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Evaluating A Typology Of Homelessness Across A Midwest State

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EVALUATING A TYPOLOGY OF HOMELESSNESS ACROSS A MIDWEST STATE

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DEDICATION

This is dedicated to the men, women, and children whom society has failed to provide safe, adequate, and affordable housing. May we never tire of working to prevent and end that failure.

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The authors wish to acknowledge the hard work and dedication of service providers and administrators across the state of Michigan who are working to end homelessness in their communities. In particular, we recognize Barb Ritter, Gerry Leslie, and other leaders at the Michigan Coalition Against Homelessness for their partnership in this project.

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INTRODUCTION

Issues of homelessness have been discussed and researched heavily, especially in the last few decades. The issues have been conceptualized in different ways, and ways to solve or ameliorate homelessness and poverty have differed significantly. Johnstone and colleagues (2017) have presented an overview of some of these perspectives, including homelessness constructed as an individual and personal event with a focus on family violence, mental health, and addiction vs. homelessness constructed as a structural issue with a focus on policy.

These perspectives are important because they guide the approach that scholars, administrators, policy makers, and service providers take to implementing efforts to reduce and eliminate homelessness. Efforts by researchers to quantify and evaluate homelessness therefore also carry with them values and perspectives which are important to consider. As Jones (2015) outlined, social and behavioral science, along with the politics of how that is funded and conducted, has impacted homelessness and unwittingly led to a focus on the individual perspective rather than the structural aspects of poverty and homelessness.

As politics and policy have shifted, the mechanics of research on homelessness have progressed as well. In a review of the history of approaches to enumerating homeless people, Culhane and colleagues (1994) explained the importance of improved methods of utilizing computer records for unduplicated counts as opposed to past methods such as extrapolated guesses from surveys of key informants and point-in-time counts. In the United States, as technology has improved and Congress has incentivized compliance, homeless social service agencies have implemented computerized record systems and began cooperating in regional units – Continua of Care (CoCs). In a seminal article on utilizing large computerized record systems, Kuhn and Culhane (1998) made use of cities which were early adopters of electronic records in their public shelter system (New York City and Philadelphia) and used cluster analysis to validate a theoretical typology of homelessness by pattern of shelter utilization. They identified three clusters; the transitionally homeless who are homeless for a short period, the episodically homeless who shuffle in and out of homelessness, and the chronically homeless who experience prolonged and regular periods of homelessness.

Researchers in Canada sought to replicate these findings by analyzing the patterns of emergency shelter utilization in three Canadian cities of varying sizes: Toronto, Ottawa, and Guelph (Aubry, Farrell, Hwang, & Calhoun, 2013). They found clusters of shelter utilization that were similar to those found by Kuhn and Culhane and they compared and discussed the differences observed between the large, small, and medium-sized cities.

While some researchers have expressed doubts about the utility of the three-group typology (McCallister, Lennon, & Kwang, 2011) and expanded the approach to a time-patterned typology (McCallister et al., 2010, Brown et al., 2017), the approach established by Kuhn and Culhane has influenced the way policy on alleviating homelessness has been made, in the United States in particular, and requires attention as policy makers continue to rely on the ideas of that typology.

Kuhn and Culhane (1998) expanded this cluster analysis approach to families experiencing homelessness by using the same methodology in six U.S. cities (Culhane, Metraux, Park, Schretzman, & Valente, 2007). Aubry et al. replicated this cluster approach in three cities in Canada and discussed implications for program and policy development 20 years after Kuhn and Culhane's initial work. The current study seeks to expand on this work to examine the patterns of shelter utilization across a large and varied geographic area: a whole U.S. state. Questions of interest include whether a similar typology arises across an entire state and whether there are discrepancies in the typologies of homelessness in varying geographic and population centers. In particular, the cluster analysis approach has not been utilized in this way with rural populations. People in rural areas have been profiled as having poorer health status, engaging in more economic and lifestyle risk behaviors, attaining lower education levels, and having fewer socio-economic resources (for a review of issues of rural homelessness, see Forchuk et al., 2010; Whitley, 2013). Unique challenges of healthcare and poverty have been explored in suburban areas in the United States as well (Schnake-Mahl & Sommers, 2017; Tsai, Ramaswamy, Bhatia, & Rosenheck, 2015). A comparison of the typology of homelessness in three geographic and population areas (urban, suburban, and rural) will be conducted along with policy implications for any distinctions.

METHOD

For this study, data were obtained from a statewide agency, The Michigan Coalition Against Homelessness, which oversees the operation of networked data systems across the state of Michigan. These data systems, often referred to as Homeless Management Information Systems (HMIS) provide a longitudinal dataset of emergency shelter usage. Agencies within a city or regional unit called a continuum of care (CoC) collect demographic and shelter usage data for all people who make use of their services and share that information within the network of agencies. In order to maintain the confidentiality of the data across CoCs in the state, the data were aggregated into three geographic and population samples: rural, suburban, and urban. Data used in this study were gathered over a 6-year period between June 2010 and June 2016. Internal Review Board exemption was granted, as the data on individuals was anonymous in nature.

Description of Data

All records collected pertain to admission information gathered when individuals enter an emergency shelter and information entered when individuals leave that shelter. At entry, pertinent demographic information is gathered, including an individual’s age, gender, and primary race, as well as various components of their current life situation (e.g., prior living situation, extent of homelessness, disability status). Information entered when an individual exits a shelter includes an individual's reason for leaving and their intended destination upon leaving.

Data Preparation

When Kuhn and Culhane completed their analysis of multiple years of shelter data in New York City and Philadelphia, they were concerned about finding the most accurate representation of the pattern of shelter usage possible given the data they had. One element they focused on was 'left' and 'right' censoring. Left censoring, or a 'left-censoring bias' refers to a bias in the data which would cause some cases to show much less intense shelter utilization patterns than they have in reality. In effect this refers to cases and data points which exist 'to the left' of an imaginary starting line on a timeline – in this case the point at which data began to be included in the sample. While a data point in the sample may appear to be the 'first entry' of homelessness for an individual, we know that they may or may not have actually been in shelter any number of times before the cut-off point for the sample, therefore the sample discounts their previous homelessness potentially making them appear 'transitional' when they may have a chronic or episodic pattern of homelessness. Kuhn and Culhane attempt to mitigate this effect by discarding records for anyone with recorded entry to shelter in the years before their beginning time point. Therefore, individuals who remain in the sample did not experience homelessness in two years prior to the start point of the sample and are likely to not have experienced much if any episodes of homelessness in their past. While it is possible that individuals may have experienced homelessness three or more years ago, then not at all for two years, and then again during the sample period – this would be uncommon and a degree of 'left-censoring' bias that must be lived with given the method of analysis being conducted.

