Yale University

AHRQ Grant Final Progress Report

Title of Project: The Role of Telehealth in COVID-19 Response

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Structured Abstract

Purpose: To examine whether the addition of telehealth data to existing surveillance infrastructure can improve forecasts of cases and mortality. In addition, further examine associations between uncertainty and action bias during the COVID-19 pandemic.

Scope: Understanding the role of telehealth in response to a pandemic and the outcomes using administrative health claims data provided by large commercial and Medicare Advantage plans.

Methods: The study was performed in a national telehealth service provider and administrative claims. We characterized the impact of the COVID-19 pandemic and telehealth on utilization, outcomes, disparities, and public health surveillance. The observational study compared the accuracy of 14-day forecasts using public data on COVID cases and mortality.

Results: **Aim 1** - Telehealth-based forecasts improved 14-day case forecasting accuracy by 1.8 percentage points to 30.9% ($p=0.06$), mortality forecasting by 6.4 percentage points to 26.9% ($p<0.048$). **Aim 2** - 52,843 encounters with COVID-19 related claims were identified. After adjusting for patient characteristics and state COVID-19 prevalence, the probability of an ED referral was 0.03 higher in urgent care than telehealth at the onset of the pandemic but equalized thereafter. The probability of an inappropriate prescription in urgent care was 0.19 higher than telehealth in quarter 1 and 0.07 lower than telehealth in quarter 4. The probability of a test order was 0.09 lower in urgent care than telehealth in quarter 1 and 0.19 higher in urgent care than telehealth in quarter 4.

Key Words: Syndromic Surveillance, Case and Mortality Forecast, Telehealth, Action bias, Antibiotic Stewardship, COVID-19, Antibiotics

I. Purpose

To investigate how near-real time data can be incorporated into existing and newly implemented local and national public health reporting infrastructure.

Specific aims

The study hypotheses were tested by pursuing the following three specific aims.
Aim 1: Assess the validity and timeliness of telehealth information for prospective public health surveillance. As home testing becomes available, laboratory-confirmed tests ordered in telehealth visits will become part of mandatory reporting for different jurisdictions, but with several days of delay when compared to cases meeting clinical suspicion criteria. Using Kappa statistics we will assess agreement between home testing and more accurate laboratory results. Using hierarchical linear regression we will assess the surveillance value of immediately available reports of cases and symptoms in comparison to the more accurate laboratory test results. Informed by these results, we will develop a quantitative approach for future reporting and syndromic surveillance.
Aim 2: Assess the role of telehealth in responding to the primary impact of COVID-19. We will characterize the variation in treatment and outcomes of non-hospitalized patients with diagnosis codes associated with COVID-like illness and influenza-like illness. In **Aim 2A** we will characterize physician-level variation in diagnostic and treatment patterns after an initial encounter and differences between telehealth and standard outpatient care. In **Aim 2B** we will assess how much variation in health outcomes is explained by variation in physicians' treatment patterns using a 2-stage least squares regression instrumental variables analysis.
Aim 3: Assess the role of telehealth in responding to the secondary impact of COVID-19. The secondary impact of COVID-19 has been a dramatic reduction in ambulatory services. In **Aim 3A**, we will characterize changes in care gaps based on quality indicators for AHRQ Ambulatory Care Sensitive Conditions and associated outcomes. In **Aim 3B**, we will assess how much of the observed variation is explained by telehealth services and patient-physician relationships. We will compare indicators that can be addressed with telehealth directly (e.g. medication refills) and those that might be triaged with telehealth (e.g. earlier arrival for emergency services). In **Aim 3C** we will measure whether known disparities in care gaps and outcomes persist with COVID-19-related utilization reductions and policy changes. These analyses will utilize time-series regressions and synthetic controls to make counterfactual predictions informed by observed data.

II. Scope

Background

Concern over the safety of in-person visits and related policies resulted in an unprecedented uptake of telehealth in 2020. Simultaneously, utilization of other outpatient services plummeted. Telehealth service providers with national penetration were uniquely positioned to address the resulting gap in near real-time syndromic surveillance. 51,929 patients from our sample met one of the two international case identification standards for COVID-19, yet these reports were only required and included in surveillance systems of 9 states.

