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The Use of Electronic Health Record Data to Identify Variation in Referral, Consent, and Engagement in a Pediatric Intervention for Overweight and Obesity: A Cross-Sectional Study

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Abstract

Clinical weight management programs face low participation. The authors assessed whether using electronic health record (EHR) data can identify variation in referral, consent, and engagement in a pediatric overweight and obesity (OW/OB) intervention. Using Epic EHR data collected between August 2020 and April 2021, sociodemographic and clinical diagnostic data (ie, *International Classification of Disease* [ICD] codes from visit and problem list [PL]) were analyzed to determine their association with referral, consent, and engagement in an OW/OB intervention. Bivariate analyses and multivariable logistic regression modeling were performed, with Bayesian inclusion criterion score used for model selection. Compared with the 581 eligible patients, referred patients were more likely to be boys (60% vs. 54%, respectively; $P=0.04$) and have a higher $\%BMI_{p95}$ (119% vs. 112%, respectively; $P<0.01$); consented patients were more likely to have a higher $\%BMI_{p95}$ (120% vs. 112%, respectively; $P<0.01$) and speak Spanish (71% vs. 59%, respectively; $P=0.02$); and engaged patients were more likely to have a higher $\%BMI_{p95}$ (117% vs. 112%, respectively; $P=0.03$) and speak Spanish (78% vs. 59%, respectively; $P<0.01$). The regression model without either ICD codes or PL diagnoses was the best fit across all outcomes, which were associated with baseline $\%BMI_{p95}$ and health clinic location. Neither visit nor PL diagnoses helped to identify variation in referral, consent, and engagement in a pediatric OW/OB intervention, and their role in understanding participation in such interventions remains unclear. However, additional efforts are needed to refer and engage younger girls with less extreme cases of OW/OB, and to support non-Hispanic families to consent.

Keywords: pediatric overweight and obesity, electronic health record, primary care, eHealth

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Introduction

Pediatric obesity is an epidemic in the United States that disproportionately affects minority populations and has immediate and future health risks, ranging from nonalcoholic fatty liver disease to early death.[1–5] Moreover, the rate of change in body mass index (BMI) of children in the United States doubled during the COVID-19 pandemic, compared with the pre-pandemic period, further increasing the urgency to find both effective and sustainable interventions to treat pediatric obesity.[6,7]

Existing research, including the US Preventive Services Task Force (USPSTF) best practices, shows that children with overweight and obesity (OW/OB), conditions defined as having a BMI ≥85th percentile adjusted for age and sex and expressed as a percentage of the 95th percentile (%BMI_{p95}), benefit from comprehensive, family-based, moderate- to high-intensity weight-control interventions.[8–10] However, the current health care system in the United States cannot effectively deliver such programs due to key barriers such as limited time during clinical visits, insufficient funding for weight management programs, and lifestyle barriers (ie, childcare, transportation, scheduling),[8,11–13] especially to minority populations that are disproportionately impacted by OW/OB. Therefore, clinical weight management programs commonly face low participation and high attrition.[14]

Existing research on participation in pediatric OW/OB interventions has primarily focused on sociodemographic risk factors, family involvement, insurance status, logistical barriers, and self-image.[11–13] Specifically, children who are male, non-Hispanic Black, have a higher BMI, have a lower socioeconomic status, have parents with low educational levels, express depressive symptoms, and face logistical barriers (ie, distance to the intervention site) have higher dropout rates than do their counterparts.[11–13]

Yet, interventions that are family-based, employ motivational interviewing techniques, and have had an in-person orientation have been found to have low attrition rates.[14] Although sociodemographic factors are useful in identifying at-risk patients, they do not assess the patient's clinical profile that is available in the patient's electronic health record (EHR), which may provide a more robust and comprehensive assessment, and perhaps key therapeutic targets, of who may benefit most from access to healthy weight interventions.

To date, clinical diagnostic data captured in the EHR have not been included in analyses of participation in clinic-based pediatric OW/OB interventions despite such information being readily available.[15,16] Previous research has found that clinical diagnostic data, such as *International Classification of Disease* (ICD) codes, are important predictors for other chronic diseases such as asthma.[17]

Specifically, it found that using EHR data (ie, clinically relevant features) helped predict pediatric chronic disease progression and persistence and suggested that future research assess generalizability of this approach. The present study builds on this limited research by investigating whether clinical diagnostic data captured in the EHR help predict referral, consent, and engagement in an intervention for other pediatric chronic diseases such as OW/OB.

Accordingly, this study assessed whether using additional patient data captured by the clinical EHR, namely, ICD codes for well-child visit diagnoses (WCVD) and diagnoses on the problem list (PL), can help identify significant explanatory predictors of participation in an OW/OB intervention. Specifically, data were used from Dynamo Kids!, a novel customized and self-paced eHealth multicomponent pilot intervention informed by the Obesity Chronic Care Model,[18] and launched during the COVID-19 pandemic at 3 public primary care clinics in Dallas, TX, to address pediatric OW/OB.

Methods

Study design

This study was a *post hoc* cross-sectional study using data gathered at each well child visit as part of Dynamo Kids!, a quasi-experimental eHealth (non-randomized) pilot program that was launched in March 2020 at 3 primary care health clinics in a public hospital system in Dallas, TX.

The formative needs assessment,[19] study protocol,[20] and results[21] are published elsewhere. Briefly, Dynamo Kids! includes an EHR alert that fires for eligible patients (described below), a customized and self-paced online learning website that could be accessed on a computer or cell phone device by consented parents of children who have OW/OB, and a customized report with suggested talking points based on the parents' completion for a follow-up visit on intervention completion.

Inclusion criteria

Any child who went for a well child visit at 1 of 3 primary care health clinics between August 2020 and April 2021 was eligible to participate in Dynamo Kids! and was included in the analysis. Children aged 6–12 years with a BMI ≥85th percentile for age and sex and a parent or guardian who spoke either English or Spanish were included.

