CHAPIN HALL

Youth Homelessness Data Solutions Project Final Report

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Disclaimer

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EXECUTIVE SUMMARY

The Youth Homelessness Data Solutions Project used innovative methods and linked data to reveal when, where, and why youth experience homelessness–offering communities actionable insights to drive prevention and improve outcomes

The Youth Homelessness Data Solutions Project (YHDSP) is a partnership between Chapin Hall and the Partnership Center, Ltd. (PCL) that was funded by the U.S. Department of Housing and Urban Development (HUD) to develop innovative and replicable methods for using linked administrative data to (1) produce counts of homeless youth, (2) estimate the prevalence and incidence of youth homelessness, (3) describe the characteristics of the homeless youth population, (4) analyze pathways into homelessness from youth-serving systems, and (5) identify predictors of youth homelessness through those different pathways. YHDSP included four main activities: (1) facilitating a learning consortium; (2) inventorying and appraising administrative data; (3) linking and analyzing administrative data from Continuums of Care (CoCs) and state agencies in South Carolina; and (4) producing a guide for leveraging administrative data, an HMIS data application, and an application user guide.

Chapin Hall and PCL engaged the CoC for Travis County (Austin), Texas, the CoC for New York City, and the Midlands CoC in South Carolina in a virtual Youth Homelessness Data Learning Consortium (YHDLC).[1] The YHDLC informed the direction of this project by focusing our attention on how CoCs can make better use of their homeless management information system (HMIS) data to understand the prevalence and incidence of youth homelessness and pathways into homelessness from youth-serving systems.

Chapin Hall inventoried and appraised administrative data from four state agencies in South Carolina—the Department of Education, the Department of Social Services, the Department of Juvenile Justice, and the Department of Mental Health—to inform the data we would request from the state's Office of Revenue and Fiscal Affairs (RFA). To facilitate this process, we created a data catalogue template that captures high-level information about the administrative data available from each source. We also produced a practical guide for communities that want to link their HMIS data to other administrative data to learn more about their population of youth experiencing homelessness.

We used the HMIS data from South Carolina's four CoCs to produce statewide and CoC-specific counts of unaccompanied homeless youth for the period between January 1, 2016 and December 31, 2020. We defined unaccompanied youth as individuals between 12 and 24 years old whose household did not include anyone age 25 or older at the time of enrollment. We determined whether a youth in HMIS was homeless on a given day during our observation period using five different methods: (1) documented enrollment in an HMIS housing project, (2) documented contact with an HMIS service project, (3) exit destinations from HMIS projects, (4) self-reported homelessness prior to HMIS project enrollment, and (5) definitional (that is, days between documented days of homelessness).

We produced statewide and CoC-specific annual counts of youth experiencing homelessness in the years 2016 through 2020. Some counts were based on enrollment in HMIS projects alone; others captured experiences with homelessness when youth were not being served by CoC providers. Statewide, the number of young people experiencing homelessness was lower in 2020 than it had been in 2016. However, that was not the case in every CoC. We also produced daily counts rather than only annual counts. The daily counts revealed a huge disparity between the number of homeless youth enrolled in an HMIS project and the number of youth experiencing homelessness who were not being served on any given day. They also exposed seasonal fluctuations in youth homelessness that annual counts obscure.

We used the homeless youth counts to estimate the annual prevalence and incidence of youth homelessness among 15- to 24-year-olds in South Carolina and in each CoC. Across our 5-year observation period, the mean statewide annual prevalence was 0.152 and the mean statewide annual incidence was 0.133, where homelessness was based on enrollment in an HMIS project. This means that approximately 15 out of 10,000 15- to 24-year-olds in South Carolina experienced homelessness and that approximately 13 out of 10,000 15- to 24-year-olds in South Carolina experienced a new episode of homelessness in an average year. Including self-reported homelessness increased the prevalence of youth homelessness by about 40% statewide,

The statewide annual prevalence and incidence of youth homelessness fell between 2016 and 2020. However, the change in prevalence and incidence varied in both size and direction across the four CoCs. The prevalence of youth homelessness was higher among young men than among young women and among Black youth than among White youth statewide. However, each CoC had different gender and racial disparities in the prevalence of youth homelessness.

We applied machine learning, an innovative computational technique, to identify predictors of homelessness among youth enrolled in public schools, exiting foster care, and involved with the juvenile justice system. Four features stood out as being strong predictors of homelessness for youth enrolled in public schools: grade retention, race, school mobility, and history of receiving free lunch. Five features stood out as being strong predictors of homelessness for youth exiting foster care: exit type, juvenile justice system involvement, hospitalization, race, and multiple spells. Six features stood out as being strong predictors of homelessness for youth involved with the juvenile justice system: race, referral source, urbanicity, multiple referrals, gender, and sentence type. Some of the features that stood out as strong predictors of youth homelessness were aligned with our expectations and prior research; others were surprising and difficult to explain.

The YHDSP has a number of implications for using administrative data to understand youth homelessness. First, we demonstrated that HMIS data can be used to generate counts of homeless youth and that these counts can be combined with U.S. Census Bureau data to produce both statewide and CoC-specific prevalence and incidence estimates of youth homelessness. Second, we demonstrated that HMIS data can be used to describe the characteristics of youth experiencing homelessness, examine differences in those characteristics across CoCs, and, when combined with U.S. Census Bureau data, identify disproportionalities across demographic groups. Third, we demonstrated that HMIS data could be linked to other administrative data and that those linked data can be used to understand pathways into homelessness though youth-serving systems. Finally, we demonstrated that machine learning can be applied to linked data to identify youth with an increased (or decreased) odds of experiencing homelessness. CoCs can use the results of these analyses to inform program planning, design interventions for groups overrepresented among the homeless youth population; and take steps to prevent homelessness among youth identified as being most "at risk."

The results of these analyses have several policy and practice implications for youth homelessness prevention.

- Youth are most at risk of experiencing homelessness during the first few months after they exit foster care. Child welfare agencies should do more to ensure that youth have the supports they need to avoid homelessness during this period.
- Changing schools during the academic year was a strong predictor of homelessness. School districts should try to minimize transfers during the school year or provide additional supports to students who must change schools
- Legal guardianship or relative placement were both associated with lower odds of experiencing homelessness after exiting foster care. Child welfare agencies should do more to promote permanency through these avenues.
- The odds of experiencing homelessness among youth involved with the juvenile justice system were higher for young women than young men. More attention should be paid to addressing the housing needs of young women involved with the juvenile justice system.
- Being involved with both the child welfare and juvenile justice systems increased the odds of experiencing homelessness. Greater cross-system collaboration is needed to ensure that "dually involved" or "cross-over" youth are stably housed.
- Solutions to youth homelessness should center race equity and address factors that contribute to higher odds of homelessness among Black youth as compared to White youth.

INTRODUCTION

Credible data on the number and characteristics of youth who experience homelessness are essential for several reasons. Continuums of Care (CoCs) use them to make decisions about the number of youth shelter beds or housing units they need. Policymakers use them to make decisions about the allocation of resources for homeless youth programs. Credible data are also vital to assessing whether progress toward the goal of preventing and ending youth homelessness is being made.

Despite their importance, credible data on number and characteristics of youth experiencing homelessness are not readily available. Point-in-time (PIT) counts, the primary method for counting homeless individuals and families, are less effective for counting homeless youth.[2-4] Homeless youth are routinely underrepresented in the annual HUD PIT counts.[2,5] Youth often experience more hidden forms of homelessness, such as couch surfing, that do not meet the PIT count's definition, or move frequently between being homeless and being housed.[6]

Some communities have undertaken counts exclusively of homeless youth. These "youth counts" typically apply a broader definition of homelessness and implement a more expansive methodology than that used during the annual HUD PIT count, including strategies designed to engage and empower youth.[2-4,7,8] Although these targeted efforts generally produce higher counts of homeless youth than the annual HUD PIT count, they still only provide a snapshot of the number of youth experiencing homelessness at a single point in time.

An alternative to PIT counts is to estimate the prevalence of youth homelessness over some defined period, typically a year. One way to estimate the prevalence of homelessness among youth is to survey a representative sample of U.S. households. This was the approach taken by Chapin Hall as part of Voices of Youth Count, the largest national study of youth homelessness to date.[6] Although representative household surveys are a promising approach for estimating the prevalence of youth homelessness and tracking changes in prevalence over time, they require a substantial investment of resources. Thus, they are probably not a viable option at state or local levels.

A much less costly option is to leverage administrative data that are routinely collected not only by CoCs through their Homelessness Management Information Systems (HMIS) but also by state and local agencies that serve youth. In 2020, the U.S. Department of Housing and Urban Development (HUD) released a Notice of Funding Availability to develop innovative and replicable methods for using linked administrative data from multiple sources to count and describe the characteristics of homeless youth, estimate the prevalence and incidence of youth homelessness, and explore pathways into homelessness among youth. Chapin Hall and the Partnership Center, Ltd. (PCL) were awarded one of three cooperative agreements for the Youth Homelessness Data Solutions Project (YHDSP).

This report describes the YHDSP, the activities in which we engaged, the methods that we used, the results of our analyses, and the implications of those results.

YOUTH HOMELESSNESS DATA SOLUTIONS PROJECT

The primary objective of the Youth Homelessness Data Solutions Project (YHDSP) is to develop innovative and replicable methods for using linked administrative data to (1) produce counts of homeless youth, (2) estimate the prevalence and incidence of youth homelessness, (3) describe the characteristics of the homeless youth population, (4) analyze pathways into homelessness from youth-serving systems, and (5) identify predictors of youth homelessness through those different pathways. The secondary objectives are to (1) better understand the advantages and disadvantages of using linked administrative data to learn about youth homelessness and (2) inform the development of youth homelessness prevention and early intervention models as well as systemic solutions to racial inequities in homelessness among youth.

YHDSP included four main activities: (1) facilitating a learning consortium; (2) inventorying and appraising administrative data; (3) linking and analyzing administrative data from CoCs and state agencies in South Carolina; and (4) producing a guide for leveraging administrative data, an HMIS data application, and an application user guide. Through these four activities YHDSP sought to answer the following research questions:

- What innovative methods can be used to produce counts of homeless youth and estimates of the prevalence and incidence of youth homelessness based on HMIS data?
- How can we use data from other systems to improve counts of homeless youth and estimates of the prevalence and incidence of youth homelessness based on HMIS data alone?
- How can linked administrative data be used to describe the characteristics of homeless youth?
- How can linked administrative data be used to analyze pathways into homelessness from youth-serving systems?

LEARNING CONSORTIUM

Chapin Hall and its partner, PCL, engaged the CoC for Austin/Travis County, Texas (CoC TX-503), the CoC for New York City (CoC NY-600), and the CoC for Midlands, South Carolina (CoC SC-502) in a virtual Youth Homelessness Data Learning Consortium (YHDLC). The YHDLC met seven times during the first year of the project. These meetings covered a range of topics related to the use of HMIS data and administrative data from other sources (see Table 1).

Table 1. Learning Consortium Activities

#	Title	Date	What Partners Did
1	*Familiarization & agenda setting*	2/23/21	• Shared experiences with counting homeless youth, estimating the prevalence of youth homelessness, & linking HMIS data to other administrative data • Learned about their respective strengths and revised the YHDLC's expectations, goals, and plans
2	*Diagnostics Part 1. What do we know?*	3/24/21	• Took stock of what they know about youth homelessness in their respective jurisdictions, how they know it, and their confidence in this information • Reacted to a summary report produced from Sage's aggregation of their APR, CAPER, and PIT data • Discussed how they are using or would like to use HMIS data to learn more about their homeless youth and what they know or would like to know by linking those data to other administrative data
3	*Diagnostics Part 2: Who's missing?*	4/30/21	• Engaged in a participatory group model building exercise to delineate pathways into and through homelessness & identify youth who are missing from homelessness data
4	*Data Mapping Part 1: Reviewing and Improving Homeless Youth Counts and Information in HMIS*	5/28/21	• Explored strategies for improving the completeness, reliability, and validity of HMIS data on homeless youth
5	*Data Mapping Part 2: Identifying Other Administrative Data for Improving Counts*	6/21/21	• Identified non-HMIS administrative data that could be linked to HMIS data and strategies for linking and de-duplicating linked data to improve counts of homeless youth/estimates of youth homelessness
6	*Data Sharing Agreements: Policies and Practices*	7/27/21	• Reviewed best practices for data sharing agreements and policies related to sharing HMIS data for minors
7	*Data Linking Strategies*	9/28/21	• Explored the science of and strategies for effectively linking data and discussed data linking challenges and solutions

The YHDLC informed the direction of this project by focusing Chapin Hall and PCL's attention on how CoCs can make better use of their HMIS data to understand the prevalence and incidence of youth homelessness and pathways into homelessness from youth serving systems. Below are several of the ideas to emerge from the YHDLC that guided our work.

- **Daily counts:** YHDLC participants highlighted the need for a more refined understanding of the variability in youth homelessness throughout the year. CoCs tend to focus on annual counts of youth served (measured using HMIS data) or annual point-in-time (PIT) counts of homeless youth when estimating service needs. Although both have some utility, they fail to account for seasonal fluctuations that can affect the demand for services.

- **Use of different HMIS counting methods:** YHDLC participants discussed the possibility of using the amount of time youth report being homeless prior to HMIS project enrollment and exits to homeless destinations to improve daily counts of homeless youth. In particular, these data would allow CoCs to include youth in their daily counts even when those youth are not enrolled in an HMIS project. Additionally, if CoCs link their HMIS data to administrative data from other sources, the self-report data could shed light on when youth first became homeless after exiting a youth-serving system, such as the juvenile justice or child welfare system, and how long they were homeless before HMIS project enrollment. YHDLC participants recognized that self-reports of homelessness and exit data can be inaccurate due, at least in part, to the lack of incentives to collect accurate data.[9] If those responsible for collecting the data knew that the data were being used, the quality of the data might improve.

- **Use of prevalence and incidence to uncover disparities:** YHDLC participants discussed the use of prevalence and incidence estimates to understand disparities based on age, race/ethnicity, and gender in their CoCs. By themselves, disaggregated counts of homeless youth cannot be used to determine whether a demographic group is disproportionately experiencing homelessness.

- **Increasing access to disaggregated census data:** YHDLC participants also emphasized the need to increase access to American Community Survey (ACS) data from the U.S. Census Bureau. ACS data are indispensable for producing prevalence and incidence estimates, and hence, for determining whether a demographic group is disproportionately experiencing homelessness. While ACS data are publicly available, most CoCs do not have the resources needed to access and transform those data to map onto their CoCs. This is especially true for CoCs that include multiple or partial Census geographies.

- **Using linked administrative data:** Although YHDLC participants understood the general principles of data linking, they recognized that it can be challenging for CoCs to know what data to request and how they will be used, both of which should be specified in a data sharing agreement (DSA).

These ideas informed our HMIS data analysis, the reports generated by the Equip App that we created as part of this project, and the data mapping guide that we produced.

CONTEXT

Due to resource constraints, our data inventorying and appraisal, data integration, and data analysis focused on South Carolina. South Carolina is divided into four CoCs (see Table 2). Three of the CoCs are largely suburban; the fourth is largely rural.

Table 2. South Carolina's Continuums of Care

	SC-500	SC-501	SC-502	SC-503
Name	Lowcountry	Upstate	Midlands	Total Care for the Homeless Coalition (TCHC)
Area	Charleston	Greenville, Anderson, Spartanburg	Columbia	Myrtle Beach & Sumter
CoC category	Largely suburban	Largely suburban	Largely suburban	Largely rural
Number of counties	7	12	13	13

Figure 1 shows the area covered by each of the state's four CoCs.

Figure 1. Map of South Carolina's CoCs

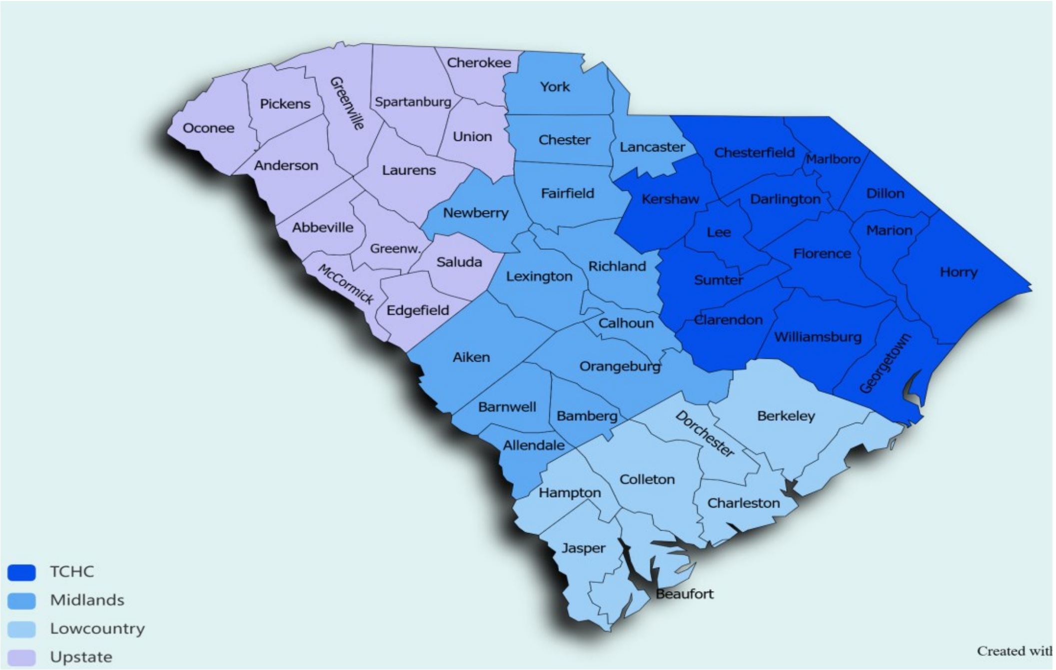


Table 3 provides information about the total number of year-round beds and the number of year-round beds dedicated to youth in each CoC in 2023.[10] The availability of beds and housing units varies widely across the four CoCs.

