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RESEARCH ARTICLE

Racial Disparities in Telemedicine Uptake during the COVID-19 Pandemic among Patients with Hematologic Malignancies in the United States

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ABSTRACT:

Background: The COVID-19 pandemic impacted healthcare visit trends, transitioning care to utilize telemedicine. We aimed to investigate if the uptake in telemedicine during pandemic was equitable across racial groups for patients with hematologic malignancies.

Methods: Using the nationwide Flatiron Health electronic health record (EHR)-derived de-identified database we analyzed patients with diagnosis of acute myelogenous leukemia (AML), diffuse large B-cell lymphoma (DLBCL), follicular lymphoma (FL), mantle cell lymphoma (MCL), chronic lymphocytic leukemia (CLL) or multiple myeloma (MM). Patients were categorized into treatment types within lines of therapy: outpatient (oral therapy and outpatient infusions combined with oral therapy) vs. inpatient treatments (chemotherapy, cellular therapy). Monthly visit rates were calculated as the number of visits (telemedicine or in-person [in-clinic treatment administration, vitals, and/or labs]) per active patient per 30-day standardized month. We used time-series forecasting methods on pre-pandemic monthly visit rate data (March 2016 - February 2020) to estimate projected counterfactual monthly visit rates between March 2020 - February 2021. Telemedicine uptake was descriptively analyzed over time (t).

Results: We included 18,924 active patients (2,394 Black and 16,530 White) and 884,504 visits (117,673 Black and 766,831 White). 4,053 AML, 3,468 diffuse large B cell lymphoma, 1,943 follicular lymphoma, 2,151 mantle cell lymphoma, 5,926 chronic lymphocytic leukemia and 7,752 myeloma patients. Black patients had no significant reductions in in-person visit rates throughout the pandemic period compared to the projected rates. Conversely, White patients experienced an 18% (95% PI 9.9% - 25%) lower rate of in-person visits for outpatient therapy during the early pandemic (March - May 2020) (actual monthly visit rate 1.61; projected visit rate 2.0 [95% CI 1.8-2.2]). Telemedicine uptake was significantly higher for White patients compared with Black patients for all diseases and treatment categories between March 2020-February 2021 (t = 9.5, p < 0.01), AML inpatient (t = 2.4, p = 0.04), MM outpatient (Figure 3C) (t = 6.0, p < 0.01) and MM inpatient treatment categories (Figure 3D) (t = 2.3, p = 0.04).

Conclusions: White patients had significantly higher telemedicine uptake compared with Black patients for all treatment categories. These findings challenge healthcare systems to direct efforts toward reducing the gap in healthcare access.

Introduction

Telemedicine technology and its use became prevalent during the COVID-19 pandemic. Telemedicine is an important tool in delivering services while keeping patients safe during the outbreak. Differences in telemedicine usage trends across racial groups need to be further elucidated and more studies are needed in oncology. Technology has the potential to improve the health and quality of life of diverse populations and may play a significant role in addressing health disparities. Concerns have been raised regarding the inequities in healthcare access. Multiple lines of evidence have indicated racial inequities in diagnosis and treatment of many health conditions, including cancer; and these inequities may be exacerbated by the lack of access to technology.^{1, 2}

There have been reported inequities in healthcare technology utilization among racial and ethnic groups during the pre-COVID-19 pandemic period. Prior studies have demonstrated lower utilization of technology for health-related purposes among Black and Hispanic patients in a general population, and among Black patients with head and neck cancers.^{3, 4} The Health Information National Trends Survey demonstrated that the implementation of communication technology was relatively high across Black, Indigenous, People of Color (BIPOC) groups, its use seemed to play distinctive roles in different racial/ethnic populations. The internet and patient portals showed no associations with patient-clinician communication except for Black internet users who reported poorer experiences with patient-clinician communication than non-users.⁵

A cross-sectional study evaluating mental telehealth services in the United States reported that while there were no differences in the availability of mental telehealth based on the prospective patient's clinical condition, perceived race or ethnicity, or sex; the differences were found at the facility-, county-, and state-level. These data indicated pervasive disparities in access to telehealth services.⁶ Another study revealed that Black patients had less participation in telehealth visits, proposing basic structural disparities in access to digital health. Black participants reported absence of internet access more frequently as compared with White patients.⁷ Different modalities of remote healthcare are extremely important specifically in oncology care. A recent study describing utilization of telehealth highlighted that ongoing support for telehealth and audio-only visits, is essential in overcoming health disparities especially for those patients without access to

technology like computers and smartphones. Similarly, utilization of telehealth in clinical trials and more prevalent acceptance of hospital at home programs, electronic consults for speedy access to care, and other innovative interventions are essential in making cancer care more equitable and efficient.⁸

The COVID-19 pandemic may have widened the gap in access to healthcare across different socioeconomic groups.⁹ As the pandemic introduced a rise in telemedicine use in oncology clinics to minimize in-person visits as a part of early safety precautions, this uptake could have been unequal among patients from different racial and societal backgrounds. The use of telemedicine to avoid COVID-19 risk is particularly important because the pandemic had disproportionately worse clinical outcomes for Black patients with COVID-19,¹⁰ and worse clinical outcomes for patients with hematologic malignancies.¹¹ Choice of treatment types were important factors to consider during the pandemic. Prioritizing outpatient treatments over high intensity inpatient treatments if clinically appropriate and decreasing in-person visits in the early pandemic were considered as part of mitigating COVID risk in these vulnerable populations. Our study aimed to assess potential racial disparities in-person visits and telemedicine use during the very early COVID pandemic in 2020 and through the subsequent year for patients with documented active treatment for hematologic malignancies.