Right censoring, or a 'right-censoring bias' refers to the effect of neglecting entries into shelter which may come to the right of the imaginary end point on a timeline – in this case the point in which data are no longer included in the sample. Here, an individual may appear improperly to be 'transitional' with few entries to shelter when in fact they will accrue many entries after the end point in the sample. To mitigate this effect, Kuhn and Culhane included only records for individuals whose first admission to shelter came at least three years before the end date in the data.

In their cluster analysis, Aubry and colleagues did not correct for left or right-censoring bias to ensure sufficient sample size for the analyses. Given large samples at the outset, the analysis used in the present study largely utilized Kuhn and Culhane's approach to: (a) addressing left-censoring by excluding individuals with episodes of homelessness in the first two years of the data period (2010 and 2011) and (b) addressing right-censoring by including only individuals whose first admission occurred at least a year before the last year of the data (2015). Thus while there is some variability in the sample between amount of 'opportunity' for episodes of homelessness in the dataset, it is thought that in aggregate the potential effects of left and right-censoring have been limited by the exclusion criteria.

Calculation of Variables

Age: This variable was categorized in the three samples into categories which were utilized by Aubry et al., (2013): 16-19, 20-39, 40-59, 60+ years. Age was also maintained as a continuous variable.

Days in shelter: This variable was created by summing the number of days between admission and discharge for all shelter stays for each participant.

Episodes of homelessness: This variable was created by calculating the number of unique episodes of shelter stay for each individual utilizing their unique identification number. Kuhn and Culhane set 30 days as a time period in-between which entries to shelter were considered novel and distinct with the idea that if an individual has been admitted, discharged, and admitted again to shelter within less than 30 days they have not actually experienced a new episode of homelessness but rather one continuing episode. Aubry et al. (2013) utilized the same approach, and the present study did as well.

Average days per episode: This variable is a calculation of the number of days in shelter divided by the number of unique episodes of homelessness for each individual.

Ratio % days % clients: This variable is a ratio of the relative amount of individuals within a cluster and the relative amount of shelter days for individuals in that cluster. For example a cluster which included 25% of the sample and which accounted for 25% of the total days of shelter stay for the sample would have a ratio of one, a cluster with a higher proportion of shelter days relative to its' size would have a ratio greater than one, and a cluster with a smaller proportion of shelter days relative to its' size would have a ratio less than one. This ratio allows for a simple comparison of the amount of stays in shelter accounted for by individuals that are in the same cluster.

Standardization: For the purposes of the data analyses the 'days' and 'episodes' variables were standardized as z-scores with a mean of zero and a standard deviation of one. This was done to mitigate the overpowering effect that the 'days' variable would have on an analysis due to the large variability and greater magnitude of scores (with a range from one to hundreds) than the 'episodes' variable (with a range from one to the teens).

Data Analyses

In order to facilitate comparison of previous results, the data analysis approach developed by Kuhn and Culhane (1998) was utilized. A *k*-means cluster analysis was conducted entering in standardized variables of episodes of homelessness and days in shelter (described above) with a defined number of clusters set at three. Setting the number of clusters at three is a theoretical as well as methodological decision which Kuhn and Culhane examine in great detail in their original work. Fundamentally, the argument for three clusters is that the research literature on patterns of homelessness has consistently described three types of homelessness, though researchers have called these types by somewhat different names. The methodological decision includes an argument that some degree of constraint is required to have a usable model.

After the clusters were established in each of the three data samples (urban, suburban, and rural) between-cluster comparisons were conducted using an Analysis of Variance (ANOVA) and post-hoc test (Tukey's HSD) for parametric variables, and chi-square tests of independence for non-parametric variables (Tables 4-9). The same approach was also used in exploring differences between the three samples themselves (Tables 10 and 11).

RESULTS

In distinct population regions in the state of Michigan, a three cluster typology of shelter usage was evaluated for reliability and stability. One way that the reliability and stability of the clusters produced can be evaluated is through a reliability analysis, in which the dataset is split into two randomly generated subsamples. The *k*-means cluster analysis is then run on each subsample and the results of the two are compared (Rapkin & Luke, 1993). In their analysis of shelter data in New York & Philadelphia, Kuhn and Culhane found subsamples with a difference of less than 2% on the variables of episodes of homelessness and days in shelter, Aubry and colleagues reported results for two of the three data sets in their study (the larger cities of Toronto and Ottawa, not the smaller city of Guelph) and found a difference of less than 4% in most subsamples and a difference of 9% in one of the comparisons. In the larger datasets of this study (Urban and Suburban) a comparison of random subsamples yielded difference values less than 5%. Exceptions included the mean number of days in shelter in the episodic (5.59%; 90 vs. 85) and chronic (8.8%; 406 vs. 371) clusters of the urban sample. Thus in these two random subsample comparisons there was a difference of less than 9%, and in most of the comparisons a difference of less than 5% (see Tables 1 - 3 for complete data of sub-samples). For sake of completeness this same analysis was conducted with the rural sample which produced subsample differences of 4% and less for most of the comparisons, except for in the chronic cluster which yielded relatively striking difference values of 21.21% and 18.17% for the number of episodes and days in shelter respectively (1.71 vs. 1.34, and 235 vs. 193). It is hypothesized that the smaller sample size led to the discrepancy in random subsamples. The chronic cluster in each sample was by far the smallest – therefore the smallest cluster in the smallest sample was the most prone to issues of stability of the cluster model.

