Big Health Data from Wearable Electronic Sensors (WES) and the Treatment of Opioid Addiction

Sean M. Shiverick
Indiana University Bloomington
smshiver@indiana.edu

ABSTRACT

Wearable electronic sensors (WES) and mobile health applications can be used to collect vital health data to supplement traditional forms of treatment for opioid addiction and may be used to predict risk factors related to overdose death.

KEYWORDS

Health Informatics, Wearable Sensors, Addiction Treatment, i535, HID335

1 INTRODUCTION

In the increasingly connected digital age, personal electronic devices are generating huge volumes of data with important applications for health informatics. Wearable electronic sensors (i.e., *wearables*) and fitness monitors (e.g, FitBit, iWatch) can record our movements and vital physiological measures such as heart rate, temperature, and blood pressure [?]. Consumers are using wearables to self-monitor stress and hypertension, and wearable sensors can be used to help track recovery following medical procedures such as surgery [?]. The development of personalized health care models are also enabling individuals to self-monitor and manage their own health in partnership with care providers. This paper explores approaches to using personal electronic devices and wearable sensors for the treatment of addiction disorders and the prevention of drug overdose. Past research has shown that *Mobile Health* platforms have been used to address prescription medication abuse in several ways: (a) monitor patient health conditions at any time and remotely, (b) monitor medication consumption, and (c) connect patients with health care providers and treatment services [?]. The following review of the literature shows that wireless digital technologies and smartphone applications are effective at providing health data in real time and can assist patients in recovery to resist physical cravings, prevent relapse, and access treatment support. Mobile applications can play an important role in addressing the opioid epidemic by supplementing traditional approaches to addiction treatment and recovery.

1.1 The Opioid Epidemic: Medication Abuse and Addiction

The abuse of prescription opioid medication in the U.S. has become a major health crisis that the Department of Health and Human Services (HHS) has described as an epidemic [?]. Approximately 2 million Americans were dependent on or abused prescription opioids (e.g., oxycodone, hydrocodone) in 2014 [?]. Overdose deaths from prescription opioids has quadrupled since 1999, resulting in more than 180,000 deaths between 1999 to 2015. Figure 1 shows that the dramatic increase in overdose deaths in the U.S. between 2000 and 2016 are from synthetic opioids (other than methadone), natural and semi-synthetic opioids, and heroin [?]. Of the estimated 64,000 drug overdose deaths in 2015, over 20,000 were from fentanyl and other synthetic opioid analogs. Public health agencies are implementing comprehensive efforts to address four major risk areas of prescription opioid abuse, overdoses, and deaths: (i) Increasing knowledge of opioid abuse and improving decisions among medication prescribers, (ii) Reducing inappropriate access to opioids, (iii) Increasing effective overdose treatment, (iv) Providing substance-abuse treatment to persons addicted to opioids. The opioid epidemic is complex, with multiple and interacting causal factors. To understand how technological interventions can play a role in mitigating the crisis, it is necessary to consider the nature of addiction itself and various approaches to treatment.

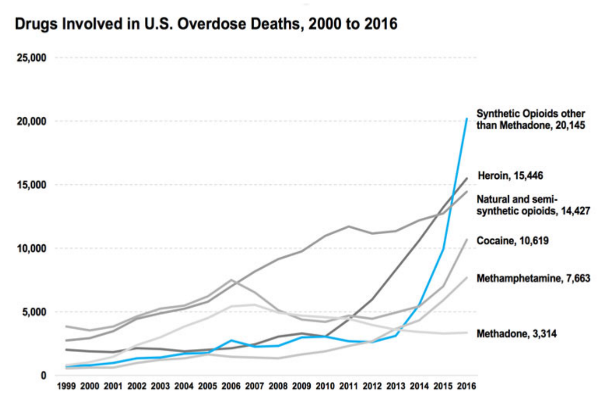

Figure 1: Drugs Involved in U.S. Overdose Deaths from 2000 to 2016, National Institute on Drug Addiction (NIDS) [?]