Methods

DATA SOURCE

We used the nationwide Flatiron Health electronic health record (EHR)-derived de-identified database to select patients with confirmed diagnosis AML, CML, CLL, DLBCL, FL, MCL or MM, at least 18 years old at initial diagnosis, and documented race in the EHR as Black/African American or White. The dataset generated for the study includes all retrospective patient-level data available for eligible patients up to the data cutoff date of April 30, 2021. Data of interest to this study includes visits between March 1, 2016 and February 28, 2021, to cover the following two time periods: (1) 60-month span preceding the declaration of the COVID-19 pandemic as a public health crisis (March 1, 2016 to February 28, 2020) and (2) 12-month span following the declaration of the COVID-19 pandemic as a public health crisis (March 1, 2020 to February 28, 2021).

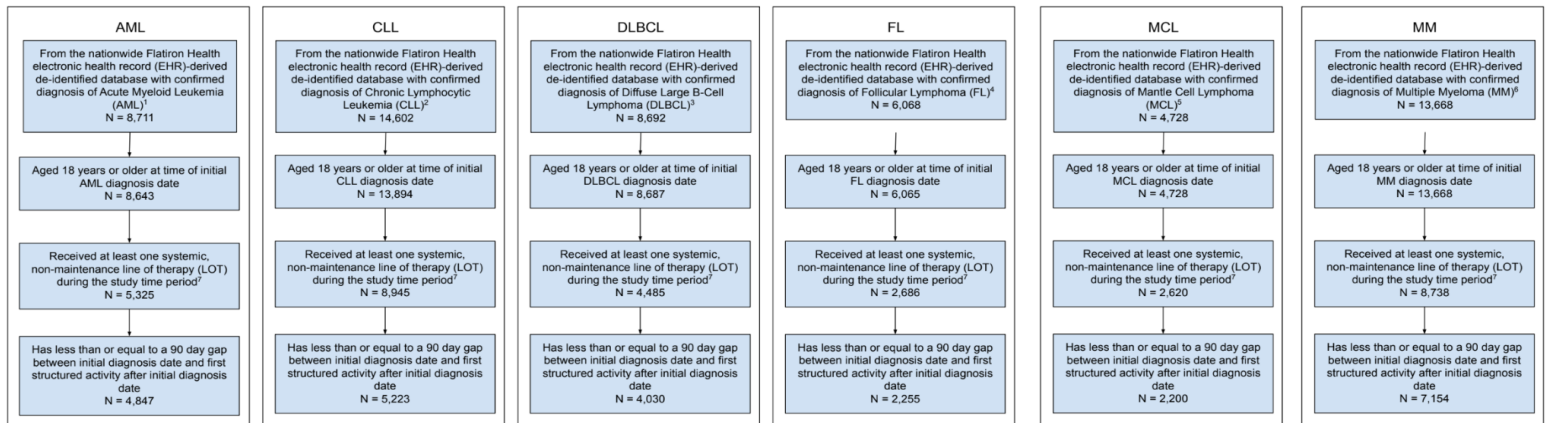
STUDY SAMPLE

Patient cohort was stratified into disease subgroups based on the following inclusion criteria: (1)

confirmed diagnosis of AML, CLL, DLBCL, FL, MCL, and/or MM; (2) aged 18 years or older at time of initial diagnosis; (3) received at least one systemic, non-maintenance line of therapy (LOT) during the study period. Patients were excluded if they had greater than 90 days between their initial diagnosis

date and first subsequent structured activity. We further excluded visits that occurred outside of study period and in periods during which patients were not on active treatment. See Figure 1 for CONSORT diagram detailing attrition at each criterion.

Figure 1: CONSORT diagram
Drawing



Footnotes:

1. AML patients met the following criteria: (1) Has an ICD diagnosis code of Acute Myeloid Leukemia (AML) [ICD 9: 205.0x, 205.9x, 206.0x, 207.0x, 207.2x; ICD 10: C92.0x, C92.4x, C92.5x, C92.6x, C92.9x, C92.Ax, C93.0x, C94.0x, C94.2x, C94.4x]; (2) Has at least two documented clinical visits, on different days, occurring on or after January 1, 2011; (3) Included in probabilistic sample of patients queued for confirmation of AML diagnosis via abstraction; (4) Has evidence of AML with an initial diagnosis date on or after January 1, 2014
2. CLL patients met the following criteria: (1) Has an ICD diagnosis code of Chronic Lymphocytic Leukemia (CLL) [ICD-9: 204.1x or ICD-10: C91.1x, C83.0x]; (2) Has at least two documented clinical visits, on different days, occurring on or after January 1, 2011; (3) Has at least one order for an antineoplastic occurring on or after January 1, 2011; (4) Included in probabilistic sample of patients queued for confirmation of CLL diagnosis via abstraction; (5) Has physician documentation of CLL and evidence in unstructured documents of having been treated specifically for CLL
3. DLBCL patients met the following criteria: (1) Has an ICD diagnosis code of Non-Hodgkin's Lymphoma (NHL) [ICD 9: 202.0x, 202x; ICD 10: C82x, C83x, C84x, C85x, C86x, C88x, C89x]; (2) Has at least two documented clinical visits, on different days, occurring on or after January 1, 2011; (3) Included in probabilistic sample of patients queued for confirmation of DLBCL diagnosis via abstraction; (4) Has evidence of DLBCL with an initial diagnosis date on or after January 1, 2011
4. FL patients met the following criteria: (1) Has an ICD diagnosis code of NHL; (2) Has at least two documented clinical visits, on different days, occurring on or after January 1, 2011; (3) Included in probabilistic sample of patients queued for confirmation of FL diagnosis via abstraction; (4) Has evidence of FL with an initial diagnosis date on or after January 1, 2011
5. MCL patients met the following criteria: (1) Has an ICD diagnosis code of NHL; (2) Has at least two documented clinical visits, on different days, occurring on or after January 1, 2011; (3) Included in probabilistic sample of patients queued for confirmation of MCL diagnosis via abstraction; (4) Has evidence of MCL with an initial diagnosis date on or after January 1, 2011
6. MM patients met the following criteria: (1) Has an ICD diagnosis code of Multiple Myeloma (MM) [ICD-9 203.0x or ICD-10 C90.0x, C90]; (2) Has at least two documented clinical visits, on different days, occurring on or after January 1, 2011; (3) Included in probabilistic sample of patients queued for confirmation of MM diagnosis via abstraction; (4) Has evidence of MM with an initial diagnosis date on or after January 1, 2011
7. The study period ran from March 1, 2016 to February 28, 2021.