Weight status in children is assessed through BMI percentile, rather than BMI, to adjust for the child's sex and changing height and age. The Centers for Disease Control and Prevention (CDC) established norms for BMI percentile, based on the distribution of a healthy pre-obesity epidemic population.[22] Although more precise measures of adiposity exist, they are not practical to implement in a clinical setting.[13]

An additional modification of percentile is needed when participants have BMIs above the 97th percentile, because percentiles are compressed. This phenomenon hinders accurate interpretation of different degrees of and changes in obesity. Therefore, percent of the 95th percentile of BMI (%BMI_{p95}) is an accepted metric that can better reflect differences in degree of obesity when obesity is severe.[23] Children with a chronic condition that interferes with typical physical activity (eg, requiring a wheelchair) or that requires nonstandard feedings (eg, gastrostomy feeds, type 1 diabetes) were excluded.

EHR data

Well-child visit diagnoses. Originally developed by the World Health Organization, the CDC affirmed that ICD codes are currently the cornerstone of classifying health conditions, procedures, and morbidity, and have important uses in conducting surveillance, assessing health care utilization, developing public data sets, and billing/claims reimbursement.[24] Government policy requires that every clinical visit have at least 1 ICD code. The data set provided used ICD-9 codes that capture the purpose of the visit and ongoing medical issues.

Problem list. Originating in 1968, the PL was created to empower primary care providers (hereafter referred to as ‘‘providers’’) to take a systematic approach to recording patient medical data to reduce missing data and improve the continuity of care. Currently, it serves as a repository for all active, controlled, and resolved medical issues the patient has experienced.

Records can include an ICD code or a personalized title and should include the onset date, status, and additional relevant notes. Providers in outpatient settings are more likely to use the PL than specialists in in-patient settings, and although 70% of providers affirm that the PL is a helpful tool, major issues remain in terms of accuracy and completeness.[25,26]

Study procedures

During well-child visits, providers received an EHR alert when the family met the eligibility criteria cited earlier. The provider could then choose to ignore the referral request, refuse the referral request because they felt the family was a poor fit, or because the family either refused or accepted the referral request. These options were dichotomized into whether the patient was referred or not referred.

Data collection

The study’s hospital system uses Epic for its EHR system, and during the intervention period, providers charted both sociodemographic data and WCVD and PL diagnoses using descriptors, and the EHR linked the providers’ descriptors to ICD codes. Each well-child visit requires that at least 1 ICD code be attached to it (ie, the WCVD). However, the PL is not required, and providers manually update it to provide better care for patients; the PL can but is not required to include a diagnosis. Both WCVD and PL diagnoses were included in the analysis.

Outcome measures

Primary outcomes. The 3 primary outcomes of interest were referral, consent, and engagement in Dynamo Kids! Referral was measured by the number of referrals providers made to the research team. Consent was measured by the number of parents who consented when the research team contacted them and explained the study. Engagement was measured by the number of parents or guardians who completed the baseline survey.

Primary exposure. The primary exposures were categorical variables derived from the WCVD and PL. First, a thematic analysis of all WCVD diagnoses was conducted to transform this covariate into a 4-category variable. A second thematic analysis of all PL diagnoses was conducted. It was determined that the same 4-category organization was appropriate for the PL as well, and the PL was transformed using the same categories as the WCVD.

Briefly, the first category includes all diagnoses such as ‘‘pediatric BMI >99% for age’’ that directly describe high weight. The second category includes diagnoses such as ‘‘acanthosis nigricans’’ that are common comorbidities and suggestive of high weight. The third category includes diagnoses such as ‘‘cut of finger’’ that neither are related to high weight nor are administrative.

The fourth category includes administrative diagnoses such as ‘‘Encounter for well child visit at 10 years of age.’’ A description of the 4 categories of diagnosis, including associated diagnoses, and a full list of all ICD-9 codes, with categorization, are provided in the Supplementary Appendix SA1.

Covariates. Covariates included the child’s age, sex, insurance status, language preference, primary health clinic location, race, and ethnicity. All covariates were abstracted from the EHR in their recorded form. Covariates were selected for inclusion based on previous Dynamo Kids! analysis, existing literature reporting an association with weight status, or gaps in the existing literature.[27]

Statistical analysis

According to our *a priori* analysis plan, descriptive statistics were performed on all variables, both aggregate and stratified by referral, consent, and engagement statuses. For the univariate analysis on the continuous variables, means and standard deviations were calculated for child age and $\%BMI_{p95}$. For the univariate analysis on the dichotomous and categorical variables, frequencies and percentages were calculated for the child’s sex, insurance status, language preference, health clinic location, race, ethnicity, WCVD, and PL diagnoses.

Bivariate analyses included correlation coefficients, *t*-tests, chi-squared (χ^2), and/or Fisher exact tests, as appropriate, to assess the relationship between the 3 dependent outcomes and all independent variables. Given the few ($n=3$) hypotheses tested and the fact that actual data were assessed, no adjustments were made for multiple comparisons.[28]

In a *post hoc* exploratory analysis, bivariate analyses were also performed on all variables to determine whether there were significant associations among subpopulations (ie, consented patients among only referred patients and engaged patients among only consented patients).

The authors used multivariable logistic regression modeling to assess the effect of the covariates on the odds of referral, consent, and engagement, as well as to account for possible confounding. The covariates were selected based on available data from the EHR system and the existing literature. Then, the Bayesian Information Criterion (BIC) score was used for model selection.[29] All data analyses were conducted in Stata 16 (StataCorp 2019, College Station, TX).

Results

Sociodemographic data

Eligible patients. Eligible patients ($N=581$) were, on average, 8.92 years old, whereas engaged patients ($n=73$) were 9.24 years old. Among the eligible and engaged patients, there were more boys than girls: 54% in the eligible population and 56% in the engaged population. The mean

Child %BMI_{p95} was 112% among eligible patients, whereas it was 117% among engaged patients.

