Spatial and Temporal Analysis of Trends in Opioid Abuse within the US

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1. INTRODUCTION (Q1)

Prescription opioid abuse in the United States is an epidemic that has affected millions, with an estimation of drug abusers in recent years exceeding 15 million [Basak et al, 2019]. Determining the factors that create a greater risk of opioid overdose hospitalisation or death (overdose harm) is key to creating effective public health interventions to reduce the effects of the epidemic. Our objective for this project is to build an interactive visual tool to identify emerging trends in the opioid epidemic, utilising available open-source data to analyse opioid abuse trends regionally, demographically, and over time. If successful, this could provide a new way for local public health departments and organisations to identify the unique circumstances that contribute to opioid abuse in their region, or determine which demographics in their jurisdictions are the most at-risk for prescription opioid abuse, to focus their interventions where they are most needed.

2. LITERATURE REVIEW (Q2/Q3)

In recent years, an increasing amount of studies have used analytical approaches to potentially identify contributing factors, causal relationships and geographical variations of the opioid epidemic. However, the current practice is often restricted to small regional approaches or limited in the scope of potential factors. Recent studies have used machine learning approaches to predict the risk of opioid use disorder on a population level [Hasan et al. 2021] or applied probabilistic models to find variation in prescription trends [Hu et al., 2015], but were restricted to Massachusetts or areas in Queensland (Australia), respectively. Areas of higher prescription rates have also been a central focus of research, in an attempt to identify areas of urgent action and causality factors. One approach used spatial cluster detection to monitor local patterns of prescription opioid abuse in New Mexico [Brownstein et al.]. A similar approach identified smaller hot-spot areas where the opioid prescription rate was significantly higher than the baseline measured as the rate of the whole state [Basak et al. 2019]. All these studies highlight the potential of using quantitative approaches to identify areas and predictive factors associated with the opioid abuse emergency, but also reveal limitations in the data.

Understanding the spatial-temporal effect of opioid abuse in the United States is a crucial aspect of this effort, as it might help highlight systemic differences that are at the basis of the increase in opioid usage. An argument is to be made that the misuse of opioids reflects the most substantial public health crisis that the US has faced [Maclean et al., 2020]. A multi-level analysis has shown as much as 10% of the variation in opioid intake can be explained by geographical data itself [Webster et al. 2009], even if using state-level data only. More recent studies have shown how there is a large geographical variation in opioid prescription rate and a general lack of consensus regarding opioid use to treat pain [McDonald et al. 2012; McDonald and Carlson, 2014].

Opioid abuse data can be hard to track as many health problems, including causes of death, may not seem opioid-related. Polysubstance abuse often occurs in those who are addicted to opioids. Studies have shown that the less widely used, the more likely a drug is to be used with other drugs [Compton et al., 2021]. Because of this, we could potentially use other types of drug overdoses as potential predictors in our analysis [Unick & Ciccarone, 2017; Unick et al., 2013].

There seem to be clear differences in opioid intake between urban and rural areas. An analysis of prescription opioid poisoning across counties in California indicated factors, such as higher pharmacy density in urban areas and low income with more manual labour industries in rural areas as potential causes for this variation [Cerda et al., 2017]. In the case of Purdue Pharma, they would target low-income miners in rural communities to target Oxycontin which led to a major crisis [Whelan & Asbridge, 2013]. Availability of healthcare services, differences in demographics and unemployment rates have also been indicated as potential causes of this difference [Sun et al. 2022; Duan & Hand, 2021]. All these indicate the importance of including the rural/urban aspect in our analysis, while also clearly highlighting the limitation associated with single-state data or lack of accountability of confounding variables.

3. PURPOSE / EXPECTED INNOVATIONS (Q4/Q5/Q6)

An interactive visual tool identifying opioid overdose trends over time will allow public health departments to design intervention techniques and policies focused on specific geographic areas and demographics. This could impact countless people such as physicians, pharmacists, public health and the government, who continue to push resources to combat the opioid epidemic.

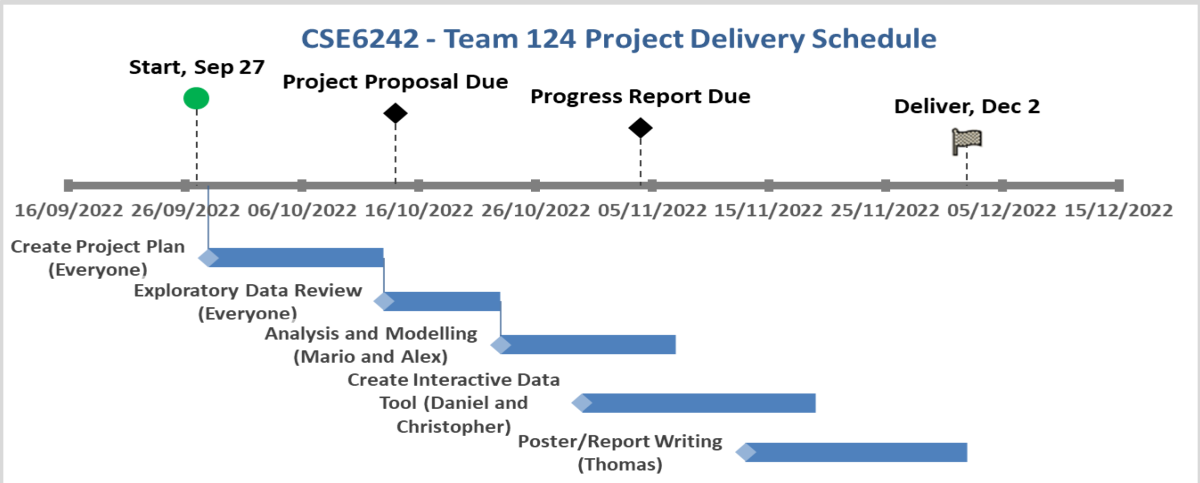
If successful, our study will help to identify factors that contribute to the increasing rate of opioid overdose hospitalisations and deaths and to indicate specific areas where these issues are increasing at a more urgent rate. Our goal is to identify the factors that may be contributing to these geographic/demographic hot spots to allow public health to implement strategies efficiently. A longitudinal study is needed to measure the success of our project. A specific hotspot would allocate resources to the factors identified in our analysis and continued monitoring of the opioid abuse epidemic is needed to determine if there is a decline in that hotspot. Since there are many proposed methods to combat the opioid epidemic, it would be difficult to distinguish if the results of our study impacted this success, but if it is a tool that may have led to a decline, it would be considered successful.

A risk of the study is to incorrectly identify a factor contributing to an area's increased opioid use. If resources are allocated to this factor, it would be a waste of time and money. The opioid epidemic has been greatly studied with lots of research identifying common factors. Therefore, the factors we identify for an area are most likely to correspond to factors identified in other studies. It is unlikely that public health would allocate resources to a potentially incorrect factor. The potential payout of contributing to the decline of opioid use and overdose would be far more rewarding than the drawbacks.

4. PLAN OF ACTIVITIES (Q7/Q8/Q9)

The data used in this project will be open-source that will not present any financial cost. The software used, such as Python, HTML, CSS, D3.js, will also be free of charge.

The project plan outlining future activities is shown below:



To date, each team member has performed a literature review for 3 papers each and proposed at least one open-source dataset for the project. The team will now be split into groups responsible for statistical analysis, creating the visual data tool and documentation, as outlined in the Gantt chart above. By the 4th of November, the datasets will be selected and most of the statistical analysis completed, which will serve as our "mid-term". This will leave us with a month to finalise the visual components and complete the documentation as our "final".

5. REFERENCES

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