variety of research on wearable technologies and how they can have positive health benefits. Within that research, there has been debate as to how useful health related information from tracking physiomes and activity using wearable biosensors can be to the medical and scientific community. In a previous study, Xiao Li and his research team recorded over 250,000 daily measurements from 43 individuals, using seven different wearable devices, combining biosensor information with medical measurements. The researchers mentioned the importance of tracking different biological measures of data on a consistent basis (Li et al., 2017). This makes a lot of sense, because many individuals are unaware of changes in these biological measures, given that doctor visits do not occur regularly and these measurements typically are not taken on a regular basis. The researchers found that this type of data was able to identify early signs of Lyme disease and inflammatory responses. They were also able to distinguish physiological differences between insulin-sensitive and insulin–resistant individuals (Li et al., 2017). While this study did not look into how wearable devices can predict and prevent risk factors leading to relapse, it did prove that a variety of wearable devices have the ability to identify early signs of disease and health issues.

Deborah Lupton discussed how the trend of self-tracking health has evolved over the years. In the past and currently, people have tracked health trends either by writing it down or by relying on their memories. She went on to discuss the wide variety of health digital technologies available today and how normalized they have become. New wearable technologies are becoming a cultural norm, and tracing different biological measures has many positive health implications (Lupton, 2017). Just to put it into perspective, “according to an IDC report, consumers and businesses will buy nearly 112 million wearable computer devices by 2018, a 78.4% growth rate from 2014's predicted sales of about 19 million units” (Heneghan, 2014). Because it has become so normalized, different populations do not feel uncomfortable having the general public see them wearing different devices. This is beneficial in the current study’s population and for other populations with different medical issues. Furthermore, Lupton discussed how patients with diabetes, mental health conditions, and high blood pressure can use these devices to engage in self-care (Lupton, 2017). In these situations, these types of patients know what to look for. High blood pressure patients know what levels of blood pressure should be concerning and diabetic patients know the same for their glucose levels. The issue with trying to use these devices for patients recovering from drug and alcohol addiction is that this population and the medical community do not know what to look for and what measures to trace.

Stepping away from the potential medical benefits of these wearables, it is important to look into some of the general health benefits as a whole and see how they can relate to this population. A Health Fitness Revolution article from 2015 outlined some of the top benefits of wristband wearables. Some of these advantages included personal accountability and group dynamic (Health Fitness Revolution, 2015). Personal accountability is great for the average wearable user in that he or she can reflect on fitness activities and other trends. If potential relapse triggers could biologically be traced, recovering alcoholics and drug addicts could counter this potential trigger by calling a sponsor or attending a meeting. This ties right into the group dynamics of wearables. Many users choose to share their fitness data with friends and other users. If an alcoholic in recovery felt comfortable sharing this data, a sponsor, family member, or friend could step in during situations that seem like a potential trigger. To make this easier, future devices would need to automatically notify one of these supporting figures in potential times of distress. This is something that has already been envisioned in different realms. There have already been some major steps towards incorporating these technologies to benefit patients. In 2015, Google unveiled a health tracking wearable band developed by Google X specifically to provide doctors with data on patients. The goal of this device is for doctors to intervene in situations where patients seem to have alarming measures that could be a cause for concern (Kokalitceva, 2015). This sort of tracking is not limited to wristband wearables. "Google X is also creating contact lenses that can monitor blood glucose levels to help in managing conditions like diabetes" (Etherington, 2015). As you can see, there is a lot of potential for what these types of devices are capable of, and this type of treatment is likely to be expanded to different communities.

It is clear that there are many advantages of wearable technologies, but there may also be some negative consequences. Advances in research for these sorts of physiological trends could bring some controversial changes to the healthcare community. A 2014 Forbes article stated that future wristband wearable devices could someday be used to determine healthcare costs. Some employers are even opting to monitor fitness data of employees and providing rewards based on fitness performance and in some cases, punishments for poor performance. Healthcare professionals are also exploring ways in which they can monitor this data to change payment plans in the future (Olson, 2016). Obviously, this brings forward many privacy concerns, and plans like these could easily be blocked in the future. This also brings some moral issues to the forefront. I understand that insurance companies want to monitor risk in the best way possible, but this may be taking it a little bit too far. In relation to the study, if biological data trends were found that link relapse risk to measurable physiological data, healthcare providers may take advantage of recovering alcoholics and drug addicts. The same goes for patients suffering from diseases such as diabetes. This is where some controversy may arise regarding privacy and moral concerns. This would give insurance companies further methods of penalizing patients who have a disease that is out of their control. Furthermore, an article in SearchHealthIT brought up an important concern about another negative consequence of further implementing wearable devices into diagnostics and treatments. The article stated, “encouraging physicians to work with data derived from wearable devices could result in a technology overload and drive physicians away from face-to-face patient-physician interactions” (SearchHealthIT, n.d.). It may not be all that feasible to expect doctors to constantly monitor all of their patients’ health data. Furthermore, all of the time spent with data analysis would take away from patient interactions. Advances in big data analytics would largely help with this, but it is clear that wearable devices can only monitor so much, and this could be difficult to implement on a large scale. This topic brings up an entire new debate over health care costs and health care reform.

Aside from the negatives mentioned above, it is clear that wearable technologies have many benefits that outweigh the potential issues. We have only seen the beginning ages of these types of technologies, and future inventions are likely to provide further health benefits. Research in this area is expanding and wearable usage amongst the world population is increasing each year.

The wearable technology being used in the current study is the Empatica E4. This device is made up of a number of sensors used to track the data for this study. The E4 has a photoplethysmography sensor that measures heart rate and heart rate variability, a 3-axis accelerometer that captures motion, and an electrodermal activity sensor that measures nervous system arousal that can be used to trace stress, engagement and excitement. All of this data can be viewed online in a readable format and data can also be downloaded for analytical purposes. (Garbarino et al., 2014). For this study, a member of our research team customized an iPhone application to send out the study's survey questions at different points in the day. Further details about these specifications can be found in the methodology section.

Chapter 3

Methodology

This section outlines how participants were recruited and what type of participants participated in the study. Furthermore, this section outlines the study design and outlines the analysis methods used in this particular study.