The three cluster typology was found to be stable and reliable in describing the pattern of shelter utilization in the samples. The three clusters that were identified included (a) one consisting of individuals with few episodes of homelessness and few days in shelter (temporary), (b) another cluster including individuals with many episodes in shelter but few days spent in shelter (episodic), and finally (c) a cluster including those with many episodes of homelessness and many days spent in shelter (chronic). The three geographic and population regions are described in detail below.

Urban

In the urban sample, 19,833 individuals were classified into the three clusters defined above. Tables 4 and 7 outline a comparison amongst the clusters on relevant shelter usage and demographic variables. The largest cluster was the 'temporary' cluster. This cluster made up 86% of the clients and comprised roughly 58% of the percentage of client days in shelter. While the 'chronic' cluster made up the smallest percentage of clients (6.24%), those in the cluster accounted for 31% of the client days. An easy way to compare these figures is to evaluate the ratio of the percentage of days of shelter stay accounted for in the cluster and the relative number of people in that cluster. For the temporary cluster this ratio was 0.67 while for the chronic cluster the figure was 5.02. For the shelter stay variables an Analysis of Variance (ANOVA) showed a significant effect of cluster type (Transitional, Episodic, and Chronic) on average number of episodes $F(2, 19830) = 19768.08$, $p < .001$, average number of days $F(2, 19830) = 13{,}196.48$, $p < .001$, and average days per episode $F(2, 19830) = 5{,}523.66$, $p < .001$. Post-hoc tests for these between-cluster comparisons showed significant differences between clusters. Individuals in the chronic cluster had on average more days per episode ($M = 179.35$, SD = 120.27), and a higher number of days in shelter ($M = 289.79$, SD = 124.35) than those in the episodic ($M = 22.07$, SD = 17.57 and $M = 84.06$, SD = 72.41) or temporary cluster ($M = 35.56$, SD = 38.76 and $M = 38.89$, SD = 40.99; Tukey's HSD $p < .001$ for each comparison), while those in the episodic cluster had significantly more episodes of shelter stay on average ($M = 3.83$, SD = 1.16) than the transitional ($M = 1.14$, SD = 0.35) or chronic clusters ($M = 1.97$, SD = 0.89; Tukey's HSD $p < .001$ for each). This pattern was consistent across the geographic regions with the episodic cluster having the most episodes of homelessness and the chronic cluster the most days in shelter and days per episode on average. Figures 1 and 2 show this pattern across the samples.

Comparisons of the demographic makeup between the three clusters within the urban sample are found in Table 7. Those in the chronic cluster had higher self-reported rates of disability than the transitional or episodic clusters (chronic > episodic; χ (1) = 6.79, $p < .01$) and were more likely to be a veteran than those in the transitional cluster (χ (1) = 15.28, $p < .001$). However, the rate of disability between the chronic and episodic cluster was not significant (χ (1) = 1.54, p = .215). A significant effect of cluster type was found for age using a one-way analysis of variance (ANOVA), F (2, 19830) = 132.77, $p < .001$. The Tukey HSD post-hoc test found that individuals in the chronic cluster were older on average (M = 45.41, SD = 13.13) than those in the transitional (M = 40.06, SD = 13.84, $p < .001$) or episodic cluster (M = 44.0, SD = 12.53, $p < .05$). A comparison of the racial and gender makeup of the clusters using a chi-square test indicated that the episodic cluster had the highest proportion of people of black race (χ (1) = 68.23, $p < .001$) and the highest proportion of males (χ (1) = 282.19, $p < .001$) when compared to the transitional and chronic clusters.

Suburban Cities

When analyzed, this sample of 18,187 produced three clusters identified as temporary, episodic, and chronic. As shown in Table 5, the temporary cluster included 89.75% of the sample, with the episodic and chronic clusters comprising 6.56% and 3.69% respectively. The chronic cluster over-accounted for client days in shelter relative to its size by a ratio of 8.32 while the temporary cluster ratio under-accounted for shelter stays at 0.63 and the episodic slightly at 1.91. Again individuals in the chronic cluster had roughly the same number of episodes of homelessness as the temporary cluster (M = 1.69 and 1.15 respectively) but had many more days in shelter (273 vs. 29) on average.

For the shelter stay variables an Analysis of Variance (ANOVA) showed a significant effect of cluster type (Transitional, Episodic, and Chronic) on average number of episodes F (2, 18184) = 15634.97, $p < .001$, average number of days F (2, 18184) = 14807.88, $p < .001$, and average days per episode F (2, 18184) = 8964.29, $p < .001$. Post-hoc tests for these between-cluster comparisons showed significant differences between clusters. Individuals in the chronic cluster had on average more days per episode (M = 272.95, SD = 179.31), and a higher number of days in shelter (M = 377.48, SD = 175.90) than those in the episodic (M = 23.72, SD = 18.77 and M = 86.6, SD = 70.02) or temporary cluster (M = 25.26, SD = 33.47 and M = 28.7, SD = 37.46; Tukey's HSD $p < .001$ for each comparison), while those in the episodic cluster had significantly more episodes of shelter stay on average (M = 3.72, SD = 1.22) than the transitional (M = 1.15, SD = 0.36) or chronic clusters (M = 1.69, SD = 0.86; Tukey's HSD $p < .001$ for each).

Comparisons of the demographic makeup between the three clusters within the suburban sample are found in Table 8. Those in the chronic cluster had higher self-reported rates of disability ($\chi(1) = 14.81$, $p < .001$) when compared to the transitional or episodic cluster, and were more likely to be a veteran than those in the transitional cluster (χ (1) = 6.60, $p < .05$). A significant effect of cluster type was found for age using a one-way analysis of variance (ANOVA), F (2, 18184) = 97.23, $p < .001$. The Tukey HSD post-hoc test found that individuals in the chronic cluster were older on average (M = 42.83, SD = 12.65) than those in the transitional (M = 36.49, SD = 13.52, $p < .001$) or episodic cluster (M = 39.64, SD = 13.06, $p < .001$). A comparison of the racial and gender makeup of the clusters using the chi-square test indicated that the episodic cluster had the highest proportion of people of black race (χ (1) = 17.26, $p < .001$) and the highest proportion of males (χ (1) = 52.66, $p < .001$) when compared to the transitional and chronic clusters.