To understand the role of telehealth in these processes and outcomes, we established an underlying model, and, where possible, causal relationships. For each Specific Aim, we first estimated a reference model for changes in processes and outcomes, and then analyzed the ways in which telehealth interacts with variations we observed. Our first aim was focused on understanding how telehealth might fit into surveillance strategies, using reference data from public health and laboratory confirmed cases. Our second and third aims used claims data to model the healthcare systems' primary and secondary response to the pandemic. The second aim investigated practice variations for patients with respiratory infections, the extent to which patterns differed in telehealth settings, and how these variations were associated with outcomes. The third aim characterized how deferrals of face-to-face visits impacted ambulatory care sensitive metrics, and 12-month outcomes associated with metrics. We investigated whether access to telehealth and physician relationships mitigated changes in processes and outcomes during lockdown periods and impacts on disparities. The first two aims of this project could have immediate impact on public health and service delivery, and the third may inform future management strategies for AHRQ ambulatory care sensitive conditions.

Public Health Surveillance Systems for COVID-19

The US does not have a single system for monitoring public health. Through the National Notifiable Diseases Surveillance System (NNDSS), the US Centers for Disease Control (CDC) curates a database of standards for mandatory (reportable) and voluntary (notifiable) conditions that are required by each of the 57 jurisdictions. Requirements for each jurisdiction vary. For example, the World Health Organization and the Council of State and Territorial Epidemiologists (CSTE) adopted two standards for COVID-19 case identification, clinician suspected (U07.2) and laboratory confirmed (U07.1),[1] but only 9 states have required reporting patients that meet only the suspicion criteria. In addition to coordinating its public health agency stakeholders, CDC also manages the National Syndromic Surveillance Program (NSSP). NSSP aggregates raw chief complaint and diagnosis data from 4000 laboratories, urgent care facilities, and emergency departments in near real-time using HL7 messaging standards.[2] Information has been disrupted by reduced utilization in these settings.[3] Our team has shown that bio surveillance experts place a high value on real-time access to this type of symptomatic data, potentially outweighing accuracy limitations;[4] the suspected cases and complaints in telehealth contain important information. However, cautionary tales from studies investigating symptom inquiries and interaction with media trends warn of limitations of raw data,[5] a risk that might be mitigated with clinical judgment (see appendix Table 1: COVID-19 concerns vs. clinician suspected). Our first aim will be to understand the data quality and technical requirements for large nationally distributed service providers like Teladoc® to participate meaningfully in these surveillance systems.

From a technical standpoint, addressing the patchwork of state and local reporting infrastructure has been a well-reported challenge, giving several electronic case reporting initiatives new urgency. Yet most state and local health departments continue to exchange data by fax and email.[6] To help address the complexity of reporting requirements, CDC, CSTE, and the Association of Public Health Laboratories have implemented shared electronic case reporting (eCR) services on the APHL AIMS platform that supports routing of eCRs to the appropriate state public health agencies for integration into their surveillance systems (https://ecr.aimsplatform.org/). The Digital Bridge public-private partnership has helped to incubate and pilot standards for a Public Health API that will be released in September of 2020. Standards were announced in April,[7] but early adopters are still in pilot phases.[8] At this time, there are 12 health care organizations that participate, and several are in the process of onboarding. Meanwhile, the *HHS Protect Now* system has been collecting COVID-19 data in a parallel system funded by the CARES Act. While several thousand hospitals have agreed to add *HHS Protect Now* federally mandated reporting to ongoing local and state reporting requirements,[9] this data coordination strategy will not capture information from service providers like Teladoc®.

There has been extensive practice variation in outpatient treatment for respiratory infections.

There have been significant changes in practices for managing respiratory infections since the start of the pandemic. Diagnostic and treatment options have been limited in all outpatient settings, particularly in early phases. Media events influence physician decisions and perception of risks and scarcity. For example, on March 19, 2020, prescriptions for chloroquine and hydroxychloroquine rose above 31,000 after President Trump discussed the hydroxychloroquine-azithromycin drug combination at a briefing. Typical daily prescription rates hover around 680-690 per day.[10],[11] Physicians are engaging in off-label use of certain drugs approved for other purposes such as chloroquine, hydroxychloroquine, Remdesivir and Camostat. These drugs have antiviral properties that offer “biologically plausible” approaches to care, but have not demonstrated efficacy and safety in the real-world. For example, the SARS-Cov-2 virus uses the endolysosomal pathway to enter the cell before uncoating within the cell. Chloroquine and hydroxychloroquine affect endosomal function and block autophagosome-lysosome fusion.[12] Moreover, these drugs have toxic effects that may lead to worsening outcomes for patients. There are several potential harms of chloroquine and hydroxychloroquine.[13],[14] Nevertheless, doctors have been prescribing chloroquine and hydroxychloroquine in large numbers.