Participant Recruitment and Consent

Before beginning the study, the research team obtained IRB approval from the Penn State Institutional Review Board. Documentation of this approval is shown in Appendix B. Participants in the study are members of a Collegiate Recovery Program at Penn State University. This program is a University program that aims to help students recovering from alcoholism and drug addiction. Participant recruitment was limited to undergraduate student above the age of 18 that are members of this CRP. Furthermore, participants were required to own an iPhone because the customized application is only operable on iOS. Three students were directly recruited from this CRP, who were provided information on the study. The sample size of this study was kept to a small number for a couple reasons. First of all, this is an exploratory study that is looking for preliminary trends and determining feasibility on a smaller scale so that a similar study can be carried out on a larger scale taking into account what trends were found and what issues were faced. Secondly, this study collects a massive amount of data from each participant over a long period of time, making data analysis a lengthy process to perform on many participants

Potential participants who positively responded to the direct recruitment were provided a consent form during an introductory session. Having read the consent form, they were free to ask further information about the study. Once all of their questions were answered and if they were still interested in participating, they were asked to sign the consent form. During the consent process the research team made sure that the participants were informed about the study's process and their questions related to the study were answered. Moreover, the team member in charge of recruitment made sure that the participants felt under no pressure to participate, and that they understood that they could quit at any time with no negative consequences.

The identities of the participants were only known by the individual who directly recruited them. This individual held a list of anonymous ID's that tied the individual subjects to the individual. The other members of the research team had access to participant data, and participant ID's, but did not have access to the names of the participants. The research team made no attempt to try to recover subjects' identities. Online data from participant surveys was collected through an iOS application, and only anonymized data was shared with collaborators. The list of participant names was also permanently destroyed at the conclusion of the study.

Study Design

In total, there are three aspects to this study: 1. The short baseline survey, 2. the wearable device, 3. the ecological momentary assessment (EMA) iPhone surveys about craving levels and mood. The baseline was given prior to beginning the 21-day within-person part of the study during which the participants were asked to wear the wearable and respond to EMA surveys.

1. The first part of the study, the baseline survey was used to obtain information that will be helpful to use as a baseline for data collection.

2. The second part of the study is for the participants to use a wearable device that functions similar to a Fitbit. All participants in the study are asked to wear an Empatica E4 physiological wristband, the functions of which (e.g., recharging and uploading data) were explained to participants. The E4 wristband measures skin temperature, heart rate, and electrodermal response constantly during contact. Participants were asked to simply wear the wristband while living their daily lives. Participants were informed that the wristband device remains university property and cannot be used for purposes other than participation in the study.

3. In the third part of the study, participants were asked to install an app on their phone, which delivers a short mood, activity, and cravings survey several times a day, with slightly longer surveys during the first and last surveys of the day. Upon installation, participants were asked to walk through a sample survey to familiarize themselves with the questions presented and to ensure they understood both what they mean and how to provide their responses. Following installation, the app presented additional survey questions to the participants several times each day until the end of the study. The survey questions used can be found in Appendix A.

iPhone Survey Application

This study used two different forms of technology to collect participant data. The first technology used is the application that delivers survey questions to participants five times each day. This application was designed for iOS on the iPhone and could not be downloaded on Android devices. Every three hours from 8:00AM to 11:00PM, a cronjob ran a script that assigned users a survey based on what time it was. At a random time between 8:00AM and 11:00AM they got assigned their first survey. Then they received a notification to take 4 additional surveys during the proceeding four three-hour increments that lead up to 11:00PM. Below, Figure 1 shows what these notifications look like.

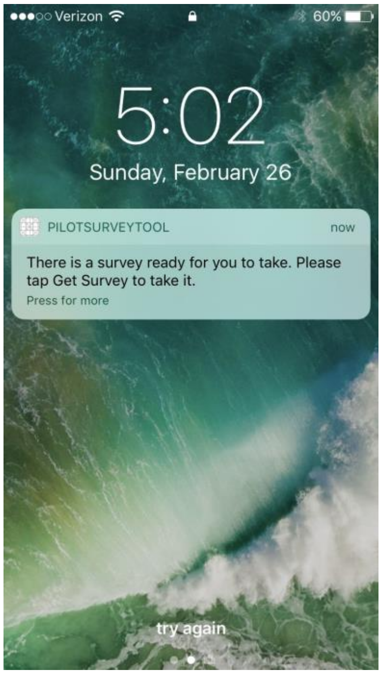

Figure 1 Survey Notification

Participants could also decide to take a survey whenever they wanted. Upon opening the application, all they had to do was hit the “Get Survey” button. Participants were told to take this survey at times they may have felt under distress or in a cravings state. Figure 2 shows what this button looks like to the participant.

Figure 2 Get Survey Button

After opening a survey, participants were presented with 3 cravings questions and 12 mood questions. The cravings questions ask about intensity and frequency of drug cravings. All of these questions were answered based on a sliding bar scaled from 0.0 to 10.0 ranging from “No Cravings” to “Very Intense” Figure 3 shows what these questions look like to the user.

Figure 3 Cravings Questions

After hitting the next buttons, participants were then presented with 12 mood items. The full list of these questions is shown in Appendix A, but Figure 4 below shows how some of these questions were seen by the user.

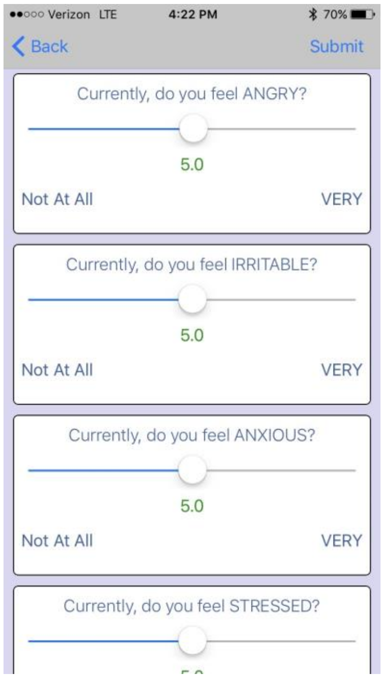

Figure 4 Mood Questions

The last survey of the day includes these cravings and mood questions, but also includes an additional set of questions asking about support meeting attendance. The full list of questions is also included in Appendix B, but Figure 5 below shows what these questions look like to the participant.

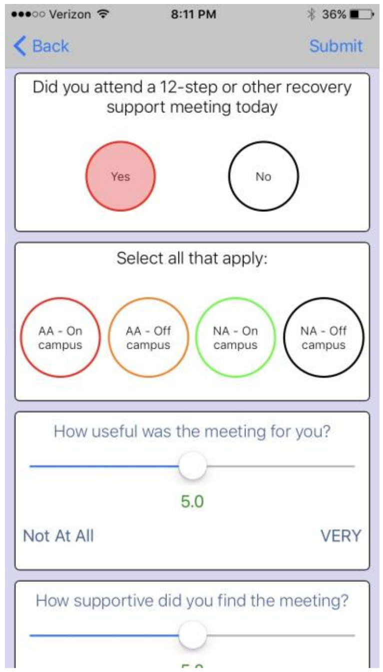

Figure 5 Support Meeting Questions

Empatica E4

The second technology used to collect data was the Empatica E4. Participants wore these wristband wearables for a span of 21 days. Figure 6 shows what these devices look like on the wrist of a participant.