Most patients (78%) were insured by Medicaid. Clinic 1 had 18% more eligible patients than Clinic 3, but each clinic accounted for 31% of all eligible patients, demonstrating heterogenous referral and engagement patterns. Most patients (79%) were Hispanic. Descriptive details about the population sociodemographics are presented in Table 1.

In terms of WCVD and PL diagnoses, the mean number (standard deviation) of WCVD for eligible patients was 1.52 (0.9), compared with 1.58 (1.0) for engaged patients, but this difference was not statistically significant ($t=-0.479$, $P=0.63$). The mean number (standard deviation) of PL diagnoses for eligible patients was 17.90 (13.9), compared with 17.56 (10.7) for engaged patients, but this difference was not statistically significant ($t=0.539$, $P=0.59$). Descriptive details about the WCVD and PL diagnoses are presented in Tables 2 and 3.

Referred patients. Compared with eligible patients ($N=581$), referred patients ($n=215$) were more likely to be male (60% vs. 54%, respectively; $\chi^2=4.14$, $P=0.04$); have a higher BMI (Child BMI_{p95} 119% vs. 112%, respectively; $t=-6.31$, $P<0.01$); to be treated at a certain clinic (36% at Clinic 1 vs. 24% at Clinic 3 of patients were referred; $\chi^2=50.03$, $P<0.01$); have a high-weight diagnosis in their WCVD (62% vs. 54%, respectively; $\chi^2=9.81$, $P<0.01$); have a high-weight diagnosis in their PL (76% vs. 69%, respectively; $\chi^2=8.46$, $P<0.01$); have diagnoses that suggest high weight in their PL (64% vs. 50%, respectively; $\chi^2=26.68$, $P<0.01$); and be more likely to have diagnoses that are not associated with high weight in their PL (100% vs. 97%, respectively; $\chi^2=9.10$, $P<0.01$).

Consented patients. Compared with eligible patients ($N=581$), consented patients ($n=100$) were more likely to have a higher BMI (child BMI_{p95} 120% vs. 112%, respectively; $t=-3.03$, $P<0.01$); to speak Spanish (71% vs. 59%, respectively; $\chi^2=8.29$, $P=0.02$); to be treated at a certain clinic (37% at Clinic 2 vs. 29% at Clinic 1 of patients consented; $\chi^2=10.01$, $P<0.01$); include a high-weight diagnosis in their WCVD (67% vs. 54%, respectively; $\chi^2=8.38$, $P<0.01$); include a high-weight diagnosis in their PL ($\chi^2=5.05$, $P=0.03$); and be more likely to have diagnoses that are not associated with high weight in their PL (78% vs. 69%, respectively; $\chi^2=4.31$, $P=0.04$).

Compared with referred patients, consented patients were older (9.25 years old vs. 9 years old, respectively; $\chi^2=-2.26$, $P=0.02$); less likely to be Medicaid patients (70% vs. 78%, respectively; $\chi^2=8.64$, $P=0.03$); and more likely to speak Spanish (70% vs. 58%, respectively; $\chi^2=-12.71$, $P<0.01$).

Engaged patients. Compared with eligible patients ($N=581$), engaged patients ($n=73$) were more likely to have a higher BMI (child BMI_{p95} 117% vs. 112%, respectively; $t=-2.17$, $P=0.03$); to have commercial health insurance (27% vs. 16%, respectively; $P=0.02$); and to speak Spanish (78% vs. 59%, respectively; $\chi^2=13.24$, $P<0.01$).

Compared with consented patients, engaged patients were more likely to speak Spanish (78% vs. 71%, respectively; $\chi^2=6.59$, $P=0.01$) and to be non-Black Hispanic (86% vs. 84%, respectively; $\chi^2=8.38$, $P=0.02$).

Regression modeling

Of the multivariable logistic regression models built to identify significant explanatory predictors of participation in an OW/OB intervention, the simplest model (model 1) that did not include any WCVD or PL data was deemed the best model fit across all 3 outcomes of interest based on BIC score (Tables 4–6).

Referral. Both baseline Child %BMI_{p95} and health clinic location were significantly associated with referral. Specifically, while adjusting for all other covariates, a 1% increase in Child %BMI_{p95} was associated with increasing the odds of being referred by 17.29 ([6.37–46.97]; $P\leq0.01$). In addition, while adjusting for all other covariates, a patient at Clinic 2 had 3.07 [1.97–4.79] times the odds ($P\leq0.01$) as a patient at Clinic 1 of being referred, and a patient at Clinic 3 had 4.85 [2.98–7.91] times the odds ($P\leq0.01$) as a patient at Clinic 1 of being referred.

Consent. While adjusting for all other covariates, a 1% increase in Child %BMI_{p95} was associated with increasing the odds of consenting by 6.25 ([2.03–19.22]; $P\leq0.01$). In addition, while adjusting for all other covariates, a patient at Clinic 2 had 1.76 [1.02–3.04] times the odds ($P=0.04$) as a patient at Clinic 1 of consenting, and a patient at Clinic 3 had 2.63 [1.24–4.31] times the odds ($P\leq0.01$) as a patient at Clinic 1 of consenting. Finally, while adjusting for all other covariates, Spanish-speaking patients had 2.31 [1.24–4.31] times the odds ($P=0.01$) as non-Spanish-speaking patients of consenting.

Engagement. Baseline Child %BMI_{p95}, health clinic location, insurance coverage type, and language were significantly associated with engagement. Specifically, while adjusting for all other covariates, a 1% increase in Child %BMI_{p95} was associated with increasing the odds of engaging by 5.60 ([1.54–20.28; $P=0.01$]). In addition, while adjusting for all other covariates, a patient at Clinic 3 had 2.04 [1.05–3.95] times the odds ($P=0.03$) as a patient at Clinic 1 of engaging.