Rural

The rural sample included 8,095 individuals also classified into three clusters. Table 6 shows that, like the urban sample, 86.22% of the individuals in the sample were classified into the 'temporary' cluster. In the rural sample only 3.21% of clients were classified as 'chronic'. Because of the smaller sample size of this sample, the stability of the clusters was lessened. For example, all of the 6,762 individuals in the temporary cluster in the rural sample had exactly one episode of homelessness. Many of the clients in the chronic cluster also had one episode of homelessness (65.1%) however the number of admissions per episode was dramatically higher in the chronic cluster than in the temporary or episodic clusters (160 vs. 16 and 17 respectively). A similar pattern in the ratio of shelter days and clients was found in the rural sample, with the 'chronic' cluster ratio equaling 7.66, the temporary 0.63, and the episodic 1.50.

For the shelter stay variables an Analysis of Variance (ANOVA) showed a significant effect of cluster type (Transitional, Episodic, and Chronic) on average number of episodes $F(2, 8092) = 10610.70$, $p < .001$, average number of days $F(2, 8092) = 5045.97$, $p < .001$, and average days per episode $F(2, 8092) = 3446.48$, $p < .001$. Post-hoc tests for these between-cluster comparisons showed significant differences between clusters. Individuals in the chronic cluster had on average more days per episode (M = 160.53, SD = 96.02), and a higher number of days in shelter (M = 203.08, SD = 96.46) than those in the episodic (M = 17.16, SD = 14.15 and M = 39.67, SD = 33.79 respectively) or temporary cluster (M = 16.82, SD = 22.38 and M = 16.82, SD = 22.38 respectively; Tukey's HSD $p < .001$ for each comparison), while those in the episodic cluster had significantly more episodes of shelter stay on average (M = 2.30, SD = 0.66) than the transitional (M = 1.0, SD = 0.0) or chronic clusters (M = 1.47, SD = 0.73; Tukey's HSD $p < .001$ for each).

Comparisons of the demographic makeup between the three clusters within the rural sample are found in Table 9. In the rural sample the episodic cluster had the highest self-reported rate of disability (χ (1) = 18.20, p < .001), while those in the chronic cluster were more likely to be a veteran (χ (1) = 6.53, p < .05). A significant effect of cluster type was found for age using a one-way analysis of variance (ANOVA), F (2, 8092) = 35.56, p < .001. The Tukey HSD post-hoc test found that individuals in the chronic cluster were older on average (M = 41.65, SD = 12.48) than those in the transitional (M = 34.90, SD = 13.13, p < .001) or episodic cluster (M = 34.06, SD = 12.79, p < .001). A comparison of the racial and gender makeup of the clusters using the chi-square test found no significant differences in the racial makeup of the three clusters, and that the chronic cluster had the highest proportion of males when compared to the transitional and episodic cluster (χ (1) = 12.34, p < .001).

Geographic-Population Comparisons

Tables 10 and 11 and Figures 1 and 2 present a comparison of the shelter stay and demographic data across the geographic and population centers. These show that the demographic makeup of the clusters across the centers is largely in synchrony with significant differences in the shelter stay variables. One-way between subjects ANOVA found an effect of region for the three primary shelter stay variables; ‘episodes’ (F (2, 46,112) = 178.98, p < .001), ‘days’ (F (2, 46,112) = 506.13, p < .001), and ‘days per episode’ (F (2, 46,112) = 423.04, p < .001). The urban population appeared to have more chronic homelessness with more days per admit (M = 43.57, SD = 58.86), days in shelter (M = 57.78, SD = 80.70), and episodes of homelessness on average (M = 1.39, SD = 0.87) than the suburban and rural samples (post-hoc comparisons all at p < .001). The suburban sample included the highest proportion of reported disability (40.4%; χ (1) = 198.72, p < .001) and veteran status (7.1%; χ (1) = 32.05, p < .001).

DISCUSSION

We had several goals when we set out to complete this analysis of shelter usage in the state of Michigan. One was to replicate analyses of shelter usage conducted in places like New York City and Philadelphia, as well as cities in Canada (Ottawa, Toronto, and Guelph). It was hypothesized that the perceived variability of homelessness in geographic / population centers in a US state would lead to significant variability in the makeup of homelessness in those centers. What we found is that although the amount of homelessness may vary, a 3-cluster typology of shelter usage is largely consistent across areas which are more urban, suburban, and rural respectively. These results are also consistent with what researchers have found in the places identified above. For example, in their paper published in 1998 Kuhn and Culhane found that 78.5% and 81% of clients fell in the 'transitional' cluster of shelter usage in New York City and Philadelphia respectively. Aubry and colleagues in 2013 found roughly 87% of people in Toronto fell in the transitional cluster (which they identified as 'temporary'). In the urban sample of the present study, 86% of clients fell into this same cluster of shelter usage. When compared side by side, various ways of measuring the shelter usage clusters in the state of Michigan yielded remarkably similar findings to those of previous researchers.

This analysis included a unique component of analyzing data taken from a rural geographic portion of a state. As discussed above, it was hypothesized that there may be differences in the makeup of the clusters of shelter usage based on variability in the homeless population or service provision systems in rural areas in a state. What we found is that the pattern for the rural area is generally the same as that of the urban and suburban geographic / population centers. One area of difference was in the magnitude of self-reported disability. In the rural sample a smaller proportion of individuals who were in the 'chronic' cluster reported having a disability than in the other clusters (27% in the chronic compared to 38% in the episodic and 31% in the temporary). A second interesting component is that less than half of the rural sample was male (49.4%) which is in contrast to the suburban and urban samples which were 55% and 66% male respectively. Given that the rural sample was the smallest and therefore had potentially less reliable clusters, it is important not to over analyze these results; however they suggest a difference in the composition of rural poverty in Michigan that is meaningful and worthy of continued assessment.