Figure 6 Empatica E4

Throughout these 21 days, these wristbands tracked heartrate, temperature, and electrodermal activity. The batteries on these devices last about 36 hours, so participants were asked to charge the device every other night. Furthermore, participants were asked to upload their data to their assigned Empatica account every other night. Data was uploaded on each individuals' computer to an application called Empatica Manager. Participants were given instructions on how to do this at the introductory session. These wearables do not have a screen, but they have one button that participants were asked to press when they felt a craving, moment of distress, or some other moment of strong emotion. Pressing this button would put a timestamp in the results for the research team to look back to during data analysis. In some cases, participants also would take a survey after pressing this button.

Analysis Methods

To begin the analysis, it was important to make sure that there was some validity to the EMA survey data that the participants took. To ensure that participants were responding honestly, correlation tests were run based on responses to the mood questions. To do this, similar and opposite mood items were paired together to make sure that these correlations made sense. For example, if there was not a negative correlation between anger and joy, we would know that this data did not make sense and there may be some sort of an issue with participant responses.

To analyze all of the wristband wearable data, this information was downloaded from the Empatica website. One of the members of the research team broke down this data using analytical computer software so that it would be easier to make sense of the data. Calculations were performed to determine the average heart rate, temperature, and electrodermal activity levels for each half hour block prior to when a survey was taken. Also, calculations were performed to find the average levels for that same half hour each day the device was worn. Furthermore, calculations were performed to determine the average level of these measures for each day.

All of this data combined with the iPhone survey data was exported to an Excel Spreadsheet. This data was broken down by question and analyzed separately for each participant. The heartrate, temperature, and electrodermal activity data was then grouped with survey data and a number of multiple regression tests were carried out to see which pairings had the strongest relationships. These multivariate linear regression analyses were performed to see if temperature, electrodermal activity, or temperature could accurately predict craving levels and mood items. These tests used three independent variables. For example, in tests looking to see if heartrate could predict anxiety levels, the independent variables of average heart rate during the half hour before the survey was taken, average heartrate during that half hour each day, and average heart rate during that day were grouped with the dependent variable, anxiety.

Multiple regression was the best option to work with this data because the physiological measures that were analyzed vary throughout the day and on different days. For example, someone may have a higher heartrate during the morning or someone's temperature may be at different levels from day to day. This is why it did not make sense to simply run correlation tests between average heartrate, temperature, or electrodermal activity and specific mood items.

In these multiple regression analyses, two specific outcomes were analyzed: adjusted R-squared value, and significance value between the mood item and the average value of heartrate, temperature, or electrodermal activity during the half hour prior to taking the survey. R-squared is also known as the coefficient of determination. "The coefficient of determination is a measure used in statistical analysis that assesses how well a model explains and predicts future outcomes. It is indicative of the level of explained variability in the data set" (Investopedia, 2009). The adjusted R-squared value was used because there were three different predictors for each regression test and the adjusted R-squared value adjusts for the number of predictors. R-squared values result in a number between 0 and 1, where values closer to 1 represent a greater proportion of variance represented by the predictors. With adjusted R-square, negative values can also occur when independent variables do not help predict the dependent variable.

The significance value was also calculated in these equations. This value also comes in between 1.0 and 0.0, with a lower value representing a higher significance. Typically, a significance value of 0.05 is the cutoff for significance, meaning that you can reject the null hypothesis if the significance value is below that cutoff. So overall, these tests looked to find relationships with higher adjusted R-squared values and lower significance values.

These tests were performed on an individual level because when participant data are paired together, values could be misinterpreted. For example, participant 1 could have an average heartrate that is 10 beats per minute higher than participant 3's. The same goes for other measures. This is why the most accurate way to run these regression tests was on an individual level. Furthermore, data was only analyzed in cases where participants were wearing the Empatica and took the survey. There were many cases where participants took an EMA survey, but were not wearing the Empatica. Along with that, there were some cases where Empatica data did not upload correctly, making it impossible to pair that data with the survey data.

This issue was especially apparent with participant 2. This participant's device ran into many issues and none of the Empatica data was saved during this 21-day period. For this reason, Empatica and Survey data was only analyzed for participants 1 and 3.

Chapter 4

Findings

This section outlines the results of each portion of the study. Included in this section are the results of the baseline survey and a description of how all of the data was analyzed. Furthermore, you will find a description of the correlation and regression tests that were carried out and the results of these tests.

Baseline Survey

The baseline survey indicated that all three participants were between the ages of 20 and 24. Furthermore all three participants have been in recovery from drug addiction for over a year, and each participant indicated their drug of first choice as alcohol. Based on the responses to the baseline survey, although each participant differs in many ways, the population of this study covers College-aged students in recovery for over a year whose drug of first choice was alcohol.

Description of Analysis

Regression analyses were carried out to analyze the pairings of measured physiological data and mood items from participants one and three. Appendix A shows all of the questions that were asked, and this analysis does not include tests run on every single question for a couple reasons. The goal of this research was to determine if the physiological measures could accurately predict cravings and negative mood, which is seen as a warning sign for relapse. For this reason, the majority of analyses run used variables that were categorized as negative mood.

One factor that was noticed almost immediately was that this particular population almost never reported cravings. Responses to the first question of each survey that asked “Currently, how intense are your drug cravings?” were almost always reported as a 0.0 out of 10. The same occurrence was seen in the questions that asked about cravings frequency. These responses may have been because this particular population had not used alcohol or other drugs in over a year and honestly did not experience any cravings during this time period. Also, social desirability may have been a contributing factor. For this reason, regression tests were not performed using these variables and analysis methods shifted to focusing on negative mood items and a couple positive mood items. The variables analyzed were anxiety, stress, anger, irritability, sadness, happiness, and calmness. Another interesting result that was seen was that participant 3 reported negative mood states far less than participant one. For example, on a scale from one to 10, for each survey, participant 1 averaged 2.317 for anxiety while participant 2003 averaged 0.522. Similarly, for stress, participant 1 averaged 2.648, while participant 3 averaged 0.956. This is one of the reasons why tests were carried out on an individual basis. It is difficult to subjectively report well-being, and different participants interpret surveys in different ways. Four correlation tests were carried out to analyze how accurately participants reported their mood. These tests paired the variables of happy and sad, sluggish and lethargic, anxious and irritable, and anger and joy.

Correlation Tests

Below are the results of the correlation tests carried out on participant 1. These tests paired similar and opposite mood items to ensure data validity.