While adjusting for all other covariates, Medicaid patients had 0.49 [0.27–0.89] times the odds ($P=0.02$) of engaging as patients with commercial insurance. Finally, while adjusting for all other covariates, Spanish-speaking patients had 3.77 [1.64–8.68] times ($P<0.01$) the odds as non-Spanish-speaking patients of engaging.

Discussion

This study provides important insights into the clinical characteristics of patients at outpatient practices of a public hospital system who are eligible, referred, consented, and engaged in a pediatric OW/OB intervention. Specifically, this cross-sectional study assessed whether including clinical diagnostic data—WCVD and PL diagnoses—in addition to sociodemographic characteristics captured by the EHR can identify significant explanatory predictors of participation in OW/OB interventions by using data from the Dynamo Kids! program.

The WCVD and PL diagnoses were not significantly associated with referral, consent, and engagement in the Dynamo Kids! program in the regression modeling, although they were significantly associated with provider referral in

Table 1. Sociodemographic Descriptive Data and Results of Bivariate Analysis for the Study Population (N = 581; Patients for Whom the Electronic Health Record Alert Fired [N = 575] or Who Were Referred by Their PCP [N = 6])

	Eligible population (N = 581)	*Referred (n = 215)*	P^a	*Consented (n = 100)*	P^b	P^c	*Engaged (by completing baseline survey) (n = 73)*	P^d	P^e
Child age			0.89[f]		0.09[f]	**0.03**[f]		0.15[f]	0.99[f]
Age, years, mean (SD)	8.98 (1.72)	9 (1.73)		9.25 (1.75)			9.24 (1.7)		
Child sex, *n* (%)			**0.04**[g]		0.27[g]	0.88[g]		0.70[g]	0.34[g]
Male	314 (54)	128 (59.5)		59 (59)			41 (56.2)		
Female	267 (46)	87 (40.5)		41 (41)			32 (43.8)		
Child race, *n* (%)			0.49[g]		0.69[g]	0.36[g]		0.31[h]	0.10[h]
White	470 (80.9)	173 (80.5)		84 (84)			63 (86.3)		
Black	83 (14.3)	34 (15.8)		12 (12)			9 (12.3)		
Other	28 (4.8)	8 (3.7)		4 (4)			1 (1.4)		
Child ethnicity, *n* (%)			0.82[g]		0.37[h]	0.30[h]		0.18[h]	**0.03**[h]
Non-Hispanic	104 (17.9)	37 (17.2)		13 (13)			10 (13.7)		
Hispanic	461 (79.4)	171 (79.5)		84 (84)			63 (86.3)		
Other	16 (2.8)	7 (3.3)		3 (3)			0 (0.0)		
Child BMI_{p95}			**<0.01**[f]		**<0.01**[f]	0.48[f]		**0.03**[f]	0.54[f]
Mean (SD)	112% (20%)	119% (20%)		120 (20%)			117% (19%)		
Child insurance status, *n* (%)			0.99[g]		0.20[g]	**0.03**[g]		**0.02**[h]	0.06[h]
Commercial	95 (16.4)	35 (16.3)		22 (22)			20 (27.4)		
Medicaid	451 (77.6)	168 (78.1)		70 (70)			48 (65.8)		
Self-pay	17 (2.9)	6 (2.8)		3 (3)			1 (1.4)		
Charity/financial assistance/title V	18 (3.1)	6 (2.8)		5 (5)			4 (5.5)		
Child language, *n* (%)			0.11[g]		**0.02**[h]	**<0.001**[g]		**<0.01**[h]	0.01[g]
English	233 (40.1)	90 (41.9)		29 (29)			16 (21.9)		
Spanish	341 (58.7)	125 (58.1)		71 (71)			57 (78.1)		
Other	7 (1.2)	0 (0.0)		0 (0)			0 (0)		
Site locations, *n* (%)			**<0.01**[g]		**0.01**[g]	0.31[g]		0.11[g]	0.58[g]
Clinic 1	247 (42.5)	52 (24.2)		29 (29)			23 (31.5)		
Clinic 2	190 (32.7)	85 (39.5)		37 (37)			27 (28.0)		
Clinic 3	144 (24.8)	78 (36.3)		34 (34)			23 (31.5)		

Bold refers to statistical significance, as defined by a *p*-value that is less than 0.05.
[a] *P*-value comparing referred patients with all eligible patients.
[b] *P*-value comparing consented patients with all eligible patients.
[c] *P*-value comparing consented patients with all referred patients.
[d] *P*-value comparing engaged patients with all eligible patients.
[e] *P*-value comparing engaged patients with consented patients.
[f] *t*-Test.
[g] χ^2 test.
[h] Fisher's exact test.
BMI, body mass index; PCP, Primary Care Provider; SD, standard deviation.

Table 2. Relationship Between Well-Child Visit Diagnosis at Encounter and the Referral, Consent, and Engagement Outcome for Study Population (N=581)

WCVD category	*EHR alert fired or referred (N=581)*	*Referred (n=215)*	P^a	*Consented (n=100)*	P^b	P^c	*Engaged (by completing baseline survey) (n=73)*	P^d	P^e
WCV diagnoses per participant, mean (SD)	1.52 (0.9)	1.61 (1.0)		1.62 (1.0)			1.58 (1.0)		
Category 1 (high-weight diagnoses) WCVD category 1 is present in participants, *n* (%)	313 (53.9)	134 (62.3)	**<0.01**[f]	67 (67.0)	**<0.01**[f]	0.18	47 (64.4)	0.05[f]	0.36[g]
Category 2 (diagnoses that are common comorbidities and suggestive of high weight) WCVD category 2 is present in participants, *n* (%)	215 (37.0)	73 (34.0)	0.24[f]	34 (34.0)	0.49[f]	0.99[f]	25 (34.3)	0.60[f]	0.93[g]
Category 3 (diagnoses not related to high weight) WCVD category 3 is present in participants, *n* (%)	267 (46.0)	109 (50.7)	0.08[f]	47 (47.0)	0.82[f]	0.31[f]	35 (48.0)	0.72[f]	0.76[g]
Category 4 (administrative codes) WCVD category 4 is present in participants, *n* (%)	48 (8.3)	17 (7.9)	0.81[f]	8 (8.0)	0.92[f]	0.96[f]	4 (5.5)	0.36[f]	0.13[g]

