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ORIGINAL PAPER

Ethnic enclaves, neighborhood socioeconomic status, and obesity among Hispanic women in Chicago: a latent profile analysis approach

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Abstract

Purpose The prevalence of obesity, a crucial risk factor for breast cancer, is markedly higher among Hispanic women. The interaction between ethnic enclaves and neighborhood socioeconomic status (SES) as a determinant of this disparity warrants further research. We aimed to identify neighborhood profiles based on ethnic enclaves and socioeconomic status to evaluate the association with obesity among Hispanic women in the metropolitan Chicago region.

Methods We used a convenience sample of 24,884 Hispanic women over age 40 who obtained breast imaging from the largest healthcare organization in Chicago between 2010 and 2017. We conducted LPA to characterize neighborhood composition based on tract indicators of ethnic enclaves, disadvantage, and affluence. Multivariate linear and multinomial logistic regression models were used to evaluate the association of neighborhood profiles with BMI.

Results The LPA model identified four latent profiles, labeled based on their most significant characteristic as "middling," "disadvantage" "ethnic enclaves," and "affluent". Close to 50% of women in the disadvantage profile were obese and obese class II. Women in the disadvantage profile had the highest relative risk of being obese II (OR: 2.74 CI 95% 2.23, 3.36), compared to women in the middling profile. Women in the ethnic enclave and affluent profile were positively and negatively associated with obesity, respectively.

Discussion Using LPA to group individuals according to their combined traits provides empirical evidence to strengthen our understanding of how neighborhoods influence obesity in Hispanic women. The study findings suggest that ethnic enclaves, that are also disadvantage, are associated with obesity in Hispanic women.

Keywords Obesity · Ethnic enclaves · Hispanics · Latent profile analysis · Breast cancer risk factors

Background

The Hispanic population in the United States (U.S.) constitute of close to 65 million individuals. They are the largest, second-fastest-growing, and the second most segregated minority group in the U.S., following Asians, [1, 2]. The prevalence of obesity among Hispanic women is disproportionately high, by 2020 near 50% of Hispanic women were obese [3]. Breast cancer (BrCa) is the most prevalent cancer and the leading cause of cancer-related mortality among Hispanic women in the United States. Notably, the incidence of hormone receptor-positive BrCa has been increasing among Hispanic women over the past two decades [4, 5]. Obesity, which further increases the risk of obesity-related diseases and mortality, including BrCa, [6–8] is likely due to suboptimal engagement in healthy lifestyle behaviors [9]. This association is particularly concerning as obesity contributes to

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elevated estrogen levels and chronic inflammation, which are significant risk factors for hormone receptor-positive BrCa [6–8]. Consequently, investigating the multilevel factors contributing to obesity among Hispanic women is a critical public health priority.

As the U.S. Hispanic population has grown, ethnically dense geographic areas have emerged, particularly in urban areas, resulting in ethnic enclaves [10]. These enclaves are neighborhoods with a high concentration of individuals from the same ethnic origin, high linguistic isolation, high percent of recent immigrants, and ethnic-specific businesses and resources [11, 12]. Two frameworks have been proposed to understand how segregation through ethnic enclaves affects health outcomes for Hispanics in the U.S. [13].

The first framework suggests that ethnic enclaves provide a health promoting effect through social ties, cultural norms (i.e., healthier diet), and less discrimination [12], that may reduce exposure to stress, and promote healthy behaviors and physiological benefits. This framework suggests that ethnic enclaves are organized at the community level to foster culturally targeted opportunities, such as physical activity programs at community centers [13–15].

The second framework proposes that neighborhood disadvantage associated with locations where enclaves are often situated has a negative impact on health, due to low access to health care [16, 17], stress due to higher exposure to violence [13], and/or poor social and built environments [18, 19] all of which could offset the protection conferred by social networks [20]. For instance, residence in a low socioeconomic status neighborhood has been associated with unhealthy behaviors and poor health outcomes [21–23] whereas more affluent neighborhoods are associated with higher education, greater accessibility to resources, and healthier behaviors [11]. Therefore, the potential protective effects of residence in an Hispanic enclave could be attenuated or masked by the tendency for these neighborhoods to be socioeconomically disadvantaged [24].