OUTCOME VARIABLES

This study had two main outcome measures of interest: monthly standardized 30 patient-day rates of (1) in-person visits and (2) telemedicine visits. In-person (telemedicine) visit rates were calculated as the number of in-person (telemedicine) visits per 30 active patient-days. Active patient-days were defined as the number of active patients (i.e. patients receiving systemic therapy at the time) in a given month divided by the number of days in that calendar month.

OTHER KEY VARIABLES

The full cohort was stratified into subgroups by disease (AML, CLL, FL, DLBCL, MCL, MM), treatment type (Outpatient, Inpatient), race (White vs. Black), and region (West, Northeast, South, Midwest) for analyses.

Patient visits were categorized into two treatment types: (1) outpatient, defined as outpatient treatments and time limited infusional treatments taken in combination with orals, and (2) inpatient, defined as inpatient infusional treatments including bone marrow transplant (BMT) and chimeric antigen T cells (CAR-T). The allowed treatments/regimens per treatment type were unique to each disease.

Each patient's LOT was first categorized into a treatment type based on the therapies received during their LOT. If the LOT included outpatient and inpatient combination treatment, the LOT was considered an inpatient. If an active patient spanned across two treatment types in a given month (e.g. patient starts as outpatient and switched to inpatient halfway through the calendar month), the patient was mapped to the higher intensity treatment type for the whole month (inpatient in this example). Active patients were defined as patients who were on a systemic, non-maintenance LOT for at least one day during the given month.

STATISTICAL ANALYSIS

Telemedicine visit rates

We descriptively calculated the time series of monthly standardized 30 patient-day rates of telemedicine visits stratified by disease, race, and treatment type.

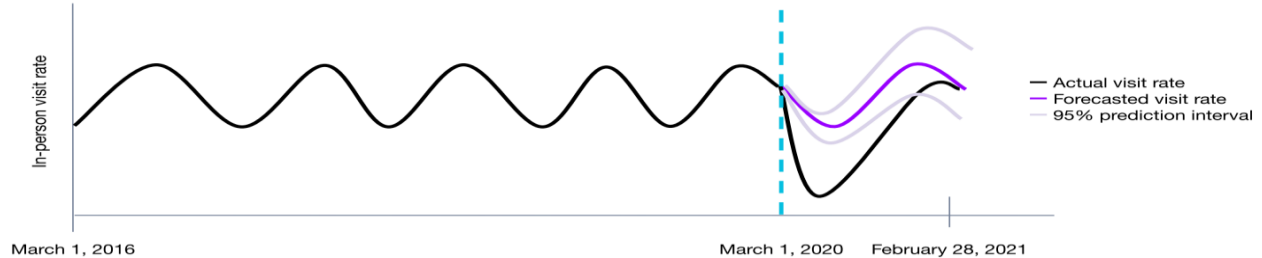
In-person visit rates

To assess differences for in-person visit rates by race, we first calculated average in-person visit rates prior to and during the pandemic to describe trends in care. Time series forecasting via Autoregressive Integrated Moving Average (ARIMA) models was then used to measure the

impact of the pandemic on monthly standardized 30 patient-day in-person visit rates. ARIMA models were fitted to pre-pandemic data (March 2016 - February 2020) and used to predict in-person visit rates during the pandemic period (March 2020 -

February 2021). In this model historical monthly visit rates are used to predict future monthly visit rates (see Figure 2). For more information on ARIMA, please see supplemental section 1.

Figure 2: Methods: ARIMA demo
[Drawing](#)



Cross-correlation analysis

To determine any statistical differences between two time series of visit rates for White and Black patients, cross-correlation analysis was performed for each disease, visit type, region, and treatment type stratification.

Black and 16,530 /87.3% White) and 884,504 visits (117,673 Black and 766,831 White) included in the study. Age was similarly distributed between 50-64-year-olds, 65-74-year-olds and 75+-year-olds for both Black and White patients. Gender was evenly balanced for Black patients while there were more Male White patients (60%) (Table 1). See Table 2 for a breakdown of patient-visits by disease, treatment type, and race.