In general, the results are consistent with current conceptualizations of the three-part typology of homelessness. Comparisons of the demographic makeup of clusters across the samples suggest that women, younger people, and people without disabilities are more likely to be able to get out of homelessness quickly, and thus experience *transitional* homelessness. We might expect race, as a known correlate of poverty and other elements of disadvantage, to predict more pronounced levels of homelessness in the samples – but the results indicate that *chronic* homelessness as measured in these analyses was best conceptualized as a function of disability and age more so than race. Across samples, age and being a veteran were the factors that were most consistently elevated in the chronic cluster compared to the transitional or episodic clusters.

The findings from this analysis bring up larger points of reflection. When considering perspectives on homelessness, the questions and analysis have mostly been framed in terms of understanding the way that people are homeless. This is largely true of the cluster analysis approach developed by Kuhn and Culhane, utilized by other researchers, and made use of in this study as well. Underlying this approach is a desire to understand the ‘types’ of people who are homeless in order to shift and create resources that will help the different kinds of people who are homeless. The prevailing notion of this typology is that some people (most in fact) are able to exit homelessness quickly, some cycle in and out episodically, and one small group stays homeless for long periods. We define the state of those who are chronically homeless by elements of their life situation or naturally occurring elements of their identity (e.g., age, race, gender). We use these factors, either explicitly or implicitly, to explain why they struggle and do not bounce out of homelessness as the others do. However, when viewing the results of this analysis across decades and across varying geographic and population centers in North America, it is striking that there is such little variability in this pattern. There are two important potential explanations for this lack of difference. The first acknowledges a limitation of the design of these analyses. Utilizing homeless shelter episodes and days in shelter as the main measure of homelessness carries important advantages in having a consistent measure which is comparable across geographic regions and from person to person. Shelter stays are also a non-ambiguous reflection of homeless status – if someone is staying in a shelter they are unambiguously homeless at that time. However, focusing on shelter utilization alone may fail to identify the ways that the experience of homelessness is unique across geographic and population areas. Perhaps doubling up, couch-surfing, or other elements of precarious housing better explain variability in the typology of homelessness across these areas – this information is by definition less structured and less available, but potentially crucial.

A second, more abstract perspective on the lack of difference in homeless typology across time and place, is that typologies of homelessness may exist largely because we create them. Any potential variability in the experience of homelessness in these different geographic and population areas is superseded by the systems of housing and homeless social services which we as a society impose. In short, the services we provide and the laws we enact, create the typology of homelessness. Rather than looking at this matter from the perspective of who the homeless people are and what they are doing – how they are performing their homelessness - another perspective is to consider how we, as a society of policies and laws, are creating homelessness.

An interesting question is what this typology would look like if there was 'improvement'? Because the analysis creates clusters the 'chronic' cluster may persist despite improvements in the overall level of homelessness in communities. Identifying a typology of homelessness is useful only insomuch as it improves the way that we prevent and end homelessness for people. Kuhn and Culhane utilized a novel approach of identifying patterns of shelter usage by means of comprehensive shelter records. All of this led to a recognition and confirmation that people experience homelessness in different ways: i.e., in a transitional, episodic, or chronic fashion. They made the case that the way that each group experiences homelessness should be considered and it should lead to different approaches in addressing their needs. Over 20 years later, a contemporary analysis of the typology of homelessness throughout a sizable US state leads to important questions about how well that advice has been heeded. On one hand, we know that federal policy has shifted to more of a 'prevention-centered' approach where people who present with an element of risk are assessed and service prioritized depending on their level of risk and current state of homelessness. On the other hand, based on these findings it is hard to tell if this shift has led to a real change in the makeup of homelessness. Kuhn and Culhane speculated that early intervention for people who were in the 'temporary' category of homelessness experiencing residential instability could lead to a reduction in the number of people who go on to become episodically and chronically homeless. But, they also recognized that underlying systems of income, employment, health, and housing could impact the amount and experience of homelessness above and beyond early intervention efforts.

What this analysis shows is that the transitional-episodic-chronic typology of homelessness is largely stable today, and that the typology applies about equally well across different geographic and population areas in a US state. Moving forward, a two-pronged approach seems warranted. The first, continuing to fine-tune programs aimed at reducing homelessness by making them more effective and efficient by targeting services to the different clusters of homelessness. The second, recognizing that systems of income, employment, health, and affordable housing likely play a large underlying role in the amount and type of homelessness in communities across the country. A focus on either of these prongs exclusively will likely be insufficient in reaching the goals of ending homelessness.

Table 1. Cluster Sizes and Means for Subsample Cluster Models—Urban

	Transitional	Episodic	Chronic
Subsample 1			
Sample size	8,528	727	630
Average No. of episodes	1.14	3.83	1.99
Average No. of days	38.79	86.82	289.99
Subsample 2			
Sample size	8,637	692	619
Average No. of episodes	1.14	3.84	1.91
Average No. of days	38.79	81.31	287.59

Table 2. Cluster Sizes and Means for Subsample Cluster Models—Suburban

	Transitional	Episodic	Chronic
Subsample 1			
Sample size	8,168	621	343
Average No. of episodes	1.15	3.71	1.69
Average No. of days	29.51	89.76	406.45
Subsample 2			
Sample size	8,190	575	290
Average No. of episodes	1.15	3.73	1.69
Average No. of days	28.67	84.74	370.70

Table 3. Cluster Sizes and Means for Subsample Cluster Models—Rural

	Transitional	Episodic	Chronic
Subsample 1			
Sample size	3,374	576	146
Average No. of episodes	1	2.27	1.71
Average No. of days	17.4	40.28	235.41
Subsample 2			
Sample size	3,401	511	87
Average No. of episodes	1	2.33	1.35
Average No. of days	16.69	40.10	192.64