1.1.1 *Drug Addiction and Treatment.*

For millions of people struggling with substance abuse and dependency in the U.S., addiction and relapse are chronic health conditions [?]. Drug addiction has many similar characteristics to other chronic medical illnesses; however, there are unique challenges to the treatment of addiction illnesses. For example, drug addicted patients undergo intense detoxification in rehabilitation treatment programs, which reduces their drug tolerance, and then are released back into the same environment associated with their drug use, putting them at greater risk for relapse and potential drug overdose. The lack of continuity in the treatment of addiction disorders leaves persons in recovery at high risk of relapse for substance use and abuse. Second, individuals with severe addiction disorders end up at emergency rooms for care following acute intoxication, often following law enforcement interventions. Emergency personal are very competent at crisis interventions for drug overdose, but lack resources to evaluate severe addiction disorders or provide follow-up. Furthermore, addicted individuals seeking treatment often relapse at night or on weekends when treatment centers are not open. Various theories of addiction and relapse have been proposed. According to the classical conditioning model, situational cues or events can elicit a motivational state underlying relapse to drug use. A slightly more complex model suggests that addictive behavior can be reinstated after extinction of dependency by exposure to drugs, drug-related cues, or environmental stressors [?]. Understanding that a user's affective (i.e., motivational) response to cues in the environment can lead to relapse and drug use are key to developing strategies for prevention and treatment.

1.2 Technology-Based Interventions for Addiction Treatment

Technology-based interventions have been used for drug addiction assessment, treatment, prevention, and recovery [?]. In terms of assessment, data about substance use can be obtained from mobile cell phone reporting outside of treatment settings. Web-based approaches to treatment have been implemented online to improve behavioral and psychosocial functioning for addicted individuals in recovery [?]. For example, the *Therapeutic Education System* (TES) is a self-directed, web-based interactive treatment program consisted of 65 training modules that focused on cognitive-behavioral skills and psychosocial functioning (family/social relations). This online approach helped to increase access to treatment for individuals in rural areas, and included an optional contingency management module. A computer based *Training in Cognitive Behavioral Therapy* (CBT) program was found to enhance treatment outcomes when provided in conjunction with traditional substance abuse treatment, and helped improve coping skills and decision-making skills [?]. In evaluating the effectiveness of mobile applications for addiction treatment, several questions remain to be answered: First, if mobile applications are regarded primarily as supplements to traditional therapeutic treatment, can their effectiveness be evaluated independently from the approach used in treatment? Second, over what time period period can the benefits of mobile applications be observed? Research evidence suggests that the benefits of mobile interventions may be limited to 12 or 15 weeks [?]. It is unclear whether individuals struggling from addiction would continue to use mobile treatment applications in the long term, beyond a limited course of treatment.

1.2.1 Mobile-Based Applications. Mobile applications have been used for monitoring and treatment of substance abuse and addiction disorders for several decades [?]. Early applications included the use of electronic pagers (i.e., beepers) for experience sampling with paper-based assessments that generated data about daily life behavior and experiences [?]. In the 1990s, programmable personal digital assistants (e.g., palm-pilot) enabled collection of data electronically, and subsequent mobile research tools facilitated the collection of information about psychological factors (e.g., daily stressors, emotional states, thoughts) and other variables related to addiction (e.g., craving, contextual cues, actual substance use). Assessments performed several times throughout the day (commonly, every 2 to 4 hours) allowed for analysis of the daily fluctuations of these symptoms and features. Historically, addiction research has faced some unique challenges that the use of mobile technologies may help to overcome. Methodological aspects of traditional research using retrospective, cross-sectional, or longitudinal assessments (over periods of weeks, months, or years) have been problematic for investigating risk factors including behaviors and symptoms (severe physiological cravings, withdrawal, and substance use) that can span a relatively short time. An additional factor is the co-morbidity, or co-occurence, of substance use disorders (SUDs) with other psychological disorders, such as anxiety and mood disorders. For example, the *self-medication* model has commonly been used to explain the association between alcohol abuse as an effort by an individual to reduce or cope with a high degree of anxiety (or depression). It has also been challenging for researchers to capture the role of environmental or contextual cues (e.g., people, places, things) associated with substance abuse, which can act as triggers of relapse for individuals in recovery.