Participant 1 Correlation Data

- Happy and Sad
    - Pearson Correlation: -0.739
    - Significance: 0.000
- Sluggish and Lethargic
    - Pearson Correlation: 0.939
    - Significance: 0.000
- Anxious and Irritable
    - Pearson Correlation: 0.552
    - Significance: 0.000
- Angry and Joy
    - Pearson Correlation: -0.440
    - Significance: 0.000

As you can see, these data seem to make sense. There is a strong negative correlation between happiness and sadness, which are opposite mood states. There is a strong positive correlation between sluggish and lethargic, which are similar mood items. There is a pretty moderate correlation between anxiety and irritability, which are similar mood states. There is also a moderate negative correlation between anger and joy, which are pretty opposite mood states. Looking at these correlation tests, it can be assumed that participant 1 accurately reported mood data. These same tests were also carried out on participant 3 and the results can be seen below.

Participant 2 Correlation Data

- Happy and Sad
    - Pearson Correlation: 0.202
    - Significance: 0.194
- Sluggish and Lethargic
    - Pearson Correlation: 0.748
    - Significance: 0.000
- Anxious and Irritable
    - Pearson Correlation: -0.070
    - Significance: 0.655
- Angry and Joy
    - Pearson Correlation: -0.939
    - Significance: 0.000

These results were not as clear-cut as participant 1's, but the results still make sense in most ways. The tests between anger and joy and sluggish and lethargic came out as expected, but the tests between happiness and sadness and anxiety and irritability did not result exactly as one would think. Still, anxiety and irritability are not the same mood state and subjective responses to these questions can be interpreted in different ways. The correlation between happy and sad did not result as expected, but because that test came out with a significance value of 0.194, that result was not statistically significant. Because the statistically significant results made sense, these tests show that participant 3 reported mood states relatively accurately.

Regression Tests

As mentioned previously, regression tests were carried out to look into anxiety, stress, anger, irritability, sadness, happiness, and calmness. There were three independent variables in each of these tests to control for average measures of that particular physiological measure at that time each day and over the course of each day. An example of one of these tests goes as follows:

- One data point for the dependent variable would be participant 1's reported level of sadness at 11:00AM on March 1st.
- One data point for the first independent variable would be participant 1's average heartrate from 10:30AM-11:00AM on March 1st
- One data point for the second independent variable would be participant 1's average heartrate from 10:30AM-11:00AM every day that the participant wore the Empatica
- One data point for the third independent variable would be participant 1's average heartrate during the entire day on March 1st

Overall, data could only be used on occasions where all of this data was recorded. This is why the length of the study needed to be 21 days, because it was assumed that there would be many occurrences where all of this data was not recorded. Over this span, participant 1 took 65 surveys that were able to be paired with all of this Empatica data. As mentioned previously, participant 2's device malfunction prevented the examination of the physiological data. The research team did examine the EMA survey data for this participant, so the data was still useful in some way. Participant 3 took 43 surveys that were able to be paired with the Empatica data. Below are tables showing the results of the tests run on participants 1 and 3 with a description of the results below the table.

Table 1: Participant 1 Anxiety Regression Analyses

Participant 1 Anxiety	**Adjusted R-Squared**	**Significance**
Heart rate	0.077	0.320
Electrodermal Activity	0.006	0.521
Temperature	0.107	0.006

- A multiple regression test was run to predict Participant 1 Anxiety levels from average heart rate during the half hour prior to taking a survey, average heart rate during that same half hour each day, and average heart rate on the day the survey was taken. These variables did not statistically significantly predict anxiety levels.
- A multiple regression test was run to predict Participant 1 Anxiety levels from average electrodermal activity during the half hour prior to taking a survey, average electrodermal activity during that same half hour each day, and average electrodermal activity on the day the survey was taken. These variables did not statistically significantly predict anxiety levels.
- A multiple regression test was run to predict Participant 1 Anxiety levels from average temperature during the half hour prior to taking a survey, average temperature during that same half hour each day, and average temperature on the day the survey was taken. These variables significantly predicted Anxiety levels, with an adjusted R-squared value of 0.107.

Table 2: Participant 3 Anxiety Regression Analyses

Participant 3 Anxiety	Adjusted R-Squared	Significance
Heart rate	0.035	0.415
Electrodermal Activity	0.490	0.079
Temperature	0.066	0.440

- A multiple regression test was run to predict Participant 3 Anxiety levels from average heart rate during the half hour prior to taking a survey, average heart rate during that same half hour each day, and average heart rate on the day the survey was taken. These variables did not statistically significantly predict anxiety levels.
- A multiple regression test was run to predict Participant 3 Anxiety levels from average electrodermal activity during the half hour prior to taking a survey, average electrodermal activity during that same half hour each day, and average electrodermal activity on the day the survey was taken. These variables did not statistically significantly predict anxiety levels, but the significance value was pretty close to 0.05.
- A multiple regression test was run to predict Participant 3 Anxiety levels from average temperature during the half hour prior to taking a survey, average temperature during that same half hour each day, and average temperature on the day the survey was taken. These variables did not statistically significantly predict anxiety levels.

Table 3: Participant 1 Stress Regression Analyses

Participant 1 Stress	Adjusted R-Squared	Significance
Heart rate	0.098	0.166
Electrodermal Activity	-0.038	0.682
Temperature	0.117	0.075

- A multiple regression test was run to predict Participant 1 Stress levels from average heart rate during the half hour prior to taking a survey, average heart rate during that same half hour each day, and average heart rate on the day the survey was taken. These variables did not statistically significantly predict stress levels.
- A multiple regression test was run to predict Participant 1 Stress levels from average electrodermal activity during the half hour prior to taking a survey, average electrodermal activity during that same half hour each day, and average electrodermal activity on the day the survey was taken. These variables did not statistically significantly predict stress levels.
- A multiple regression test was run to predict Participant 1 Stress levels from average temperature during the half hour prior to taking a survey, average temperature during that same half hour each day, and average temperature on the day the survey was taken. These variables did not statistically significantly predict stress levels, but the significance value was pretty close to 0.05.

Table 4: Participant 3 Stress Regression Analyses

Participant 3 Stress	**Adjusted R-Squared**	**Significance**
Heart rate	-0.034	0.433
Electrodermal Activity	-0.005	0.439
Temperature	-0.002	0.271

- A multiple regression test was run to predict Participant 3 Stress levels from average heart rate during the half hour prior to taking a survey, average heart rate during that same half hour each day, and average heart rate on the day the survey was taken. These variables did not statistically significantly predict stress levels.
- A multiple regression test was run to predict Participant 3 Stress levels from average electrodermal activity during the half hour prior to taking a survey, average electrodermal activity during that same half hour each day, and average electrodermal activity on the day the survey was taken. These variables did not statistically significantly predict stress levels.
- A multiple regression test was run to predict Participant 3 Stress levels from average temperature during the half hour prior to taking a survey, average temperature during that same half hour each day, and average temperature on the day the survey was taken. These variables did not statistically significantly predict stress levels.