Table 3. Number of Year-Round Beds and Housing Units by CoC

	Lowcountry		Upstate		Midlands		TCHC	
	Total	Youth	Total	Youth	Total	Youth	Total	Youth
Beds								
Emergency shelter	151	12	901	16	764	16	483	8
Transitional housing	103	0	217	17	326	18	162	0
Save haven	0	0	12	0	0	0	0	0
Total Beds	254	12	1,130	33	1,090	34	645	8
Housing Units								
Rapid Rehousing	240	19	149	0	145	22	293	15
Permanent Supportive Housing	441	0	354	0	717	6	409	0
Other Permanent Housing	0	0	0	0	37	0	450	0
Total Housing Units	681	19	503	0	899	28	1,152	15

Table 4 provides data on the number of individuals of all ages and the number of unaccompanied youth experiencing sheltered and unsheltered homelessness in each CoC on the night of the 2023 Point in Time (PIT) Count.[11] The PIT count numbers vary widely across the CoCs. Upstate counted more individuals but Midlands counted more unaccompanied youth.

Table 4. Number of Individuals Experiencing Homelessness on the 2023 PIT Count Night

	Lowcountry	Upstate	Midlands	TCHC
Individuals	404	1,424	1,165	1,060
Unaccompanied youth < age 25	15	49	86	44
Parenting youth < age 25	4	3	8	7

DATA INVENTORY & APPRAISAL

We inventoried and appraised non-HMIS administrative data that could be linked to HMIS data to improve counts of homeless youth, estimate the prevalence and incidence of youth homelessness, and better understand pathways into homelessness from youth-serving systems in South Carolina. We used data dictionaries provided by the Midlands CoC to inventory and appraise the administrative data available from multiple state agencies through the state's Office of Revenue and Fiscal Affairs. To facilitate this process, Chapin Hall created a data catalogue template that captures high-level information about the administrative data available from each source. We also shared this template with our other two CoC partners so they could inventory and appraise their administrative data.

Based on the results of the inventory and appraisal process, we executed data sharing agreements with and requested data from four state agencies: the Department of Education, the Department of Social Services (which operates the state's child welfare agency), the Department of Juvenile Justice, and the Department of Mental Health.[12] The results of the inventory and appraisal process also informed the data fields we requested from each of those agencies.

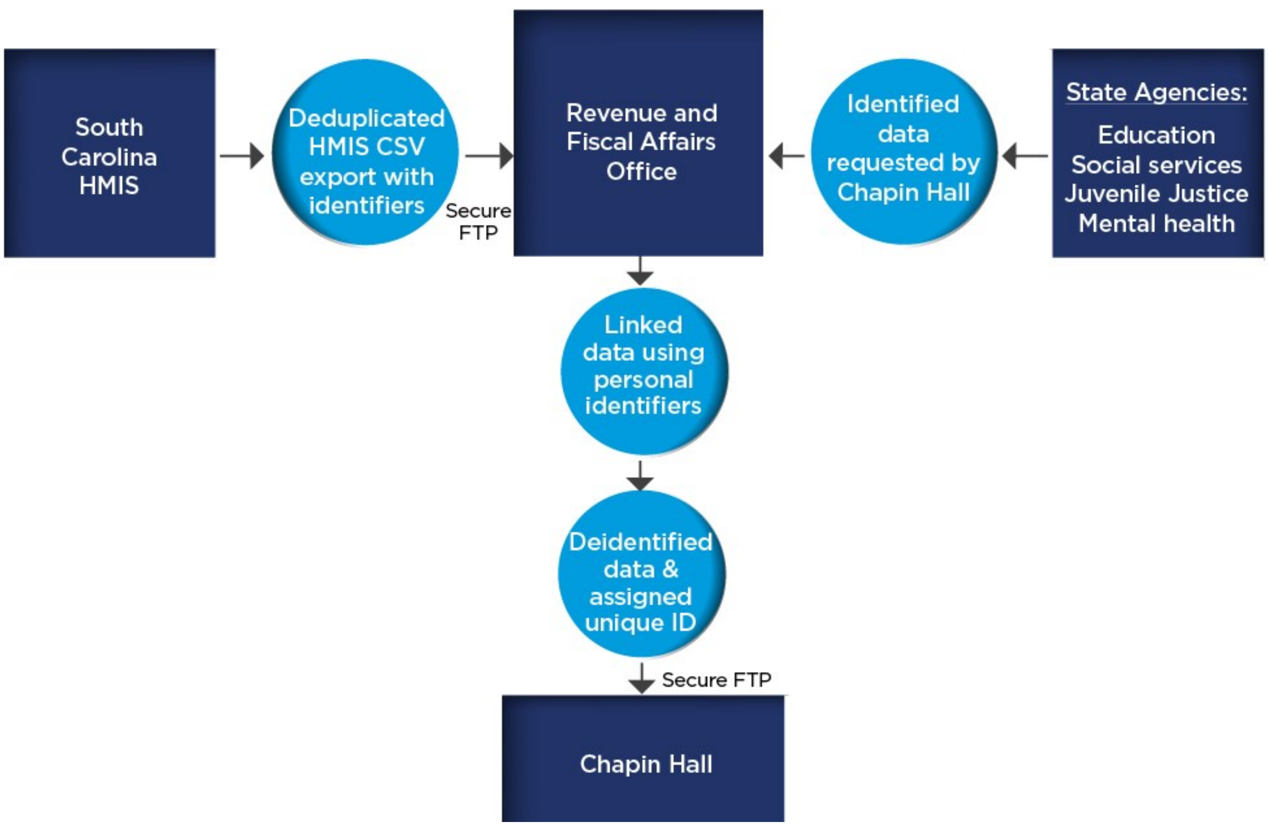
We produced a practical guide for communities that want to link their HMIS data to other administrative data to learn more about their population of youth experiencing homelessness. The guide explains how to identify, catalogue, access, and assess potentially relevant administrative data and provides useful tools to help with each of those steps. The guide was informed by the experiences of the YHDSP project team, our partner CoCs, and other experts.

DATA INTEGRATION

After executing data sharing agreements with each of South Carolina's four CoCs, we collaborated with each CoC's HMIS lead and other CoC staff to produce a list of all HMIS projects that served people experiencing homelessness during the years 2016 through 2020 (that is, the reporting period), used those lists to produce an export of .csv files from the HMIS using HUD's FY2020 HMIS csv format specifications, and combined the four HMIS csv exports. Next, we filtered the exports to include only clients who were 12 to 24 years old and enrolled in at least one project during the reporting period. We then added the birthdate of the oldest member of each client's household to the records to determine whether the client was an unaccompanied youth.

We manually deduplicated the HMIS csv export so that it included only one record for each youth, assigned each youth a unique ID, and shared the deduplicated HMIS .csv export with the Office of Revenue and Fiscal Affairs (RFA). RFA used the personal identifiers (including SSN, first name, middle initial, last name, date of birth, race, and gender) included in the HMIS csv export to link those data to the data we requested from the four state agencies: the Department of Education, the Department of Social Services, the Department of Juvenile Justice, and the Department of Mental Health. Then RFA encrypted the unique HMIS IDs, assigned each youth in the data a new unique ID, and removed any personal identifiers from the linked data (see Figure 2).

Figure 2. Data Acquisition and Linking Process



COUNTS OF HOMELESS YOUTH

Methods

We used the HMIS data from South Carolina's four CoCs to produce statewide and CoC-specific counts of homeless youth, where count is defined as the number of unaccompanied youth who were enrolled in an HMIS project between January 1, 2016 and December 31, 2020. We defined unaccompanied youth as individuals between 12 and 24 years old whose household did not include anyone age 25 or older at the time of enrollment.[13] The total number of individuals who experienced unaccompanied youth homelessness at least once during our observation period was 4,190.

For the data set, we collected an HMIS CSV Report from each of the four CoCs, merged the data records, and filtered the data set to include data only for clients who meet the definition of an unaccompanied youth for at least one project enrollment during the observations period. This method preserved data on enrollments where the client was not unaccompanied and these data were used to verify that only unaccompanied youth were included in the counts. For example, if a youth was simultaneously enrolled in a Services Only project as an unaccompanied youth and in an Emergency Shelter along with their parent, the youth would not be included in our count.

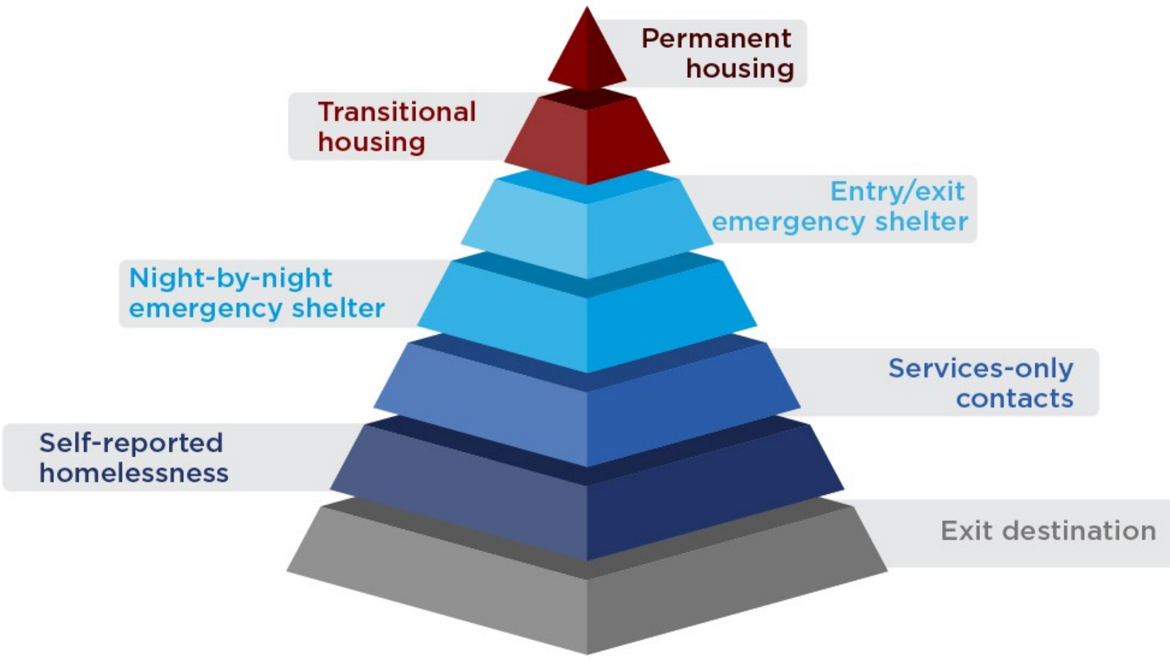
We counted youth as homeless using five different methods (see Table 5).

Table 5. Methods for Counting Homeless Youth

Method	Description
Documented enrollment in an HMIS housing project	• Each day a youth is enrolled in an emergency shelter, safe haven, or transitional housing project • Each day a youth is enrolled in a rapid re-housing or permanent supportive housing project prior to their move-in date.
Documented contact with an HMIS service project	Each day a youth has contact with a services-only project (such as coordinated entry, street outreach, or services only) if they entered their current living situation due to homelessness plus the first 14 days following a contact date unless other data indicate that the youth is housed. This allows for continuity between contacts without counting youth as homeless after more than 2 weeks without contact.
Exit destination	Each day for 14 days after a youth has exited an HMIS project to a destination defined as being homeless unless other data indicate that the youth became housed.[14]
Self-report	Each day a youth self-reported being homeless based on the approximate date on which their current episode of homelessness began according to HMIS data element 3.917.
Definitional	Each day for up to 6 days between documented days of homelessness even if a youth was documented as being permanently housed during that period.[15]

We also made several assumptions that are typically made for HUD reporting.[16] Some of these assumptions are based on a hierarchy for deciding how to treat contradictory HMIS data (see Figure 3). This hierarchy assumes that data entry errors are less likely as the duration and stability of housing increases. HMIS data higher up in the hierarchy are given precedence over HMIS data lower down in the hierarchy.

Figure 3. Hierarchy for Treating Contradictory HMIS Data



For example, if a youth was documented as being both homeless and permanently housed on the same day, we assumed that the youth was permanently housed on that day. Similarly, if a youth was documented as being homeless, we assumed the youth was homeless even if self-reported or exit destination data indicated otherwise. We also assumed that a youth had been continuously homeless if the youth was documented as homeless on 2 days, no more than 6 days apart.

Self-reported homelessness data are only accurate to the extent that individuals can remember the date on which their homelessness episode began and understand how homelessness is defined by HUD. That said, they can provide information about experiences with homelessness prior to HMIS project enrollment. As such, they can contribute to our knowledge about the prevalence and incidence of homelessness in a CoC beyond what can be gleaned by relying exclusively on HMIS project enrollment. In analyzing the HMIS data, we tracked self-reported homelessness separately from documented homelessness or homelessness based on exit destination. Throughout this report, we indicate whether self-reported homelessness was included.

Results

Table 6 shows the statewide and CoC-specific annual counts of homeless youth for the years 2016 through 2020. These counts include youth who were documented as homeless in the HMIS data and youth who were documented as exiting an HMIS project to a destination defined as homeless.[17]

Table 6. Annual Counts of Homeless Youth Ages 12 to 24, Excluding Self-Reported Homelessness

Year	Statewide	SC-500 Lowcountry	SC-501 Upstate	SC-502 Midlands	SC-503 TCHC
2016	852	118	191	279	277
2017	823	79	172	317	269
2018	724	57	125	335	215
2019	784	72	132	333	254
2020	844	59	135	337	322
Mean	805.4	77	151	320.2	267.4
% change 2016–2020	-0.9	-50.0	-29.3	20.8	16.2

Overall, the statewide count of homeless 12- to 24-year-olds declined by less than 1% between 2016 and 2020 (see Figure 4). However, a closer inspection reveals that the number of homeless youth fell by 15% between 2016 and 2018 and then rose 17% between 2018 and 2020. Between 2016 and 2020, the counts declined in Lowcountry and Upstate and increased in Midlands and TCHC. Lowcountry experienced, by far, the greatest drop; its count fell by 50%.

Figure 4. Annual Counts of Homeless Youth Ages 12 to 24, Excluding Self-Reported Homelessness

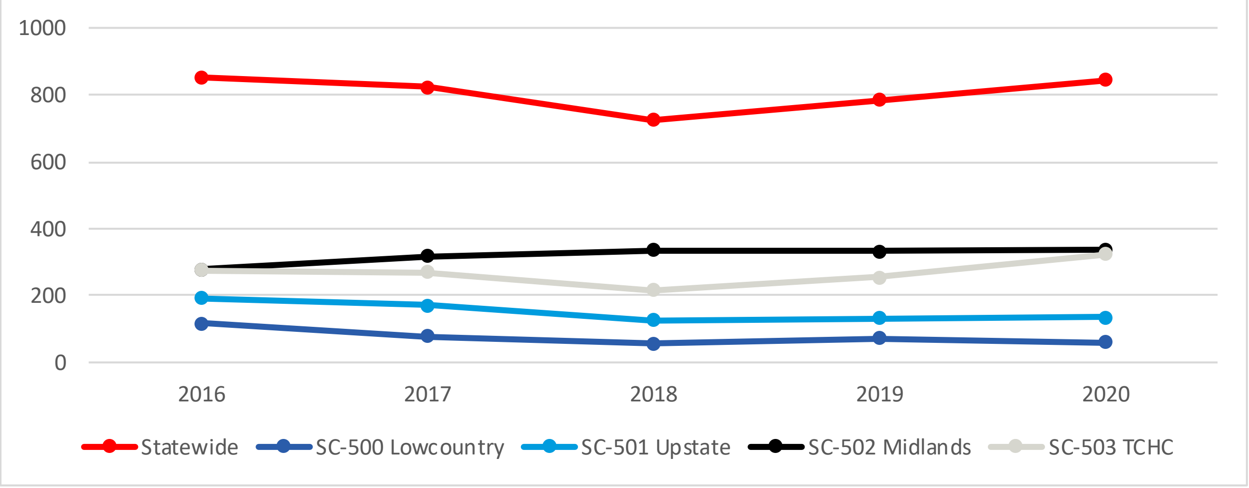


Table 7 shows the same data as Table 6, but only for 18- to 24-year-olds.

Table 7. Annual Counts of Homeless Youth Ages 18 to 24, Excluding Self-Reported Homelessness

Year	Statewide	SC-500 Lowcountry	SC-501 Upstate	SC-502 Midlands	SC-503 TCHC
2016	781	118	185	270	220
2017	754	79	159	311	217
2018	683	57	123	326	184
2019	696	70	130	321	182
2020	684	59	134	325	175
Mean	719.6	76.6	146.2	310.6	195.6
% change 2016 - 2020	-12.4	-50.0	-27.6	20.4	-20.5

Overall, the statewide count of homeless 18- to 24-year-olds declined by 12% between 2016 and 2020 (see Figure 5), but all the decline occurred between 2016 and 2018. The counts declined in Lowcountry, Upstate, and TCHC but increased in Midlands. Although Lowcountry experienced, by far, the biggest drop, only TCHC experienced reductions every year.

