Individual-Level and Neighborhood-Level Factors Associated with Longitudinal Changes in Cardiometabolic Measures in Participants of a Care Coordination Program

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Abstract

Background: Identifying clinical, sociodemographic, and neighborhood-level risk factors associated with less improvement or worsening cardiometabolic measures despite access to a clinic-based care coordination program may help identify candidates that need additional disease management support outside clinic walls.

Methods*:* Secondary data analysis of data from care coordination program cohort**,** **L**everaging **I**nformation Technology to **G**uide **H**igh **T**ech, **H**igh **T**ouch Care (LIGHT^2). *Setting/Participants:* Medicare, Medicaid, dual-eligible adults from ten Midwestern primary care clinics in the US. *Intervention:* Two-year nurse-led care coordination program. *Outcome Measures*: Hemoglobin A1C, low-density-lipoprotein (LDL) cholesterol, and blood pressure. Multivariable generalized linear regression models assessed each patient's clinical, sociodemographic, and neighborhood-level factors associated with change in outcome measures from before to after completion of LIGHT^2 program.

Results: 6378 participants had pre-and post-intervention levels reported for at least one outcome measure (61.6% women, 86.3% White, non-Hispanic ethnicity, mean age 62.7 [SD, 18.5] years). In adjusted models, higher pre-intervention measures were associated with worsening of all cardiometabolic measures (LDL-cholesterol β 0.56, 95% CI 0.52 to 0.60, $p < 0.001$; HbA1C β 0.51, 95% CI 0.43 to 0.59, $p < 0.001$; Systolic blood pressure β 0.95, 95% CI 0.83 to 1.08, $p < 0.001$). Women had worsening LDL- cholesterol compared to men (β 7.76, 95% CI 5.21 to 10.32, $p <0.001$). Women with pre-intervention HbA1C > 6.8% and systolic blood pressure >131 mm of Hg had worse post-intervention HbA1C (main effect β -1.29, 95% CI -1.95 to -0.62, $p < 0.001$; interaction effect β 0.19, 95% CI 0.09 to 0.28, $p < 0.001$), and systolic blood pressure (main effect β -7.86, 95% CI -15.55 to -0.17 $p = 0.04$; interaction effect β 0.06, 95% CI 0.002 to 0.12, $p = 0.043$) compared to men. Adding individual's neighborhood-level risks or sensitivity analysis for clustering by clinics and census tracts did not change effect sizes significantly.

Conclusions: Higher baseline cardiometabolic measures and women with high baseline cardiometabolic measures (compared to men) were associated with worsening of cardiometabolic outcomes in participants of a solely clinic-based care coordination program. Understanding the contextual causes for these associations may aid in tailoring disease management support outside clinic walls.

Background

Cardiovascular disease (CVD) is the leading cause of death in the US, and cardiometabolic risk factors for CVD are prevalent and well-known.[1, 2] Despite the availability of effective treatments, significant disparities in CVD and cardiometabolic outcomes persist.[3–6] Care coordination can deliver better access and quality of care, whereas community-based interventions can help address behavioral and social determinants of cardiometabolic health.[7–12] However, most primary care practices do not have time or resources to offer widespread care coordination, individual-level social and behavior risk screenings, and community-based support.[13–18] Tailoring community-based approaches to high-burden communities, people living in poverty, or those with low literacy is recommended for reducing CVD disparities.[11] Support outside clinic walls needs to be tailored to individuals who do not benefit from clinic-based interventions. Advances in geospatial technologies have increased electronic health record (EHR) access to community-level geocoded data for social and behavioral risks associated with each patient's residential address.[19, 20] Identifying clinical, sociodemographic, and "community vital signs" that predict an individual's health outcomes after participating in clinic-based interventions can help identify potential candidates for supplementary clinic-community linked interventions.[19, 21] We found no studies examining patient-level moderating factors of cardiometabolic outcomes with nurse-led care coordination. Hence, we aimed to identify patient's clinical, sociodemographic, and neighborhood-level factors associated with less improvement or worsening cardiometabolic outcomes despite participation in a 2-year clinic-based nurse-led care coordination program.