Bold refers to statistical significance, as defined by a *p*-value that is less than 0.05.
Diagnoses are categorized into 4 groups and are presented as binary (category present/absent) and total quantity.
[a]*P*-value comparing referred patients with all eligible patients.
[b]*P*-value comparing consented patients with all eligible patients.
[c]*P*-value comparing consented patients with all referred patients.
[d]*P*-value comparing engaged patients with all eligible patients.
[e]*P*-value comparing engaged patients with all consented patients.
[f]χ^2 test.
[g]Fisher's exact test.
EHR, electronic health record; SD, standard deviation; WCVD, well-child visit diagnoses.

Table 3. Relationship Between Problem List Condition at Encounter and the Referral, Consent, and Engagement Outcome for Study Population (N=581)

Problem list category	*EHR alert fired or referred (N=581)*	*Referred (n=215)*	P^a	*Consented (n=100)*	P^b	P^c	*Engaged (by completing baseline survey) (n=73)*	P^d	P^e
PL diagnoses per participant, mean (SD)	17.90 (13.9)	19.54 (13.0)		17.56 (10.7)			17.55 (11.2)		
Category 1 (high-weight diagnoses) PL category 1 is present in participants, *n* (%)	398 (68.5)	163 (75.8)	**<0.01**[f]	78 (78.0)	**0.03**[f]	0.49[f]	57 (78.1)	0.06[f]	0.97[f]
Category 2 (diagnoses that are common comorbidities and suggestive of high weight) PL category 2 is present in participants, *n* (%)	289 (49.7)	137 (63.7)	**<0.01**[f]	63 (63.0)	0.15[f]	0.84[f]	42 (57.5)	0.15[f]	0.36[f]
Category 3 (diagnoses not related to high weight) PL category 3 is present in participants, *n* (%)	561 (96.6)	214 (99.5)	**<0.01**[f]	100 (100.0)	**0.04**[f]	0.35[f]	73 (100)	0.08[f]	N/A[f]
Category 4 (administrative codes) PL category 4 is present in participants, *n* (%)	572 (98.5)	213 (99.1)	0.36[f]	99 (99.0)	1.0[g]	1.0[g]	72 (98.6)	1.0[g]	0.54[g]

Bold refers to statistical significance, as defined by a p-value that is less than 0.05.
Diagnoses are categorized into 4 groups and are presented as binary (category present/absent) and total quantity.
[a] P-value comparing referred patients with all eligible patients.
[b] P-value comparing consented patients with all eligible patients.
[c] P-value comparing consented patients with all referred patients.
[d] P-value comparing engaged patients with all eligible patients.
[e] P-value comparing engaged patients with all consented patients.
[f] χ^2 test.
[g] Fisher's exact test.
EHR, electronic health record; N/A, not applicable; PL, problem list; SD, standard deviation.

Table 4. Predictors of Provider Referral of Eligible Patients to Dynamo Kids!: Multivariable Logistic Regression Modeling of Demographic, Well-Child Visit Diagnoses, and Problem List Diagnoses

Predictors	*Model 1 outcome: descriptors only, OR [95% CI]*	*Model 2 outcome: descriptors and WCVD, OR [95% CI]*	*Model 3 outcome: descriptors, WCVD and PL, OR [95% CI]*
Child sex (Female)	1.0 [0.99–1.01]	1.0 [0.99–1.01]	1.0 [0.99–1.01]
Child age, months	0.90 [0.62–1.31]	0.89 [0.61–1.30]	0.89 [0.60–1.31]
Baseline child %BMI$_{p95}$, kg/m^2	17.29 [6.37–46.97]**	15.0 [5.39–41.75]**	17.46 [5.69–53.58]**
Child insurance status (Commercial)	1.0 (Ref)	1.0 (Ref)	1.0 (Ref)
Medicaid	1.10 [0.67–1.83]	1.15 [0.69–1.92]	1.10 [0.65–1.85]
Self-pay	1.67 [0.53–5.28]	1.71 [0.54–5.47]	1.98 [0.60–6.60]
Charity	1.11 [0.35]	1.25 [0.39–4.02]	1.31 [0.40–4.28]
Child language (English)	1.0 (Ref)	1.0 (Ref)	1.0 (Ref)
Spanish	1.14 [0.72–1.80]	1.14 [0.72–1.80]	1.15 [0.72–1.83]
Other	1	1	1
Clinic 1	1.0 (Ref)	1.0 (Ref)	1.0 (Ref)
Clinic 2	3.07 [1.97–4.79]**	3.30 [2.08–5.26]**	3.01 [1.87–4.84]**
Clinic 3	4.85 [2.98–7.91]**	4.88 [2.88–8.29]**	4.39 [2.55–7.58]**
Child race (White)	1.0 (Ref)	1.0 (Ref)	1.0 (Ref)
Black	2.20 [0.61–7.91]	2.25 [0.62–8.17]	2.26 [0.61–8.35]
Other	0.33 [0.037–3.02]	0.34 [0.04–3.05]	24.04 [1.41–408.8744]*
Child ethnicity (non-Hispanic)	1.0 (Ref)	1.0 (Ref)	1.0 (Ref)
Hispanic	2.93 [0.87–9.88]	2.98 [0.87–10.17]	3.01 [0.87–10.42]
Other	11.39 [0.79–164.29]	9.80 [0.69–139.77]	24.04 [1.41–408.87]
WCVD category 1, high-weight diagnoses (not present)		1.29 [0.86–1.93]	1.57 [0.93–2.66]
WCVD category 2, diagnoses that are common comorbidities and suggestive of high weight (not present)		1.31 [0.84–2.02]	1.19 [0.76–1.86]
WCVD category 3, diagnoses not related to high weight (not present)		1.22 [0.81–1.85]	1.20 [0.78–1.84]
WCVD category 4, administrative codes (not present)		0.69 [.35–1.38]	0.66 [0.33–1.34]
PL category 1, high-weight diagnoses (not present)			0.60 [0.32–1.11]
PL category 2, diagnoses suggestive of high weight (not present)			1.47 [0.95–2.28]
PL category 3, non-high-weight diagnoses (not present)			22.37 [2.03–246.77]*
PL category 4, administrative codes (not present)			0.98 [0.16–6.09]
Constant	0.004 [0.0005–0.03]**	0.003 [0.0004–0.03]	0.0001 [0.000004–0.01]**
Model BIC score	755.81	777.15	785.86