Results

There were 18,924 active patients (2,394 /12.7%

Table 1: Patient Characteristics

	Black or African American N = 2,417	White N = 16,788
Age at initial diagnosis		
≤49	274 (11%)	1,129 (7%)
50-64	848 (35%)	4,693 (28%)
65-74	777 (32%)	5,727 (34%)
75+	518 (22%)	5,239 (31%)
Gender		
Male	1,217 (50%)	6,743 (40%)
Female	1,200 (50%)	10,043 (60%)
Unknown	< 5 (< 1%)	< 5 (< 1%)

Note: Some patients have multiple hematological malignancies and thus have different ages at initial diagnosis depending on the disease. These patients are counted multiple times for this characteristic, resulting in a total N for this characteristic that is greater than the total N in the cohort.

Table 2: Number of patient-visits by disease and treatment type

Treatment Type	Visit Type	Race	Overall (N = 25,293)	AML (N = 4,053)	CLL (N = 5,926)	DLBCL (N = 3,468)	FL (N = 1,943)	MCL (N = 2,151)	MM (N = 7,752)
Outpatient	In-Person	Black or African American	1,655 (6.5%)	36 (< 1%)	361 (6.2%)	14 (< 1%)	8 (< 1%)	24 (1.1%)	1,212 (15.6%)
		White	7,992 (31.6%)	395 (9.7%)	2,569 (43.4%)	169 (4.9%)	91 (4.7%)	578 (26.9%)	4,190 (54.1%)
	Telemedicine	Black or African American	235 (< 1%)	< 5 (< 1%)	65 (1.1%)	NA	NA	1 (< 1%)	166 (2.1%)
		White	1,235 (4.9%)	44 (1.1%)	497 (8.4%)	21 (< 1%)	12 (< 1%)	75 (3.5%)	586 (7.6%)
Inpatient	In-Person	Black or African American	1,200 (4.7%)	283 (7%)	207 (3.5%)	239 (6.9%)	111 (5.7%)	58 (2.7%)	302 (3.9%)
		White	11,650 (46.1%)	2,983 (73.6%)	1,983 (33.5%)	2,594 (74.8%)	1,532 (78.8%)	1,334 (62%)	1,224 (15.8%)
	Telemedicine	Black or African American	117 (< 1%)	34 (< 1%)	18 (< 1%)	35 (1%)	13 (< 1%)	2 (< 1%)	15 (< 1%)
		White	1,209 (4.8%)	275 (6.8%)	226 (3.8%)	396 (11.4%)	176 (9.1%)	79 (3.7%)	57 (< 1%)

Notes: Some patients may have more than one disease, treatment type, and/or visit type and may therefore be counted multiple times in these estimates; Percentages are calculated out of the total number of patients in the disease/overall

Telemedicine uptake trends are similar between Black and White patients in early pandemic months, however there is more persistent uptake among White patients compared to Black patients in later pandemic months. This trend exists across different treatment types as well (Supplementary Table 1).

Telemedicine uptake was significantly higher for White patients compared to Black patients for all diseases combined across both treatment types (Outpatients: $t = 9.0, p < 0.01$; Inpatients: $t = 8.6, p < 0.001$), for AML Inpatients ($t = 3.1, p = 0.01$), and for MM Outpatients ($t = 5.8, p = < 0.01$) (Table 3 and Figure 3).

Table 3: Cross-correlation analysis between telemedicine visit rates for Black vs. White patients

Disease	Treatment Type	White	Black	Difference	P-value
Overall	outpatient	0.07	0.06	0.01	< 0.01
	inpatients	0.05	0.05	0	< 0.01
AML	outpatient	0.15	0.64	-0.48	0.42
	inpatients	0.08	0.07	0.01	0.01
CLL	outpatient	0.06	0.05	0.01	< 0.01
	inpatients	0.04	0.04	0	0.16
DLBCL	outpatient	0.07	0	0.07	0.01
	inpatients	0.05	0.04	0.01	0.01
FL	outpatient	0.07	0	0.07	0.64
	inpatients	0.04	0.06	-0.02	0.06
MCL	outpatient	0.07	0.10	-0.03	0.10
	inpatients	0.04	0.11	-0.07	0.07
MM	outpatient	0.08	0.07	0.01	< 0.01
	inpatients	0.06	0.05	0.01	< 0.01