Figure 5. Annual Counts of Homeless Youth Ages 18 to 24, Excluding Self-Reported Homelessness

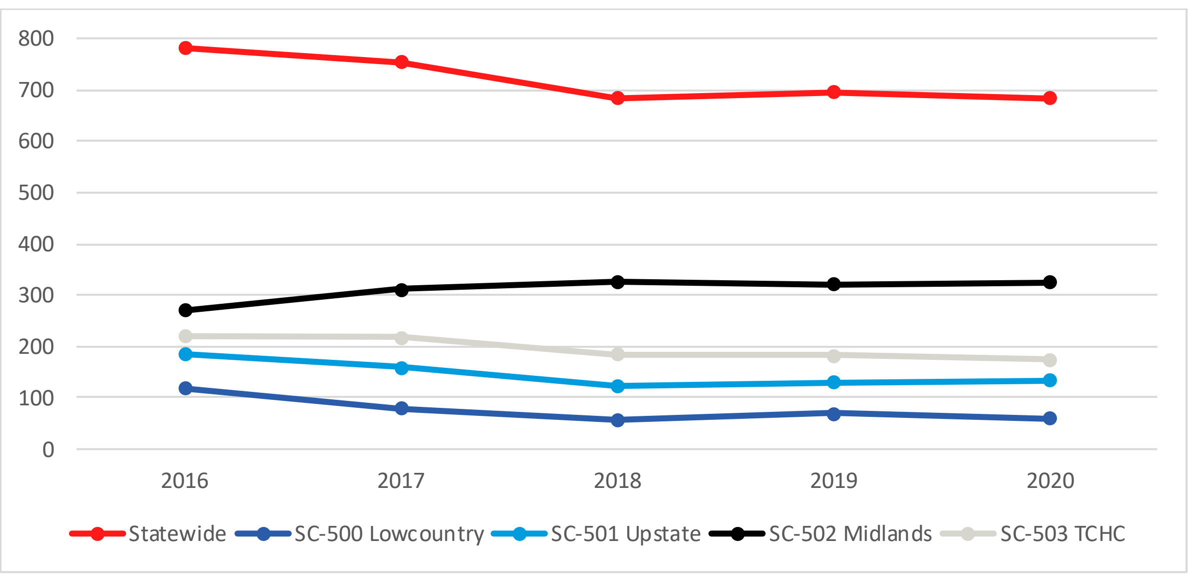


Table 8 is similar to Table 6 except that the counts include self-reported homelessness.

Table 8. Annual Counts of Homeless Youth Ages 12 to 24, Including Self-Reported Homelessness

Year	Statewide	SC-500 Lowcountry	SC-501 Upstate	SC-502 Midlands	SC-503 TCHC
2016	1,201	168	267	369	424
2017	1,131	109	226	401	423
2018	1,056	96	180	426	369
2019	1,085	104	213	405	377
2020	1,064	105	188	356	425
Mean	1,107.4	116.4	214.8	391.4	403.6
% change 2016 - 2020	-11.4	-37.5	-29.6	-3.5	0.2

Overall, the statewide count of homeless 12- to 24-year-olds declined by 11% between 2016 and 2020 when self-reported homelessness was included (Figure 6). Lowcountry and Upstate experienced reductions in their counts of at least 30%. The counts either remained unchanged or declined slightly in Midlands and TCHC. However, the overall change between 2016 and 2020 obscures significant year-to-year fluctuation, and whether they fell or rose in any given year varied across the CoCs.

Figure 6. Annual Counts of Homeless Youth Ages 12 to 24, Including Self-Reported Homelessness

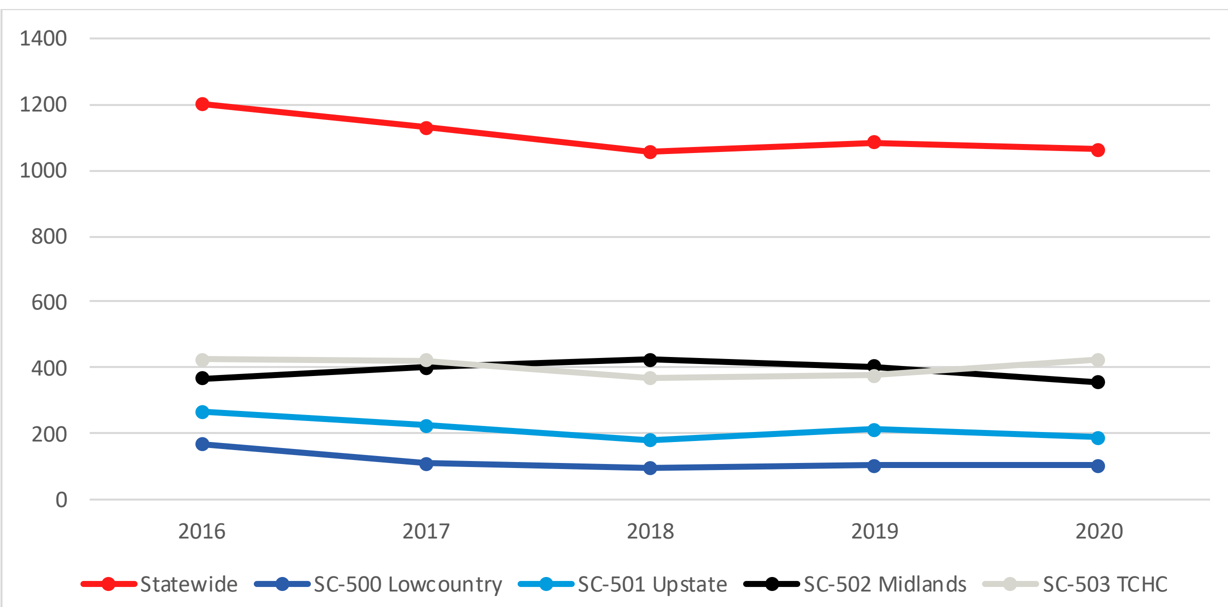


Table 9 shows the same data as Table 8 but only for 18- to 24-year-olds.

Table 9. Annual Counts of Homeless Youth Ages 18 to 24, Including Self-Reported Homelessness

Year	Statewide	SC-500 Lowcountry	SC-501 Upstate	SC-502 Midlands	SC-503 TCHC
2016	1,087	167	254	347	345
2017	1,049	107	213	389	366
2018	988	94	177	409	322
2019	978	102	209	389	292
2020	901	105	186	344	276
Mean	1,000.6	115	207.8	375.6	320.2
% change 2016 - 2020	-17.1	-37.1	-26.8	-0.9	-20.0

Between 2016 and 2020, the statewide count declined by 17%. Lowcountry, Upstate, and Midlands also experienced a reduction in their counts of at least 20% (see Figure 7). However, unlike the statewide count, which fell year after year, the CoC-specific counts fell in some years and rose in others, but whether they fell or rose in any given year varied across the CoCs.

Figure 7. Annual Counts of Homeless Youth Ages 18 to 24, Including Self-Reported Homelessness,

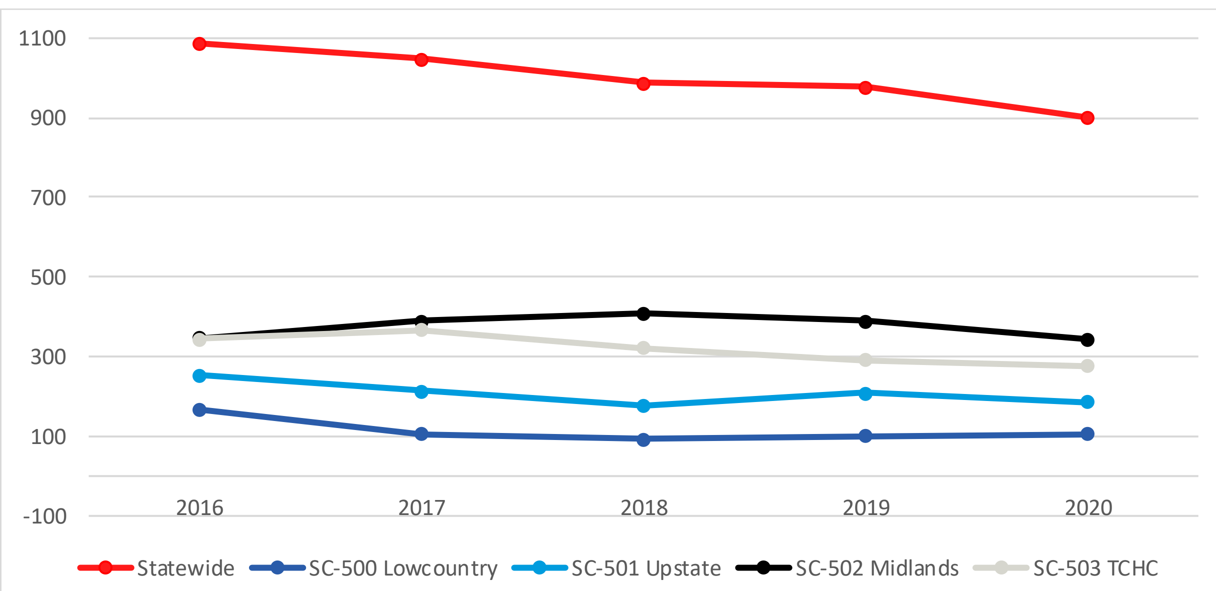
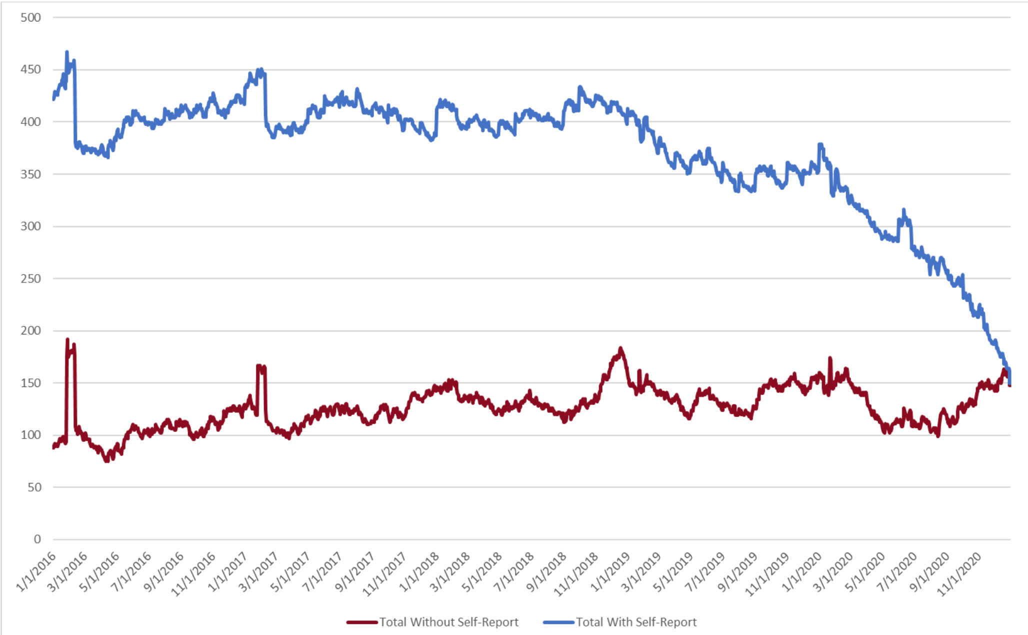


Figure 8 shows the total number of youth ages 18 to 24 experiencing homelessness statewide on each day during our observation period. The bottom line represents the number of homeless youth enrolled in a housing or service project on a given day. The top line represents the number of homeless youth when youth who were only known to be homeless on a given day based on self-report data are included. The difference between these lines represents the number of youth experiencing homelessness who were not being served by a CoC provider.

Figure 8. Daily Counts of Homeless Youth Including and Excluding Self-Reported Homelessness

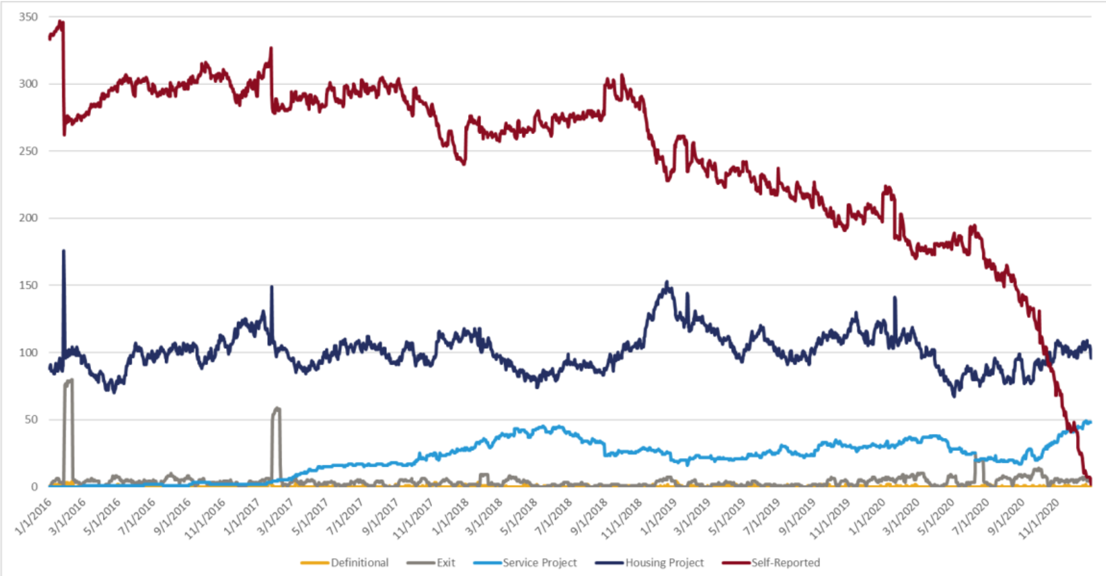


Importantly, the average daily count of youth experiencing homelessness is 3.2 times higher when self-reported homelessness is included (~407 youth) than when it is excluded (~127 youth).[18] If the self-reported data are accurate, this would mean that on any given day in South Carolina, 280 youth experiencing homelessness (who would at some future point enroll in an HMIS project) were not receiving housing or services. Stated differently, on any given day, fewer than 1 in 3 youth experiencing homelessness were being served by a CoC provider. The actual number of unserved youth is undoubtedly higher because some homeless youth never enroll in an HMIS project.

The number of homeless youth, including youth who were only known to be homeless on a given data based on self-report data, begins to decline in the middle of 2019 and then drops precipitously throughout 2020. This reflects the fact that data on self-reported homelessness are necessarily collected after the fact. Because December 31, 2020, was the last day of our observation period, we have no way of knowing who was homeless on that date but not enrolled in an HMIS project. Also worth noting are the large spikes each January. These are likely due to CoC providers entering data from their annual PIT counts into their HMIS.

Figure 9 disaggregates these totals based on the counting method used. Each youth is counted using only one method on a given day, and that method is based on the hierarchy for dealing with contradictory HMIS data described above. This means, for example, that a youth who was simultaneously enrolled in both a housing project and a service project would only be included in the housing projects counts. It also means that the line representing the service project counts only reflects the number of youth who were enrolled in a service project and not a housing project.

Figure 9. Daily Counts of Homeless Youth by Counting Method



Disaggregating the data by count method makes clear that the number of youth who were only known to be homeless on a given day based on self-report data begins to decline at the start of 2019 before dropping precipitously to zero in the second half of 2020. As already noted, this reflects the fact that data on self-reported homelessness are only collected once youth enroll in an HMIS project. The disaggregated data also reflect seasonal fluctuations in the number of homeless youth being served. Not surprisingly, daily counts of housing project enrollment tend to be higher during the winter, when youth seek shelter from the cold, than during the summer. The upticks in August are likely due to youth seeking respite from the heat. However, daily counts of service project enrollment do not reflect these same trends.

The overall variation around the mean in housing project enrollment is 19.6% across all 5 years, meaning that maximum enrollment will be about 20% higher and minimum enrollment will be about 20% lower than the mean.[19,20] Finally, daily counts of service project enrollment are zero until 2017 because that is the first year in which South Carolina's CoCs had service projects for homeless youth.

We also used the HMIS data from the four South Carolina CoCs to produce statewide and CoC-specific counts of the number of new episodes of youth homelessness that began during our observation period, where episode is defined as a continuous period of homelessness. Table 10 shows the annual counts of new episodes of youth homelessness among 12- to 24-year-olds for the years 2016 through 2020 for the entire state and for each CoC.

Table 10. New Episodes of Youth Homelessness Among Youth Ages 12 to 24

Year	Statewide	SC-500 Lowcountry	SC-501 Upstate	SC-502 Midlands	SC-503 TCHC
2016	795	117	174	231	292
2017	737	64	142	237	312
2018	682	62	113	255	262
2019	719	72	140	233	283
2020	750	74	119	216	349
Mean	805.4	77	151	320.2	267.4
% change 2016 - 2020	-0.9	-50.0	-29.3	20.8	16.2

Overall, the number of new episodes of homelessness among 12- to 24-year-olds statewide fell by less than 1% between 2016 and 2020 (see Figure 10). However, it fell by 50% in Lowcountry and by 29% in Upstate. By contrast, the number of new episodes of homelessness rose by 16% in TCHC and by 21% in Midlands. Moreover, these figures obscure a great deal of year-to-year fluctuation in the number of new episodes of homelessness both statewide and in each CoC.