*$0.001 \leq P \leq 0.05$.
**$P \leq 0.001$.
%BMI$_{p95}$, body mass index as a percent of the 95th percentile; BIC, Bayesian information criterion; CI, confidence interval; OR, odds ratio; PL, problem list; Ref, reference category; WCVD, well-child visit diagnoses.

the bivariate analysis. Significant associations may be related to provider practices and/or clinic leadership; however, given that this pilot study took place with only 10 relatively homogenous providers at 3 locations in the same hospital system in the same city, additional research is needed to understand the mixed findings of the clinical diagnostic data.

Certain sociodemographic characteristics were significantly associated with referral, consent, and engagement in the Dynamo Kids! program. First, those who were referred and engaged with Dynamo Kids! tended to be slightly older, male, and have a higher BMI than their counterparts. Second, patients who consented and engaged in Dynamo Kids! were more likely to be Hispanic than their counterparts. These findings suggest that additional efforts are needed to refer younger girls with less extreme cases of OW/OB, aid non-Hispanic families to consent, and encourage younger girls with less extreme cases of OW/OB to stay engaged.

WCVD and PL data

When examining provider referral and patient consent, the presence of a high-weight diagnosis in the WCVD and PL was significantly associated with provider referral. Therefore, these diagnoses may either serve as a visual

Table 5. Predictors of Family Consent of Referred Patients to Participate in Dynamo Kids!: Multivariable Logistic Regression Modeling of Demographic, Well-Child Visit Diagnoses, and Problem List Diagnoses

Predictors	*Model 1 outcome: descriptors only, OR [95% CI]*	*Model 2 outcome: Descriptors and WCVD, OR [95% CI]*	*Model 3 outcome: descriptors, WCVD and PL, OR [95% CI]*
Child sex (Female)	1.01 [1.00–1.02]	1.01 [1.00–1.02]	1.01 [1.00–1.02]
Child age, months	0.93 [0.58–1.48]	0.94 [0.59–1.49]	0.95 [0.59–1.52]
Baseline Child $\%BMI_{p95}$, kg/m^2	6.25 [2.03–19.22]***	4.88 [1.52–15.64]**	5.50 [1.58–19.09] **
Child insurance status (Commercial)	1.0 (Ref)	1.0 (Ref)	1.0 (Ref)
Medicaid	0.64 [0.36–1.12]	0.66 [0.37–1.17]	0.62 [0.35–1.10]
Self-pay	0.98 [0.24–3.94]	0.96 [0.23–3.96]	1.07 [0.25–4.57]
Charity	1.21 [0.37–4.00]	1.37 [0.41–4.61]	1.43 [0.42–4.93]
Child language (English)	1.0 (Ref)	1.0 (Ref)	1.0 (Ref)
Spanish	2.31 [1.24–4.31]**	2.35 [1.25–4.41]**	2.33 [1.24–4.39]**
Other	1	1	1
Clinic 1	1.0 (Ref)	1.0 (Ref)	1.0 (Ref)
Clinic 2	1.76 [1.02–3.04] ***	1.94 [1.09–3.44] *	1.74 [0.97–3.14]
Clinic 3	2.63 [1.47–4.71] ***	2.56 [1.35–4.82] **	2.28 [1.19–4.38] *
Child race (White)	1.0 (Ref)	1.0 (Ref)	1.0 (Ref)
Black	2.59 [0.45–14.88]	3.01 [0.50–18.22]	2.90 [0.46–18.14]
Other	5.56 [0.28–110.28]	1.03 [0.11–9.48]	1.07 [0.11–9.98]
Child ethnicity (non-Hispanic)	1.0 (Ref)	1.0 (Ref)	1.0 (Ref)
Hispanic	2.75 [0.53–14.24]	2.97 [0.54–16.25]	2.91 [0.51–16.57]
Other	5.56 [0.28–110.28]	4.84 [0.24–98.06]	9.04 [0.41–200.92]
WCVD category 1, high-weight diagnoses (not present)		1.63 [0.99–2.70]	1.97 [1.02–3.82]
WCVD category 2, diagnoses that are common comorbidities and suggestive of high weight (not present)		1.08 [0.64–1.83]	0.98 [0.57–1.67]
WCVD category 3, diagnoses not related to high weight (not present)		0.86 [0.52–1.43]	0.86 [0.52–1.43]
WCVD category 4, administrative codes (not present)		0.81 [0.35–1.89]	0.76 [0.32–1.78]
PL category 1, high-weight diagnoses (not present)			0.66 [0.30–1.44]
PL category 2, diagnoses suggestive of high weight (not present)			1.27 [0.74–2.18]
PL category 3, non-high-weight diagnoses (not present)			1
PL category 4, administrative codes (not present)			1.06 [0.11–10.13]
Constant	0.002 [0.0002–0.03]***	0.002 [0.0001–0.02]***	0.002 [0.001–0.06]***
Model BIC score	581.95	602.95	611.07

*$0.01 \leq P \leq 0.05$.
**$0.001 \leq P \leq 0.01$.
*** $P \leq 0.001$.
$\%BMI_{p95}$, body mass index as a percent of the 95th percentile; BIC, Bayesian information criterion; CI, confidence interval; OR, odds ratio; PL, problem list; Ref, reference category; WCVD, well-child visit diagnoses.

reminder and/or indicate that the provider is more engaged and focused on weight-related issues. The same trend can be found for high weight-related diagnoses on the PL.