Real world evidence is needed to understand how practices impact outcomes.
In addition to multiple clinical trials,[15–18],[19] there are already studies seeking real-world evidence of how different practices impact outcomes. The Association of American Physicians and Surgeons (AAPS) maintains a registry (currently N = 2,333) of clinical response to treating COVID-19 with chloroquine and hydroxychloroquine and reported a "90% chance of recovery" in a letter to Arizona's Governor.[20] Claims and EHR-based studies using propensity scoring have been published.[21] Registries and observations from administrative systems, however, rely on non-random participation with strong selection pressures. This can generate spurious associations.[9] In comparison to these settings, patients seeking care from Teladoc® providers are assigned on a first-come-first serve basis, making physician’s current diagnostic and prescribing practice potentially valuable instruments for causal inference. Aim 2B will investigate the impact of practice variations on outcomes, and assess causal relationships.

COVID-19 has introduced gaps in care for Ambulatory Care Sensitive Conditions.
The secondary impact of the pandemic was a dramatic reduction in all service utilization.[3] On April 7th, the Centers for Medicare and Medicaid published guidance and a tiering framework recommending deferral of routine healthcare services and encouraging the use of telemedicine to triage patients with non-emergent symptoms.[22] At the same time, payers dramatically reduced or eliminated telemedicine copays. AHRQ’s Ambulatory Care Sensitive quality indicators include both process and outcome measures that are affected by these shifts, as well as negative controls unlikely to be measurably impacted by deferrals (e.g. effects of briefly delayed biannual cancer screening). Aim 3A will characterize changes in validated process and outcome metrics. By comparing patients who were due for services during lockdowns to patients with services due before and after utilization drops, we can get a better sense of the impact of the pandemic and, more generally, the efficacy of services intended to prevent adverse outcomes in the patient population eligible for telehealth services. If we do identify an impact of the pandemic, there is reason to believe that telehealth adoption could have mitigated the worst effects. Prior work suggests that this might be more complicated than it appears on the surface. Strong patient-physician relationships improve adherence,[23] but there are concerns that telehealth might erode this connection.[24] We will assess if variation in access to telehealth mediates adverse outcomes associated with deferred services in 2020, and whether there is a further interaction with patient-physician relationships and known disparities. In Aim 3B, we will investigate how different variations of telemedicine relationships are associated with

care gaps, assessing whether visits with an existing provider can close care gaps and whether unrelated physicians are as effective as well-known PCPs.

Disparities in Ambulatory Care Sensitive Conditions

Research has firmly established disparities in Ambulatory Care Sensitive Conditions, even among relatively healthy and commercially insured populations we investigate in this study.[25–29] Several observers have recently pointed out concerns that the recent shift to telehealth for both urgent care and primary care services may exacerbate existing disparities.[30–32] On the other hand, equitable access to telemedicine has been shown in some populations and conditions to reduce disparities.[33] Based on results of prior studies, we hypothesize that patients from traditionally "overserved" populations will receive fewer diagnostic services with limited impact on associated outcomes, while traditionally underserved populations will experience a smaller difference.

Setting

The study was performed in a national telehealth service provider in 2020 serving 50 states and the District of Columbia.

Participants

Teladoc Health patients with encounters including a diagnosis of acute respiratory illness or COVID-19.