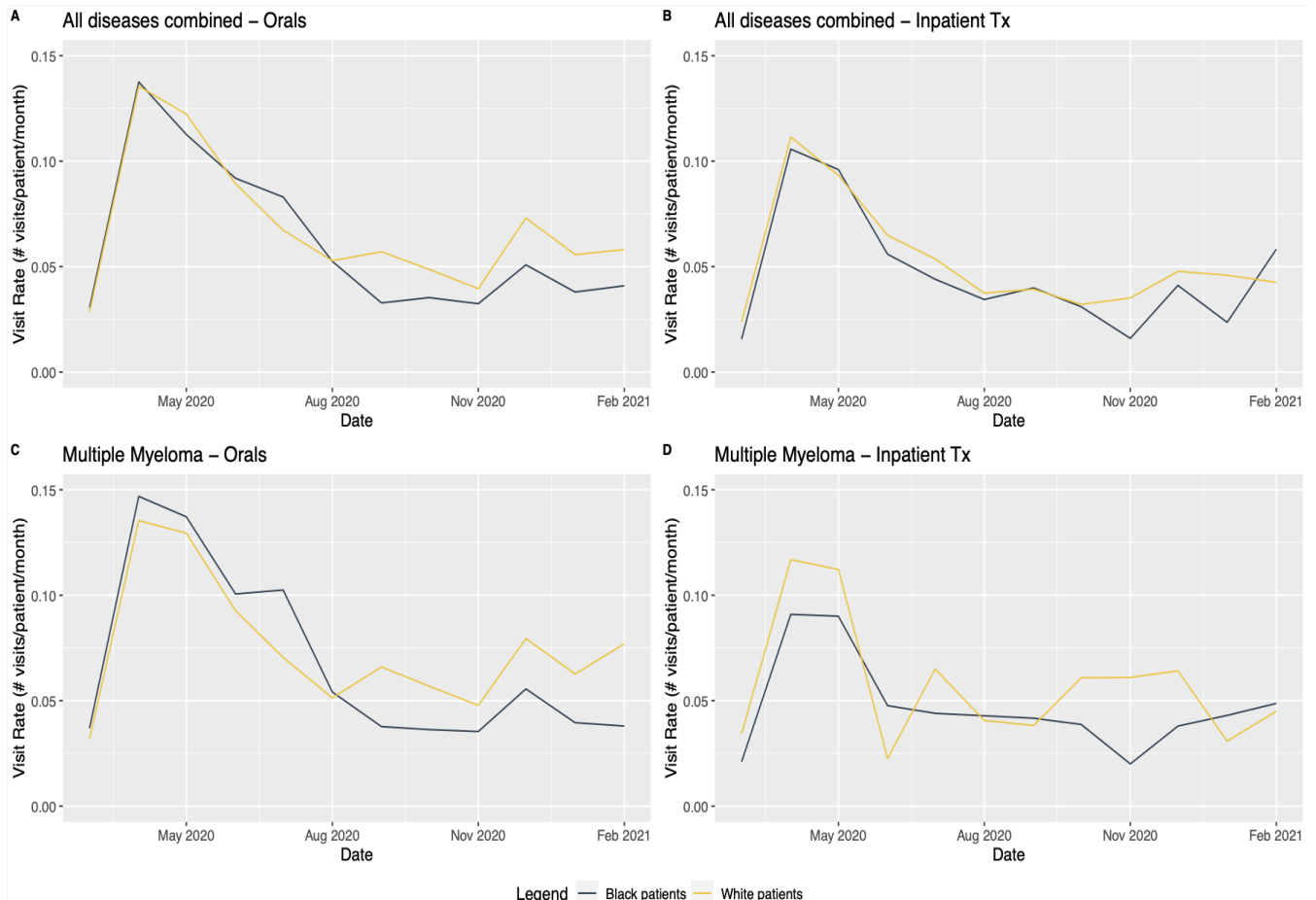


Figure 3: Telemedicine visit rates over time over all disease and MM, by Race

When broken down by region, we found significant differences in telemedicine visit rates between Black and White patients for all diseases combined for Outpatients in the Midwest, Northeast and South. Inpatients had significant differences between races in the Northeast and South. Finally, there were significant differences in telemedicine visit uptake between Black and White MM Outpatients across all regions and Inpatients in the South (Supplementary Table 2).

IN-PERSON VISIT RATES

There was a significant reduction of 16% (95% CI [7%- 24%]) in in-person visit rates for White patients over all diseases combined for Outpatients in early pandemic months (March - May, 2020). The projected average in-person visit rate was 2.0 (95% CI 1.8 - 2.2) visits per patient per month; the actual in-person visit rate was 1.7 visits per patient per month. However, there was no significant reduction in in-person visit rates compared to projected rates among White patients in the Inpatients treatment group (Supplementary Table 3).

On the contrary, there were no significant reductions in in-person visit rates compared to the projected in-person visit rates for Black patients for either treatment type during the pandemic. Black patients had in-person visits during the pandemic about as often as they were forecasted to do if there was no pandemic. Finally, we did not find significant differences by racial group for forecasted and actual in-person visit rates - therefore the impact of the COVID-19 pandemic on overall total visit rates (in-person + telemedicine visits) was similar for both Black and White patients with a higher uptake of telemedicine visits among Whites.

Discussion

The COVID-19 pandemic rapidly triggered application of telemedicine in oncology clinics. Telemedicine visits in cancer care intended to decrease the risk of COVID exposure while maintaining normal frequencies of treatment visits. Our study evaluated telemedicine utilization inequity among patients from different racial groups. We demonstrated that Black patients had relatively more in-person visits in comparison to White patients during the pandemic period, as well as relatively less use of telemedicine. We observed telemedicine uptake was significantly greater in White patients compared to the Black patients with hematologic malignancies. The trends in uptake in telemedicine utilization over time among White patients coincided with a significant decrease in in-person visits for White outpatients (but not for in-

person visits for White inpatients). In the early pandemic months, there was a decrease in overall visits and similar uptake in telemedicine visits for both Black and White patients. However, telemedicine visits decreased overtime, with more persistent use among White patients compared to Black patients.

Our sample reasonably represents the expected general demographics of the US population with hematologic malignancies. Evaluation of telemedicine visit uptake across the different treatment categories (outpatient oral/infusional vs inpatient) is the strength of our study. Overall, we observed that there was no significant reduction in in-person visits for Black patients (outpatients and inpatients) during the entire pandemic period compared to the expected in-person counterfactual visit rates. These findings underscore inequities in telemedicine visits for cancer care among a vulnerable population of Black patients with hematologic malignancies, who are disproportionately at higher risk for poor clinical outcomes with COVID-19. Given the higher risk of COVID-19 mortality, this same population of patients would have benefited from reduction in-person visits if substitution with a telemedicine visit is appropriate, particularly for outpatient.