Table 4. Cluster Statistics for Model—Urban

	Transitional (T)	Episodic (E)	Chronic (C)	Between-cluster comparisons
Sample size	17,177	1,418	1,238	
Percentage of clients	86.61	7.15	6.24	
Average No. of episodes	1.14	3.83	1.97	F (2, 19,830) = 19,768.08, $p < .001$ T < E: $p < .001$, T < C: $p < .001$ E > C: $p < .001$
Average No. of days	38.89	84.06	289.79	F (2, 19,830) = 13,196.48, $p < .001$ T < E: $p < .001$, T < C: $p < .001$ E < C: $p < .001$
No. of episodes (%):				
1	85.8	-	34.0	
2	14.2	-	42.0	
3	-	53.2	18.5	
4	-	25.4	4.5	
5	-	11.8	0.9	
6 or more	-	9.5	0.1	
Average days per episode	22.07	35.56	179.35	F (2, 19,830) = 5,523.66, $p < .001$ T < E: $p < .001$, T < C: $p < .001$ E < C: $p < .001$
Ratio % days / % clients	0.67	1.45	5.02	
No. of days per episode (%):				
1 – 30	59.9	70.5	-	
31 – 60	14.2	25.5	-	
61 – 90	16.9	3.3	21.9	
91 or >	9.0	0.8	79.1	

Table 5. Cluster Statistics for Model—Suburban

	Transitional (T)	Episodic (E)	Chronic (C)	Between-cluster comparisons
Sample size	16,323	1,193	671	
Percentage of clients	89.75	6.56	3.69	
Average No. of episodes	1.15	3.72	1.69	F (2, 18,184) = 15,634.97, $p < .001$ T < E: $p < .001$, T < C: $p < .001$ E > C: $p < .001$
No. of episodes (%):				
1	85.0	-	51.6	
2	15.0	-	32.2	
3	-	59.7	13.0	
4	-	23.5	2.1	
5	-	9.5	1.2	
6 or more	-	7.4	-	
Average No. of days	28.7	86.6	377.48	F (2, 18,184) = 14,807.88, $p < .001$ T < E: $p < .001$, T < C: $p < .001$ E < C: $p < .001$
Average days per episode	25.26	23.72	272.95	F (2, 18,184) = 8,964.29, $p < .001$ T – E: $p = .521$, T < C: $p < .001$ E < C: $p < .001$
Ratio % days / % clients	0.63	1.91	8.32	
No. of days per episode (%):				
1 – 30	68.6	22.8	-	
31 – 60	15.7	22.6	-	
61 – 90	7.7	17.6	-	
91 or >	8.0	37.0	100	

Table 6. Cluster Statistics for Model—Rural

	Transitional (T)	Episodic (E)	Chronic (C)	Between-cluster comparisons
Sample size	6,762	1,081	252	
Percentage of clients	86.22	13.78	3.21	
Average No. of episodes	1.0	2.30	1.47	F (2, 8,092) = 10,610.70, $p < .001$ T < E: $p < .001$, T < C: $p < .001$ E > C: $p < .001$
No. of episodes (%):				
1	100	-	65.1	
2	-	78.6	24.6	
3	-	14.3	8.3	
4	-	5.7	2.0	
5	-	0.9	-	
6 or more	-	0.4	-	
Average No. of days	16.82	40.67	204.08	F (2, 8,092) = 5,045.97, $p < .001$ T < E: $p < .001$, T < C: $p < .001$ E < C: $p < .001$
Average days per episode	16.82	17.16	160.53	F (2, 8,092) = 3,446.48, $p < .001$ T – E: NS, T < C: $p < .001$ E < C: $p < .001$
Ratio % days / % clients	0.63	1.50	24.63	
No. of days per episode (%):				
1 – 30	81.8	81.7	-	
31 – 60	11.1	17.6	2.0	
61 – 90	5.4	0.3	20.2	
91 or >	1.7	0.5	77.8	

Table 7. Background Characteristics by Cluster in Given Category—Urban

	% Transitional (T) (n = 17,177)	% Episodic (E) (n = 1,418)	% Chronic (C) (n = 1,238)	Between-cluster comparisons ([1]Chi-Square, [2]ANOVA and Tukey)
Demographic				
[1]Black	74.3	84.2	70.7	T < E, $\chi(1) = 68.23$, $p < .001$ OR = 0.54, CIs [0.47, 0.63] T > C, $\chi(1) = 8.03$, $p < .01$ OR = 1.05, CIs [1.01, 1.09]
White	21.6	14.5	27.1	
American Indian	0.9	0.5	1.0	
[1]Male	63.9	86.0	74.2	T < E, $\chi(1) = 282.19$, $p < .001$ OR = 0.29, CIs [0.25, 0.34] T < C, $\chi(1) = 53.74$, $p < .001$ OR = 0.86, CIs [0.83, 0.89]
[2]Age M (SD)	40.06 (13.84)	44.0 (12.53)	45.41 (13.13)	F (2, 19,830) = 132.77, $p < .001$ T < E: $p < .001$, T < C: $p < .001$ E < C: $p < .05$
16 – 19	6.7	2.7	3.3	
20 – 39	40.5	29.6	25.9	
40 – 59	45.9	49.9	60.7	
60+	6.8	7.8	10.1	
[1]Self-reported disabilities	30.4	33.7	36.6	T < E, $\chi(1) = 6.79$, $p < .01$ OR = 0.95, CIs [0.92, 0.99] E ~ C, $\chi(1) = 2.41$, $p = .120$
[1]Veteran	5.8	7.3	8.6	T < C, $\chi(1) = 15.28$, $p < .001$ OR = 0.68, CIs [0.57, 0.83] E ~ C, $\chi(1) = 1.54$, $p = .215$

Note: between-cluster comparisons not shown were deemed duplicative or irrelevant