Figure 10. New Episodes of Youth Homelessness Among Youth Ages 12 to 24

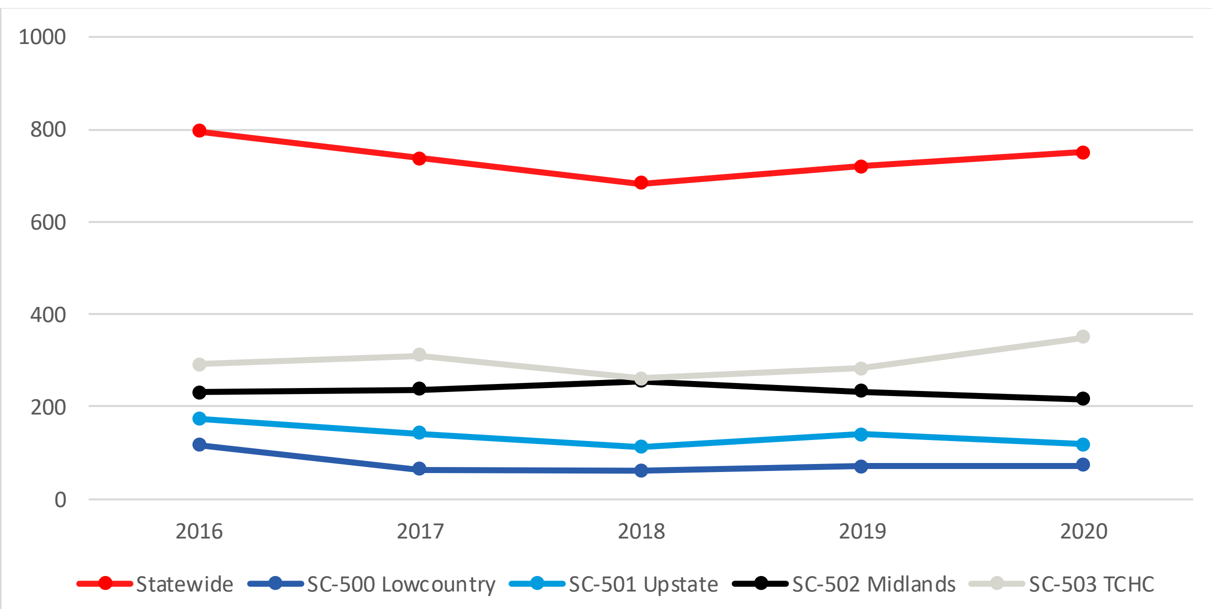


Table 11 is similar to Table 8 but includes new episodes of youth homelessness only among 18 to 24-year-olds.

Table 11. New Episodes of Youth Homelessness Among Youth Ages 18 to 24

Year	Statewide	SC-500 Lowcountry	SC-501 Upstate	SC-502 Midlands	SC-503 TCHC
2016	701	116	169	210	224
2017	650	60	130	221	254
2018	612	61	112	236	212
2019	617	70	133	218	205
2020	587	74	115	203	203
% change 2016 - 2020	-16.3	-36.2	-32.0	-3.3	-9.4

Overall, the number of new episodes statewide fell 16% percent between 2016 and 2020 (see Figure 11). It fell by even more in Lowcountry (36%) and Upstate (32%). However, it fell by less than 10% in Midlands (3%) and TCHC (9%). Moreover, in some years the number of new episodes fell and in other years it increased both statewide and in each CoC.

Figure 11. Annual Number of New Episodes of Youth Homelessness

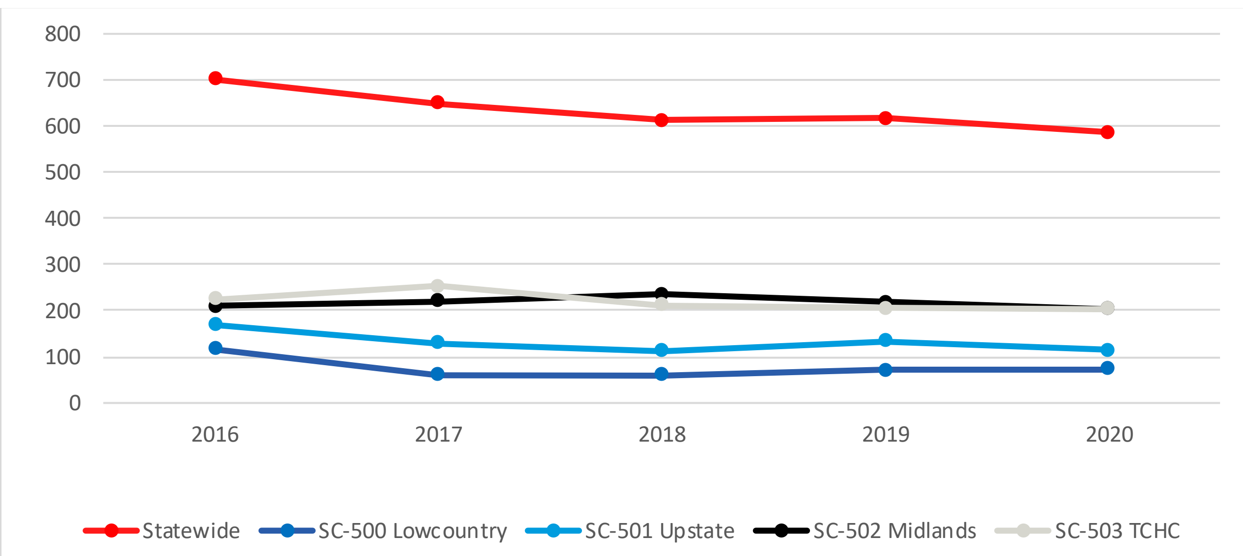
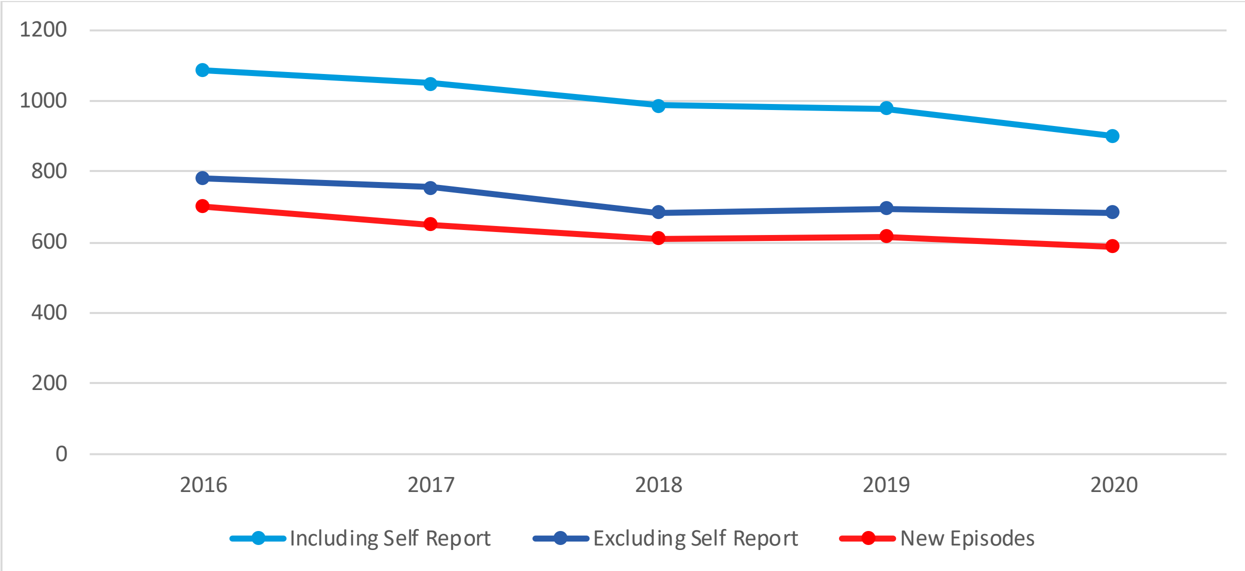


Figure 12 compares the statewide count when self-reported homelessness is included versus excluded. On average, the count is 28% higher when self-reported homelessness is included. Figure 12 also compares both counts to the number of new episodes.

Figure 12. Annual Statewide Counts of Homeless Youth and New Episodes of Homelessness



PREVALENCE OF YOUTH HOMELESSNESS

We used the homeless youth counts to estimate the annual prevalence of youth homelessness for each year during our observation period, where prevalence is defined as the number of youth ever homeless during a given period (in this case, the annual count of homeless youth) divided by the total youth population. We used American Community Survey (ACS) data to estimate the youth population. Because the ACS reports data for 15- to 24-year-olds, we did not include 13- and 14-year-olds in our prevalence estimates.

Table 12 shows the estimated annual prevalence of youth homelessness in the years 2016 through 2020 for the entire state and each CoC. The annual counts on which the prevalence estimates are based include youth who were documented as homeless in the HMIS data and youth who were documented as exiting an HMIS project to a destination defined as homeless. The statewide mean prevalence (0.152) was higher than the mean prevalence in Lowcountry (0.082) and Upstate (0.101) and lower than the mean prevalence in Midlands (0.203) and TCHC (0.237).

Table 12. Annual Prevalence of Youth Homelessness, Excluding Self-Reported Homelessness

Year	Statewide	SC-500 Lowcountry	SC-501 Upstate	SC-502 Midlands	SC-503 TCHC
2016	0.163	0.125	0.127	0.174	0.260
2017	0.158	0.084	0.110	0.202	0.260
2018	0.144	0.061	0.085	0.212	0.224
2019	0.148	0.075	0.090	0.211	0.224
2020	0.145	0.063	0.093	0.214	0.217
Mean	0.152	0.082	0.101	0.203	0.237
% change 2016 - 2020	-11.0	-49.6	-26.8	23.0	-16.5

Statewide, the prevalence of youth homelessness (excluding self-reported homelessness) fell by 11% between 2016 and 2020 (see Figure 13). The prevalence of youth homelessness also fell by 17% in TCHC, by 27% in Upstate, and by 50% in Lowcountry. However, it rose by 23% in Midlands. That said, prevalence fell in some years and rose in others, and the direction of these changes was not consistent across the CoCs.

Figure 13. Annual Prevalence of Youth Homelessness, Excluding Self-Reported Homelessness

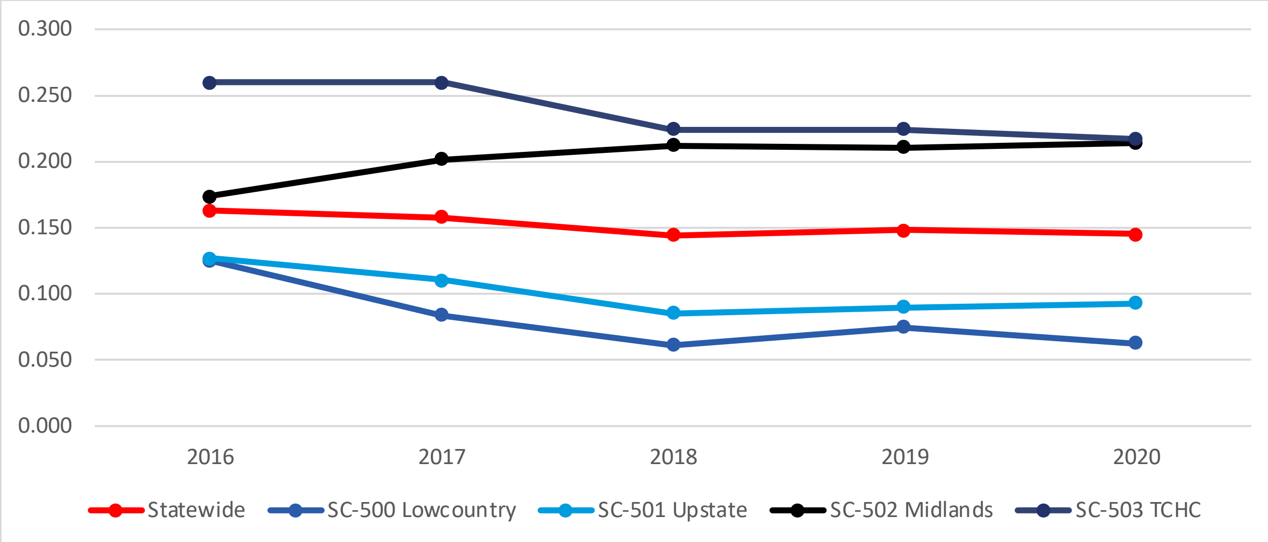


Table 13 is similar to Table 10, except that the counts on which the prevalence estimates are based include self-reported homelessness. The statewide mean prevalence (0.211) was higher than the mean prevalence in Lowcountry (0.122) and Upstate (0.144) and lower than the mean prevalence in Midlands (0.245) and TCHC (0.388).

Table 13. Annual Prevalence of Youth Homelessness, Including Self-Reported Homelessness

Year	Statewide	SC-500 Lowcountry	SC-501 Upstate	SC-502 Midlands	SC-503 TCHC
2016	0.227	0.177	0.175	0.224	0.408
2017	0.220	0.113	0.147	0.253	0.438
2018	0.208	0.100	0.122	0.266	0.391
2019	0.207	0.109	0.145	0.256	0.359
2020	0.192	0.112	0.129	0.227	0.342
Mean	0.211	0.122	0.144	0.245	0.388
% change 2016 - 2020	-15.4	-36.7	-26.3	1.3	-16.2

Statewide, the prevalence of youth homelessness (including self-reported homelessness) fell by 15% between 2016 and 2020 (see Figure 14). The prevalence of youth homelessness also fell by 16% in TCHC, by 26% in Upstate, and by 37% in Lowcountry. It was essentially unchanged in Midlands. Regardless of the CoC, prevalence fell in some years and rose in others, and the direction of these changes were not consistent.

Figure 14. Annual Prevalence of Youth Homelessness, Including Self-Reported Homelessness

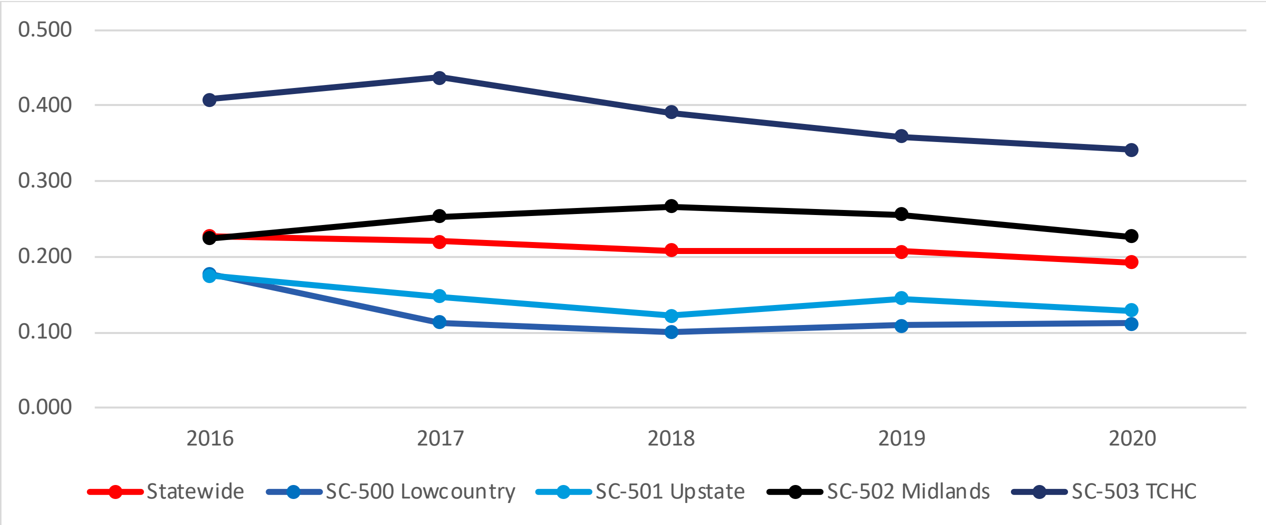
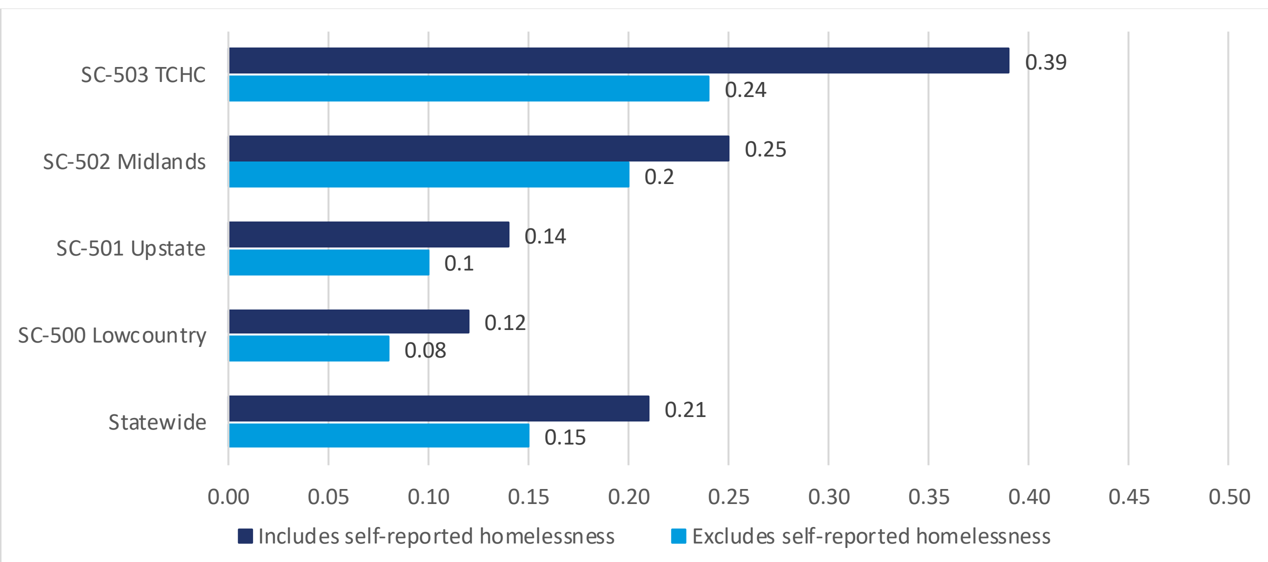


Figure 15 compares the statewide and CoC-specific mean prevalence when self-reported homelessness is included to the statewide and CoC-specific mean prevalence when self-reported homelessness is excluded. On average, including self-reported homelessness increases the statewide prevalence of youth homelessness by 40%, from 0.15 to 0.21. However, including self-reported homelessness has a much bigger effect in TCHC than in any other CoC.