Similar racial differences in telemedicine visit uptake were observed by disease type. Among MM outpatients receiving treatment regimens, higher use of telemedicine visits was observed in Whites as compared with Blacks, and among AML inpatients. Large number of the available oral treatment options in MM likely explain the high uptake of telemedicine visits in this disease group. When assessed by US region we found significant differences in telemedicine visit rates between Black and White outpatients for all diseases combined in the Midwest, Northeast and South. In the Northeast and South there were significant differences between races among inpatients. Regional insurance coverage requirements in each state may have influenced the degree of telemedicine utilization for certain patients.

Findings of our study align with other published experiences. Namely, during the COVID-19 pandemic, electronic health record review from New York University Langone study reported that Black patients had 0.6 times the adjusted odds (95% CI: 0.58-0.63) of accessing care through telemedicine visits compared to Whites.¹² Another study revealed inequities in video-visit use by race, ethnicity and other demographic factors.¹³ When evaluating inequities in healthcare technology access through telephone interviews,

patients were acutely aware of the “digital divide” and described influences beyond health care, including employment, education, community and social contexts, and personal economic stability.¹⁴ A study of telemedicine technologies among Medicare beneficiaries revealed that compared with other racial groups, Black patients experienced the lowest rate of increase in telemedicine availability during the pandemic.¹⁵ Our study provides insights on inequities in telemedicine visit uptake among patients with different hematologic cancers receiving diverse types of treatments across various geographic regions in US during the critical time of early pandemic.

These findings highlight the concept of digital divide in healthcare across diverse societal layers.

Notably, greater than 50% of the population in our cohort was represented by individuals over age 65, implying that digital health solutions may not be tailored to elderly. A plausible explanation for our findings is inequitable access to technologies like broadband adoption, computer ownership and digital literacy especially among older patients. Patient’s computer literacy and their access to healthcare technologies could be a surrogate indicator of their socioeconomic status; and this feature may highlight the areas with persistent poverty in regions with larger proportions of BIPOC residents. However, there may be a missing context needed to understand these differences beyond simply access to technology as a barrier to care.

This digital divide may explain impacts beyond health care, including employment, education, community and social contexts, and personal economic stability. Proposed solutions to address the divide include conducting community technology needs evaluation and enhancing technology access, literacy training, and resource awareness. More research is needed to evaluate how introduction of digital technology can be harnessed to reduce healthcare inequities. Healthcare system and medical societies in US must channel more resources toward extending high-quality professional health services and research into the domain of minority populations, to reduce the gap in healthcare access and improve health equity.

Our study has several limitations. In observational real-world studies, there is expected missingness, patients lost to follow up, and potential miscategorization of lines of therapy in the documented notes. Race is a social construct and we cannot specifically measure the social factors implicated in low telemedicine visit rates in different racial groups. Time series forecasting with ARIMA model may pose difficulty in predicting turning points. There is also substantial subjectivity involved in determining order of the model and it may have poorer performance for long term forecasts over the years. Our telemedicine visit variable does not distinguish telemedicine video visit versus an audio only telephone visit.

Conclusion

In this retrospective observational study reductions in in-person visits and uptake of telemedicine visits were observed among patients with hematologic malignancies during the early COVID-19 pandemic. White patients had significantly higher telemedicine visit uptake compared with Black patients for both outpatient and inpatient treatments. In-person visit rates reflect documented telemedicine use inequities, which requires further study into possible compound causes, including economic and societal factors.

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NN, GG and ES designed the study, performed research and wrote the paper.

KL performed research, analyzed data and wrote paper.

NN, GG, ES and KL contributed to the study design, data analysis. All authors contributed to the edits and writing of the paper.

Disclosures:

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References:

1. Siegel RL, Miller KD, Jemal A. Cancer statistics, 2019. *CA Cancer J Clin.* Jan 2019;69(1):7-34. doi:10.3322/caac.21551
2. Patt DA, Wilfong L, Toth S, et al. Telemedicine in Community Cancer Care: How Technology Helps Patients With Cancer Navigate a Pandemic. *JCO Oncol Pract.* Jan 2021;17(1):e11-e15. doi:10.1200/OP.20.00815
3. Mitchell UA, Chebli PG, Ruggiero L, Muramatsu N. The Digital Divide in Health-Related Technology Use: The Significance of Race/Ethnicity. *Gerontologist.* Jan 9 2019;59(1):6-14. doi:10.1093/geront/gny138
4. Jella TK, Cwalina TB, Sachdev RR, Otteson T, Fowler N. Sociodemographic disparities in the use of health information technology by a national sample of head and neck cancer patients. *Am J Otolaryngol.* Mar-Apr 2022;43(2):103308. doi:10.1016/j.amjoto.2021.103308
5. Kim HS, Kim HJ, Juon HS. Racial/Ethnic Disparities in Patient-Provider Communication and the Role of E-Health Use. *J Health Commun.* Mar 4 2021;26(3):194-203. doi:10.1080/10810730.2021.1919248
6. Cantor J, Schuler MS, Matthews S. Availability of Mental Telehealth Services in the US. *JAMA Health Forum.* 2024 Feb 2;5(2):e235142.
7. Iasiello JA, Rajan A, Zervos E. Racial Differences in Patient-Reported Access to Telehealth: An Important and Unmeasured Social Determinant of Health. *JCO Oncol Pract.* 2023 Dec;19(12):1215-1223.
8. Thomas E, Kennedy A, Walsh W. Telehealth through the pandemic at a safety net hospital: observations and next steps for cancer care delivery. *Front Public Health.* 2023 Jun 2;11:1186350.
9. Masias Gil, Marcelin JR, Zuniga-Blanco B, et al. COVID-19 Pandemic: Disparate Health Impact on the Hispanic/Latinx Population in the United States. *J Infect. Dis.* 2020; 222(10):1592-1595.
10. Price-Haywood EG, Burton J, Fort D, Seoane L. Hospitalization and Mortality among Black Patients and White Patients with Covid-19. *N Engl J Med.* Jun 25 2020;382(26):2534-2543. doi:10.1056/NEJMsa2011686
11. Vijenthira A, Gong IY, Fox TA, et al. Outcomes of patients with hematologic malignancies and COVID-19: a systematic review and meta-analysis of 3377 patients. *Blood.* Dec 17 2020;136(25):2881-2892. doi:10.1182/blood.2020008824
12. Chunara R, Zhao Y, Chen J, et al. Telemedicine and healthcare disparities: a cohort study in a large healthcare system in New York City during COVID-19. *J Am Med Inform Assoc.* Jan 15 2021;28(1):33-41. doi:10.1093/jamia/ocaa217
13. Neeman E, Lyon L, Sun H, et al. Future of Teleoncology: Trends and Disparities in Telehealth and Secure Message Utilization in the COVID-19 Era. *JCO Clin Cancer Inform.* Mar 2022;6:e2100160. doi:10.1200/CCI.21.00160
14. Alkureishi MA, Choo ZY, Rahman A, et al. Digitally Disconnected: Qualitative Study of Patient Perspectives on the Digital Divide and Potential Solutions. *JMIR Hum Factors.* Dec 15 2021;8(4):e33364. doi:10.2196/33364
15. Jacobs M, Ellis C. Telemedicine disparities during COVID-19: Provider offering and individual technology availability. *J Am Geriatr Soc.* Sep 2021;69(9):2432-2434. doi:10.1111/jgs.17280