Results from previous research on the relationship between ethnic enclaves and obesity outcomes have been inconsistent [20, 21, 25–29]. This could be due to differing conceptualizations of ethnic enclaves [6, 30]. Some definitions treat enclaves as interchangeable with measures of segregation based solely on ethnic density [21], proportion of foreign-born individuals, or proportion of linguistically isolated neighborhoods [29], while others use a composite of multiple measures or formal segregation measures [31]. However, relying solely on ethnic density to define enclaves neglects aspects of neighborhood composition related to migration, neighborhood socioeconomic status (SES), and other neighborhood characteristics that are linked to health behaviors and social outcomes among Hispanics [32–34].

Although previous studies have evaluated the effect of neighborhood characteristics on obesity among Hispanic women, most of these studies have applied independent measures or variable-centered analyses (e.g., multiple linear regression, principal component analysis) that disaggregate the contributions of enclaves and neighborhood SES on obesity outcomes and ignore the complex interaction of neighborhood SES with enclaves. Person-centered approaches, such as latent profile analysis (LPA), do not disaggregate an individual's traits (e.g., neighborhood SES or social determinants of health) to examine them separately. Rather, they group individuals according to their combined traits and may offer new insights into the way in which neighborhood characteristics influence obesity.

The objective of this study was to use LPA to better understand how three neighborhood indicators (enclaves, disadvantage, and affluence) might interact to affect BMI among a sample of Hispanic women that attended the biggest healthcare organization in the metropolitan Chicago region from 2010 to 2017.

Methods

Data sources and population

This study drew on data from women who underwent breast imaging for screening and/or diagnosis at a large healthcare organization in Illinois, with sites located in Cook and surrounding counties [35, 36]. The patient population within this healthcare organization is diverse in terms of geographic location (urban and suburban), and with respect to racial/ethnic and socioeconomic backgrounds. Women were eligible for this study if they self-identified as Hispanic, were over 40 years of age, and had undergone a breast imaging examination between 2010 and 2017.

To obtain information regarding neighborhood characteristics, each participant's residential address was geocoded to its 2010 census tract. Census tracts were then linked to the 2010 decennial census and the American Community Survey (2006–2010), using the Neighborhood Change Database and IPUMS (https://www.ipums.org/). A total of 1,717 census tracts were included in the study, out of 3,123 census tracts in Illinois.

Measures

Dependent variable

Body Mass Index. BMI was defined as a person’s weight in kilograms divided by the square of height in meters (kg/m^2). Both height and weight were self-reported in data collected for clinical purposes during the participant’s most recent breast imaging exam. We evaluated BMI as a continuous variable and as categorical based on the Centers for Disease Control and Prevention (CDC) guidelines, which include underweight (< 18.5 kg/m^2), normal weight (18.5 kg/m^2–24.9 kg/m^2), overweight (25 kg/m^2–29.9 kg/m^2), obese (≥ 30 kg/m^2–34.9 kg/m^2), and obese class II (≥ 35 kg/m^2). CDC considers a BMI ≥ 30 kg/m^2 as metabolically unhealthy [37].

Neighborhood characteristics

Neighborhood characteristics including census tract level ethnic enclaves, disadvantage, and affluence were obtained from 2010 US census and American Community Survey 2006–2010 and defined as composite measures using weighted sums across relevant neighborhood features.

The ethnic enclave measure was defined as a weighted sum of the proportion of individuals in each census tract that were Hispanic; foreign-born; spoke English either not well or not at all; the proportion who were recent immigrants; and the proportion of households that were linguistically isolated [11]. For neighborhood SES, we included established measures of both affluence and disadvantage to account for the differences in available resources. Together, these two measures account for both ends of the neighborhood SES spectrum in a manner that could not be accomplished with either measure alone, and each has potentially distinct implications for health [38]. The two continuous measures have been used in BrCa research to examine the role of neighborhood SES on BrCa outcomes [22, 38–40]. Tract-level disadvantage was defined as a weighted sum of the proportions of families with incomes below the federal poverty level, families receiving public assistance, persons unemployed, and female-headed households with children. Tract-level affluence was defined as a weighted sum of the proportions of families with income of ≥ $75,000, adults with a college education or more, and proportion of the civilian labor force employed in professional and managerial occupations (Appendix A1.).