III. Methods

Study Design

Aim 1

This observational study compared the accuracy of 14-day forecasts using the type of real-time data available to NSSP (standard forecasts) to forecasts that also included telehealth information (telehealth forecasts). To minimize confounding performance factors, standard forecasts used a minimalistic approach similar to reference models in prior work,[34] but did not include any outside information about demographics, policies, sub-national geographic detail, or immunity. Thus, the accuracy of results cannot be compared to more complex approaches reported elsewhere.[35] The original data submitted by healthcare providers to NSSP was not available for comparison, public data on test-confirmed cases curated by CDC contractors is representative of (or better than) real-time information available through NSSP,[36] allowing for a conservative performance comparison between telehealth models and standard models. We also considered forecasts of deaths attributed to COVID-19 as an alternative measure given that prior work concluded that mortality forecasting has been found to be more reliable than case forecasting.[37] De-identified probable COVID-19 case rate data, based on clinical symptoms and epidemiologic linkage, aggregated at a national level, was provided by Teladoc Health to generate telehealth forecasts. Taken together, these methods present a conservative perspective on the added value of telehealth information when comparing forecast performance. Statistical analysis was performed in November 2021. This study was approved by the University of Southern California Institutional Review Board (IRB #HS-20-00941). A waiver of informed consent was approved consistent with 45 CFR 46.116(f).

Data Sources

Data was collected from publicly available sources online associated with reputable health organizations, health research centers, national organizations, research journals, and academic institutions. COVID-19 case counts were taken from the different data sources, including

COVID-19 Dashboard by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University (JHU) and Teladoc Health vendor. The JHU CSSE data is publicly available at https://systems.jhu.edu/. Some data cannot be shared publicly because it is owned by a third party and authors do not have permission to share the data. Data may be available upon request and completion of necessary agreements.

Aim 2

Our sample included patients with COVID-19-like illness diagnoses during a visit in an urgent care telehealth setting or an in-person urgent care center in 2020. Telehealth settings and urgent care centers were classified based on the clinician group's proportion of all outpatient visits that were in telehealth or urgent care settings in 2019 (see appendix Table 2). Appointment setting (telehealth, urgent care center) was defined using place of service, CPT codes, HCPCS codes, revenue codes, CPT modifiers, or type of service codes. Clinician groups in the 90th percentile of the proportion of urgent care visits were included as urgent care centers. The 90th percentile cutoff was also used to identify telehealth groups. If a clinician had an appointment at one of these settings in 2019 and had an outpatient appointment with exposed COVID-19, suspected COVID-19, or confirmed COVID-19 diagnosis in 2020, then the clinician and patient were included in our sample. COVID-like illness diagnosis codes were adapted from CDC guidance and adopted by a large dedicated telehealth company (see appendix Table 3) [38,39]. Patient inclusion criteria included an insurance enrollment window overlapping index date and one state of residence listed on the index date. Patients with unknown state or sex were excluded from the sample.

Data Sources

We used Optum administrative medical and pharmacy claims data for years 2018-2020 from the De-Identified Clinformatics® Data Mart (CDM) for this analysis (Optum's de-identified Clinformatics® Data Mart Database (2007-2020)) which received IRB approval on 3/19/2021. The Optum CDM was derived from a database of administrative health claims for members of large commercial and Medicare Advantage health plans. The Optum CDM contained de-identified patient-level information on inpatient and outpatient medical claims including ICD International Classification of Diseases, Tenth Revision, Clinical Modification (ICD-10-CM) diagnosis and procedure codes, Current Procedural Terminology (CPT) and Healthcare Common Procedure Coding System (HCPCS) procedure codes, pharmacy claims, member enrollment, and date of death for commercially insured individuals in the United States. The database included approximately 17-19 million annual covered lives. Data was longitudinal and records were linked via unique anonymized patient identifiers that are Health Insurance Portability and Accountability Act (HIPAA) compliant. State-level COVID-19 case data came from the John Hopkins COVID-19 Unified Data Set [40].

Measures

Patient-level variables included age, sex, race/ethnicity (Asian, Black, Hispanic, White, Unknown), Charlson Comorbidity Index (CCI), insurance type (Commercial or Medicare), COVID-19 prevalence, and state. The patient's CCI was calculated based on diagnosis codes in the 2 years prior to the index appointment. The COVID-19 prevalence was measured as a 7-day moving average of the number of cases per 100,000 in that state. Appointment-level variables included setting (i.e. telehealth or urgent care center). Random effects for each practice group in our analysis model captured clinic-level variation.

Aim 3

Aim 3 of the project was not completed due to a combination of time, logistical, and institutional constraints encountered toward the end of the grant period. Efforts were made to address these challenges, but the timeline was exceeded. However, the team remains committed to pursuing this aim in future work, either as an extension of this project or in a different capacity. Despite these setbacks, the project achieved significant progress toward its primary goals, laying a strong foundation for continued efforts in this area.

