Methods. This was a retrospective review of central-line-associated bloodstream infections (CLABSI), catheter-associated urinary tract infections (CAUTI), C. difficile infections (CDI), and ventilator-associated events (VAE) in 51 hospitals from 2018 to 2021. Descriptive statistics were reported as mean hospital-level monthly incidence rates (IR) and compared using Poisson regression GEE models with period as the only covariate. Segmented regression (SR) analysis was performed to estimate changes in monthly IR of CLABSI, CAUTI, CLABSI and CDI in the baseline period (01/2018 – 02/2020) and the Pandemic period (03/2020 – 03/2021). SR model was not appropriate for VAE based on the plot. All models were constructed using SAS v.9.4 (SAS Institute, Cary NC).

Results. Compared to the baseline period, CLABSI increased significantly by 50% from 0.6 to 0.9/1000 catheter days (P< 0.001). In contrast, no significant changes were identified for CAUTI (P=0.87). Similar trends were seen in SR models for CLABSI and CAUTI (Figures 1, 2 and Table 1). While overall CDIs decreased significantly from 3.5 to 2.5/10,000 patient days in the pandemic period (P< 0.001), SR model showed increasing pandemic trend change (Figure 3). VAEs increased >700% from 6.9 to 59.7/1000 ventilator days (P<0.015), but displayed considerable variation during the pandemic period (Figure 4). Compared to baseline period, there was a significant increase in central line days (647 vs 677, P=0.02), ventilator days (156 vs 215, P< 0.001), but no change in urinary catheter days (675 vs 686, P=0.32) during the pandemic period.

Figure 1: Segmented Regression model showing baseline and pandemic period trends of CLABSI

Figure 2: Segmented Regression model showing baseline and pandemic period trends of CAUTI

Figure 3: Segmented Regression model showing baseline and pandemic period trends of C. difficile (HO-CDI) infections

Conclusion. The COVID-19 pandemic was associated with substantial increases in CLABSI and VAEs, no change in CAUTI, and an increasing trend in CDI incidence. These variations in trends of different HAI are likely due, in part, to unique characteristics of the underlying infection, resource shortages, staffing concerns, increased device use, changes in testing practices, and the limitations of surveillance definitions.

Figure 4: Trend of Ventilator-Associated Events (VAE) in the baseline and pandemic period (Segmented Regression model not appropriate)

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173. Deciphering COVID-19-Associated Effects on Hospital MRSA Transmission and Social Networks

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Background. The COVID-19 pandemic was associated with a significant (28%) reduction of methicillin-resistant Staphylococcus aureus (MRSA) acquisition at UVA Hospital (P=0.016). This “natural experiment” allowed us to analyze 3 key mechanisms by which the pandemic may have influenced nosocomial transmission: 1) enhanced infection control measures (i.e., barrier precautions and hand hygiene), 2) patient-level risk factors, and 3) networks of healthcare personnel (HCP)-mediated contacts.

Figure 1. Monthly MRSA Acquisition Rates Pre- and Post-COVID-19
Hospital MRSA acquisition was defined as a new clinical or surveillance positive in patients with prior unknown or negative MRSA status occurring >72h after admission. 10 month time periods pre- (5/6/2019 to 2/23/2020) and post-COVID-19 (5/4/2020 to 2/28/2021) were chosen to mitigate the effects of seasonality. A 6-week wash-in period was utilized coinciding with the onset of several major hospital-wide infection control measures (opening of 2 special pathogen units with universal contact/airborne precautions on 4/21/21 and 5/1/21, universal mask 4/10/21 and eye protection 4/20/20 policies instituted along with staff education efforts including the importance of standard precautions). Box and whisker plots depict quartile ranges, median (dotted line), and mean values. Mean MRSA acquisition rates pre- (0.92 events per 1,000 patient days) significantly declined post-COVID-19 (to 0.66; P=0.016). Independent-samples t tests were used (2-tailed) for statistical comparisons except for variables without a normal distribution (Shorr Scores), for which a Mann-Whitney U test was used.

Methods. Census-adjusted hospital-acquired MRSA acquisition events were analyzed over 10 months pre- (5/6/2019 to 2/23/2020) and post-COVID-19 (5/4/2020 to 2/28/2021), with a 6-week wash-in period coinciding with hospital-wide intensification of infection control measures (e.g., universal masking). HCP hand hygiene compliance rates were examined to reflect adherence to infection control practices. To examine impacts of non-infection control measures on MRSA transmission, we analyzed pre/post-COVID-19 differences in individual risk profiles for MRSA acquisition as well as a broad suite of properties of the hospital social network using person-location and person-person interactions inferred from the electronic medical record.