The inter-item reliabilities for ethnic enclave scores, neighborhood disadvantage, and neighborhood affluence were 0.82, 0.97, and 0.92, respectively. These equally weighted sums were then standardized (Z scores) to have a mean of zero and a standard deviation (SD) of one. For descriptive analysis, Z scores were categorized into low (< -1), intermediate ($-1 < Z < 1$), and high (> 1) levels.

Individual level covariates were defined from the most recent imaging exam and included patient demographics (age, race/ethnicity, health insurance) and menopausal status (pre- vs. post-menopausal based on natural and surgical menopause).

A total of 30,130 Hispanic women older than 40 years and with available census tract data were eligible for inclusion in these analyses. We excluded participants with missing BMI ($n = 5{,}246$). Our final analytical sample consisted of 24,884 women with available BMI. To assess the potential impact of missing BMI data on our study results, we compared the characteristics of individuals with missing BMI data to those with complete data. The differences in risk factor distribution for women with versus without BMI were minor. Women with BMI information were less likely to be older than 70 years and more likely to be postmenopausal and parous (Appendix A2.).

Latent profile analysis

Latent Profile Analysis (LPA) is considered a "person-centered" approach, in contrast to a variable-centered approach because it focuses on grouping individuals based on patterns across numerous characteristics (in this example, within the features of each participant's neighborhood) [41]. Different levels of census tract affluence, disadvantage and ethnic enclaves co-exist within an individual's place of residence simultaneously, and associations produced from disaggregating these characteristics may not have real-world implications. We used LPA to identify a parsimonious set of mutually exclusive and exhaustive patient profiles that allowed us to capture the shared variance across the three continuous neighborhood features [42]. Indicators with missing data were retained in the model and imputed using full information maximum likelihood estimation.

We tested 2–6 possible profiles, the optimal number was determined considering both statistical model fit indices, including the lowest Akaike information criterion (AIC) and Bayesian information criterion (BIC), as well as the highest entropy [43], and interpretability. We named each profile based on its most noteworthy characteristic to reflect the meaning of the underlying values of the three indicators—ethnic enclaves, disadvantage, and affluence. We corrected for classification error when assigning individuals to their profiles by using the Bolck–Croon–Hagenaars (BCH) approach. This methodology assigns weight to the analysis of distal outcomes by utilizing the reciprocal of the posterior probabilities that associate individual women with specific profiles [44].

We conducted linear regression models to estimate the differences in mean of continuous BMI by neighborhood profiles. To assess the association of neighborhood profiles with categorical BMI, we estimated odds ratios (OR) and 95% CIs with multinomial logistic regression. Robust standard errors were estimated to account for clustering within census tracts. Evaluated covariates included age, menopausal status, parity (nulliparous, parous), age at first birth (nulliparous, < 35, > 35), age at menarche (≤ 10,11–14, > 14). Covariates included in our final model based on backward elimination (p-value > 0.1) and a priori knowledge.

As a sensitivity analysis, we repeated the analysis excluding underweight women (BMI < 18.5). MPLUS version 8.5 was used to conduct LPA and STATA 17.0 for statistical analysis.

Results

The mean age of our study participants was 56 years; the mean BMI was 30 ± 6.32. Roughly 80% of participants had a BMI > 25, with 36% classified as overweight, 25% as obese, and 18% as obese class II, respectively (Table 1).

The model with four profiles was selected based on statistical model fit indices, had the lowest AIC (101,436), highest entropy (0.805) and provided the profile interpretations that were the most meaningful. Table 2 shows the within-profile means for each indicator. Each profile was labeled according to their most distinguishable indicators based on within -profile means farthest from the mean value of 0 (range: − 1.95 to 4.38). The ethnic enclaves profile represented 40% of the population and was characterized by ethnic enclave, disadvantage and low affluence; The disadvantage profile accounted for 5% of the sample, and had high disadvantage, and low affluence. The affluence profile represented 15% of our sample and had high affluence, low disadvantage and ethnic enclave; and the middling profile, accounted for 39% of the participants, and was the most balanced profile, all three indicators had average scores within a 0.5 SD of their overall mean.