Figure 15. Difference in Mean Prevalence Related to Self-Reported Homelessness



INCIDENCE OF YOUTH HOMELESSNESS

We used the counts of new episodes of youth homelessness to estimate the incidence of youth homelessness, where incidence is defined as the number of new youth homelessness episodes during a given period divided by the total youth population. Because we used ACS data to estimate the youth population, and the ACS only reports data for 15- to 24-year-olds, we did not include 13- and 14-year-olds in our incidence estimates.

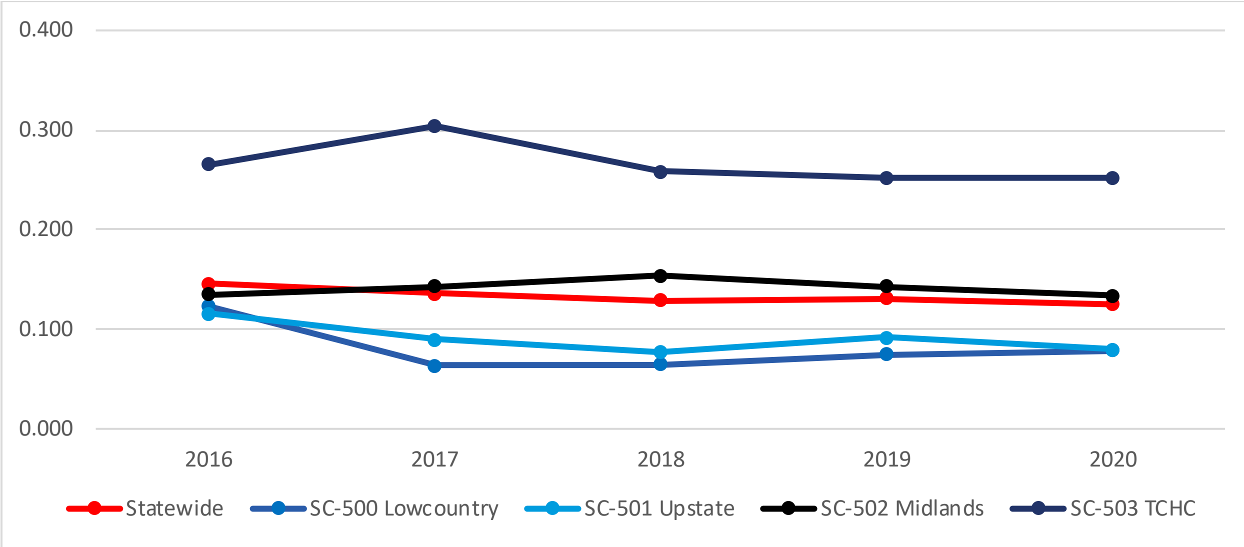
Table 14 shows the estimated annual incidence of youth homelessness in the years 2016 through 2020 for the entire state and each CoC. The incidence estimates are based on annual counts that include youth who were documented as homeless in the HMIS data or documented as exiting an HMIS project to a destination defined as homeless.[21] The statewide mean incidence (0.133) was higher than the mean incidence in Lowcountry (0.081) and Upstate (0.091) and lower than the mean incidence in Midlands (0.142) and TCHC (0.266).

Table 14. Annual Incidence of Youth Homelessness

Year	Statewide	SC-500 Lowcountry	SC-501 Upstate	SC-502 Midlands	SC-503 TCHC
2016	0.146	0.123	0.116	0.135	0.265
2017	0.136	0.064	0.090	0.143	0.304
2018	0.129	0.065	0.077	0.154	0.258
2019	0.131	0.075	0.092	0.143	0.252
2020	0.125	0.079	0.080	0.134	0.252
Mean	0.133	0.081	0.091	0.142	0.266
% change 2016 - 2020	-14.4	-35.8	-31.0	-0.7	-4.9

The statewide incidence of youth homelessness was 14% lower in 2020 than in 2016 (see Figure 16). The incidence of youth homelessness was also lower in 2020 than in 2016 in all four CoCs. However, it fell by more than 30% in Lowcountry and Upstate and by less than 5% in Midlands and TCHC. Additionally, regardless of the CoC, incidence fell in some years and rose in others, and the direction of the changes were not consistent across the CoCs.

Figure 16. Annual Incidence of Youth Homelessness



EFFECT OF MOBILITY ON COUNTS

Movement of youth across CoCs can affect CoC-level counts of homeless youth and, hence, state-level prevalence and incidence estimates based on those counts. Specifically, to the extent that youth are counted as homeless in more than one CoC or episodes of homelessness span across CoCs, prevalence and incidence estimates of youth homelessness will be inflated. We examined the extent to which youth experiencing homelessness moved between the state's four CoCs by identifying youth who were included in the counts of more than one CoC in a given year during our observation period.

Table 15 shows that across the 5 years, 102 youth were included in more than one CoC's HMIS in a single calendar year. This represents only 2.4% percent of the 4,190 youth counted as homeless in at least one year over the five-year observation period. This count rises to 317 (7.6%) when the entire five-year observation period is considered; that is, when also including instances when youth were enrolled in HMIS projects in multiple CoCs in different calendar years.

Table 15. Number of Homeless Youth Included in Multiple CoC Counts

Year	*N*
2016	27
2017	27
2018	19
2019	18
2020	11
Total	102
Counts across combined 5 years	317

CHARACTERISTICS OF HOMELESS YOUTH

We used the HMIS data to "paint a picture" of the population of 18- to 24-year-olds who were enrolled in an HMIS project at some point between January 1, 2016 and December 31, 2020. Table 16 shows the characteristics of the 3,769 young people between the ages of 18 and 24 who experienced homelessness at least once during those 5 years. Young men outnumber young women, and Black youth comprise the largest racial group. It is also worth noting that nearly 3 in 10 of these young people have a mental health disorder and 1 in 10 has a substance use disorder.

Table 16. Demographic Characteristics of Statewide Homeless Youth Population (*N* = 3,769)

Characteristic	*N*	%
Gender		
Female	1,821	48.3
Male	1,944	51.6
Unknown	4	0.1
Race		
American Indian	10	0.3
Asian	15	0.4
Black	1,943	51.6
Pacific Islander	15	0.4
Multiracial	230	6.1
White	1,525	40.5
Unknown	31	0.8
Ethnicity		
Hispanic	191	5.1
Non-Hispanic	3,532	93.7
Unknown	46	1.2

Table 16, cont'd

Characteristic	*N*	%
Veteran status		
Veteran	102	2.7
Disability status		
Physical disability	199	5.3
Developmental disability	231	6.1
Chronic health condition	179	4.7
HIV/AIDS	16	0.4
Mental health disorder	1044	27.7
Substance abuse disorder	377	10.0

Table 17 shows the same demographic characteristics separately for each CoC. Several differences across the CoCs can be observed. In wo of the four CoCs (Midlands and TCHC), homeless young men outnumber homeless young women, but in the other two (Lowcountry and Upstate), homeless young women outnumber homeless young men. Similarly, more homeless youth are Black than White in two of the four CoCs (Midlands and Lowcountry), but more homeless youth are White than Black in the other two (Upstate and TCHC). The percentage of homeless youth with a mental health or substance use disorder also varies widely. Depending on the CoC, between 15% and 36% of the homeless youth have a mental health disorder and between 6 and 12% have a substance use disorder.

Table 17. Demographic Characteristics of Homeless Youth Population by CoC

	SC-500 Low Country *n* = 421		SC-501 Upstate *n* = 734		SC-502 Midlands *n* = 1201		SC-503 TCHC *n* = 1511	
	#	%	#	%	#	%	#	%
Gender								
Female	228	54.2	395	53.8	529	44.0	715	47.3
Male	192	45.6	338	46.0	672	56.0	794	52.5
Unknown	1	0.24	1	0.1	0	0.0	2	0.1
Race								
American Indian	1	0.24	2	0.3	4	0.3	4	0.3
Asian	0	0.0	4	0.5	6	0.5	4	0.3
Black	254	60.3	311	42.4	749	62.4	672	44.5
Pacific Islander	3	0.71	3	0.4	4	0.3	6	0.4
Multiracial	48	11.4	60	8.2	43	3.6	92	6.1
White	104	24.7	347	47.3	393	32.7	722	47.8
Unknown	11	2.6	7	1.0	2	0.2	11	0.7
Ethnicity								
Hispanic	27	6.4	34	4.6	44	3.7	91	6.0
Non-Hispanic	378	89.8	695	94.7	1152	95.9	1400	92.7
Unknown	16	3.8	5	0.7	5	0.4	20	1.3
Veteran status								
Veteran	26	6.2	14	1.9	40	3.3	26	1.7

Table 17, cont'd

	SC-500 Low Country *n* = 421		SC-501 Upstate n = 734		SC-502 Midlands n = 1,201		SC-503 TCHC *n* = 1,511	
	#	%	#	%	#	%	#	%
Disability status								
Physical disability	21	5.0	37	5.0	69	5.7	39	2.6
Developmental disability	9	2.1	40	5.4	92	7.7	44	2.9
Chronic health condition	22	5.2	29	4.0	74	6.2	28	1.9
HIV/AIDS	3	0.7	4	0.5	6	0.5	2	0.1
Mental health disorder	105	24.9	181	24.7	430	35.8	226	15.0
Substance abuse disorder	25	5.9	81	11.0	141	11.7	88	5.8

We also used the data we received from the Department of Education, the Department of Social Services, and the Department of Juvenile Justice to better understand the characteristics of the young people enrolled in an HMIS project. Sixteen percent of these young people had been in foster care and 24% had been involved with the juvenile justice system during the years for which we had data.

Knowing about the characteristics of the population of youth who experienced homelessness in South Carolina and in each CoC during our 5-year observation period is valuable. However, these data cannot, by themselves, tell us whether any demographic groups are experiencing homelessness at a disproportionately high or low rate. To address this question, we first computed the mean number of homeless youth in each demographic group across the 5 years. Then we used that mean count to estimate the annual prevalence of homelessness for each demographic group. These prevalence rates can be directly compared.

Table 18 shows the statewide prevalence of youth homeless for different demographic groups. Young men were 6% more likely than young women to experience homelessness in a typical year. More striking is the Black-White difference in the prevalence of homelessness. In a typical year, Black youth were 2.6 times more likely than White youth to experience homelessness.

Table 18. Demographic Differences in the Statewide Prevalence of Youth Homelessness (*N* = 1,000)

Characteristic	Average annual statewide count	Statewide prevalence
Gender		
Female	468	0.204
Male	532	0.217
Race		
American Indian	3	0.179
Asian	4	0.044
Black	520	0.348
Pacific Islander	5	1.059
Multiracial	69	0.472
White	396	0.136
Ethnicity		
Hispanic	43	0.135
Non-Hispanic	948	0.214
Veteran status		
Veteran	29	0.006
Disability status		
Physical disability	52	0.011
Developmental disability	64	0.013
Chronic health condition	48	0.010
HIV/AIDS	5	0.001
Mental health disorder	301	0.063
Substance abuse disorder	112	0.024

Table 19 shows how the average annual prevalence of youth homelessness for different demographic groups varies across the four CoCs. In the Lowcountry CoC, young women were 38% more likely to experience homelessness than young men. By contrast, in the Midlands CoC, young men were 32% more likely to experience homelessness than young women. Additionally, although Black youth were more likely to experience homelessness in all four CoCs, the prevalence of youth homelessness is 5.7 times higher among Black youth than among White youth in the Lowcountry CoC but only 1.2 times higher among Black youth than among White youth in the TCHC CoC.

Table 19. CoC-Specific Average Annual Counts and Prevalence of Youth Homelessness by Demographic Characteristics

	SC-500 Lowcountry *N* = 114		SC-501 Upstate *N* = 208		SC-502 Midlands *N* = 276		SC-503 TCHC *N* = 320	
	#	%	#	%	#	%	#	%
Gender								
Female	61	0.143	105	0.147	95	0.211	153	0.378
Male	53	0.104	102	0.140	122	0.278	167	0.397
Race								
American Indian	0	0.000	2	0.638	1	0.335	1	0.213
Asian	1	0.071	2	0.055	4	0.094	1	0.151
Black	70	0.256	87	0.281	138	0.405	138	0.408
Pacific Islander	2	2.160	2	1.463	1	2.162	2	2.212
Multiracial	15	0.437	18	0.460	8	0.274	24	1.272
White	27	0.045	99	0.096	69	0.146	154	0.349
Ethnicity								
Hispanic	8	0.101	8	0.078	8	0.140	15	0.357
Non-Hispanic	103	0.120	199	0.148	209	0.251	301	0.385
Veteran status								
Veteran	7	0.007	3	0.002	12	0.008	7	0.008
Disability status								
Physical disability	6	0.007	14	0.010	23	0.015	11	0.014
Developmental disability	3	0.004	12	0.008	37	0.024	14	0.017
Chronic health condition	7	0.007	10	0.007	25	0.016	8	0.010
HIV/AIDS	1	0.001	2	0.001	2	0.002	1	0.001
Mental health disorder	32	0.034	53	0.036	161	0.105	67	0.081
Substance abuse disorder	8	0.008	25	0.017	57	0.037	27	0.033

PATHWAYS INTO HOMELESSNESS FROM YOUTH-SERVING SYSTEMS

We used the linked data to identify young people in the education, child welfare, and juvenile justice systems who experienced homelessness. Table 20 shows the size of each population.[22]

Table 20. Analytic Population by System

System	Description	*N*
Education	All young people in grades 7 through 12 who were enrolled in school at some point during the 2017–2018 or 2018–2019 academic year.	560,597
Child welfare	All young people in foster care and at least 13 years old at some point during the years 2009 through 2020.	6,406
Juvenile justice	All young people referred to the juvenile justice system and at least 13 years old at some point during the years 2009 through 2020.	35,326

Table 21 shows the number and percentage of young people in each system who experienced homelessness. Because our focus is on pathways from these systems into youth homelessness, we excluded young people who exited foster care prior to January 1, 2016. We also excluded young people involved with the juvenile justice system whose decision date was prior to January 1, 2016,[23] the first date for which we have HMIS data. Despite these exclusions, we found very low rates of homelessness across all three systems. Fewer than 1% of the young people in the education system or involved with the juvenile justice system, and fewer than 4% of the young people who exited foster care experienced homelessness during our observation period.

Table 21. Experiences with Homelessness by Youth-Serving System

System	*N*	Frequency	%
Education	560,597	3,756	0.7
Child welfare	6,406	221	3.5
Juvenile justice	35,326	300	0.9

We applied survival analysis using the lifelines Python package to understand when youth were most at risk for homelessness. Unlike logistic regression, survival analysis allows us to estimate not only whether an event (in this case, homelessness) will occur but also when it is most likely to happen. This approach is ideal for analyzing time-to-event data, such as time to homelessness. Our survival analysis focused on youth in the child welfare system (such as youth in foster care). We used survival analysis to examine the time between their last exit from foster care and their first experience with homelessness as an unaccompanied youth. We could not apply survival analysis to youth exiting the juvenile justice or education systems because neither the juvenile justice system data nor the education system data included exit dates.[24]

Methodology

Data Preparation

We created a child welfare dataset that included three variables: the date the youth most recently exited foster care, a binary indicator representing whether the youth became homeless during the observation period (1 = homeless, 0 = not homeless), and the date the youth first entered the HMIS if the youth became homeless. We used these data to calculate the number of days from foster care exit to homelessness for youth who became homeless and the number of days from foster care exit to the end of the observation period for youth who did not become homeless (that is, youth whose cases were right censored). Then we produced descriptive statistics for the distribution of days to homelessness,[25] including the number of observations, the average number of days to homelessness, the standard deviation, the shortest time to homelessness, the first quartile of the distribution, the midpoint of the distribution, the third quartile of the distribution, and the longest time to homelessness.