Smartphone Applications. Continued care is an important ingredient for recovery from addiction that involves monitoring, outreach, planning, case management, and social support [?]. Smartphone applications can help individuals in recovery to monitor cravings at critical points in daily life, track contextual cues associated with substance use, and provide outreach to support services. A team of researchers at the University of Wisconsin evaluated the effectiveness of a smartphone application called *Addiction Comprehensive Health Enhancement Support System* (A-CHESS), designed to provide recovery support for patients leaving a residential alcohol treatment center [?]. A-CHESS provided anytime, anywhere access to support services in audio-visual format, GPS monitoring and warnings for risky locations related to past substance use, and communication with counselors. Over an 8-month period (and 4 month follow-up), patients who used the A-CHESS intervention reported fewer risky drinking days, on average, per month than patients in a comparable control group. The findings provide evidence that the smartphone intervention was effective at treating a critical behavioral measure for treatment of alcohol use disorder (AUD). The methods described in this study could be extended by re-purposing built-in smartphone sensors to record physiological measures related to opioid usage, and communicate data to health care providers or treatment specialists to initiate interventions for opioid addiction [?].

1.3 Medication Adherence and Abuse Monitoring System

Mobile health applications can be used to monitor medication adherence and as an advanced warning system for potential abuse of prescription medication [?]. Medication abuse can consist of higher medication dosages or rapid escalation of a prescribed dosage, and the general goal of a prediction model is to analyze patient data for sudden changes in medication consumption. Figure 2 illustrates several steps in a process and decision support structure for a medication monitoring system, with adjustable parameters, such as

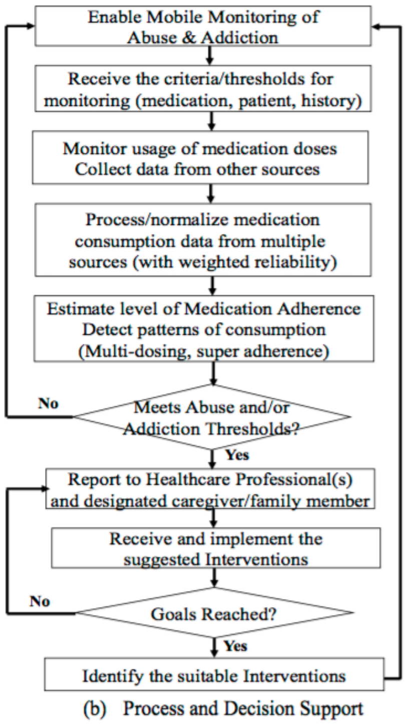

Figure 2: Process and Decision Support for Abuse Monitoring System [?]

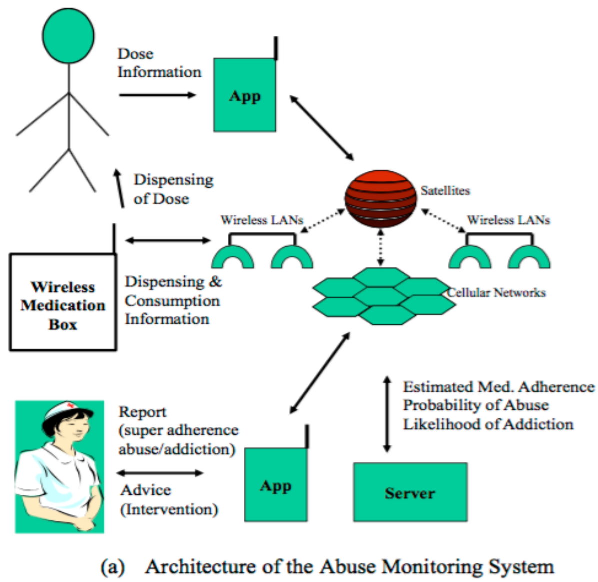

Figure 3: Architecture for Abuse Monitoring System [?]