Table 3 shows the distribution of BMI, sociodemographic and reproductive characteristics by profile membership. Women assigned to the middling profile were the youngest on average, compared to those in the other profiles, whereas women in the disadvantaged profile were the oldest, menopausal, obese, and obese class II compared to women in the other profiles. Women in the ethnic enclave profile were more likely to be obese, less likely to have a family history of BrCa, and more likely to be parous compared to women in the other three profiles. Finally, women assigned to the affluent profile were more likely to be younger than 60 years, more likely to be normal weight, and to have the lowest mean BMI (Table 3).

We selected the middling profile as the referent for our analysis because it was the most common profile and exhibited a moderate representation of all three indicators. Results from the linear regression models showed that compared to women assigned to the middling profile, women assigned to the disadvantage profile had a mean BMI nearly 2 units greater (β = 1.98, 95% CI 1.56, 2.40), and women assigned to the ethnic enclaves' profile had a mean BMI nearly one unit greater (β = 0.77, 95% CI 0.54, 0.99). On the other hand, women assigned to the affluent profile had a mean BMI more than one unit lower (β = − 1.36, 95% CI − 1.64, 0.99) (Table 4).

Table 1 Distribution of sociodemographic characteristics among Hispanic women in Chicago, 2010–2017 (*N* = 24,884)

	N	%
Age		
40–49	9,597	32
50–59	9,509	32
60–69	6,337	21
70 +	4,683	16
Concentrated disadvantage		
< 1 SD below mean	2,621	9
Within 1 SD of mean	25,224	84
> 1 SD above mean	2,276	8
Concentrated affluence		
< 1 SD below mean	4,988	17
Within 1 SD of mean	21,204	70
> 1 SD above mean	3,929	13
Ethnic enclaves		
< 1 SD below mean	5,722	19
Within 1 SD of mean	19,684	65
> 1 SD above mean	4,720	16
BMI		
Normal/Underweight	5,163	21
Overweight	9,007	36
Obese	6,251	25
Obese Class II	4,463	18
Parity		
Nulliparous	2,974	10
Parous	27,152	90
Age at first Birth		
Nulliparous	2,974	10
< 35	25,942	86
35 +	1,210	4
Menopause		
Premenopausal	12,596	42
Postmenopausal	17,530	58
Age at menarche		
< = 10 years old	2,362	8
11 to 14 years old	17,511	62
14 + year old	8,428	30

Compared to women in the middling profile, women in the disadvantage profile had the strongest associations with overweight, obese, and obese class II (vs. normal weight), with ORs of 1.57 (95% CI 1.29, 1.92), 1.99 (95% CI 1.63, 2.44), and 2.74 (95% CI 2.23, 3.36), respectively. Compared to women in the middling profile, women in the enclave profile also had greater ORs for overweight (OR = 1.23, 95% CI 1.13, 1.33), obese (OR = 1.36, 95% CI 1.25, 1.48), and class II (OR = 1.44, 95% CI 1.32, 1.58)

Table 2 Parameters estimates for the four neighborhood profiles model from the latent class analysis among Hispanic women in Chicago

	Neighborhood profiles			
	Middling	Disadvantage	Affluence	Ethnic enclave
	$n = 10{,}174$ (39%)[a]	$n = 1{,}258$ (5%)[a]	$n = 3{,}756$ (15%)[a]	$n = 10{,}258$ (40%)[a]
Neighborhood characteristics	Within-profile means[b]			
Ethnic enclaves	−0.394	−0.030	−0.851	0.709
Disadvantage	−0.309	1.872	−0.784	0.358
Affluence	0.219	−0.880	1.582	−0.700

[a]Percentage of Hispanic women attending mammogram clinic in each profile

[b]Numbers represent the within-profile means for each neighborhood indicator. A higher value, positive or negative, suggests that the indicator is a strong predictor of the neighborhood profile

Table 3 Distribution of sociodemographic and reproductive characteristics of Hispanic women attending for breast cancer screening in Chicago by neighborhood profiles, 2010–2017 ($n = 24{,}884$)