Table 5: Participant 1 Anger Regression Analyses

Participant 1 Anger	Adjusted R-Squared	Significance
Heart rate	0.102	0.561
Electrodermal Activity	0.017	0.234
Temperature	0.112	0.930

- A multiple regression test was run to predict Participant 1 Anger levels from average heart rate during the half hour prior to taking a survey, average heart rate during that same half hour each day, and average heart rate on the day the survey was taken. These variables did not statistically significantly predict anger levels.
- A multiple regression test was run to predict Participant 1 Anger levels from average electrodermal activity during the half hour prior to taking a survey, average electrodermal activity during that same half hour each day, and average electrodermal activity on the day the survey was taken. These variables did not statistically significantly predict anger levels.
- A multiple regression test was run to predict Participant 1 Anger levels from average temperature during the half hour prior to taking a survey, average temperature during that same half hour each day, and average temperature on the day the survey was taken. These variables did not statistically significantly predict anxiety levels.

Table 6: Participant 3 Anger Regression Analyses

Participant 3 Anger	Adjusted R-Squared	Significance
Heart rate	-0.050	0.438
Electrodermal Activity	-0.007	0.798
Temperature	-0.046	0.479

- A multiple regression test was run to predict Participant 3 Anger levels from average heart rate during the half hour prior to taking a survey, average heart rate during that same half hour each day, and average heart rate on the day the survey was taken. These variables did not statistically significantly predict anger levels.
- A multiple regression test was run to predict Participant 3 Anger levels from average electrodermal activity during the half hour prior to taking a survey, average electrodermal activity during that same half hour each day, and average electrodermal activity on the day the survey was taken. These variables did not statistically significantly predict anger levels.
- A multiple regression test was run to predict Participant 3 Anger levels from average temperature during the half hour prior to taking a survey, average temperature during that same half hour each day, and average temperature on the day the survey was taken. These variables did not statistically significantly predict anger levels.

Table 7: Participant 1 Irritable Regression Analyses

Participant 1 Irritable	Adjusted R-Squared	Significance
Heart rate	0.060	0.506
Electrodermal Activity	-0.045	0.766
Temperature	0.065	0.322

- A multiple regression test was run to predict Participant 1 Irritability levels from average heart rate during the half hour prior to taking a survey, average heart rate during that same half hour each day, and average heart rate on the day the survey was taken. These variables did not statistically significantly predict irritability levels.
- A multiple regression test was run to predict Participant 1 Irritability levels from average electrodermal activity during the half hour prior to taking a survey, average electrodermal activity during that same half hour each day, and average electrodermal activity on the day the survey was taken. These variables did not statistically significantly predict irritability levels.
- A multiple regression test was run to predict Participant 1 Irritability levels from average temperature during the half hour prior to taking a survey, average temperature during that same half hour each day, and average temperature on the day the survey was taken. These variables did not statistically significantly predict irritability levels.

Table 8: Participant 3 Irritable Regression Analyses

Participant 3 Irritable	Adjusted R-Squared	Significance
Heart rate	-0.010	0.214
Electrodermal Activity	-0.025	0.989
Temperature	-0.004	0.209

- A multiple regression test was run to predict Participant 3 Irritability levels from average heart rate during the half hour prior to taking a survey, average heart rate during that same half hour each day, and average heart rate on the day the survey was taken. These variables did not statistically significantly predict irritability levels.
- A multiple regression test was run to predict Participant 3 Irritability levels from average electrodermal activity during the half hour prior to taking a survey, average electrodermal activity during that same half hour each day, and average electrodermal activity on the day the survey was taken. These variables did not statistically significantly predict irritability levels.
- A multiple regression test was run to predict Participant 3 Irritability levels from average temperature during the half hour prior to taking a survey, average temperature during that same half hour each day, and average temperature on the day the survey was taken. These variables did not statistically significantly predict irritability levels.

Table 9: Participant 1 Sad Regression Analyses

Participant 1 Sad	Adjusted R-Squared	Significance
Heart rate	-0.002	0.814
Electrodermal Activity	0.024	0.217
Temperature	0.066	0.553

- A multiple regression test was run to predict Participant 1 Sadness levels from average heart rate during the half hour prior to taking a survey, average heart rate during that same half hour each day, and average heart rate on the day the survey was taken. These variables did not statistically significantly predict sadness levels.
- A multiple regression test was run to predict Participant 1 Sadness levels from average electrodermal activity during the half hour prior to taking a survey, average electrodermal activity during that same half hour each day, and average electrodermal activity on the day the survey was taken. These variables did not statistically significantly predict sadness levels.
- A multiple regression test was run to predict Participant 1 Sadness levels from average temperature during the half hour prior to taking a survey, average temperature during that same half hour each day, and average temperature on the day the survey was taken. These variables did not statistically significantly predict sadness levels.

Table 10: Participant 3 Sad Regression Analyses

Participant 3 Sad	Adjusted R-Squared	Significance
Heart rate	-0.022	0.727
Electrodermal Activity	0.006	0.631
Temperature	-0.060	0.948

- A multiple regression test was run to predict Participant 3 Sadness levels from average heart rate during the half hour prior to taking a survey, average heart rate during that same half hour each day, and average heart rate on the day the survey was taken. These variables did not statistically significantly predict sadness levels.
- A multiple regression test was run to predict Participant 3 Sadness levels from average electrodermal activity during the half hour prior to taking a survey, average electrodermal activity during that same half hour each day, and average electrodermal activity on the day the survey was taken. These variables did not statistically significantly predict sadness levels.
- A multiple regression test was run to predict Participant 3 Sadness levels from average temperature during the half hour prior to taking a survey, average temperature during that same half hour each day, and average temperature on the day the survey was taken. These variables did not statistically significantly predict sadness levels.

Table 11: Participant 1 Happy Regression Analyses

Participant 1 Happy	Adjusted R-Squared	Significance
Heart rate	0.053	0.745
Electrodermal Activity	-0.010	0.459
Temperature	0.231	0.234

- A multiple regression test was run to predict Participant 1 Happiness levels from average heart rate during the half hour prior to taking a survey, average heart rate during that same half hour each day, and average heart rate on the day the survey was taken. These variables did not statistically significantly predict happiness levels.
- A multiple regression test was run to predict Participant 1 Happiness levels from average electrodermal activity during the half hour prior to taking a survey, average electrodermal activity during that same half hour each day, and average electrodermal activity on the day the survey was taken. These variables did not statistically significantly predict happiness levels.
- A multiple regression test was run to predict Participant 1 Happiness levels from average temperature during the half hour prior to taking a survey, average temperature during that same half hour each day, and average temperature on the day the survey was taken. These variables did not statistically significantly predict happiness levels.