Supplemental Material

Supplemental Tables

Supplemental Table 1: Telemedicine visit rates early vs. late pandemic, Black vs. White patients by treatment type & disease

Disease	Treatment Type	Black		White	
		Early Pandemic (March 1, 2020 - May 31, 2020)	Late Pandemic (June 1, 2020 - February 28, 2021)	Early Pandemic (March 1, 2020 - May 31, 2020)	Late Pandemic (June 1, 2020 - February 28, 2021)
Overall	outpatient	0.09	0.05	0.10	0.06
	inpatients	0.07	0.04	0.08	0.04
AML	outpatient	0.32	0.73	0.18	0.13
	inpatients	0.08	0.06	0.12	0.07
CLL	outpatient	0.06	0.04	0.08	0.05
	inpatients	0.09	0.02	0.06	0.03
DLBCL	outpatient	NA	NA	0.10	0.06
	inpatients	0.07	0.03	0.07	0.04
FL	outpatient	NA	NA	0.10	0.06
	inpatients	0.12	0.05	0.06	0.03
MCL	outpatient	0.11	0.10	0.12	0.05
	inpatients	0.16	0.08	0.06	0.03
MM	outpatient	0.11	0.06	0.10	0.07
	inpatients	0.07	0.04	0.09	0.05

Supplemental Table 2A: Differences in telemedicine visit rates by region

Disease	Treatment Type	Region	White	Black	Difference	P-value
Overall	outpatient	Midwest	0.03	0.04	-0.01	< 0.01
		Northeast	0.12	0.14	-0.02	< 0.01
		South	0.03	0.03	0.00	< 0.01
		West	0.08	0.10	-0.02	0.05
	inpatients	Midwest	0.02	0.06	-0.04	0.59
		Northeast	0.10	0.12	-0.02	< 0.01
		South	0.02	0.02	0.00	0.02
		West	0.06	0.10	-0.04	0.61
AML	outpatient	Midwest	0.35	0.00	0.35	0.44
		Northeast	0.24	0.97	-0.73	0.39
		South	0.06	0.00	0.06	0.46
		West	0.13	0.00	0.13	0.81
	inpatients	Midwest	0.04	0.00	0.04	0.63
		Northeast	0.17	0.19	-0.02	0.01
		South	0.02	0.04	-0.02	0.34
		West	0.06	0.00	0.06	0.47
CLL	outpatient	Midwest	0.03	0.10	-0.07	< 0.01
		Northeast	0.10	0.10	0.00	0.26
		South	0.03	0.03	0.00	< 0.01
		West	0.08	0.19	-0.11	0.71
	inpatients	Midwest	0.03	0.15	-0.12	0.02
		Northeast	0.07	0.18	-0.11	0.13
		South	0.02	0.06	-0.04	0.48
		West	0.05	0.18	-0.13	0.49
DLBCL	outpatient	Midwest	0.23	0.00	0.23	0.13
		Northeast	0.13	0.00	0.13	0.67
		South	0.07	0.00	0.07	0.93
		West	0.45	0.00	0.45	0.21
	inpatients	Midwest	0.03	0.17	-0.14	0.66
		Northeast	0.08	0.10	-0.02	< 0.01
		South	0.03	0.03	0.00	< 0.01
		West	0.07	0.22	-0.15	0.63