		Middling	Disadvantage	Affluence	Ethnic enclave	
		$n = 10{,}065$ (40%)	$n = 1{,}208$ (5%)	$n = 3{,}660$ (15%)	$n = 9{,}951$ (40%)	
	n	%	%	%	%	*P* value
Age[a]	Mean (SD)	56.2 (0.13)	59.6 (0.35)	57.1 (0.21)	56.6 (0.12)	< 0.001
40–49	7999	33	24	33	32	
50–59	7947	32	31	30	33	
60–69	5350	21	24	21	22	
70 +	3588	13	21	16	14	
BMI[a]	Mean (SD)	30.4 (0.21)	32.4 (0.30)	29.1(0.23)	31.2 (0.21)	< 0.001
Under/normal weight	5163	22	12	31	17	
Overweight	9007	37	34	35	36	
Obese	6251	25	28	21	27	
Obese class II	4463	17	26	13	20	
Menopause						< 0.001
Premenopausal	10,150	42	34	42	40	
Postmenopausal	14,734	58	66	58	60	
Parity						< 0.001
Nulliparous	2080	8	9	11	7	
Parous	22,804	92	91	89	93	
Age at first Birth						< 0.001
Nulliparous	2080	8	9	11	7	
< 35	21,723	87	88	81	90	
35 +	1081	5	3	8	3	
Age at menarche						< 0.001
≤ 10 years old	2073	9	11	8	8	
11 to 14 years old	15,298	62	62	64	61	
14 + year old	7246	29	26	28	31	

[a]Mean and standard deviations are presented for age and BMI

(vs. normal weight). Conversely, compared to women in the middling profile, women in affluent neighborhoods were less likely to be overweight (OR = 0.66, 95% CI 0.60, 0.73), obese (OR = 0.58, 95% CI 0.52, 0.65), or obese class II (vs. normal weight) (OR = 0.55 95% CI 0.48, 0.62) (Table 4).

Discussion

Our study presents a novel approach to evaluating the association between ethnic enclaves, neighborhood SES, and obesity, among Hispanic women in Chicago. To our

Table 4 Association of neighborhood profiles with BMI among Hispanic women in Chicago, 2010–2017 ($n = 24{,}884$)

Neighborhood profiles	BMI								
	Normal Weight[b]	Overweight[b]		Obesity[b]		Obese class II[b]		Continuous[a]	
		OR	(95% CI)	OR	(95% CI)	OR	(95% CI)	β	(95% CI)
Middling	Ref	Ref		Ref		Ref		Intercept: 30.4	
Disadvantage	Ref	1.57	(1.29, 1.92)	1.99	(1.63, 2.44)	2.74	(2.23, 3.36)		1.98 (1.56, 2.40)
Affluence	Ref	0.66	(0.60, 0.73)	0.58	(0.52, 0.65)	0.55	(0.48, 0.62)		−1.36 (−1.64, −1.07)
Ethnic Enclave	Ref	1.23	(1.13, 1.33)	1.36	(1.25, 1.48)	1.44	(1.32, 1.58)		0.77 (0.54, 0.99)

[a]Linear regression model with robust standard errors was used for continuous BMI

[b]Multinomial logistic regression models with robust standard errors were used for categorical BMI. All models were adjusted by age

knowledge, this is the first study to use LPA to examine associations between ethnic enclaves, neighborhood SES, and obesity. Our LPA analysis revealed four distinct neighborhood profiles that describe where Hispanic women in our sample reside, including an ethnic enclave profile, which was additionally characterized by higher disadvantage. Women assigned to the disadvantage profile had the highest odds of being obese class II, compared to women in the middling profile. Similarly, women assigned to the enclave profile (vs. the middling profile) were more likely to be obese and obese class II. We also found a strong inverse association with obesity for women in the affluent (vs. middling) profile. This study observed and increased odds for obesity among Hispanic women in ethnic enclaves' profiles; and underscores the importance of considering neighborhood SES when evaluating the association of ethnic enclaves with obesity in Hispanic women.

We observed a significant association between residence in an ethnic enclave profile and increased odds of obesity, particularly for obesity class II, with 47% of women in the enclave profile classified as obese or class II obese. These results may be interpreted through the lens of the epidemic model, that posits that obesity risk is positively correlated with the prevalence of obesity within a neighborhood due to the socially contagious effects of human behaviors [45]. The enclave profile was also characterized by low neighborhood SES, underscoring the role of socioeconomic factors in shaping access to resources and opportunities for Hispanic women. While ethnic enclaves may offer protective social and cultural benefits, such as adherence to healthier traditional diets, these potential advantages may be counterbalanced by structural barriers such as reduced physical activity levels and limited access to health-promoting infrastructure [13, 46]. Furthermore, aspects of the built environment, including reduced walkability, limited access to fitness facilities, and a less healthy food environment, may further explain the observed association between ethnic enclave residence and higher obesity prevalence [32, 47–49]. It is worth noting the slightly lower odds of obesity in ethnic enclaves compared to disadvantaged profile. Further research is warranted to disentangle these complex interactions and assess whether any protective effects of ethnic enclave residence can be leveraged for intervention strategies.