Table 12: Participant 3 Happy Regression Analyses

Participant 3 Happy	Adjusted R-Squared	Significance
Heart rate	-0.017	0.422
Electrodermal Activity	0.002	0.948
Temperature	0.000	0.526

- A multiple regression test was run to predict Participant 3 Happiness levels from average heart rate during the half hour prior to taking a survey, average heart rate during that same half hour each day, and average heart rate on the day the survey was taken. These variables did not statistically significantly predict happiness levels.
- A multiple regression test was run to predict Participant 3 Happiness levels from average electrodermal activity during the half hour prior to taking a survey, average electrodermal activity during that same half hour each day, and average electrodermal activity on the day the survey was taken. These variables did not statistically significantly predict happiness levels.
- A multiple regression test was run to predict Participant 3 Happiness levels from average temperature during the half hour prior to taking a survey, average temperature during that same half hour each day, and average temperature on the day the survey was taken. These variables did not statistically significantly predict happiness levels.

Table 13: Participant 1 Calm Regression Analyses

Participant 1 Calm	Adjusted R-Squared	Significance
Heart rate	0.133	0.465
Electrodermal Activity	0.027	0.217
Temperature	0.085	0.087

- A multiple regression test was run to predict Participant 1 Calmness levels from average heart rate during the half hour prior to taking a survey, average heart rate during that same half hour each day, and average heart rate on the day the survey was taken. These variables did not statistically significantly predict calmness levels.
- A multiple regression test was run to predict Participant 1 Calmness levels from average electrodermal activity during the half hour prior to taking a survey, average electrodermal activity during that same half hour each day, and average electrodermal activity on the day the survey was taken. These variables did not statistically significantly predict calmness levels.
- A multiple regression test was run to predict Participant 1 Calmness levels from average temperature during the half hour prior to taking a survey, average temperature during that same half hour each day, and average temperature on the day the survey was taken. These variables did not statistically significantly predict calmness levels.

Table 14: Participant 3 Calm Regression Analyses

Participant 3 Calm	Adjusted R-Squared	Significance
Heart rate	-0.029	0.387
Electrodermal Activity	0.030	0.532
Temperature	-0.008	0.355

- A multiple regression test was run to predict Participant 3 Calmness levels from average heart rate during the half hour prior to taking a survey, average heart rate during that same half hour each day, and average heart rate on the day the survey was taken. These variables did not statistically significantly predict calmness levels.
- A multiple regression test was run to predict Participant 3 Calmness levels from average electrodermal activity during the half hour prior to taking a survey, average electrodermal activity during that same half hour each day, and average electrodermal activity on the day the survey was taken. These variables did not statistically significantly predict calmness levels.
- A multiple regression test was run to predict Participant 3 Calmness levels from average temperature prior to taking a survey, average temperature during that same half hour each day, and average temperature on the day the survey was taken. These variables did not statistically significantly predict calmness levels.

Chapter 5

Discussion

As shown by the results this particular study was not able to accurately predict cravings or negative mood states. As mentioned previously in this paper, the research questions went as follows.

- Can wristband wearables that track heart rate, temperature, and electrodermal activity predict to some extent when a participant in this population is experiencing cravings?
- Can wristband wearables that track heart rate, temperature, and electrodermal activity predict to some extent when a participant in this population is experiencing a negative mood state?

For both of these research questions, the results showed that we could not reject the null hypotheses and that these particular physiological measures could not accurately predict cravings or negative mood states.

The first hypothesis was quite difficult to explore because the participants in this particular study reported cravings level of 0.0 in almost every survey. For this reason, an accurate test could not be carried out on this data. With a larger population, it is possible that craving levels could accurately be predicted. Looking back into the study design, I can see why a recovering alcoholic would not want to report that he or she is experiencing cravings. This particular population is working very hard to stay away from alcohol and drugs, and even if they were experiencing cravings, they may not want to report that. Furthermore, because each participant has been sober for over a year, it makes sense that cravings are less frequent. Also, these participants are in a great recovery situation because they have their Collegiate Recovery Program as a resource to aid in their recovery. I can imagine the survey results of a similar study being carried out on a different population being much different. For example, if this study was carried out on a population of alcoholics who just entered rehab or recently relapsed, the frequency and intensity of the reported cravings levels may have been much higher with much more variability.

Looking into the mood items, there were a number of regression tests carried out to attempt to predict mood. While mood is not as closely related to potential relapse as cravings, as mentioned previously in this paper, negative mood is a warning sign for potential relapse. Again, because this population has been sober for over a year, negative mood is not as big of a warning sign as it would be in a different population of recovering alcoholics and drug addicts. We did see a lot of variability in mood and the variability made sense for the most part. This was shown in the correlation tests. In this data set, it was rare to see a long span of negative mood responses. This would be the largest warning sign based on mood data. One regression test did return statistically significant results. In participant 1, temperature was able to predict anxiety to some extent. The adjusted r-square value was pretty low for this particular test, so it is difficult to say how much of a predictor it really was for that participant. If the regression tests showed more statistically significant results for these mood items, further conclusions could have been made.

Although this particular study did not find any major new conclusions, it was effective and useful for a number of reasons. First of all, this small-scale study was able to determine the feasibility of doing this on a larger scale. There were many obstacles that were faced that can be avoided in future studies. For example, there were many occasions where participants forgot to upload their data. Sometimes it was difficult for the member of the research team who knew the identities of the participants to get in contact with these participants. This led to analysis issues with a good portion of the survey data because it had no physiological data to be paired with. One other observation was that despite the data collection issues with the Empatica data, survey data was collected frequently and participants responded to almost every survey assigned. This showed that the surveys that were assigned were not too lengthy and that it was not too much work on the participants.

Looking back at the Empatica devices, it would have been helpful if participants did not have to upload the data themselves. This would mean that the devices would need to be connected to the Internet and automatically upload data on certain time intervals. There are already devices out there that measure similar physiological traits that can connect to the Internet, so this is certainly feasible.

The length of the study seemed to be a good fit for what was trying to be achieved. It is difficult to ask participants to carry out a study for a long period of time, and three weeks seemed to be a good amount. If you could be sure that there would be no data loss issues or long occasions where participants did not wear the Empatica device, similar studies could probably be slightly shortened. One reason for the length being longer is for the possibility of capturing more extreme mood and cravings items.

