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changes in population mobility patterns across the province of Ontario, Canada and the state of California, U.S.A. Data from the Ontario-Marginalization Index at the Census Subdivision (CSD) level, as well as the California Healthy Places Index (HPI) at the Census Tract (CT) level, were used to determine the census geographical units in the lowest and highest quantiles of socioeconomic indicators during the COVID-19 pandemic.

Ontario was under three province-wide stay-at-home orders between March 17, 2020 and June 2, 2021. California was under state-wide stay-at-home orders from March 19, 2020 to January 25, 2021. Weekly data from March 15, 2020 to June 19, 2021 were analyzed for Ontario, and weekly data were analyzed from March 15, 2020 to March 20, 2021 for California. We used the percentage of time spent away from home as the indicator for mobility and analyzed differences in mobility trends between the populations grouped by material deprivation score (Ontario) and HPI scores.

**Results:** In Ontario, populations with highest material deprivation spent an average of 25.7% of time away from home, while the populations with lowest material deprivation spent an average of 22.6% of their time away from home (difference: 3.1%,  $p < 0.001$ ) across the entire duration of the COVID-19 pandemic.

Similarly, in California, the least advantaged populations spent an average of 30.0% of time away from their home, while the most advantaged populations spent 24.3% of their time away from home (difference: 5.7%,  $p < 0.001$ ).

**Conclusion:** Across both geographical locations, the least advantaged populations observed highest mobility compared to the most advantaged populations throughout the pandemic. This indicates that populations in communities with the least advantage in Ontario and California may have less ability or inadequate resources to comply with stay-at-home orders, leading to increased risk of COVID-19 exposure among these more mobile populations. Strategies to protect those most at risk of exposure to COVID-19 are imperative for controlling spread within communities.

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**PS04.06 (673)**

**Characteristics and Early Predictors of Intensive Care Unit Admission among COVID-19 Patients in Qatar**

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**Purpose:** This study aimed to explore the early predictors of intensive care unit (ICU) admission and in-hospital mortality among patients diagnosed with Coronavirus disease (COVID-19).

**Methods & Materials:** This was a case-control study of adult patients with confirmed COVID-19. Cases were defined as patients admitted to ICU during the period February 29 - May 29, 2020. For each case enrolled, one control was matched by age and gender. Univariate and multivariate logistic regression models were used to identify the predictors for ICU admission and in-hospital mortality among the COVID-19 patients.

**Results:** A total of 1560 patients with confirmed COVID-19 were included. Each group included 780 patients with a predominant male gender (89.7%) and a median age of 49 years

(interquartile range, IQR=18). Predictors independently associated with ICU admission included having cardiovascular disease (CVD) (adjusted odds ratio (aOR)=1.64, 95% confidence interval (CI): 1.16 - 2.32,  $p = 0.005$ ), diabetes (aOR=1.52, 95% CI: 1.08 - 2.13,  $p = 0.016$ ), body mass index  $\geq 30$  kg/m<sup>2</sup> (aOR=1.46, 95% CI: 1.03-2.08,  $p = 0.034$ ), lymphocytes  $\leq 0.8 \times 10^3/\mu\text{L}$  (aOR=2.69, 95% CI: 1.80-4.02,  $p < 0.001$ ), aspartate aminotransferase (AST)  $> 120$  U/L (aOR= 2.59, 95% CI: 1.53-4.36,  $p < 0.001$ ), ferritin  $> 600$   $\mu\text{g/L}$  (aOR=1.96, 95% CI: 1.40-2.74,  $p < 0.001$ ), C-reactive protein (CRP)  $> 100$  mg/L (aOR=4.09, 95% CI: 2.81-5.96,  $p < 0.001$ ), and dyspnea (aOR=2.50, 95% CI: 1.77-3.54,  $p < 0.001$ ). Similarly, significant predictors of mortality included CVD (aOR=2.16, 95% CI: 1.32- 3.53,  $p = 0.002$ ), diabetes (aOR=1.77, 95% CI: 1.07-2.90,  $p = 0.025$ ), cancer (aOR=4.65, 95% CI: 1.50-14.42,  $p = 0.008$ ), lymphocytes  $\leq 0.8 \times 10^3/\mu\text{L}$  (aOR=2.34, 95% CI: 1.45-3.78,  $p = 0.001$ ), and AST  $> 120$  U/L (aOR= 1.89, 95% CI: 1.04-3.43,  $p = 0.036$ ).

**Conclusion:** Having CVD, diabetes, lymphopenia, and increased AST were independent predictors for both ICU admission and in-hospital mortality in patients with COVID-19. In addition, obesity, high ferritin, and CRP levels were also associated with increased risk of ICU admission, while cancer was strongly associated with in-hospital mortality. Early identification and monitoring of patients at risk is essential in planning the level of care needed to prevent delay in medical intervention.

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**PS04.07 (935)**

**Early phase of COVID-19 epidemic in Albania**

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**Purpose:** The index case of COVID-19 was diagnosed on March 8th with symptoms onset identified on March 6th, with a travel history within Italy. During the first month the number of identified imported cases was 25. The first 291 laboratory-confirmed cases of the COVID -19 outbreak are used to characterize the epidemiological pattern and estimate the epidemiological parameters such as serial interval, basic and effective reproduction numbers and to evaluate the effectiveness of first timely disease spread containment measures.

**Methods & Materials:** Epidemiological data were collected through case-based disease COVID -19 surveillance, outbreak investigation and contact tracing data for every confirmed case comprising information on demographics, travel history, date of symptom onset, clinical symptoms, laboratory results, hospitalization, and contacts details. Estimates of the reproduction number and serial interval were performed in R statistical software using R packages developed by the R Epidemics Consortium.