IV. Results

Principal Findings

Aim 1

169,672 probable COVID-19 cases out of 10.5 million telemedicine encounters diagnosed by 5050 clinicians, with a rate between 0.79 and 47.8 probable cases per 100,000 encounters per day (mean=8.37, SD 10.75). Publicly reported case counts ranged from 0.5 to 237916 (mean: 53,913, SD: 47,466) and 0 to 2328 deaths (mean: 1035, SD: 550) per day. Telehealth-based forecasts improved 14-day case forecasting accuracy by 1.8 percentage points to 30.9% ($p=0.06$), mortality forecasting by 6.4 percentage points to 26.9% ($p<0.048$).

Aim 2

52,843 encounters with COVID-19 related claims were identified. Telehealth patients were, on average, younger and healthier than patients in urgent care. After adjusting for patient characteristics and state COVID-19 prevalence, the probability of an emergency department referral was 0.03 higher in urgent care than telehealth at the onset of the pandemic ([95% CI: 0.01 to 0.06] $P < 0.01$), but did not differ in Quarters 2-4. The probability of an inappropriate prescription in urgent care was 0.19 higher than telehealth in quarter 1 ([95% CI: 0.12 to 0.26] $P < 0.001$) and 0.07 lower than telehealth in quarter 4 ([95% CI: -0.11 to -0.03] $P < 0.01$). The probability of a test order was 0.09 lower in urgent care than telehealth in quarter 1 ([95% CI: -0.15 to -0.03] $P < 0.01$) and 0.19 higher in urgent care than telehealth in quarter 4 ([95% CI: 0.18 to 0.21] $P < 0.001$).

Outcomes

Aim 1 - Primary outcomes were accuracy of 14-day forecasts of COVID-19 cases and mortality, comparing the accuracy of standard forecasts—based on a standard model using only recent history of publicly reported data—to telehealth forecasts that add unreported telehealth information to the standard model. Accuracy was measured as the mean absolute percentage error of each forecast.

Aim 2 - Our outcomes were dichotomous variables for the clinician's evaluation and management action (i.e. Emergency Department (ED) referrals, inappropriate prescription, and COVID-19 test orders) at the index COVID-19-related visit. These actions were based on the most common interventions at or following an index COVID-19-related appointment. We did not include treatments administered after an ED referral on the index date or after a hospital admission. We did not include hospital-based management strategies after a new clinician had been assigned. Prescriptions written within 3 days of the index COVID-19-related appointment were included. Inappropriate prescriptions based on the COVID-19 Treatment Guidelines Panel recommendations included hydroxychloroquine, antibiotics, corticosteroids, ivermectin, baricitinib, and remdesivir [41]. All drugs were identified based on their National Drug Code, generic name, brand name, American Hospital Formulary Service Classification, or First DataBank classification. Antibiotics included those from the National Committee for Quality Assurance (NCQA) value sets for appropriate treatment of upper respiratory infections and monoclonal antibody products included those from CMS [42,43]. If the index COVID-19-related visit included diagnosis codes for which antibiotics are sometimes or always appropriate, then an antibiotic prescription was not classified as inappropriate. The same exclusion criteria was used for diagnosis codes that are appropriate for steroid treatment. The appropriateness of antibiotics and steroids are listed in appendix Tables 4 and 5 and were determined from published value sets and MEDI input [44,45]. COVID-19 tests were attributed to urgent care providers if they occurred within the same claim as the index appointment. Since tests cannot be administered directly via telehealth, the median time between the index appointment and test within the same claim in urgent care (0 days) was used to attribute test orders to telehealth clinicians. Any COVID-19 tests on the same day as the index appointment with the telehealth clinician were attributed to that clinician. COVID-19 tests were presumed positive if the patient had a U07.1 diagnosis 0-7 days after the test and presumed negative if the patient did not.

Conclusion

At the onset of the pandemic when uncertainty was highest, inappropriate prescribing was high across both settings and higher in facility-based urgent care. As the pandemic progressed and uncertainty resolved, inappropriate prescribing remained higher in telehealth than urgent care, despite younger and healthier patients, suggesting that telehealth and attendant uncertainties may be associated with greater action bias to the detriment of healthcare quality. Modest improvements in forecasting can be gained from adding telehealth data to syndromic surveillance infrastructure.