Table 8. Background Characteristics by Cluster in Given Category—Suburban

	% Transitional (T) (n = 16,323)	% Episodic (E) (n = 1,193)	% Chronic (C) (n = 671)	Between-cluster comparisons ([1]Chi-Square, [2]ANOVA and Tukey)
Demographic				
[1]Black	42.8	49.0	39.2	T < E, $\chi(1) = 17.26$, $p < .001$ OR = 0.79, CIs [0.71, 0.89] T ~ C, $\chi(1) = 3.39$, $p = 0.66$
White	52.6	47.3	56.8	
American Indian	1.6	1.4	1.3	
[1]Male	53.0	75.3	67.2	T < C, $\chi(1) = 52.66$, $p < .001$ OR = 0.79, CIs [0.75, 0.83] T < E, $\chi(1) = 223.26$, $p < .001$ OR = 0.70, CIs [0.68, 0.73]
[2]Age *M* (SD)	36.49 (13.52)	39.64 (13.06)	42.83 (12.65)	F (2, 18,184) = 97.23, $p < .001$ T < E: $p < .001$, T < C: $p < .001$ E < C: $p < .001$
16 – 19	8.9	5.2	2.7	
20 – 39	51.0	43.6	33.5	
40 – 59	35.4	45.5	57.4	
60+	4.7	5.7	6.4	
[1]Self-reported disabilities	39.5	45.3	54.5	E < C, $\chi(1) = 14.81$, $p < .001$ OR = 0.79, CIs [0.70, 0.89] T < E, $\chi(1) = 15.59$, $p < .001$ OR = 0.87, CIs [0.82, 0.93]
[1]Veteran	6.9	8.1	9.5	T < C, $\chi(1) = 6.60$, $p < .05$ OR = 0.73, CIs [0.57, 0.93] T ~ E, *NS;* E ~ C, *NS*

Note: not presented between-cluster comparisons were deemed duplicative or irrelevant

Table 9. Background Characteristics by Cluster in Given Category—Rural

	% Transitional (T) (n = 6,762)	% Episodic (E) (n = 1,081)	% Chronic (C) (n = 252)	Between-cluster comparisons ([1]Chi-Square, [2]ANOVA and Tukey)
Demographic				
Black	12.5	12.5	15.9	T ~ C, χ(1) = 2.54, p = .111 T ~ E, χ(1) = 0.00, p = .995
White	81.3	83.3	80.2	
American Indian	3.9	3.0	2.0	
Male	47.7	55.3	67.5	T < E, χ(1) = 21.53, p < .001 OR = 0.86, CIs [0.80, 0.92] E < C, χ(1) = 12.34, p < .001 OR = 0.60, CIs [0.45, 0.80]
[2]Age M (SD)	34.90 (13.13)	34.06 (12.79)	41.65 (12.48)	F (2, 8092) = 35.56, p < .001 C > E: p < .001, C < T: p < .001 E ~ T: p = .121
16 – 19	10.0	10.0	4.8	
20 – 39	56.3	56.7	36.1	
40 – 59	29.6	30.0	52.8	
60+	4.0	3.3	6.3	
[1]Self-reported disabilities	31.2	37.7	27	T < E, χ(1) = 18.20, p < .001 OR = 0.75, CIs [0.66, 0.86]
[1]Veteran	5.4	4.9	9.1	T ~ C, χ(1) = 2.03, p = .154 T ~ E, χ(1) = .43, p = .514 T < C, χ(1) = 6.53, p < .05 OR = 0.57, CIs [0.36, 0.88]

Note: between-cluster comparisons not shown were deemed duplicative or irrelevant

Table 10. Basic Tabulations of Samples

	Urban (U) (n = 19,833)	Suburban (S) (n = 18,187)	Rural (R) (n = 8,095)	Between-region comparisons ([1]Chi-Square, [2]ANOVA and Tukey)
Demographic				
Black	74.8	43.1	12.6	R < S, χ (1) = 2,621.81, $p < .001$ OR = 0.19, CIs [0.18, 0.20] S < U, χ (1) = 7,948.43, $p < .001$ OR = 0.255, CIs [0.247, 0.263]
White	21.5	52.4	81.5	
American Indian	0.9	1.6	3.8	
[1]Male	66.1	54.9	49.4	S < U, χ (1) = 498.49, $p < .001$ OR = 0.62, CIs [0.60, 0.65] S > R, χ (1) = 83.41, $p < .001$ OR = 0.80, CIs [0.76, 0.84]
[2]Age M (SD)	40.68 (13.80)	36.94 (13.53)	35.00 (13.12)	F (2, 84,132) = 1,015.56, $p < .001$ U > S: $p < .001$, U > R: $p < .001$ S > R: $p < .001$
16 – 19	6.2	8.4	9.9	
20 – 39	38.8	49.9	55.7	
40 – 59	47.8	36.9	30.4	
60+	7.1	4.8	4.0	
[1]Self-reported disabilities	31.0	40.4	32.0	R < S, χ (1) = 198.72, $p < .001$ OR = 0.69, CIs [0.66, 0.73]
[1]Veteran	6.1	7.1	5.4	R ~ U, χ (1) = 2.79, $p = .095$ S > U, χ (1) = 32.05, $p < .001$ OR = 0.86, CIs [0.81, 0.90] U > R, χ (1) = 5.29, $p = .021$ OR = 0.86, CIs [0.80, 0.98]

Note: between-cluster comparisons not shown were deemed duplicative or irrelevant

Table 11. Shelter Stay Variables by Geographic Region

	Urban (U) (n = 19,833)	Suburban (S) (n = 18,187)	Rural (R) (n = 8,095)	Between-region comparisons (ANOVA and Tukey)
Average No. of episodes (standard deviation)	1.39 (0.87)	1.34 (0.81)	1.19 (0.52)	F (2, 46,112) = 178.98, $p < .001$ U > S: $p < .001$, U > R: $p < .001$ R < S: $p < .001$
Average No. of days (standard deviation)	57.78 (80.70)	45.37 (84.56)	25.67 (43.94(	F (2, 46,112) = 506.13, $p < .001$ U > S: $p < .001$, U > R: $p < .001$ R < S: $p < .001$
Average days per episode (standard deviation)	43.57 (58.86) (58.86)	34.30 (66.30)	21.34 (36.79)	F (2, 46,112) = 423.04, $p < .001$ U > S: $p < .001$, U > R: $p < .001$ R < S: $p < .001$