the threshold for abuse (e.g., greater than N doses in X hours) [?]. A major challenge for measuring medication abuse is obtaining reliable information from potentially addicted individuals based on self report data. Ideally, information on medication consumption and adherence can be obtained from multiple sources. Addiction is a complex behavior that involves a variety of factors, including: demographics (e.g., age, gender), past history, comorbidity with other disorders, family support, social influence, employment status, and patient motivation. Figure 3 shows a model architecture of a system for monitoring potential abuse where dose information is provided via a smartphone application, relayed via wireless cellular network to analytic models that measure changes in medication consumption, relays reports to support treatment services for possible interventions, and to a smart medication box that dispenses medication. In order to function successfully a medication abuse monitoring system depends on the collection of reliable information, including data from wearable sensors that can directly measure physiological changes (e.g., heartrate, blood pressure, respiration, temperature) related to changes in medication usage. In the context of prescription opioid abuse, a medication monitoring system could be very beneficial in anticipating opioid dependency and preventing accidental death from medication overdose.

1.4 Mobile Detection with Wearable Biosensors

Portable biosensors can provide a continuous stream of data on the timing, location, context, and duration of drug use by individuals in treatment. In a small pilot study, researchers used an Affectiva Q sensor to measure electrodermal activity (EDA), skin temperature, and acceleration (8 recordings per second), in a sample of N = 4 patients during the administration of opioid medication in an emergency room setting [?]. Table 1 provides a summary of the participant characteristics. The biosensor was worn on the wrist and was similar in size and dimensions to a wristwatch or fitbit health monitor. The results showed an increase in EDA associated with intravenous opioid injection that was detected by the biosensors. In addition, there was some indication that the physiological response to opioids varied according to individual drug tolerance; patients with higher opioid tolerance showed less EDA response than patients with low tolerance. The findings provide evidence to support the use of wearable sensors to detect drug use in real time, in a controlled environment. An important limitation of the study is the small sample size, which reduces the generalizability of the findings to a broader population. The authors also acknowledged that psychological or physiological stress can produce alterations in EDA, skin temperature, and acceleration, and therefore this could not be ruled out as an alternative explanation for the findings. The results are promising, however, and encourage efforts to explore the

Table 1: Summary of Participant Characteristics in Pilot study [?]

Patient	Age	Gender	History of Use	Intervention	Pre-EI
1	82	Male	Opioid naive	4 mg morphine	4.5
2	47	Male	Recent short-term	1 mg hydromorphone	3.4
3	43	Female	Chronic opioid use	1 mg hydromorphone	0.2
4	72	Male	Chronic opioid use	4 mg morphine	0.9

effectiveness of wearable biosensors in the context of environments associated with substance use.

1.5 Emerging Sensor Technologies

Wearable wireless sensors have been used to study physiological responses, activity, and social behavior in non-human primates in the form of a fitted vest and using a mobile phone with blue tooth protocol to collect data in real time. Figure 4 shows sample ambulatory data from a rhesus macaque recorded from a wearable wireless sensor for 11 hours inside a large group primate cage [**?**]. Data was recorded on a custom Android software application, which captured measures of EDA, heart rate (HR), temperature, and acceleration. The goals of this study were to measure associations between physiological measures and social behavior in primates; however, this practical application of sensor technology demonstrated a system that was relatively low-cost, highly portable, scalable, and simple to use. Future research could explore the development of a similar system modified for use with humans to collect data on physiological measures from addicted individuals in naturalistic settings.