Importantly, in the multivariable logistic models, WCVD and PL diagnoses were not significantly associated with referral, consent, and engagement in an eHealth family-based, clinic-based program for addressing pediatric OW/OB in primary care settings. The significant associations yet poor prediction provide inconclusive evidence of what role such clinical diagnostic data may play in understanding patient referral, consent, and engagement.

To provide clarity, future research may consider using bigger datasets with more diverse populations, other health outcomes, and different settings. In addition, this finding may suggest that patient referral, consent, and engagement are more affected by health system-level factors (eg, standardized care and provider behavior) than patient-level factors (eg, child age, sex, and/or race). Alternatively,

Table 6. Predictors of Family Engagement of Consented Patients in Dynamo Kids!: Multivariable Logistic Regression Modeling of Demographic, Well-Child Visit Diagnoses, and Problem List Diagnoses

Predictors	*Model 1 outcome: descriptors only, OR [95% CI]*	*Model 2 outcome: descriptors and WCVD, OR [95% CI]*	*Model 3 outcome: descriptors, WCVD and PL, OR [95% CI]*
Child sex (Female)	1.01 [0.99–1.02]	1.01 [0.99–1.02]	1.01 [0.99–1.02]
Child age, months	1.07 [0.63–1.81]	1.08 [0.64–1.84]	1.13 [0.66–1.94]
Baseline child %BMI_{p95}, kg/m^2	5.60 [1.54–20.28] **	4.41 [1.15–16.82]*	4.61 [1.09–19.45] *
Child insurance status (Commercial)	1.0 (Ref)	1.0 (Ref)	1.0 (Ref)
Medicaid	0.49 [0.27–0.89]*	0.50 [0.27–0.92]*	0.46 [0.25–0.85]*
Self-pay	0.30 [0.04–2.57]	0.30 [0.03–2.56]	0.28 [0.03–2.43]
Charity	0.91 [0.26–3.22]	1.07 [0.30–3.82]	1.07 [0.29–3.90]
Child language (English)	1.0 (Ref)	1.0 (Ref)	1.0 (Ref)
Spanish	3.77 [1.64–8.68]**	3.79 [1.64–8.77]**	3.80 [1.64–8.81]**
Other	1	1	1
Clinic 1	1.0 (Ref)	1.0 (Ref)	1.0 (Ref)
Clinic 2	1.52 [0.82–2.82]	1.66 [0.86–3.18]	1.60 [0.82–3.12]
Clinic 3	2.04 [1.05–3.96]*	1.98 [0.95–4.10]	1.83 [0.86–3.86]
Child race (White)	1.0 (Ref)	1.0 (Ref)	1.0 (Ref)
Black	3.12 [0.44–22.18]	3.57 [0.48–26.46]	3.28 [0.43–25.03]
Other	1.20 [0.13–11.38]	1.33 [0.14–12.63]	1.27 [0.13–12.23]
Child ethnicity (non-Hispanic)	1.0 (Ref)	1.0 (Ref)	1.0 (Ref)
Hispanic	2.04 [0.34–12.23]	2.19 [0.35–13.71]	2.03 [0.31–13.23]
Other	1	1	1
WCVD category 1, high-weight diagnoses (not present)		1.52 [0.87–2.67]	1.59 [0.77–3.28]
WCVD category 2, diagnoses that are common comorbidities and suggestive of high weight (not present)		1.07 [0.58–1.95]	1.02 [0.55–1.88]
WCVD category 3, diagnoses not related to high weight (not present)		0.95 [0.54–1.68]	0.99 [0.56–1.75]
WCVD category 4, administrative codes (not present)		0.52 [0.17–1.57]	0.50 [0.16–1.5]
PL category 1, high-weight diagnoses (not present)			0.96 [0.40–2.30]
PL category 2, diagnoses suggestive of high weight (not present)			0.99 [0.54–1.82]
PL category 3, non-high-weight diagnoses (not present)			1
PL category 4, administrative codes (not present)			0.70 [0.07–6.93]
Constant	0.002 [0.0001–0.04]	0.002 [0.001–0.04]	0.003 [0.0001–0.15]
Model BIC score	481.64	503.43	517.35

*$0.01 \leq P \leq 0.05$.
** $0.001 \leq P \leq 0.01$.
%BMI_{p95}, body mass index as a percent of the 95th percentile; BIC, Bayesian information criterion; CI, confidence interval; OR, odds ratio; PL, problem list; Ref, reference category; WCVD, well-child visit diagnoses.

it is possible that WCVD and PL diagnoses are not strong indicators for patient-level factors.

Referral and the health care system

There is limited literature focused on predictors of provider referral to pediatric weight management programs; most of the literature is focused on engagement after referral.[30] Therefore, this study fills an important gap in the literature. Consistent with previous research, this study showed that referred patients tended to have a higher BMI than those who were not referred.[31]

Yet, unlike previous research, this study found that child sex was significantly associated with referral.[31] Moreover, consistent with previous research reporting that only a fraction of providers refer patients for pediatric weight management programs,[32] this study also found that providers referred a few patients and did so unevenly, as measured on a clinic site level.

Importantly, given that providers needed to have family permission to refer, it is possible that family refusal may contribute to low referral, though it is unlikely to explain differences across clinics.