Our results are consistent with previous studies that have found the association between greater ethnic segregation and obesity to be driven by higher neighborhood disadvantage [20, 49]. However, studies that have used a variable-centered approach to understand the associations of neighborhood SES and ethnic enclaves with BMI are not directly comparable to our study, which used a person-centered approach to group women into mutually exclusive and collectively exhaustive groups and show the importance of measuring neighborhoods in a more nuanced way. Furthermore, while previous studies have used either LPA or latent content analysis (LCA) to evaluate the association between features of the social and built environments and obesity in Hispanic women, such studies are relatively scarce. We identified only one prior study that included ethnic density and several neighborhood SES indicators (poverty, unemployment, and education) in their LPA to evaluate the association between neighborhood profiles and BMI in a heterogeneous population in Los Angeles. In their study, the profile characterized by a high percent Hispanic and low income showed a modestly increased BMI and the highest risk for increased BMI after a short period of time compared to the most affluent profile [50]. To our knowledge, no study has included comprehensive measures of both ethnic enclaves and neighborhood SES in their LPA/LCA models when evaluating BMI in Hispanic women only, an underserved population.

Our findings underscore the importance of considering area level socioeconomic features when investigating the complex interplay of neighborhood characteristics in shaping obesity outcomes. Moving forward, it is essential for subsequent research to dissect the specific mechanisms through which neighborhood SES exerts its influence on obesity and to ascertain how the unique features of ethnic enclaves might be strategically utilized to encourage health-enhancing behaviors and decrease obesity prevalence in this demographic. Overall, our study underscores the need for a more nuanced and context-specific approach to understanding the relationship between neighborhood SES, enclaves and obesity.

Limitations

Due to the cross-sectional nature of these analyses, associations may not reflect causal relationships between neighborhood composition and obesity. In addition, we lacked data on birthplace, length of time in the U.S., or any additional acculturation measures relevant to an individual's behaviors that may affect weight-related outcomes. We also lacked information on individual SES. However, prior studies have found that associations of neighborhood SES with obesity among Hispanic women remained after adjusting for individual SES [51]. Additionally, while BMI is widely utilized in population studies, it's an imperfect measure of body fat distribution or composition across different racial and ethnic groups [52]. Thus, future studies using additional measures of adiposity are warrant. Due to the multifactorial nature of pathways that affect obesity, additional characteristics of the neighborhood built environment, and social characteristics should be considered in future attempts to assign latent profiles via LPA. These findings are interesting and warrant further investigation, our methods should be replicated in other Hispanic populations, considering the heterogeneity within this growing ethnic group.

Conclusion

This study used a person-centered approach to group Hispanic women based on their combined traits without disaggregating them to investigate the relationship between living in a specific neighborhood profile and BMI. Through the utilization of this person-centered approach, our study contributes valuable empirical evidence to the existing literature, aiming to strengthen our understanding of the topic and ultimately reduce health disparities. Our results indicated that living in an ethnic enclave that is also disadvantage was associated with obesity for Hispanic women in our study. Moreover, neighborhood disadvantage and affluence profiles revealed stronger positive and negative associations with obesity, respectively. The study highlights the importance of considering socioeconomic factors when investigating the complex interplay of neighborhood characteristics in shaping BMI outcomes. We provide important insights that can inform multilevel interventions and strategies to address and mitigate health disparities in obesity in this population.

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Data availability De-identified data for this study are available upon request. Inquiries can be directed to the corresponding author or Dr. Garth H. Rauscher.

Declarations

Conflict of interest The authors declare no potential conflicts of interest.

Ethical approval As a secondary data analysis using de-identified data, the University of Illinois Institutional Review Board Committee has confirmed that no ethical approval is required.

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