1.5.1 LoRa Backscatter: Enabling Ubiquitous Connectivity. Emerging technologies, such as longe range (LoRa) backscatter, have the potential to extend the boundaries of wireless connectivity. Existing radio technologies (e.g., WIFI, ZigBee, SigFox, LTE-M) provide reliable long range coverage, but consume energy and would be costly to expand to large scale implementation; however, LoRa backscatter is a smaller, low-cost, low-power alternative with extended range between an RF source and receiver of approximately 475 meters (i.e., yards) [**?**]. Table 1 shows the sensitivity and supported data rates for different communication technologies and feasibility of different power sources. LoRa backscatter performed best overall, in terms of sensitivity (-149 dBm), supporting bit rates of 18 pbs to 37.5 kbps, providing whole home coverage, and capable of being powered by button cell, tiny solar cell, or printed battery. LoRa backscatter uses chirp spread activation (CSS) that can synthesize continuous frequency modulated chirps; a limitation is that backscatter is drowned out by noise and the RF source. The LoRa backscatter system was tested in various deployments: across three floors of a 4800 square- foot house, a single floor of 13,000 square foot office building, and on a one-acre farm. Figure 5 shows the layout of the house with the RF source (TX) on the second floor and receiver in the basement (RX); the plot shows the system achieved RSSI values greater than -144 dBm, with reliable wireless coverage throughout the house, and rates sufficient for temperature sensors that transmit small packages. The system was also implemented in the form flexible epidermal patch sensor shown in Figure 6, that

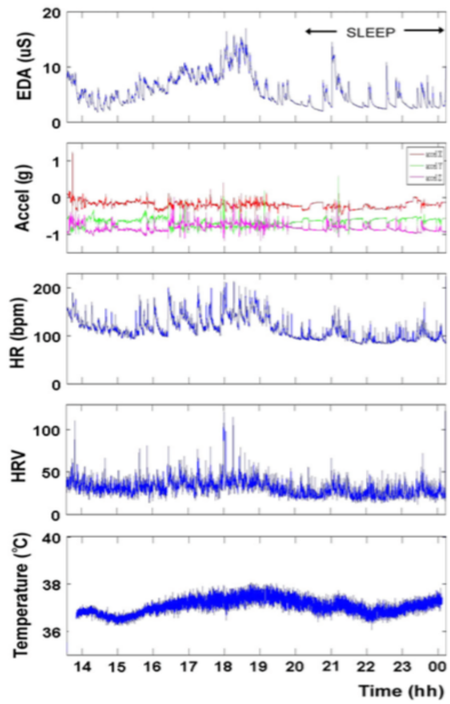

Figure 4: Sample Ambulatory Data from Rhesus Macaque Recorded on Wearable Sensor for 11+ hours Inside Large Primate Cage Facility [?]

Table 2: Comparison of Wireless Communication Technologies [?]

Technology	Sensitivity	Data Rate	Home Coverage	Button
Wi-Fi (802.11 b/g)	-95 dBm	1-54 Mbps	yes	no
LoRa	-149 dBm	18 bps-37.5 kbps	yes	no
Bluetooth	-97 dBm	1-2 Mbps	no	no
SigFox	-126 dBm	100 bps	yes	no
Zigbee	-100 dBm	250 kpbs	yes	no
Passive Wi-Fi	-95 dBm	1-11 Mbps	no	yes
RFID	-85 dBm	40-640 kbps	no	yes
LoRA Backscatter	-149 dBm	18 bps-37.5 kpbs	yes	yes

provided reliable connectivity across a 3,300 square foot atrium with RSSI greater than -132 dBm. LoRa backscatter provides a compact, energy-efficient, and affordable wireless transmission system that can be extended to scale at reasonable cost. This system could possibly transmission of biometric data from wearable sensors to capture health information from addicted individuals in treatment.

1.5.2 Graphene Electronic Tattoo sensors. Wearable, tattoo-like epidermal sensors allow for continuous, ambulatory monitoring

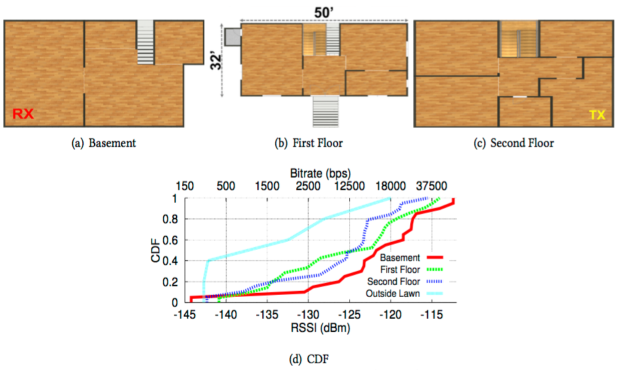

Figure 5: Home Deployment of LoRa backscatter pakcets across 4,800 sq. ft. House Apread Across Three Floors [?]