Chapter 6

Directions for Future Research

Future research will need to further look into these trends and expand to larger and different populations. Because this study was limited to just a few participants in a population of College students who were not likely to relapse during this 21-day span, the scope was somewhat limited. This study was very effective in finding out just how useful these types of technologies can be amongst a population in recovery. Further studies will need to look into populations of drug addicts currently in rehab, just out of rehab, and in other stages of recovery. Furthermore, future research will need to look into other wearable devices and physiological measures. This study only traced heart rate, temperature, and electrodermal activity. There are many more measures that can be traced with current and future technologies such as accelerometer data, blood pressure, and location data. Furthermore, new wearable devices are being invented each year such as smart eyewear and smart clothing that could expand upon this area of research.

Another finding that could be useful for future research was that participants almost always responded that their current drug craving levels were 0.0. This type of question may need to be rephrased in similar studies. For example, since the participants each responded with alcohol being their primary drug of choice, we may have wanted to ask how intense were their alcohol cravings. Furthermore, we could have simply asked if they had thought about alcohol that day or if they were in any situations where alcohol was present. Other types of questions phrased in a different way would have likely provided more survey variability.

Future research can also incorporate a qualitative interview process where participants reflect on different craving and mood situations and why they occurred. This would provide researchers with further context about the large amount of quantitative data. Furthermore, additional similar studies could incorporate how attending 12-step meetings and participating in other recovery activities can help prevent cravings and negative mood states. This study asked a few questions about these meetings, but there were not enough data points to draw any major conclusions with this data.

Additionally, location data could be very effective in certain studies. Just as Google Maps can figure out where you live, where you work, and where you go on a typical day, location services could also figure out where a participant goes on a typical day, where and when he or she attends meetings, and even when one of these participants is at a location that could be a warning sign for relapse. Again, this may bring up some privacy concerns, but it could also be a useful tool in aiding recovery.

There are many different ways that this study can be expanded upon and modified, and this study proved to be quite useful in determining feasibility and figuring out how future research can expand upon these findings. New technologies will provide more and more opportunities to seek new tools to assist recovering alcoholics and drug addict

Appendix A

iPhone Survey Questions

3 CRAVINGS ITEMS

1) Current Craving Intensity

CURRENTLY, how INTENSE are your drug CRAVINGS?

[“NO CRAVINGS---- VERY INTENSE”]

2) Cravings Since Last Entry

Since last entry, how INTENSE were your drug CRAVINGS?

[“NO CRAVINGS ------------- VERY INTENSE”]

3) Cravings Frequency

Since last entry, how FREQUENT were your drug CRAVINGS?

[“NO CRAVINGS ------ VERY FREQUENT”]

12 MOOD ITEMS

ANGRY: Currently, do you feel ANGRY? [“Not at All---------- VERY”]

IRRITABLE: Currently, do you feel IRRITABLE? [“Not at All ----- VERY”]

ANXIOUS: Currently, do you feel ANXIOUS? [“Not at All ------- VERY”]

STRESSED: Currently, have you feel STRESSED? [“Not at All---- VERY”]

CALM: Currently, do you feel CALM? [“Not at All ------------ VERY”]

RELAXED: Currently, do you feel RELAXED? [“Not at All ------ VERY”]

JOY: Currently, do you feel JOY? [“Not at All --------------- VERY”]

HAPPY: Currently, do you feel HAPPY? [“Not at All ---------- VERY”]

DEPRESSED: Currently, do you feel DEPRESSED? [“Not at All --- VERY”]

SAD: Currently, do you feel SAD? [“Not at All -------------- VERY”]

SLUGGISH: Currently, do you feel SLUGGISH? [“Not at All ----- VERY”]

LETHARGIC: Currently, do you feel LETHARGIC? [“Not at All---- VERY”]

END OF DAY ADDITIONAL QUESTIONS

1) Twelve Step Meeting Attendance

Did you attend a 12-step or other recovery support meeting today?

(Yes / No) If no, then end survey

2) Twelve Step Meeting Type

If yes, select all that apply:

[AA–On campus / AA–Off campus / NA–On campus /NA–Off campus]

3) Twelve Step Meeting Usefulness

How useful was the meeting for you?

[“Not at All ------------------------------- VERY”]

4) Twelve Step Meeting Supportiveness

How supportive did you find the meeting?

[“Not at All ------------------------------- VERY”]

5) Twelve Step Meeting Connectedness

How connected did you feel to others at the meeting?

[“Not at All ----------------------- VERY”]

Appendix B

Approval of IRB Submission

APPROVAL OF SUBMISSION

Date: February 10, 2017

From: IRB Analyst

To: Hobart Cleveland, III

Type of Submission:	Initial Study
Title of Study:	Recovery Wearables: Initial Proof-of-concept Pilot Study
Principal Investigator:	Hobart Cleveland, III
Study ID:	STUDY00006760
Submission ID:	STUDY00006760
Funding:	Not Applicable
IND,IDE, or HDE:	Not Applicable
Documents Approved:	• Baseline Survey (0.01), Category: Collaborating Approval Materials • E4 Sensors (0.01), Category: Data Collection Instrument • EMA Questions (0.01), Category: Collaborating Approval Materials • Qualitative Interview Questions (0.01), Category: Collaborating Approval Materials • Recovery Wearables Consent Form (2/9/17), Category: Consent Form • Recovery Wearables HRP591 (Feb 10 2017) (0.01), Category: IRB Protocol • Recruitment Script (V_1), Category: Recruitment Materials
Review Level:	Expedited
IRB Board Meeting Date:	

On 2/10/2017, the IRB approved the above-referenced Initial Study. This approval is effective through 2/9/2018 inclusive. You must submit a continuing review form with all required explanations for this study at least 45 days before the study's approval end date. You can submit a continuing review by navigating to the active study and clicking 'Create Modification / CR'.

If continuing review approval is not granted before 2/9/2018, approval of this study expires on that date.
To document consent, use the consent documents that were approved and stamped by the IRB. Go to the Documents tab to download them.

In conducting this study, you are required to follow the requirements listed in the Investigator Manual (HRP-103), which can be found by navigating to the IRB Library within CATS IRB (http://irb.psu.edu). These requirements include, but are not limited to:

- Documenting consent
- Requesting modification(s)
- Requesting continuing review
- Closing a study
- Reporting new information about a study
- Registering an applicable clinical trial
- Maintaining research records

This correspondence should be maintained with your records.