Kaplan-Meier Survival Estimator

We used the Kaplan-Meier estimator, a nonparametric statistic, to estimate the survival function $S(t)$. In this case, the survival function refers to the probability that a youth exiting foster care has not yet experienced homelessness by a given point in time. We calculated the survival probability, $S(t)=Pr(T>t)$, where T represents time to homelessness and t represents time since exit. Then we generated Kaplan-Meier survival curves to visualize the survival probabilities over time.

Youth exiting foster care most at risk for homelessness within the first 50 days after they exit.

Cumulative Hazard Estimation

We used the Nelson-Aalen estimator to compute the cumulative hazard function, which describes the accumulated risk of experiencing the event of interest, in this case homelessness, by time t. Then we used this estimator to generate cumulative hazard plots to visualize how the cumulative risk increased over time.

Time to Homelessness for Youth Exiting the Child Welfare System

Figure 17 shows the distribution of days to homelessness for youth exiting foster care. On average, it takes 460 days (approximately 15 months) for youth exiting foster care to become homeless. The median time to homelessness is 304 days, meaning half the youth who became homeless did so within about 10 months. The interquartile range (68 days to 775 days) reflects the variation in time to homelessness for the middle 50% of those youth. Notably, the youth who became homeless were most likely to do so within the first few days after exiting. However, youth continued to experience their first episode of homelessness throughout the observation period.

Figure 17. Distribution of Days to Homelessness After Exiting Foster Care

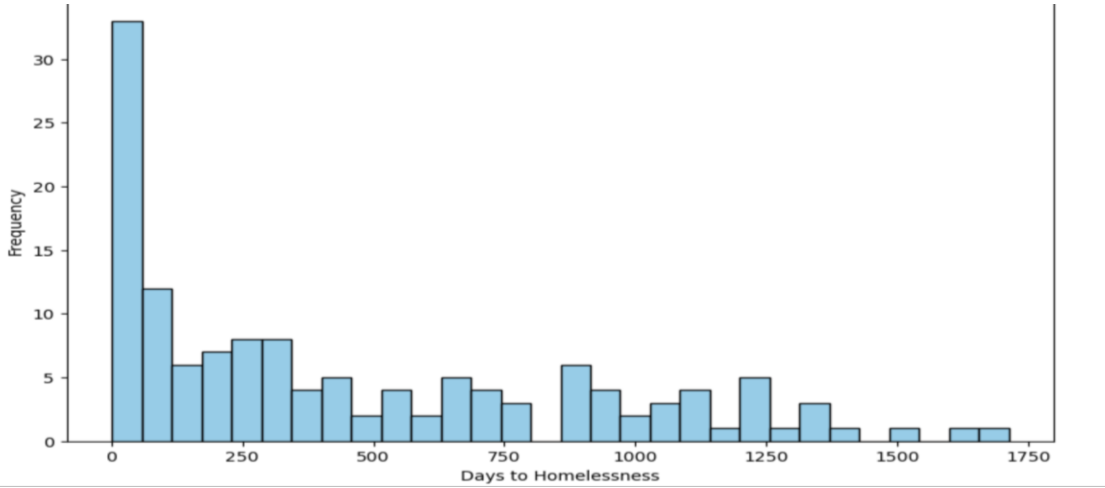


Figure 18 shows the probability that youth exiting foster care avoided homelessness over time. The survival curve declines steeply within the first 50 days, indicating a slightly increased risk of homelessness soon after exit. The probability of avoiding homelessness declines very slowly, but steadily, over time. Almost 5 years after exiting, the survival probability is just under 98%, indicating that only a small percentage of youth have experienced homelessness by this point.

Figure 18. Kaplan-Meier Survival Curve for Youth Exiting Foster Care

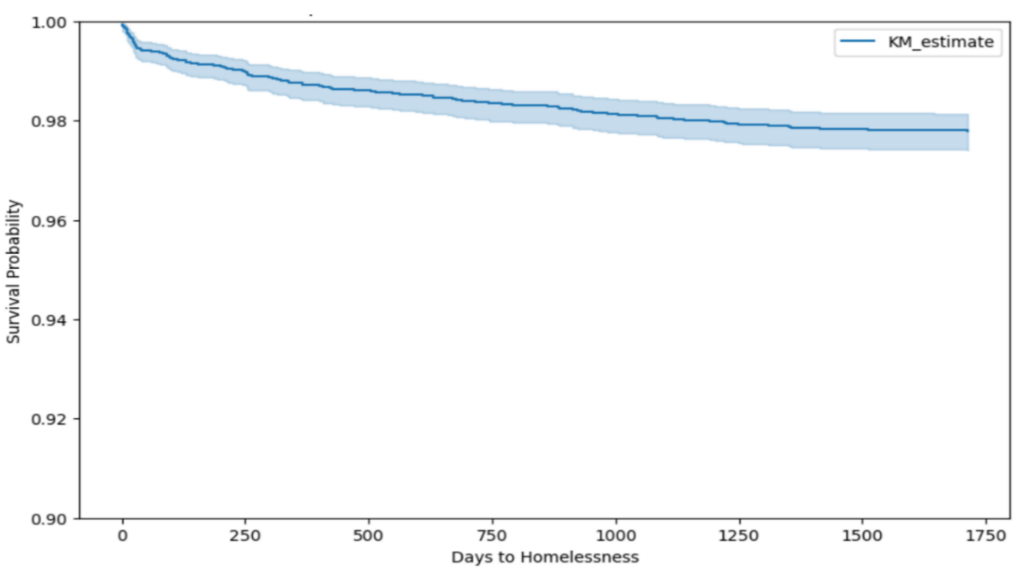
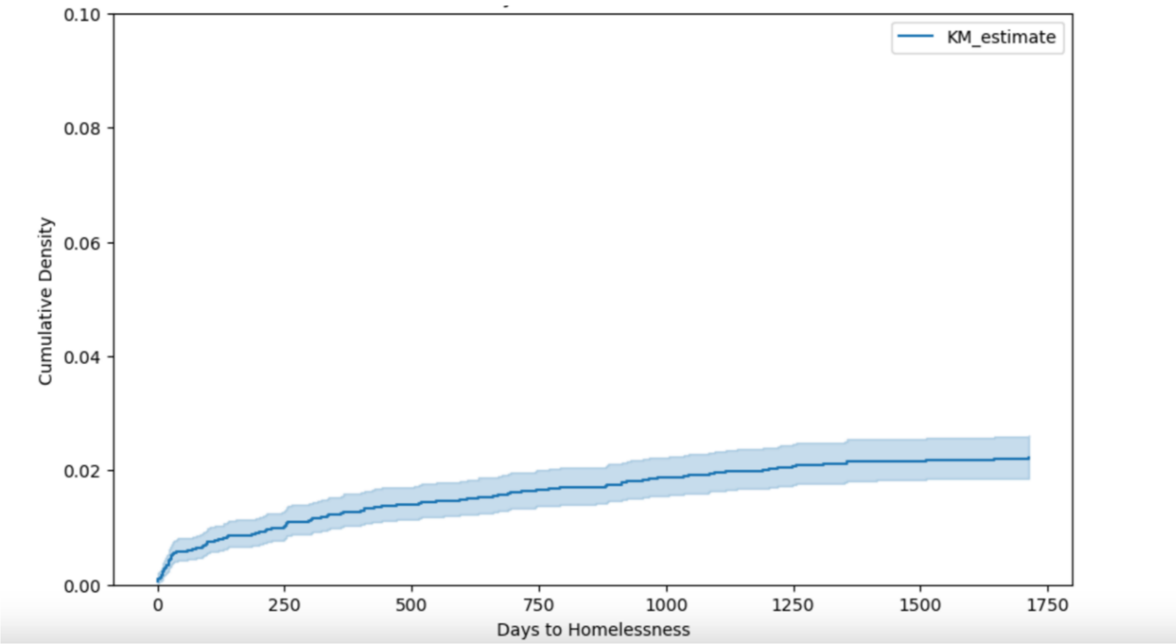


Figure 19 depicts the cumulative risk for homelessness over time for youth exiting foster care. The risk increases sharply within the first 50 days. After that, it increases slowly but steadily. Five years after exiting, just over 2% of the youth have experienced homelessness.

Figure 19. Cumulative Hazard Function for Youth Exiting Foster Care



PREDICTORS OF YOUTH HOMELESSNESS

Machine learning is a computational technique increasingly used in social science research to identify predictive patterns in large datasets, particularly when the goal is prediction rather than inference about relationships in a population. We applied machine learning to identify predictors of homelessness among youth enrolled in public schools (using Department of Education data), exiting foster care (using Department of Social Services data), and involved with the juvenile justice system (using Department of Juvenile Justice data).

Methodology

Data Organization and Preparation

We organized the HMIS data into a wide format using Python's "pandas" library. The resulting dataset included one column (variable) for each of the 1,827 days between January 1, 2016, and December 31, 2020. We coded each variable "1" if a young person was homeless on that day and "0" if the young person was not homeless. We then created a binary outcome variable that we assigned the value "1" if the young person had been homeless on at least 1 day during the observation period and "0" if the young person had not been homeless.

We also created three additional data sets using data from the Department of Education, the Department of Social Services, and the Department of Juvenile Justice. We recoded some variables and created others to ensure that the predictor variables in our models would be theoretically or empirically meaningful. We then merged the each of the three new datasets with our HMIS outcome variable using the unique identifier generated by the Revenue and Fiscal Affairs Office.

Data Preprocessing and Feature Engineering

We preprocessed all the data using Python libraries such as "scikit-learn" and "pandas." Specifically, we: (1) transformed categorical variables into binary indicators using one-hot encoding, (2) standardized ordinal and interval variables such that the effect variables are on the same scale and their effect sizes can be compared, and (4) applied Box-Cox transformations using "scipy" to normalize variables exhibiting extreme skewness or kurtosis. We also (1) performed multiple imputation using the "FancyImpute" library to handle missing data, (2) created binary indicators to identify missing data patterns that might predict homelessness, and (3) removed variables with zero variance from the datasets because they do not contribute to predictive power.

Machine Learning Models and Analysis

We analyzed the data using three machine learning models available in Python's "scikit-learn" library: logistic regression, ridge regression, and lasso regression. Logistic regression is used when the dependent variable is a binary. Ridge regression adds a penalty term to the regression model to shrink the coefficient values. It is used when the goal is to minimize the impact of less important features while keeping all variables in the model. Lasso regression also adds a penalty term to the model but some coefficients can be set to zero. It is used when the goal is to produce a more interpretable model with fewer variables. We selected these models based on their ability to handle binary classification problems and adjust for potential multicollinearity and other issues that arise when working with multiple predictor variables. We evaluated each model's performance based on five metrics (see Table 22).

Table 22. Metrics for Evaluating Model Performance

Metric	Description
Accuracy	• Overall proportion of correct predictions
Precision	• Proportion of true positive predictions (correctly identifying a homeless youth as homeless) out of all positive predictions • Important to avoid false positives (mistakenly identifying a non-homeless youth as homeless)
Recall/Sensitivity	• Proportion of homeless youth correctly identified by the model • Essential when the primary goal is to ensure no homeless youth are missed
F1 Score	• Harmonic mean of precision and recall • Balanced measure that considers false positives **and** false negatives • Assesses overall model performance when neither precision nor recall should be prioritized
Area Under the Receiver Operating Characteristic Curve (AUC-ROC)	• Measures the model's ability to distinguish between homeless and non-homeless youth across different classification thresholds • Provides a comprehensive view of the model's discriminative power • Useful in selecting the optimal threshold for classification.

After considering the recall-precision tradeoff, we decided to make recall our key performance metric. Although prioritizing recall meant accepting lower precision (that is, more false positives), we believed that this was preferable to failing to identify homeless youth (that is, more false negatives). Additionally, after testing threshold values, we settled on the default threshold of 0.5 so that the model was neither too conservative (missing too many homeless youth) nor too liberal (identifying too many youth who were not homeless). This aligns with the goal of maximizing detection without overwhelming resources.

Cross-Validation and Model Reliability

We employed K-fold cross-validation, a standard method for improving model reliability and reducing overfitting. This method splits the dataset into "K" parts; each part is used as a test set while the remaining parts are used to train the model. The process is repeated "K" times, which means that every data point is used for both training and testing. In our case, we used an 80/20 split for training and testing and applied cross-validation within the training set to ensure that the model would generalize to unseen data.

Retaining Records with Missing Data

RFA shared multiple education, child welfare, and juvenile justice datasets with us. We used the unique RFA identifier to link the education datasets to one another, the child welfare datasets to one another, and the juvenile justice datasets to one another. When working with linked datasets, it is common for some records to be incomplete. We retained records with incomplete data for two reasons. First, excluding incomplete records would result in a significant loss of useful information and compromise analytic power. By retaining these records, we capture as much relevant data as possible. Second, excluding incomplete records could introduce bias, particularly if data tend to be missing for specific groups. The decision to retain records with incomplete data aligns with best practices.

Addressing Class Imbalance

One of the challenges posed by this analysis was the class imbalance in the data. Specifically, regardless of the system, the ratio of non-homeless youth to homeless youth was very high (see Table 23).

Table 23. Class Imbalance by Youth-Serving System

System	Population	Percentage Homeless	Percentage Non-Homeless	Ratio
Education	560,597	0.7	99.3	141.9
Child welfare	6,406	3.5	96.6	27.6
Juvenile justice	35,296	0.9	99.2	110.2

We used four adjustment techniques to address this class imbalance (see Table 24).

Table 24. Techniques for Addressing Class Imbalance

Metric	Description
Synthetic minority over-sampling technique (SMOTE)	• Generate synthetic data points for homeless youth • Balances the dataset and improves the model's ability to detect homeless youth
Under-sampling the majority class	• Reduce the number of non-homeless youth to balance the dataset • Risks losing important information about the non-homeless youth
Over-sampling the minority class	• Increasing the representation of homeless youth in the dataset • Enhances the model's sensitivity
Class weight adjustment	• Assign more weight to the homeless youth during the model's learning process

The over-sampling and under-sampling methods are challenging in the absence of information about the actual ratio of homeless youth to non-homeless youth in each system. We ultimately decided to use the class weight adjustment approach to train the models because it improved recall while maintaining good precision.

Findings

We tested the ability of ridge regression, lasso regression, and logistic regression to predict homelessness among youth enrolled in public schools, exiting foster care, and involved with the juvenile justice system. In all three cases, logistic regression outperformed both ridge and lasso regression in terms of recall, our key performance metric.

Predicting Homelessness from the Education System

Table 25 shows the characteristics of the 560,597 young people in grades 7 through 12 who were enrolled in school at some point during the 2017–2018 or 2018–2019 academic year.

Table 25. Characteristics of Public School Students (N = 560,597)

Characteristic	Frequency	Percentage
Gender		
Male	79,262	14.1
Female	79,084	14.1
Missing	402,251	71.8
Race/ethnicity		
Black	66,020	11.8
Multiracial	4,557	0.8
Hispanic	2,665	0.5
White	71,672	12.8
Missing	415,683	74.2
Repeated a grade	34,885	6.2
Within-year school change	155,464	27.7
Free lunch history	97,282	17.4
Disability	123,770	22.1
	Mean	**Standard Deviation**
Absences per school year	9.0	7.9

The logistic regression model achieved a recall of 0.64, meaning that it correctly identified 64% of the youth in the public education system who experienced homelessness (see Table 26).

Table 26. Model Performance for Predicting Homelessness among Youth in the Education System

Class	Precision	Recall	F1 Score
Not homeless	1.00	0.69	0.81
Homeless	0.00	0.64	0.01
Overall accuracy		0.69	
AUC-ROC		0.66	

Key Predictors of Homelessness

Table 27 shows the coefficient values and odds ratios from the logistic regression model with minority class weight adjustment predicting homelessness among public school students. The strongest predictors of homelessness were grade retention, school mobility, and race/ethnicity. The odds of experiencing homelessness were higher for students who had repeated a grade and for students who had changed schools during the academic year. The odds of experiencing homelessness were also higher for Black and multiracial students, but lower for Hispanic students, than for White students. One less strong predictor that stands out is being eligible for free school lunch. Compared to students who never qualified for free school lunch, students who ever qualified for free school lunch had lower odds of experiencing homelessness.

Table 27. Key Predictors of Homeless from the Public Education System

Feature	Coefficient Value	Odds Ratio
Grade retention	1.35	3.88
Race/ethnicity		
Black	0.99	2.70
Multiracial	0.82	2.27
Hispanic	-1.65	0.19
Within-year school change	0.79	2.19
Free lunch history	-0.58	0.56
Disability	-0.23	0.80
Female	0.12	1.13
Absences per school year	0.12	1.13

Predicting Homelessness among Youth Exiting the Child Welfare System

Table 28 shows the characteristics of the 6,406 youth in the child welfare system who exited foster care in the years 2016 through 2020.

Table 28. Characteristics of Youth Exiting Foster Care (N = 6,406)

Characteristic	Frequency	Percentage
Gender		
Male	3080	48.1
Female	3323	51.9
Missing	3	0.0
Race		
American Indian/Alaskan Native	19	0.3
Asian	22	0.3
Black	2559	40.0
Multiracial	520	8.1
White	3284	51.2
Juvenile justice involvement	473	7.4
Hospitalization	491	7.7
Runaway history	755	11.8
Residential care placement	444	6.9
Emergency shelter placement	708	11.1
	Mean	**Standard Deviation**
Number of out-of-home care spells	1.35	0.7
Number of placements	4.49	5.1
Length of stay	631.03	853.1
Age at first placement	11.46	4.2

The logistic regression model achieved a recall of .72, meaning that it correctly identified 72% of the youth exiting foster care who experienced homelessness (see Table 29).