Figure 6: LoRa Backscatter Epidermal Patch [?]

of biometric signals from the heart, muscles, and brain, outside of hospitals and clinical lab settings [?]. A team of researchers at the University of Texas at Austin designed the graphene electronic tattoo (GET) as a long term wearable sensor that can be directly laminated on human skin, and can remain functional for several days with a liquid bandage cover [?]. Graphene is the thinnest electrically conductive material that is biocompatible, stable, and mechanically robust. The "GET is fabricated through a simple 'wet transfer, dry patterning' process directly on tattoo paper, allowing it to be transferred on human skin exactly like a temporary tattoo, except the sensor is transparent"(p.8)[?]. As depicted in Figure 7, the GET sensor is is flexible, stretchable, and transparent, and less than a sub-micrometer in thickness (463 +/- 30 nm). GET has been used successfully to measure electrocardiograph (ECK), electromyogram (EMG), electrocephalograph (EEG) signals, as well as skin temperature and skin hydration. After use, the GET can be easily removed by peeling it from the skin. A future step in the development of GET is to include an antenna to the design so that signals can be beamed off the device to a smartphone application or computer. The thin, flexible, resilient tattoo biosensor provides a durable, unobtrusive tool for collecting physiological data, and could be used to detect physical changes due to drug withdrawal in addicted individuals.

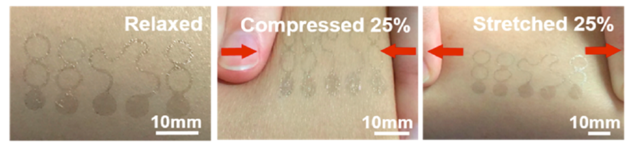

Figure 7: Graphene Electronic Tatoo Biosensor [?]

2 CONCLUSION

Can Technological Applications Reduce Opioid Addiction? The abuse of prescription medication in the U.S. has led to opioid addiction at levels of epidemic proportion. Technological interventions can play a role in addressing this crisis as a supplement to conventional forms of addiction treatment. Mobile health applications can help monitor potential medication abuse and connect individuals with treatment services. An important limitation of data based addiction interventions is the difficulty of obtaining reliable information about medication consumption based on self-reports from potentially addicted individuals. The literature reviewed indicates that wearable sensors are an effective way to measure vital health data in real time and remotely. Providing individuals in recovery with vital health data may help them to resist physical cravings and prevent relapse. Another limitation of treatment approaches is that, after detoxification, individuals in recovery are released back into the environmental settings associated with their drug use, putting them at risk for potential relapse and possible overdose. Recent advances in signal technologies such as LoRa Backscatter and Graphene tattoo sensors can lead to the more efficient collection of biometric information and cost effective transmission of health data for subsequent analysis. The opioid addiction epidemic is a complex phenomenon, with both physical and sociological contributing factors. Technological interventions will increase the amount of data about addicted individuals and relevant risk factors that may be used to predict opioid overdose death; however, it will not address the environmental factors that lead to addiction. Despite increased awareness of the potential for prescription medication abuse, Table 1 shows the rate of overdose deaths is growing more rapidly for heroin and synthetic opioids such as fentanyl compared to conventional prescription opioid medication. The implication of this is that individuals who may become addicted to prescribed medication may go on to abuse illicit or synthetic opioids, in non-clinical, unsupervised, and unregulated settings. Big data offers potential for transforming health care and addition treatment. Increasing levels of data about opioid addiction ultimately may not be sufficient to prevent or decrease rates of overdose death if the availability of illicit and synthetic opioids remains high.

ACKNOWLEDGMENTS

The author would like to thank Dr. Gregor von Laszewski, the Assistant Instructors, Juliette Zurick and others, and anonymous reviewers who helped to improve this report.