Figure 1. Episodes of homelessness by geographic region and cluster

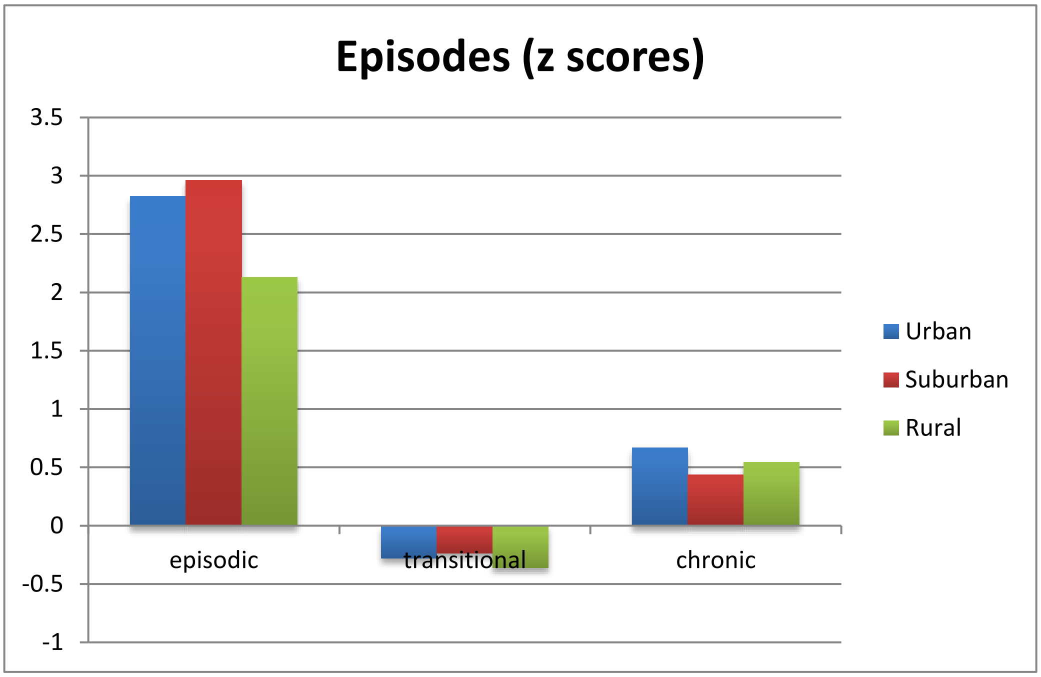
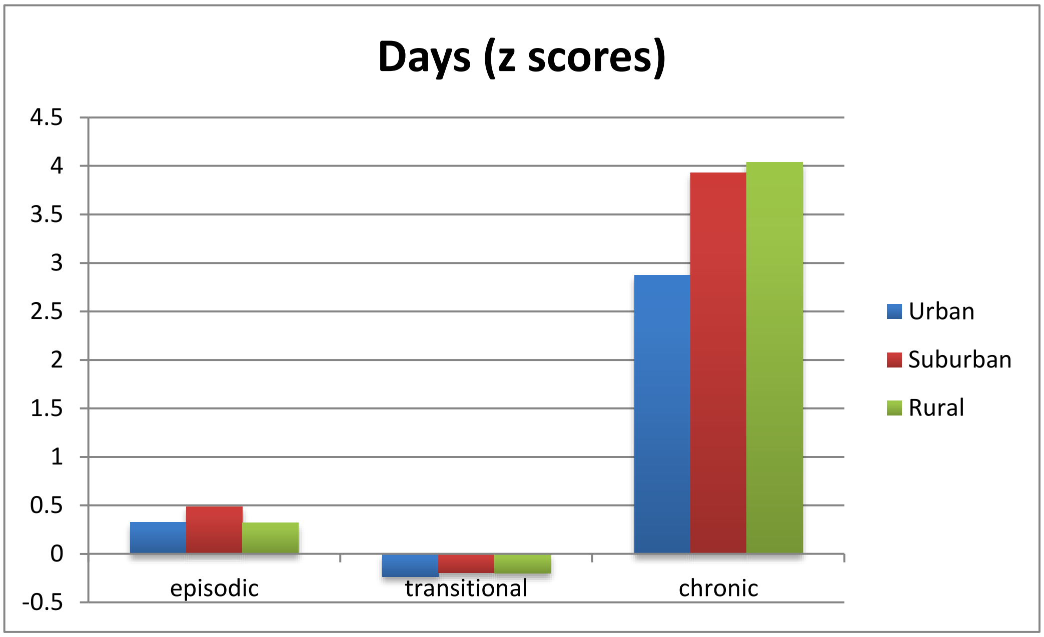


Figure 2. Days of stay in shelter by geographic region and cluster



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ABSTRACT

EVALUATING A TYPOLOGY OF HOMELESSNESS ACROSS A MIDWEST STATE

by

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Advisor: Dr. Paul Toro

Major: Psychology (Clinical)

Degree: Doctor of Philosophy

Identifying a typology remains an effective method to summarize and distinguish the different ways that people experience homelessness in communities. More than twenty years ago researchers in the northeast United States developed an approach to create a typology of homelessness by using electronic records of shelter stays and two dimensions of homelessness; number of episodes, and length of time spent homeless. The three-part typology Randall Kuhn and Dennis Culhane identified has shaped the way researchers and policy makers conceptualize homelessness and what strategies are utilized to address it. Since that time other studies have used the same approach in searching for a typology in three municipalities in Canada. This study applies Kuhn and Culhane's approach to a broader region with urban, suburban, and rural geographic and population centers. What is found is a remarkable similarity and consistency in the typology that arises in these regions, and consistency with previous work in varied settings (New York City, Philadelphia, Toronto, Ottawa, Guelph). Implications for the consistency of this typology twenty years later are discussed and a potential needed shift in approach to this effort are discussed.

AUTOBIOGRAPHICAL STATEMENT

Devin Hanson is a doctoral candidate in the Clinical Psychology program at Wayne State University. Mr. Hanson's work as a graduate student in the program has focused on research, clinical work, and policy advocacy in the areas of serious mental illness, community mental health, and homelessness. His passions for that work have led him to clinical training placements at state psychiatric hospital facilities and community mental health agencies in Detroit and southeast Michigan. Further, Mr. Hanson served as an elected member of the board of the Detroit Continuum of Care which oversees funding from the Federal Government for homeless social services in the City of Detroit. At present, Mr. Hanson is completing his pre-doctoral internship at the Ann Arbor VA Healthcare System with focused training in substance use, serious mental illness, and psychosocial recovery.