Table 29. Model Performance for Predicting Homelessness among Youth Exiting the Child Welfare System

Class	Precision	Recall	F1 Score
Not homeless	0.99	0.76	0.86
Homeless	0.10	0.72	0.18
Overall accuracy		0.76	
AUC-ROC		0.74	

Key Predictors of Homelessness

Table 30 shows the coefficient values and odds ratios from the logistic regression model with minority class weight adjustment predicting homelessness among young people exiting foster care. The strongest predictors of homelessness were exit reason, juvenile justice system involvement, hospitalization, and race. Exiting foster care through court termination, guardianship, and relative placement reduced the odds of experiencing homelessness more than exiting foster care through reunification (that is, returning home to parents) or adoption, although all of these exit outcomes had a protective effect.[26] The odds of experiencing homelessness were higher for youth who had been hospitalized and for youth who were involved with the juvenile justice system. Compared to the odds of experiencing homelessness for White youth, the odds of experiencing homelessness were higher for Black youth but lower for multiracial, American Indian/Native Alaskan, and Asian youth. Two less strong predictors that also stand out are number of out-of-home care spells and residential care placement. The more times youth entered foster care, the higher their odds of experiencing homelessness. Additionally, youth who were ever placed in residential care had higher odds of experiencing homelessness than youth who were never placed in residential care.

Table 30. Key Predictors of Homeless among Youth Exiting the Child Welfare System

Feature	Coefficient Value	Odds Ratio
Exit outcome		
Court termination	-2.01	0.13
Guardianship	-1.39	0.25
Living with relatives	-1.15	0.32
Return home to parents	-0.57	0.57
Reached age of majority or emancipation	0.42	1.52
Adoption	-0.61	0.54
Race		
American Indian/Alaskan Native	-0.99	0.37
Asian	-0.85	0.43
Black	0.73	2.08
Multiracial	0.17	0.18
Juvenile justice involvement	0.82	2.27
Hospitalization	0.80	2.22
Runaway history	-.04	0.96
Number of out-of-home care spells	0.65	1.92
Number of placements	-0.25	0.78
Length of stay	0.28	1.31
Residential care placement	0.55	1.74
Emergency shelter placement	0.25	1.29
Age at first placement	0.47	1.61
Male	0.39	1.47

Predicting Homelessness among Youth Involved with the Juvenile Justice System

Table 31 shows the characteristics of the 35,296 young people involved with the juvenile justice system.

Table 31. Characteristics of Youth Involved with the Juvenile Justice System (N = 35,326)

Characteristics	Frequency	Percentage
Gender		
Female	12,341	34.9
Male	22,749	64.4
Missing	236	0.7
Race/ethnicity		
Asian or Pacific Islander	80	0.2
American Indian/Alaskan Native	59	0.2
Multiracial	442	1.3
Black	15,976	45.2
Hispanic	1,373	3.9
White	17,396	49.2
County type		
Urban	27,710	78.4
Rural	7,143	20.2
Missing	473	1.3
	Mean	**Standard Deviation**
Number of referrals	2.4	2.6
Age of first offense	14.3	1.6
Decision charge weight	3.6	3.8

The logistic regression model achieved a recall of 0.71, meaning that it correctly identified 71% of the youth exiting the juvenile justice system who experienced homelessness (see Table 32).

Table 32. Model Performance for Predicting Homelessness among Juvenile Justice System-Involved Youth

Class	Precision	Recall	F1 Score
Not homeless	1.00	0.82	0.90
Homeless	0.03	0.71	0.07
Overall accuracy		0.82	
AUC-ROC		0.76	

Key Predictors of Homelessness

Table 33 shows the coefficient values and odds ratios from the logistic regression model with minority class weight adjustment predicting homelessness among young people involved with the juvenile justice system. The strongest predictors of homelessness were prior child welfare system involvement, race/ethnicity, referral source, and final disposition. The odds of experiencing homelessness were higher for youth who had spent time in foster care than for youth who had not.[27] Being referred to the juvenile justice system by a court office also increased the odds of experiencing homelessness. The odds of experiencing homelessness were higher for youth whose final disposition was a pickup order or bench warrant but lower for youth who were ordered to complete a drug court program or pay monetary restitution. Compared to the odds of experiencing homelessness for White youth, the odds of experiencing homelessness were lower for Asian or Pacific Islander youth, American Indian/Alaskan Native youth, and multiracial youth. Three less strong predictors are also worth noting: The odds of experiencing homelessness were higher for youth from urban counties, higher for females than for males, and higher for Black youth than for White youth.

Table 33. Key Predictors of Homeless among Youth Involved with the Juvenile Justice System

Feature	Coefficient Value	Odds Ratio
Race/ethnicity		
Asian or Pacific Islander	-1.80	0.17
American Indian/Alaskan Native	-1.67	0.19
Multiracial	-1.34	0.26
Black	0.41	1.51
Hispanic	-0.24	0.79
Referral source		
Court office	0.85	2.33
Police department	0.46	1.59
Juvenile justice system	-0.24	0.78
School	-0.09	0.95
Number of referrals	0.19	1.21
Child welfare involvement	2.10	8.14
Urban county	0.65	1.91
Female	0.38	1.47
Age of first offense	0.14	1.15
Decision charge weight	-0.08	0.93
Final disposition		
Ordered to complete drug court program	-4.18	0.02
Monetary restitution	-1.84	0.16
Pickup order/Bench warrant	1.13	3.09
Evaluation	0.62	1.86
House arrest order	-0.53	0.59
Indeterminate sentence	0.45	1.57
Probation	0.40	1.49
Determinate sentence	0.37	1.44
Adjudicated	0.33	1.39
Community service	0.28	1.32
Dismissal	0.15	1.16
School attendance order	0.05	1.05

DISCUSSION

By linking data across systems, this project generated actionable insights into the prevalence of and pathways into youth homelessness—revealing who is most at risk, when interventions matter most, and how communities can better target prevention efforts.

We began this project with the goal of developing innovative and replicable methods for using linked administrative data to (1) produce counts of homeless youth, (2) estimate the prevalence and incidence of youth homelessness, (3) describe the characteristics of the homeless youth population, (4) analyze pathways into homelessness from youth-serving systems, and (5) identify predictors of youth homeless through those pathways. Throughout this report, we have described how we used linked administrative data to achieve these goals. Here we summarize what we learned from both a substantive and methodological perspective.

Counts of Homeless Youth

We produced statewide and CoC-specific counts of youth experiencing homelessness in the years 2016 through 2020. Statewide, the number of 12- to 24-year-olds experiencing homelessness was about the same in 2016 as it was in 2020; the number of 18- to 24-year-olds experiencing homelessness was lower in 2020 than it had been in 2016. However, whether the counts increased, decreased, or remained about the same varied across the CoCs.

Rather than limiting our counts to youth enrolled in HMIS projects, as has traditionally been done, we also produced counts that captured experiences with homelessness when youth were not being served by CoC providers. Although incorporating these experiences into our counts means that our counts are probably less accurate than counts based exclusively on HMIS project enrollment data, we believe any inaccuracy is outweighed by the knowledge gained about the number of homeless youth not being served.

Additionally, by producing daily, rather than only annual, counts, we were able to observe the huge disparity between the number of homeless youth enrolled in an HMIS project and the number of youth experiencing homelessness who were not being served on any given day. In fact, the HMIS data indicate that the daily count of youth experiencing homelessness was, on average, 320% higher when youth not currently being served but who would later enroll in an HMIS project were included.

The daily counts also provided a window into the seasonal fluctuations in youth homelessness that annual counts obscure. While the pattern we observed is not surprising—that is, higher enrollment in housing projects during the winter as compared to summer months—the daily counts illustrate the innovative ways in which HMIS data can be used.

The low number of young people who were included in the counts of more than one CoC suggests that, at least in the case of South Carolina, deduplicating youth across the CoCs had relatively little impact on the accuracy of the counts (or on the prevalence and incidence estimates). It could, however, make a substantial difference in states where youth move more frequently across CoCs.

Prevalence and Incidence of Youth Homelessness

We used the homeless youth counts to estimate the annual prevalence and incidence of youth homelessness among 15- to 24-year-olds in South Carolina and in each CoC. Across our 5-year observation period, the mean statewide annual prevalence was 0.152, indicating that, on average, approximately 15 out of 10,000 15- to 24-year-olds in South Carolina experienced homelessness each year, where homelessness is defined as enrollment in an HMIS project. Including self-reported homelessness, the mean statewide annual prevalence was 0.211—or approximately 21 out of 10,000 15- to 24-year-olds.

Although including self-reported homelessness increased the prevalence of youth homelessness by about 40% statewide, prevalence did not increase uniformly across the CoCs. On the contrary, it increased by as much as 64% in one CoC and as little as 21% in another. This suggests that the share of homeless youth being served by CoC providers varies widely depending on where they live.

The statewide annual prevalence of youth homelessness was either 11% lower (when self-reported homelessness was excluded) or 15% lower (when self-reported homelessness was included) in 2020 than in 2016. The prevalence of youth homelessness was also lower in 2020 than in 2016 in three of the four CoCs, although the size of that change depended both on the CoC and whether self-reported homelessness was included in the counts. In the fourth CoC, prevalence either increased (when self-reported homelessness was excluded) or remained about the same (when self-reported homelessness was included).

Across our 5-year observation period, the mean statewide annual incidence was 0.133, indicating that, on average, approximately 13 out of 10,000 15- to 24-year-olds in South Carolina experienced a new episode of homelessness each year, where homelessness is defined as enrollment in an HMIS project. The mean incidence of youth homelessness across the 5 years was lower than the statewide mean in two of the four CoCs (Lowcountry and Upstate) and twice as high as the statewide mean in one of the other two (TCHC).

Between 2016 and 2020, the incidence of youth homelessness fell by 14% statewide and by more than 30% in two of the four CoCs. Additionally, regardless of the CoC, incidence fell in some years and rose in others, and the direction of these changes was not consistent.

Characteristics of the Homeless Youth Population

A majority of the nearly 3,800 young people who experienced homelessness in South Carolina during our observation period were male (52%) and Black (52%). Additionally, nearly three in ten had a mental health disorder and one in ten had a substance use disorder. However, these figures obscure variation in the characteristics of the homeless youth population within each CoC. For example, in two of the

CoCs, a majority of the youth who experienced homelessness were female and in two of the CoCs, a plurality of the youth who experienced homelessness were White. The proportion of young people experiencing homelessness with mental health or substance use disorder also varied widely across the CoCs.

Sixteen percent of the young people who were included in our count of homeless youth had been in foster care and 24% had been involved with the juvenile justice system. These percentages are much lower than what might have been expected based on the results of the Voices of Youth Count (VoYC) survey, which was conducted in 22 counties across the U.S. Over 4,000 13 to 25 year olds experiencing homelessness participated in the survey. Twenty-nine percent of those young people reported ever being in foster care and 46% reported ever spending time in detention, jail, or prison. A number of factors probably contribute to the differences between two sets of results. First, some young people experiencing homelessness in South Carolina may have been in foster care or involved with the juvenile justice system prior the years for which we had data. Second, the VoYC survey asked about "detention, jail, or prison" rather than juvenile justice system involvement, and some young people who responded affirmatively to the question may have been involved with the criminal-legal system. And third, VoYC applied a much broader definition of homelessness that included young people who were couch surfing or living doubled up. It is possible that the characteristics of those young people are different from the characteristics of young people defined as homeless based on HMIS project enrollment.

Statewide, the prevalence of youth homelessness was higher among young men than among young women. However, young women were more likely to experience homelessness than young men in two of the four CoCs. The higher prevalence of homelessness among Black youth (as compared to White youth) is not surprising. One national study found that the relative risk of experiencing homelessness was 83% higher among young adults who identify as Black than among young people who identify as White.[6] aboveWhat is striking is how much the prevalence of youth homelessness among Black youth as compared to White youth varied across the CoCs. In the CoC with the lowest rate of disproportionality, Black youth were 20% more likely to experience homelessness than White youth; in the CoC with the highest rate of disproportionality, Black youth were 470% more likely than White youth to experience homelessness.

Pathways into Homelessness from Youth-Serving Systems

Our analysis of the linked administrative data indicated that fewer than 1% of the youth in the public education system during the 2017–2018 or 2018–2019 academic years experienced homelessness as an unaccompanied youth (as measured by enrollment in an HMIS project) between 2016 and 2020. For states to be eligible for grants under the McKinney-Vento Homeless Assistance Act, they must report the number of students experiencing homelessness enrolled in their public schools to the U.S. Department of Education annually. Consequently, a number of studies have examined rates of homelessness among students enrolled in public school. However, we are not aware of any studies that have linked statewide public education data to HMIS data to examine homelessness among former public school students. This makes it difficult to contextualize our findings.

Linked data and innovative methods revealed which youth in public systems are most at risk for homelessness.

Our analysis of the linked administrative data also indicated that 3.5% of the youth who exited foster care experienced homelessness between 2016 and 2020. We know from prior prospective studies that homelessness is far too common among young people who aged out of foster care. Estimates vary depending on the study, but research suggests that between one-quarter and one-third of these young people will experience homelessness after they age out.[28,...,31] However, our population included not only youth who exited foster care by aging out, but also those who exited foster care through reunification, adoption, and legal guardianship. Although some research suggests that young people who exit foster care to what are supposed to be "permanent" homes are also at risk for homelessness,[32] their risk of homelessness is likely lower than the risk for homelessness among young people who exited foster care by aging out.

Finally, our analysis of the linked administrative data also indicated that fewer than 1% of the youth involved with the juvenile justice system with a decision date between 2016 and 2020 experienced homelessness during those 5 years. This was much lower than we had expected. Cross-sectional studies have consistently found that between one-third and one-half of young people experiencing homelessness had spent at least one night in a jail, prison, or juvenile detention facility.[33,...,36] Additionally, one longitudinal study found that 20% of young people leaving state juvenile rehabilitation or correctional facilities in Washington State experienced homelessness within 12 months of exiting.[31] However, an important difference between that study and ours is that most of the juvenile-justice-system-involved youth in South Carolina were still living in the community.

We were only able to examine the number of days that elapsed between system exit and the first episode of homelessness for youth who exited foster care. It took about 15 months, on average, for youth exiting foster care to experience their first episode of homelessness. However, about half the youth who became homeless experienced their first episode within about 10 months after exiting, and the risk of becoming homeless was highest during the first 50 days.

Predictors of Youth Homelessness

To our knowledge, this is the first study to use machine learning to identify predictors of youth homelessness. Because the data we received from each of the three systems (education, child welfare, and juvenile justice) included a different set of potential predictors, we cannot compare the features that stood out as strong predictors of youth homelessness across the three systems. Instead, we highlight some of the strong predictors that aligned with our expectations and others that did not.

For public school students, repeating a grade and changing schools during the academic year were both associated with an increased odds of experiencing homelessness. This makes sense. Grade retention and within-year school mobility are associated with an increased risk of dropping out,[37,...,41] and not completing high school is one of the strongest predictors of homelessness among young adults.[6] More difficult to explain is why the odds of experiencing homelessness were lower (rather than higher) for students who were eligible for the free lunch program. Eligibility for that program is limited to students whose family income is at or below 130% of the federal poverty line. Although one might expect family poverty to be a driver of youth homelessness, we know surprisingly little about how youth homelessness and family poverty are related. This relationship merits further investigation.

For youth exiting foster care, the strongest predictor of homelessness was juvenile justice system involvement. Having been involved with the juvenile justice system more than doubled the odds of experiencing homelessness. This finding is consistent with prior studies that have found juvenile justice system involvement or delinquency to be a predictor of homelessness among youth in foster care.[28,42,43] Hospitalization was another strong predictor of homelessness after exiting foster care. Although youth can be hospitalized for a wide range of reasons, hospitalization could be a proxy for mental or behavioral health problems, which prior studies have identified as a predictor of youth homeless.[44] This includes at least one study of youth in foster care.[28]

Race was also a strong predictor of homelessness among youth who exited foster care. Consistent with prior studies,[42,45] the odds of experiencing homelessness were higher for Black youth than for their White peers. At the same time, multiracial, Asian, and American Indian/Native Alaskan youth had a lower odds of experiencing homelessness relative to youth who are White.

Although it was not among the strongest predictors, placement in residential care was associated with increased odds of experiencing homelessness. Like hospitalization, residential care placement could also be a proxy for mental or behavioral health problems. Youth are typically placed in residential care because their mental or behavioral health needs cannot be addressed in less restrictive settings,[46] and prior studies have found that placement in congregate care settings (such as residential care) increases the likelihood that youth will experience homelessness after they age out.[29,43,45]

Unlike prior studies, we did not find placement instability or running away while in foster care to be a strong predictor of homelessness.[28,**Error! Bookmark not defined.**,43,45] However, the odds of experiencing homelessness were higher the more times youth entered foster care. Repeatedly entering and exiting foster care could make it difficult for young people to establish relationships with supportive adults, disrupt their education, and otherwise destabilize their lives.

We are not aware of any prior studies that have examined the relationship between how youth exit foster care and whether they experience homelessness after exiting. This reflects the fact that research on the nexus between foster care and youth homelessness has focused almost exclusively on youth who “aged out” between the ages of 18 and 21 years old, depending on their state. This research has consistently documented a high rate of homelessness among young people who have aged out foster care.[28-31,42,43,45,] Although aging out of care did increase the odds of experiencing homelessness, it was not among the strongest predictors. We also found that exiting foster care through guardianship or relative placement had a stronger protective effect than exiting foster care through reunification or adoption. This is interesting because reunification is generally preferred to other “permanency” outcomes (that is, outcomes that will ensure enduring and meaningful connections to supportive and caring adults).[47] Additional research is needed to better understand the relationship between exit outcomes and homelessness among youth in foster care.