3 ISSUES

DONE:

Example of done item: Once you fix an item, change TODO to DONE

3.1 Assignment Submission Issues

DONE:

Do not make changes to your paper during grading, when your repository should be frozen.

3.2 Uncaught Bibliography Errors

DONE:

Missing bibliography file generated by JabRef

DONE:

Bibtex labels cannot have any spaces, _ or & in it

DONE:

Citations in text showing as [?]: this means either your report.bib is not up-to-date or there is a spelling error in the label of the item you want to cite, either in report.bib or in report.tex

3.3 Formatting

DONE:

Incorrect number of keywords or HID and i523 not included in the keywords

DONE:

Other formatting issues

3.4 Writing Errors

DONE:

Errors in title, e.g. capitalization

DONE:

Spelling errors

DONE:

Are you using *a* and *the* properly?

DONE:

Do not use phrases such as *shown in the Figure below*. Instead, use *as shown in Figure 3*, when referring to the 3rd figure

DONE:

Do not use the word *I* instead use *we* even if you are the sole author

DONE:

Do not use the phrase *In this paper/report we show* instead use *We show*. It is not important if this is a paper or a report and does not need to be mentioned

DONE:

If you want to say *and* do not use *&* but use the word *and*

DONE:

Use a space after . , :

DONE:

When using a section command, the section title is not written in all-caps as format does this for you

```
\section{Introduction} and NOT \section{INTRODUCTION}
```

3.5 Citation Issues and Plagiarism

DONE:

It is your responsibility to make sure no plagiarism occurs. The instructions and resources were given in the class

DONE:

Claims made without citations provided

DONE:

Need to paraphrase long quotations (whole sentences or longer)

DONE:

Need to quote directly cited material

3.6 Character Errors

DONE:

Erroneous use of quotation marks, i.e. use “quotes” , instead of ” ”

DONE:

To emphasize a word, use *emphasize* and not “quote”

DONE:

When using the characters & # % _ put a backslash before them so that they show up correctly

DONE:

Pasting and copying from the Web often results in non-ASCII characters to be used in your text, please remove them and replace accordingly. This is the case for quotes, dashes and all the other special characters.

DONE:

If you see a ﬀigure and not a figure in text you copied from a text that has the ﬁ combined as a single character

3.7 Structural Issues

DONE:

Acknowledgement section missing

DONE:

Incorrect README file

DONE:

In case of a class and if you do a multi-author paper, you need to add an appendix describing who did what in the paper

DONE:

The paper has less than 2 pages of text, i.e. excluding images, tables and figures

DONE:

The paper has more than 6 pages of text, i.e. excluding images, tables and figures

DONE:

Do not artificially inflate your paper if you are below the page limit

3.8 Details about the Figures and Tables

DONE:

Capitalization errors in referring to captions, e.g. Figure 1, Table 2

DONE:

Do use *label* and *ref* to automatically create figure numbers

DONE:

Wrong placement of figure caption. They should be on the bottom of the figure

DONE:

Wrong placement of table caption. They should be on the top of the table

DONE:

Images submitted incorrectly. They should be in native format, e.g. .graffle, .pptx, .png, .jpg

DONE:

Do not submit eps images. Instead, convert them to PDF

DONE:

The image files must be in a single directory named "images"

DONE:

In case there is a powerpoint in the submission, the image must be exported as PDF

DONE:

Make the figures large enough so we can read the details. If needed make the figure over two columns

DONE:

Do not worry about the figure placement if they are at a different location than you think. Figures are allowed to float. For this class, you should place all figures at the end of the report.

DONE:

In case you copied a figure from another paper you need to ask for copyright permission. In case of a class paper, you must include a reference to the original in the caption

DONE:

Remove any figure that is not referred to explicitly in the text (As shown in Figure ..)

DONE:

Do not use textwidth as a parameter for includegraphics

DONE:

Figures should be reasonably sized and often you just need to add columnwidth

e.g.

```
/includegraphics[width=\columnwidth]{images/myimage.pdf}
```

re