In fact, in the multivariable logistic regression models assessing all 3 outcomes, health clinic location was significantly associated with both referral and consent. Specifically, by attending 1 clinic, patients were almost 20 times more likely to be referred to the Dynamo Kids! program than attending another clinic. This indicates that the health care system is providing uneven and heterogenous experiences for its patients, who are all entitled to the same level of care.

It is possible that providers had a bias toward more extreme cases, and that they had a higher or lower level of comfort with discussing OW/OB diagnoses and treatment options with certain patient populations. It is also possible that leadership at different clinics demonstrated differing levels of support and enthusiasm regarding the Dynamo Kids! program, and that the enthusiasm trickled down to provider practices.

Further, varying patient loads at different clinics may also explain the heterogenous patient experiences. Qualitative and mixed-methods research with the health care system and providers could uncover the reasons for the heterogeneity in provider referral, so that unnecessary variation can be addressed through trainings and resources, such as clinical decision support. Given that such findings have been reported in previous research,[33] this phenomenon is not a problem unique to this health care system and deserves further study.[34]

Engagement and attrition

Of referred patients, other studies show that hospital-based clinics have attrition rates greater than 50%,[31,35] and the Dynamo Kids! program showed a similar trend, although with higher engagement and retention rates. Specifically, 73% of patients engaged with the Dynamo Kids! program by completing the baseline survey, and 46% of patients used the Dynamo Kids! website.[21]

Although racial and ethnic minorities from low socioeconomic statuses and Medicaid recipients are labeled as high-risk populations with high rates of attrition,[36,37] this study advances the conversation by showing that certain subgroups including non-Hispanic Black populations[38] are at a higher risk than Hispanic populations to drop out of pediatric weight management programs.

Although this study adds to the literature on understanding who is referred, consents, and engages in pediatric weight management programs, there is little consensus regarding risk factors for attrition in the literature, other than that attrition is a major problem.[39] Transdisciplinary future research could explore motivators for parent decision making at each phase in this process, especially in non-Hispanic Black populations.

Moreover, no studies investigate how WCVD and PL diagnoses describe the full spectrum of patient referral, consent, and engagement; existing research focuses on only one moment in the patient's experience and/or avoids using such data altogether. When ICD codes have been used in newer artificial intelligence algorithms,[17] the outcomes of interest are health conditions such as pediatric obesity rather than patient referral, consent, and engagement, especially in primary care settings.[40]

Therefore, there is a need to investigate how ICD codes may predict and improve patient referral, consent, engagement, and, ultimately, clinical outcomes.[41,42] Specifically, transdisciplinary future research could explore motivators for and utility of additional diagnostic codes for providers and health care systems and parent awareness and understanding of diagnostic codes.

Such endeavors may standardize and improve clinical care, ultimately reducing the significant gap in translation.[34]

Limitations

This study has some limitations. First, the generalizability of this study is limited by the 581-patient sample size, which all came from the same health care system in the same city. Similarly, given that both the WCVD and PL diagnoses are selected by providers who are all part of the same hospital system, they may neither represent how most providers engage with the EHR nor the true clinical condition of the child.

Second, it is possible that there is residual confounding because the WCVD and PL categories used to organize the EHR data were subject to design bias. Third, this study focused on a single intervention that employed relatively novel technology, and it is possible that results would be different for an in-person or hybrid intervention.

Strengths

Despite these limitations, this study has several strengths. First, the study was developed in an ethical manner to focus on the most vulnerable populations who are disproportionately affected by pediatric OW/OB. Second, given its focus on implementation science outcomes in vulnerable populations, it reached the most vulnerable populations in terms of race, ethnicity, and OW/OB status, thus improving health equity.[43]

Third, it used lifelong patient records from real-world conditions in a safety-net hospital in Dallas, TX, maximizing both the internal and external validity of the study. Lastly, it suggested that there may be different barriers for different pediatric populations across the stages of participation (in this case, referral, consent, and engagement) in such OW/OB programs.

Conclusion

Based in a safety-net hospital, this study assessed how high-risk and vulnerable patients were referred, consented, and engaged in an eHealth intervention for pediatric OW/OB using EHR data. In a novel way, it included both WCVD and PL diagnoses as part of the analysis. However, unlike certain sociodemographic characteristics, WCVD and PL diagnoses were not significant explanatory predictors of referral, consent, and engagement in the Dynamo Kids! program.

It is essential to understand for whom such programs are offered, how they engage, and at what point and why in the process patients begin to drop out in real-world settings, regardless of how effective an intervention may be under controlled settings. Similarly, it is important to assess the role that tools such as the WCVD and PL in research may play in real-world settings. Such endeavors may help reduce both health inequities and translation lags while improving health outcomes for patients.

Future research

Future research should focus on the health care system to discern why there was not a standardized care experience across the 3 pilot clinics for the Dynamo Kids! program.

As a field, given the documented issues and heterogenous findings with respect to patient referral, consent, and engagement rates, future analyses should continue to employ novel research approaches to focus on finding significant associations and predictors for these moments in a weight management program by better understanding how—and when—to use existing data.

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Ethical Approval

This study [STU 2019-0876] was approved by the Institutional Review Board at UTSW and the Committee For the Protection of Human Subjects at UTHealth School of Public Health.

Guarantor

S.E.B.

Authors' Contributions

J.S.Y. conceived the study, conducted the analysis, and wrote the manuscript. S.E.B. and M.A.A. are the principal investigators of the study who offered their data set and consulted on the study approach. S.E.B. provided subject matter expertise on the study design and significant feedback during the analysis. FDA provided subject matter expertise during the data analysis phase of the project. S.E.M. and C.A.G. provided significant feedback during the manuscript writing. All authors reviewed and edited the manuscript and approved the final version of the manuscript.

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Supplementary Material

Supplementary Appendix SA1

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