For youth involved with the juvenile justice system, the strongest predictor of homelessness, by far, was child welfare system involvement. Race was also a strong predictor of homelessness among youth involved with the juvenile justice system. Relative to White youth, Black youth had higher odds of experiencing homelessness while Asian or Pacific Islander youth, American Indian/Alaskan Native youth, and multiracial youth had lower odds of experiencing homelessness than their White peers.

We have no clear explanation for the strong predictors related to final disposition. Moreover, because this is the first study to examine predictors of homelessness among youth involved with the juvenile justice system, we were unsure what to expect. It does make sense that being in an urban county would be a strong predictor given that we measured homelessness using HMIS data. Urban counties are likely to have more CoC providers, particularly providers that serve homeless youth.[33] Another important finding was that the odds of experiencing homelessness were higher for females than for males. This could reflect the fact that females comprise about one-third of the youth involved with juvenile justice system, and hence, that females who do become involved with the juvenile justice system are a particularly troubled group.

Implications for Using Administrative Data to Understand Youth Homelessness

Section 345 of the Runaway and Homeless Youth Act calls for using quantitative and qualitative research methods to estimate the prevalence and incidence of youth homelessness and describe the characteristics of homeless youth. Chapin Hall's Voices of Youth Count (VoYC) Study had produced prevalence and incidence estimates using survey data collected from a nationally representative sample of U.S. households. In its Notice of Funding Opportunity for Estimating the Prevalence and Probability of Homeless Youth (FR-6400-N-59), HUD asked whether prevalence and incidence estimates could be produced by linking administrative data from public agencies or systems that engage with youth, especially youth known to be at risk for homelessness. HUD was particularly interested in estimation methods that be replicated over time across jurisdictions to aid communities in assessing their local needs.

The YHDSP demonstrated that HMIS data can be used to generate counts for any interval of time, from daily to yearly and anything in between. These counts can be combined with U.S. Census Bureau data to produce both statewide and CoC-specific prevalence and incidence estimates of youth homelessness. The HMIS data can also be used to describe the characteristics of youth experiencing homelessness, examine differences in those characteristics across CoCs, and, when combined with U.S. Census Bureau data, identify disproportionalities across demographic groups.

Importantly, the approach we used to generate the counts of homeless youth, produce the prevalence and incidence estimates of youth homelessness, and identify disproportionalities can be replicated by or for any CoC. Because HMIS data from multiple CoCs can be combined, the approach can be replicated to generate statewide counts and produce statewide prevalence and incidence estimates. Combining data from multiple CoCs also makes it possible to compare prevalence and incidence estimates and identify differences in disproportionalities across CoCs.

Using HMIS data to estimate the prevalence and incidence of youth homelessness is much less costly than implementing the type of household survey that the VoYC Study undertook. Moreover, CoCs can use the HMIS data application that we developed along with the companion guide to replicate our approach. CoCs can use this approach to inform program planning and design interventions that address the needs of groups of young people who are overrepresented among the homeless youth population. They can also use it to better understand seasonal fluctuations and examine trends over time, both of which are critical to tracking progress towards the goal of ending youth homelessness

Relying exclusively on HMIS data does have drawbacks. Most notably, we simply do not know the number of young people experiencing homelessness who never enroll in an HMIS project. Nor do we know how the young people who do enroll in an HMIS project are different from those who do not. Additionally, HMIS data are not error free. Although our method for counting homeless youth gives precedence to data that are more likely to be accurate over data that are less likely to be accurate, some of the data we use—particularly the self-report and exit destination data—will be inaccurate to some (unknown) degree.

The YHDSP also demonstrated that that HMIS data could be linked to other administrative data and that those linked data could be used to understand pathways into and identify predictors of youth homelessness. Our survival analysis shed light on when young people exiting foster care are most at risk of experiencing homelessness. Similarly, by applying machine learning, we were able to identify youth whose odds of experiencing homelessness are either higher or lower due to their characteristics. Both of these approaches can be replicated using data from other jurisdictions and other state or local agencies to understand when youth exiting systems of care are most at risk for homelessness and which youth are most at risk. The biggest challenges to using these approaches is that both survival analysis and machine learning require a level of expertise that most CoCs are unlikely to have in-house. However, CoCs or government agencies could partner with researchers who have the requisite skills.

Policy and Practice Implications

Linking administrative data is a powerful, cost-effective way to study youth homelessness. The methods are replicable, the insights actionable, and the potential to guide policy and practice is significant.

The results of our analyses have several policy and practice implications for youth homelessness prevention. First, our survival analysis indicated that it is during the first couple of months after youth exit foster care that they are most at risk for homelessness. This suggests that child welfare systems should do more to ensure that youth have the supports they need to avoid homelessness during that critical period.

Second, the fact that changing schools during the academic year was a strong predictor of homelessness highlights the importance of school stability to homelessness prevention. Some mid-year school changes may be unavoidable (for example, a family moves across the state). However, school districts should try to minimize transfers during the school year whenever possible (for example, by allowing students to finish out the year in the same school) or by providing additional supports to students who transfer schools in the middle of the academic year. School districts should also consider providing more supports to students who repeat a grade since grade retention also increases the odds of experiencing homelessness.

Third, exiting foster care through legal guardianship or relative placement was associated with lower odds of experiencing homelessness. That youth who exited foster care to live with a guardian or family member were, in some sense, protected from experiencing homelessness is not surprising, and suggests that child welfare agencies should do more to promote permanency through legal guardianship or relative placement. What is puzzling, however, is why neither return to family (reunification) nor adoption seemed to have a similarly protective effect, and conversely, why aging out of foster care did not appear to put youth at increased risk.

Fourth, the urban-rural difference we found in the odds of experiencing homelessness among youth involved with the juvenile justice system could be an artifact of how we measured homelessness. That is, youth in urban areas may have more "opportunities" to enroll in an HMIS project because HMIS projects are more concentrated in those areas. However, it could also reflect the higher cost of housing in urban versus rural areas and, hence, the need for more affordable housing options for youth in urban areas, especially for youth involved with the juvenile justice system.

Fifth, the higher odds of experiencing homelessness for females relative to males among youth involved with the juvenile justice system could be due to pre-existing gender differences, although it is not clear what those differences might be. Alternatively, it could result from differential treatment by the juvenile justice system, such as gender differences in discharge planning or post discharge supports. Whatever the cause, greater attention should be paid to ensuring that young women are discharged from the juvenile justice system with a stable place to live.

Sixth, the fact that being involved with both the child welfare system and the juvenile justice system increased the odds that youth would experience homelessness suggests that youth at the intersection of these two systems are a particularly vulnerable group in need of targeted interventions and additional supports. It also highlights the need for cross-system coordination when youth are transitioning out of two systems of care. Additional research is needed to understand why the odds of experiencing homelessness is so much higher for these "dually involved" youth.

Finally, the odds of experiencing homelessness were higher for Black youth in the public school system, Black youth exiting foster care, and Black youth involved with the juvenile justice system than for their White peers. This is not surprising. A national prevalence study found that Black young adults are more likely to experience homelessness than young adults who are White.[6] Additionally, our analysis of the HMIS data revealed that Black youth were more likely to experience homelessness than White youth in a typical year. Taken together, these findings suggest that Black youth may be a particularly vulnerable group in need of targeted interventions. They also highlight the need for solutions to youth homelessness that center on race equity and address factors that contribute to these disparities, such as overt or covert discrimination and structural racism.

Limitations

YHDSP developed innovative and replicable methods for using linked administrative data, but faced challenges with data gaps and linkage quality.

The YHDSP achieved all the primary objectives laid out in our Research Design, Data Collection and Analysis Plan. We developed innovative methods for using linked administrative data to (1) produce counts of homeless youth, (2) estimate the prevalence and incidence of youth homelessness, (3) describe the characteristics of the homeless youth population, (4) analyze pathways into homelessness from youth-serving systems; and (5) identify predictors of youth homeless through those different pathways. That said, we encountered several unexpected challenges.

First, we planned to include students identified by their schools as experiencing homelessness without their parent or legal guardian but not enrolled in an HMIS project in some of our counts of homeless youth. Unfortunately, the Department of Education could not provide us with the data needed to distinguish between students who experienced homelessness with their families and those who experienced homelessness as unaccompanied youth. Hence, we were unable to supplement our counts. Second, we planned to use machine learning to identify factors associated with an increased risk for homelessness among youth who received outpatient mental health services. However, the data we received from the Department of Mental Health included only a handful of meaningful variables. Third, we planned to examine whether the child abuse and neglect histories of youth involved with the child welfare system could predict homelessness. Problems with the Department of Social Services investigations data precluded this analysis.

Fourth, we planned to reconvene the Learning Consortium participants during the final months of the project to elicit their feedback. However, we discovered that most of our partners in Travis County, Texas and New York City have moved on to other positions. Finally, the HMIS data we received from the four South Carolina CoCs were linked to the other administrative data we used by the Office of Revenue and Fiscal Affairs. We did not have access to any of the personally identifying information RFA used to link the data. We know that some of the unique identifiers RFA created were "bad" in that the same unique identifier was assigned to multiple youth. We are not aware of any other specific problems with the data linking but do have concerns about the quality of the linkage given the low percentage of youth in those other administrative data with HMIS records.

Research replicating the YHDSP method with data from other states is needed to assess generalizability.

Finally, because we only analyzed data from South Carolina, we do not know the extent to which our findings might generalize to other states. Additional research linking HMIS data to administrative data from other states is needed to assess the generalizability of our results.

CONCLUSION

The YHDSP demonstrated that HMIS data can be used to generate counts for any interval of time, from daily to yearly and anything in between. These counts can be combined with U.S. Census Bureau data to produce both statewide and CoC-specific prevalence and incidence estimates of youth homelessness. The HMIS data can also be used to describe the characteristics of youth experiencing homelessness, examine differences in those characteristics across CoCs, and, when combined with U.S. Census Bureau data, identify disproportionalities across demographic groups.

Importantly, the approach we used to generate the counts of homeless youth, produce the prevalence and incidence estimates of youth homelessness, and identify disproportionalities can be replicated by or for any CoC. Because HMIS data from multiple CoCs can be combined, the approach can be replicated to generate statewide counts and produce statewide prevalence and incidence estimates. Combining data from multiple CoCs also makes it possible to compare prevalence and incidence estimates and identify differences in disproportionalities across CoCs.

Using HMIS data to estimate the prevalence and incidence of youth homelessness is much less costly than implementing the type of household survey that the VoYC Study undertook. Moreover, CoCs can use the HMIS data application that we developed, along with the companion guide, to replicate our approach. CoCs can use this approach to inform program planning and design interventions that address the needs of groups overrepresented among the homeless youth population. They can also use it to better understand seasonal fluctuations and examine trends over time, both of which are critical to tracking progress towards the goal of ending youth homelessness

The YHDSP also demonstrated that that HMIS data could be linked to other administrative data and that those linked data could be used to understand pathways into and identify predictors of youth homelessness. Our survival analysis sheds light on when young people exiting foster care are most at risk of experiencing homelessness. Similarly, by applying machine learning, we were able to identify youth whose odds of experiencing homelessness were either higher or lower due to their characteristics. Both of these approaches can be replicated using data from other jurisdictions and other state or local agencies to understand when youth exiting systems of care are most at risk for homelessness and which youth are most at risk.

Key Takeaways

Daily Counts Reveal Hidden Trends

Producing daily, rather than only annual, counts of homeless youth revealed a huge disparity between the number of homeless youth enrolled in an HMIS project and the number of youth experiencing homelessness who were not being served on any given day. It also provided a window into the seasonal fluctuations in youth homelessness that annual counts obscure.

Revalence varies across CoCs and racial groups

Changes in the annual prevalence and incidence of youth homelessness were different at the state level than at the level of the four CoCs. Likewise, although the statewide prevalence of youth homelessness was higher among Black youth than among White youth, the disproportionality was much higher in some CoCs than in others.

Support immediately after foster care exit is critical

It took about 15 months, on average, for youth exiting foster care to experience their first episode of homelessness, but the risk of experiencing homelessness was greatest during the first 50 days.

Key Predictors Vary by System

The strongest predictors of homelessness were grade retention, school mobility, and race/ethnicity for public school students; exit outcome, juvenile justice system involvement, hospitalization, and race for youth exiting foster care; and child welfare system involvement, race/ethnicity, referral source, and final disposition for youth involved with the juvenile justice system.

Focus prevention on the most vulnerable youth

Increased attention should be paid to addressing the housing needs of Black youth, young women involved with the juvenile justice system, and youth involved with both the juvenile justice and child welfare systems due to their increased odds of experiencing homelessness.

ENDNOTES

[1] The Midlands CoC is located in the center of South Carolina and includes 13 counties: Aiken, Allendale, Bamberg, Barnwell, Calhoun, Chester, Fairfield, Lancaster, Lexington, Newberry, Orangeburg, Richland, and York.

[2] Auerswald, C., Lin, J., Petry, L., & Hyatt, S. (2013). *Hidden in plain sight: An assessment of youth inclusion in point-in-time counts of California's unsheltered homeless population*. California Homeless Youth Project.

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[7] Dworsky, A., & Horwitz, B., (2018). *Missed opportunities: Counting youth experiencing homelessness in America*. Chapin Hall at the University of Chicago.

[8] Horwitz, B., Hinsz, J., Karczmar, A., Matjasko, J., Patel, S., & Vidis, J. (2016). *Conducting a youth count: A toolkit*. Chapin Hall at the University of Chicago.

[9] Self-report data are primarily used to calculate the length of time an individual has been homeless and to identify individuals experiencing chronic homelessness. Exit data are primarily used to measure positive housing outcomes. CoCs have policies that promote the collection of accurate data and the value of measuring these outcomes. However, collecting these data often requires additional effort and there is little incentive to collect them if they do not show shorter spells of homelessness and fewer exits to homeless destinations.

[10] The figures in Table 3 are based on the Housing Inventory Count (HIC) data for 2023. These data are available on the HUD Exchange at http://www.hudexchange.info/resource/3031/pit-and-hic-data-since-2007/.

[11] The figures in Table 3 are based on the Housing Inventory Count (HIC) data for 2023. These data are available on the HUD Exchange at http://www.hudexchange.info/resource/3031/pit-and-hic-data-since-2007/.

[12] Although we requested and received data from the Department of Mental Health, those data did not include enough information to incorporate them into our machine learning analysis.

[13] These are individuals who were born between January 1, 1996, and December 31, 2001.

[14] Homeless situations include places not meant for habitation (for example, a vehicle, an abandoned building, bus/train/subway station/airport, or anywhere outside) as well as emergency shelters, hotels or motels paid for with an emergency shelter voucher, or safe havens.

[15] This method of defining homelessness is documented in HUD's [Client Level System Use and Length of Time Homeless Report.]

[16] U.S. Department of Housing and Urban Development. (2018). *Client-level system use and length of time homeless report*. HUD. https://www.hudexchange.info/resource/5689/client-level-system-use-and-length-of-time-homeless-report/

[17] We produced an HMIS application that CoCs can use to produce counts of homeless youth. An accompanying guide includes strategies for preparing HMIS data for the application and using the application to generate reports and create data visualizations.

[18] The mean count of 2018 data was used in order to measure the difference between the average daily count with self-reported data vs. without self-reported data. The data prior to 2018 contain several large anomalies (seen in spikes in the data) due to particular efforts related to the Point-in-Time count and database cleaning. Data after 2018 begin to show increasingly fewer self-reported homeless days due to the fact that such data are collected retroactively. Therefore, comparing the mean counts in 2018 represents the time period in which the fewest exceptions occurred based on the particularities of this data collection method.

[19] The mean number of youth enrolled in a housing project is 101. The mean difference between the annual maximum and minimum daily count youth served is 39 youth (when outliers for PIT counts are removed).

[20] The total number of youth enrolled in service projects might vary seasonally if service projects operated in conjunction with housing projects.

[21] We do not report separate incidence based on counts that include self-reported homelessness because it does not change the results in any meaningful way. Because we only have self-report data for youth who eventually enroll in an HMIS project, we would not capture any additional youth by including self-reported homelessness. It would only change the date on which they first became homeless from the date on which they first entered HMIS to the date on which they first experienced homelessness.

[22] The number of youth shown in Table 17 is higher than the number of youth included in our analyses because some youth for whom data were missing were dropped.

[23] The decision date is the date on which the Solicitor decides whether to dismiss the case, divert the youth to a community-based program, require the youth to make restitution for the offense, or proceed with prosecution.

[24] The juvenile justice data included the disposition date, the date a decision was made about whether the youth would be sentenced to a secure facility or receive a suspended sentence and whether the youth would be placed on probation or placed in a community-based residential setting.

[25] Right censoring occurs when study ends before the event of interest can be observed.

[26] The court could terminate a voluntary foster care placement.

[27] The very large odds ratio can be attributed to the severe class imbalance in the dataset. That is, the "class" of youth who did not experience homelessness was much larger than the "class" of youth who did experience homelessness.

[28] Dworsky, A., Napolitano, L., & Courtney, M. (2013). Homelessness during the transition from foster care to adulthood. *American Journal of Public Health,* 103, 318–23.

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