**Results:** Public health authorities were able to identify and trace an average of 10 close contacts per for every positive case. The number of transmission events reported per infector ranges from 1 to 16, with 30% having two secondary cases per infector. The median value of every positive case was with 2 secondary infected cases (mean 3.3, standard deviation 3.2). Based on 43 pairs of primary infectors and secondary cases the mean serial interval was estimated 4.8 days (standard deviation 3.9). The basic reproduction number has been estimated at 2.19 (95% CI 1.6 to 2.8), while effective reproduction number showed a decreasing trend by the second week and reaching a plateau around the critical value during the first month. The social distance measures such as were im-

plemented March 12 going to a total lockdown on March 15 with all travels suspended.

**Conclusion:** Following the detection of the first COVID-19 case, Albania acted swiftly to implement immediate social distancing and lockdown measures. Such drastic measures had a huge effect on COVID-19 control in the beginning. However, the trend of effective reproduction numbers show a plateau for almost the last two weeks of the month with no signs of further decline.

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#### PS04.08 (528)

##### Comparison of different approaches in estimating the time-varying reproductive number for COVID-19

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**Purpose:** The time-varying reproductive number ( $R_t$ ) is an indicator of transmissibility that has utility in evaluating public health interventions and assessing transmission factors. However, the  $R_t$  may be biased by generation time misspecification, reporting delays, underestimation of cases, and day-to-day variations. We compared several methods of adjustments in developing an approach to estimating an unbiased  $R_t$ .

**Methods & Materials:** A meta-analysis of generations times was conducted to reduce misspecification. A probabilistic bias approach was compared to standardization by a test positivity of 5% in adjusting for underestimation. A Poisson deconvolution process using an incubation period of 5.2 days (95% CI: 4.9-5.5) and laboratory turnover times between 2-, 5- and 10-days was utilized to adjust for reporting delays. We compared smoothing (7- and 14-day moving averages), a generalized additive model (GAM), and a local regression (LOESS) model to adjust for day-to-day variation. The adjusted  $R_t$  was compared to a crude  $R_t$  by eyeballing, Mean Average Percentage Error (MAPE), and Mean Absolute Deviation (MAD). We estimated the  $R_t$  using Malaysian COVID-19 daily case data from 7 March 2020–20 June 2021 utilizing Cori et al.'s method.

**Results:** We estimated a pooled serial interval of 4.95 days (95% CI: 4.62-5.29). The  $R_t$  estimated using case counts adjusted for underestimation using standardization by test positivity (MAPE: 0.31; 95% CI: 0.30-0.49, MAD: 0.5; 95%CI: 0.5-0.54) were more volatile, exhibited larger peaks and wider confidence intervals, especially in periods of lower incidence, compared to the probabilistic bias approach (MAPE: 0.07; 95% CI: 0.06-0.07, MAD: 0.26; 95%CI: 0.26-0.28). GAM (MAPE: 1.85, 95% CI: 1.63-2.08) and LOESS (MAPE: 0.29, 95% CI: 0.29-0.29) models had smoothed out almost all variations in the  $R_t$ . Longer lab turnover periods created smoother  $R_t$  with larger peaks and resulted in greater volatility in the estimates.

**Conclusion:** Biases in the estimation of the  $R_t$  may critically change its interpretation for public health interventions. It is important to adjust for these biases and understand the underlying limitations of these estimations; primarily when utilized within the context of pandemic control.

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#### PS04.09 (549)

##### Spatial Opinion Mining from COVID-19 Twitter Data

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**Purpose:** In the first quarter of 2020, World Health Organization (WHO) declared COVID-19 as a public health emergency around the globe. Therefore, different users from all over the world shared their thoughts about COVID-19 on social media platforms i.e., Twitter, Facebook etc. So, it is important to analyze public opinions about COVID-19 from different regions over different period of time. To fulfill the spatial analysis issue, a previous work called H-TF-IDF (Hierarchy-based measure for tweet analysis) for term extraction from tweet data has been proposed. In this work, we focus on the sentiment analysis performed on terms selected by H-TF-IDF for spatial tweets groups to know local situations during the ongoing epidemic COVID-19 over different time frames.

**Methods & Materials:** The primary step is to extract terms from tweets using H-TF-IDF approach. Moreover, these terms are utilized in two ways i.e., 1) select tweets containing terms, 2) terms used as features for sentiment analysis. Thereafter, data preprocessing is performed to clean the text. Afterwards, Vectorization models i.e., bag-of-words (BOW) and term frequency-inverse document frequency (TF-IDF) are used to extract features with the help of n-gram techniques. These features are extracted to train the prediction models for sentiment analysis. Lastly, different statistical and machine learning models i.e., Logistic regression, support vector machine (SVM), etc. are applied to classify the spatial tweets groups. For preliminary results, experiments are conducted on H-TF-IDF tweets corpus having geocoded spatial information for the period of January, 2020. These tweets are extracted from the dataset collected by E.Chen (<https://github.com/echen102/COVID-19-TweetIDs>) that focuses on the early beginning of the outbreak. A uniform experiment setup of train-test (80% and 20%) split scheme is used for each prediction model.

**Results:** The results illustrate that specific terms highlighted by H-TF-IDF provide useful information that would not have been identified without this spatial analysis. The classification results spatial location tweet groups into positive, negative and neutral by subjectivity and polarity measures.

**Conclusion:** The current work is applied on English language-based Twitter information. A following work is to incorporate other languages to perform sentiment analysis. Furthermore, BERT will be used to extend these features.

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#### PS04.10 (62)

##### Longitudinal surveillance of Post-Acute Sequelae of SARS-CoV-2 among Long Beach City residents, April-December, 2020

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