Future work may continue to explore disparities in Ambulatory Care Sensitive Conditions, particularly in the context of the shift to telehealth. In addition, we may explore whether known disparities in care gaps and outcomes persist with COVID-19-related utilization reductions and policy changes. While telemedicine has the potential to reduce disparities in some populations, concerns remain that it may exacerbate inequities in access and outcomes. Investigating these dynamics could provide valuable insights into how telehealth impacts both traditionally underserved and overserved populations. This future work also reflects our continued commitment to complete the objectives of Aim 3 which will be critical in understanding these care gaps and outcomes.

V. List of Publications and Products

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Appendix

Table 1: Consults with COVID-19 inquires and clinically suspected cases March-May 2020

Week	COVID19 Clinically Suspected	COVID19 Concern*	Total Consults	Case Rate per 1K
Mar 1-7	161	483	72271	2.2
Mar 8-14	704	2112	92557	7.6
Mar 15-21	4667	14001	109158	42.8
Mar 22-28	6714	20142	123361	54.4
Mar 29-Apr4	9300	27900	136046	68.4
Apr 5-11	8,196	24588	122675	66.8
Apr 12-18	5244	15732	111036	47.2
Apr 19-25	4391	13173	104354	42.1
Apr 26 - May 2	3662	10986	97469	37.6
May 3-9	3087	9261	90164	34.2
May 10-16	2781	8343	84739	32.8
May 17-23	1769	5307	79867	22.1
May 24-30	1253	3759	75317	16.6
TOTAL	**51929**	**155787**	**1299014**	**40.0**

** Based on 30-40% of patients initiated visit based on concern about COVID-19*

Table 2: Inclusion criteria

	Inclusion	Exclusion
Telehealth (TH) Clinician Group	Proportion of 2019 outpatient visits that were telehealth is in the 90th percentile of clinician groups	
Urgent Care (UC) Face to Face Clinician Group	Proportion of 2019 outpatient visits that were urgent care is in the 90th percentile of clinician groups	
Sample	Index suspected, exposed, or confirmed COVID-19 diagnosis at TH or UC; insurance enrollment window overlapping index date	Unknown state or sex; 2 states listed on index date
Drugs	Prescribed 0-3 days after index appointment	Prescribed on or after the date of inpatient admission; prescribed on or after the ED referral
Clinician-attributed test order	Urgent Care: same claim; Telehealth: same day	

Table 3: COVID-19 diagnosis codes

ICD-10 Code	Code Description	COVID-19 classification
B34.2	Coronavirus infection, unspecified	Suspected or exposed
B97.21	SARS-associated coronavirus as the cause of diseases classified elsewhere	Suspected or exposed
B97.29	Other coronavirus as the cause of diseases classified elsewhere	Suspected or exposed
B97.89	Other viral agents as the cause of diseases classified elsewhere	Suspected or exposed
M35.81	Multisystem inflammatory syndrome	Suspected or exposed
M35.89	Other specified systemic involvement of connective tissue	Suspected or exposed
U07.2	COVID-19, virus not identified (clinically diagnosed)	Suspected or exposed
Z03.818	Encounter for observation for suspected exposure to other biological agents ruled out	Suspected or exposed
Z20.822	Contact with and (suspected) exposure to COVID-19	Suspected or exposed
Z20.828	Contact with and (suspected) exposure to other viral communicable diseases	Suspected or exposed
J12.81	Pneumonia due to SARS-associated coronavirus	Confirmed
J12.82	Pneumonia due to coronavirus disease 2019	Confirmed
U07.1	COVID-19, virus identified (lab confirmed)	Confirmed

Tables 4 and 5: Value Sets

	ICD-10 Codes
Table 4 - ICD-10 Antibiotic Always or Potentially Appropriate	See Supplemental Materials
Table 5 - ICD-10 Steroids Always or Potentially Appropriate	See Supplemental Materials

If the index claim does not contain an antibiotic (steroid) appropriate diagnosis code and an antibiotic (steroid) was prescribed within 3 days, then it is treated as an inappropriate antibiotic (steroid) prescription.