Supplemental Table 2B: Differences in telemedicine visit rates by region

FL	outpatient	Midwest	0.20	0.00	0.20	0.51
		Northeast	0.10	0.00	0.10	0.76
		South	0.10	0.00	0.10	0.66
		West	0.40	0.00	0.40	0.80
	inpatients	Midwest	0.03	0.29	-0.26	0.83
		Northeast	0.08	0.32	-0.24	0.06
		South	0.02	0.04	-0.02	0.20
		West	0.06	0.00	0.06	0.82
MCL	outpatient	Midwest	0.06	0.00	0.06	0.61
		Northeast	0.11	0.26	-0.15	0.24
		South	0.03	0.00	0.03	0.92
		West	0.15	0.00	0.15	0.08
	inpatients	Midwest	0.05	0.00	0.05	0.31
		Northeast	0.07	0.42	-0.35	0.01
		South	0.02	0.22	-0.20	0.65
		West	0.07	0.00	0.07	0.69
MM	outpatient	Midwest	0.04	0.04	0.00	< 0.01
		Northeast	0.14	0.16	-0.02	< 0.01
		South	0.03	0.03	0.00	< 0.01
		West	0.08	0.11	-0.03	0.04
	inpatients	Midwest	0.04	0.33	-0.29	NA
		Northeast	0.09	0.08	0.01	< 0.01
		South	0.06	0.05	0.01	0.02
		West	0.08	0.50	-0.42	0.35

Notes: Since the time series for MM inpatients in the Midwest for Black and White patients were too short (i.e. insufficient sample size) to perform cross-correlation analyses, the p-value is recorded as NA.

Supplemental Table 3A: In-person visit rates pre vs. during pandemic over all diseases combined and by disease, treatment type, and race

Disease	Treatment Type	Race	Pre-Pandemic (March 1, 2016 - February 28, 2020)	During Pandemic (March 1, 2020 - February 28, 2021)
Overall	outpatient	Black	1.99	1.81
		White	1.98	1.72
	inpatients	Black	1.86	1.81
		White	2.10	1.87
AML	outpatient	Black	6.70	4.62
		White	4.34	3.42
	inpatients	Black	3.94	3.83
		White	5.05	4.63
CLL	outpatient	Black	0.94	0.94
		White	1.12	1.02
	inpatients	Black	0.87	0.88
		White	0.98	0.84
DLBCL	outpatient	Black	2.86	1.21
		White	1.72	1.65
	inpatients	Black	1.28	1.15
		White	1.37	1.19
FL	outpatient	Black	1.29	1.03
		White	1.53	1.36
	inpatients	Black	1.09	1.03
		White	1.22	1.12

Supplemental Table 3B: In-person visit rates pre vs. during pandemic over all diseases combined and by disease, treatment type, and race

MCL	outpatient	Black	0.97	1.34
		White	1.37	1.23
	inpatients	Black	2.39	2.78
		White	2.05	1.71
MM	outpatient	Black	2.36	2.22
		White	2.62	2.39
	inpatients	Black	1.62	1.36
		White	1.95	2.12

Supplemental Section 1:

ARIMA Methodology

ARIMA models use a linear combination of lagged observations (autoregression) and lagged errors (moving average) to forecast future observations. They are presented as ARIMA(p,d,q), where p is the order of autoregression (number of lagged observations), d is the order of differencing, and q is the moving average order (number of lagged errors) and are modeled as:

$$(1 - B)^d \widehat{Y}_t = \alpha + \frac{\theta(B)}{\phi(B)} \varepsilon_t$$

Where \widehat{Y}_t is the forecasted monthly standardized 30 patient-day rates of in-person visits, B is a backshift operator (e.g. $BY_t = Y_{t-1}$), and α is the constant. The autoregressive (AR) operator, $\phi(B)$, is equal to $1 - \phi_1 B^1 - \phi_2 B^2 \dots - \phi_p B^p$ with order p ; the moving average (MA) operator, $\theta(B)$, is equal to $1 - \theta_1 B^1 - \theta_2 B^2 \dots - \theta_q B^q$ with order q ; ε_t is the error term.

The general model building procedure for this analysis was as follows: First, since ARIMA models must fit to stationary data with constant mean, variance, and autocorrelation over time, stationarity of the time series was determined using augmented Dickey-Fuller tests and identifying appropriate orders of differencing. Second, the combination of AR and MA orders that minimizes the Akaike Information Criterion was determined using autocorrelation and partial autocorrelation plots, respectively. Third, goodness-of-fit was tested using Portmanteau tests of autocorrelation in the residuals.

If the data exhibited seasonal/cyclical trends, seasonal components were added as needed to the ARIMA model (i.e. SARIMA). Analyses were performed stratified by treatment type, race, and region for all diseases combined and by each disease, resulting in the creation of 112 individual time series of monthly standardized 30 patient-day rates of in-person visits for each subcohort. Separate (S)ARIMA models were fitted to each time series and used to forecast a counterfactual of typical monthly rates expected in a non-pandemic year.

Months where the actual rates exceed the 95% prediction interval (PI) surrounding the counterfactual estimates were considered to be significantly impacted by the pandemic. The relative difference between the actual monthly rates of in-person visits and the counterfactual estimates were calculated per month as:

$$\frac{(\text{actual pandemic in-person visit rate} - \text{counterfactual non-pandemic in-person visit rate})}{\text{counterfactual non-pandemic in-person visit rate}}$$

If the data exhibited seasonal/cyclical trends, seasonal components were added as needed to the ARIMA model (i.e. SARIMA). Analyses were performed stratified by treatment type, race, and region for all diseases combined and by each disease, resulting in the creation of 112 individual time series of monthly in-person visit rates. Separate (S)ARIMA models were fitted to each time series and used to forecast a counterfactual of typical monthly rates expected in a non-pandemic year.

Months where the actual rates exceed the 95% prediction interval (PI) surrounding the counterfactual estimates were considered to be significantly impacted by the pandemic (see Figure 2).