Results. Hand hygiene compliance significantly improved post-COVID-19, in parallel with other infection control measures. Patient Shorr Scores (an index of individual MRSA risk) were statistically similar pre-/post-COVID-19. Analysis of various network properties demonstrated no trends to suggest a reduced outbreak threshold post-COVID-19.

Figure 2. Social Network Construction

We constructed a contact network of hospitalized patients and staff at University of Virginia Hospital to analyze the properties of both person-location and person-person networks and their changes pre- and post-COVID-19. Colocation data (inferred from shared patient rooms and healthcare personnel (HCP)-patient interactions recorded in the electronic health record, e.g., medication administration) were used to construct contact networks, with nodes representing patients and HCP, and edges representing contacts. The above schematic shows how the temporal networks are inferred. In the figure, circles represent patients and the small filled squares represent HCP, while the larger rectangles represent patient rooms. The first room is a shared room with two patients. At each time step, co-location is inferred from the EMR data, which specifies interactions between HCP and patients. This can be represented as the temporal network (t) at the bottom.

Analysis of hospital-wide hand hygiene auditing data (anonymous auditors deployed to various units across UVA Hospital with an average 1,710 observations per month (range 340 - 7,187)) demonstrated a statistically significant (6%) improvement in average monthly hand hygiene compliance (86.9% pre- versus 93.1% post-COVID-19; P=0.008).

Figure 3. Hand Hygiene Compliance Rates

We calculated the Shorr Score (a validated tool to estimate individual risk for MRSA carriage in hospitalized patients; Shorr et al. Arch Intern Med. 2008;168(20):2205-10) for patients using data from the electronic health record to test the hypothesis that individual risk factors in aggregate did not change significantly in the post-COVID-19 period to explain changes in MRSA acquisition. Values for this score ranged from 0 to 10 with the following criteria: recent hospitalization (4), nursing home residence (3), hemodialysis (2), ICU admission (1). Pictured are frequency distributions of Shorr scores in the pre-COVID-19 and post-COVID-19 periods. The Mann-Whitney effect size (E), 0.53 (P=0.51), indicated that pre- and post-COVID-19 distributions were very similar.
We analyzed three major types of network properties for this analysis: (1) Node properties of the pre- and post-COVID-19 networks consisted of all the edges in the pre- and post-COVID-19 periods, respectively. We considered a number of standard properties used in social network analysis to quantify opportunities for patient-patient transmission: degree centrality (links held by each node), betweenness centrality (times each node acts as the shortest ‘bridge’ between two other nodes), closeness centrality (how close each node is to other nodes in network), Eigenvector centrality (node’s relative influence on the network), and clustering coefficient (degree to which nodes cluster together) in the first five panels (left to right, top to bottom). (Newman, Networks: An Introduction, 2010). Each panel shows the frequency distributions of these properties. These properties generally did not have a normal distribution and therefore we used a Mann Whitney U test on random subsets of nodes in these networks to compare pre- and post-COVID properties. The mean effect size ($E$) and $P$-values are shown for each metric in parenthesis. We concluded that all of these pre- versus post-COVID-19 network properties were statistically similar. (2) Properties of the ego networks (networks induced by each node and its ‘one-hop’ neighbors). We considered density (average number of neighbors for each node; higher density generally favors lower outbreak threshold) and degree centrality (number of links held by each node) of ego networks (middle right and bottom left panels). The mean effect size and $P$-values using the Mann Whitney test are shown in parenthesis; there were no statistically significant differences in these properties in the pre- and post-COVID networks. (3) Aggregate properties of the weekly networks, consisting of all the interactions within a week. We considered modularity (measure of how the community structure differs from a random network; higher modularity means a stronger community structure and lower likelihood of transmission) and density (average number of neighbors each node; higher density generally favors lower outbreak threshold) and degree centrality (number of links held by each node) of the weekly networks (bottom middle and bottom right panels). The modularity in the post-COVID weekly networks was slightly lower (i.e., it has a weaker community structure, and the network is more well mixed), while density was slightly higher, the differences of which were statistically significant; a caveat is that these are relatively small datasets (about 40 weeks). These differences (higher density, and better connectivity) both increase the risk of transmission in the post-COVID networks. In summary, the post-COVID network properties were statistically similar. (2) Properties of the ego networks (networks induced by each node and its ‘one-hop’ neighbors). We considered density (average number of neighbors for each node; higher density generally favors lower outbreak threshold) and degree centrality (number of links held by each node) of ego networks (middle right and bottom left panels). The mean effect size and $P$-values using the Mann Whitney test are shown in parenthesis; there were no statistically significant differences in these properties in the pre- and post-COVID networks. (3) Aggregate properties of the weekly networks, consisting of all the interactions within a week. 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