BIBLIOGRAPHY

Braithwaite, J., Watson, D., Jones, R., & Rowe, M. (2015). A Guide for Analysing Electrodermal Activity (EDA) & Skin Conductance Responses (SCRs) for Psychological Experiments. Retrieved from http://www.birmingham.ac.uk/Documents/college-les/psych/saal/guide-electrodermal-activity.pdf

Breese, G. R., Chu, K., Dayas, C. V., Funk, D., Knapp, D. J., Koob, G. F., Lê, D. A., O'Dell, L. E., Overstreet, D. H., Roberts, A. J., Sinha, R., Valdez, G. R. and Weiss, F. (2005), Stress Enhancement of Craving During Sobriety: A Risk for Relapse. Alcoholism: Clinical and Experimental Research, 29: 185–195. doi:10.1097/01.ALC.0000153544.83656.3C

Cornelius, J.R., Maisto, S.A., Pollock, N.K. et al. (2003) Rapid relapse generally follows treatment for substance use disorders among adolescents.

Cooney, Ned L.; Litt, Mark D.; Morse, Priscilla A.; Bauer, Lance O.; Gaupp, Larry
Journal of Abnormal Psychology, Vol 106(2), May 1997, 243-250. http://dx.doi.org/10.1037/0021-843X.106.2.243

DePue, M.K. & Hagedorn, W.B. (2015). Facilitating college students' recovery through the use of collegiate recovery programs. Journal of College Counseling, 18(1), 66-81.

Etherington, D. (2015, June 23). Google's New Health Wearable Delivers Constant Patient Monitoring. Retrieved March 2, 2017, from https://techcrunch.com/2015/06/23/googles-new-health-wearable-delivers-constant-patient-monitoring/

Garbarino, M., Lai, M., Bender, D., Picard, R. W., & Tognetti, S. (2014). Empatica E3 - A wearable wireless multi-sensor device for real-time computerized biofeedback and data acquisition. In 2014 EAI 4th International Conference on Wireless Mobile Communication and Healthcare (Mobihealth) 39-42

Guarnotta, E. (2016, April 20). How to Stop Alcohol Cravings, Prevent Relapse and Find Help. Retrieved February 20, 2017, from http://www.recovery.org/topics/alcohol-cravings/

Health Fitness Revolution. (2016, March 25). Top 10 Benefits of Fitness Trackers. Retrieved March 3, 2017, from http://www.healthfitnessrevolution.com/top-10-benefits-of-fitness-trackers/

Heneghan, C. (2014, July 09). Who Stands to Benefit When Health Care Wearables Are Everywhere? Retrieved March 1, 2017, from https://www.fool.com/investing/general/2014/07/09/who-stands-to-benefit-when-healthcare-wearables-ar.aspx

Investopedia. (2009, May 20). Coefficient of Determination. Retrieved March 3, 2017, from http://www.investopedia.com/terms/c/coefficient-of-determination.asp

Kokalitcheva, K. (2015, June 23). Google Unveils Tracking Wristband For Medical Patients. Retrieved March 3, 2017, from http://fortune.com/2015/06/23/google-medical-wristband/

Li, X., Dunn, J., Salins, D., Zhou, G., Zhou, W., Rose, S. M., Snyder, M. P. (2017). Digital Health: Tracking Physiomes and Activity Using Wearable Biosensors Reveals Useful Health-Related Information. *PLOS Biology*, *15*(1). doi:10.1371/journal.pbio.2001402

Lupton, D. (2017). Self-tracking, health and medicine. Health Sociology Review, 26(1), 1-5. doi:http://dx.doi.org.ezaccess.libraries.psu.edu/10.1080/14461242.2016.1228149

NIDA (2012). Principles of Drug Addiction Treatment: A Research-Based Guide (Third Edition). Retrieved February 15, 2017, from https://www.drugabuse.gov/publications/principles-drug-addiction-treatment-research-based-guide-third-edition

Rajendra Acharya, U., Paul Joseph, K., Kannathal, N., Lim, C. M., & Suri, J. S. (2006). Heart rate variability: a review. *Medical & Biological Engineering & Computing*, *44*(12), 1031–1051. http://doi.org/10.1007/s11517-006-0119-0

Olson, P. (2016, March 23). Wearable Tech Is Plugging Into Health Insurance. Retrieved March 1, 2017, from https://www.forbes.com/sites/parmyolson/2014/06/19/wearable-tech-health-insurance/#345ac95218bd

Schwarz, N., & Strack, F. (1999). Reports of subjective well-being: Judgmental processes and their methodological implications. In D. Kahneman, E. Diener, & N. Schwarz (Eds.), *Well–being: The Foundations of Hedonic Psychology* (pp. 61–84). New York: Russell Sage Foundation.

SearchHealthIT. (n.d.). Wearable health technology in medical and consumer arenas. Retrieved March 3, 2017, from http://searchhealthit.techtarget.com/essentialguide/Wearable-health-technology-in-medical-and-consumer-arenas

Substance Abuse and Mental Health Services Administration, *Results from the 2013 National Survey on Drug Use and Health: Summary of National Findings*, NSDUH Series H-48, HHS Publication No. (SMA) 14-4863. Rockville, MD: Substance Abuse and Mental Health Services Administration, 2014.

Vinkers, C. H., Penning, R., Hellhammer, J., Verster, J. C., Klaessens, J. H., Olivier, B., & Kalkman, C. J. (2013). The effect of stress on core and peripheral body temperature in humans. *Stress, 16*(5), 520-530. doi:10.3109/10253890.2013.807243

Academic Vita of John Hatzell
jackhatzell@gmail.com
129 Fern Ave Collingswood, NJ

Education
The Pennsylvania State University, Spring 2017
Bachelor of Science in Information Sciences and Technology
Bachelor of Science in Security and Risk Analysis

Honors
Information Sciences and Technology

Thesis Title
An Examination of How Wristband Wearable Technology Can Be as An Aid in Recovery Amongst College Students in Recovering from Alcohol and Drug Addiction

Thesis Supervisor "H. Harrington Cleveland"

Work Experience
Business Technology Analyst Summer Scholar
Deloitte Consulting LLP; Arlington, VA
Supervisor: Jenna Stegmann
May 2016-July 2016

Student Director of The Learning Assistant Program
College of Information Sciences and Technology
Supervisor: Lisa Lenze
January 2016-May 2017

Grants Received
Richard C. Assetto Scholarship
Class of 1942 Memorial Scholarship
PSU Bookstore Scholarship
Raytheon Information Sciences and Technology Endowed Scholarship

Awards
College of IST Spring 2017 Commencement Student Marshal
Dean's List Fall 2013, Spring 2014, Fall 2014, Spring 2015, Fall 2015, Spring 2016, Fall 2016
Bunton Waller Fellowship Fall 2013-Spring 2017

International Education
Seville, Spain; Summer 2014
Brasilia, Brazil; Summer 2015