Methods

We performed a secondary analysis of data from a prospective cohort of University of Missouri Healthcare (MUHC) system patients enrolled in the Leveraging Information Technology to Guide High Tech, High Touch Care (LIGHT^2) project from July 1, 2013 to June 30, 2015.[22] The University of Missouri institutional review board determined the LIGHT^2 program to be a quality improvement activity not requiring institutional review board review. We used the Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) reporting guidelines for this study.[23]

Study design and setting

Funded with a Centers for Medicare and Medicaid Services (CMS) innovation award, the LIGHT^2 program was a combination of information technology components (High Tech) and health care coordination by nurse care managers (High Touch).[22, 24] The High-Tech component included dashboards and a patient portal for communication with physicians and nurse care managers. The High Touch component was care coordination provided by nurse care managers; 25 nurse care managers worked in 10 family and community medicine and internal medicine clinics providing services. Patients were assigned tiers based on their chronic disease diagnoses and health care utilization in the previous 12 months.[25] Nurse care managers provided as-needed education and support for patients regarding new chronic disease diagnoses or worsening of chronic conditions. A documentation system measuring the frequency and time of nurse care manager contacts was created using the Agency of Healthcare Research and Quality (AHRQ) care coordination atlas.[24, 26] The study compiled data on claims and participants' EHR data, including healthcare utilization, clinic visits, basic demographic data, diagnosis, labs, and nurse care coordination contacts, along with geocoded patient addresses. Cohort recruitment started in February 2013; 9932 participants were recruited by July 2013. Deaths and relocations decreased the number of participants to 8593 by March 2015. The goals of the LIGHT^2 intervention were to achieve net cost savings, increase preventive service use, and improve the management of chronic diseases. The final evaluation of the program showed higher spending than the comparison group, and most patients received recommended preventive services.[22] The cardiometabolic measures monitored during LIGHT^2 intervention were hemoglobin A1C (HbA1C), blood pressure (BP), and low density-lipoprotein (LDL) cholesterol. Primary results showed minimal changes in cardiometabolic outcomes. Detailed results of primary outcomes, nurse care coordination implementation and fidelity of LIGHT^2 have been previously published.[22, 24]

Participants

Participants were all Medicare, Medicaid, or dual-eligible patients receiving primary care services in any of 10 family and community medicine or internal medicine clinics in the MUHC system during the project period. Because we examined factors associated with a change in cardiometabolic measures, we included only participants with at least one of the three outcomes, HbA1C, LDL cholesterol, or BP reported before and after the intervention completion.

Outcomes

We extracted HbA1C, BP, and LDL-cholesterol levels before and after the LIGHT^2 program. Recruitment was complete, and the care coordination documentation system was implemented on July 1, 2013. We used measures reported within 6 months before that date or before the first nurse care manager contact within the first 3 months of the intervention as the pre-intervention values. For post-intervention measures, we used the values reported within 6 months after the intervention completion date. If there were no values reported in the 6 months after the completion of the intervention, we used the last reported value within the last 3 months of the intervention. We used the average of the last 2 reported BP readings if there were multiple readings in the defined pre-intervention and post-intervention time-period. Individuals with very low pre-intervention values were not included in the analyses. More specifically, if pre-intervention LDL < 60 mg/dL, pre-intervention HbA1C < 5.5%, pre-intervention diastolic BP < 40 mm of Hg, and pre-intervention systolic BP < 90 mm of Hg, individuals were excluded from the respective analysis. We also excluded individuals with 2 extremely high values (above 350) of post-intervention LDL cholesterol from the analysis for LDL-cholesterol outcomes. The population comprised of 6378 individuals after exclusions.

Variables

Factors that affect the effectiveness of health interventions: We included clinical and geospatial variables accounting for the majority of the National Academy of Medicine (NAM) recommended social and behavioral domains and measures that influence health outcomes and effectiveness of treatments.[27, 28] We identified clinical, sociodemographic, and area-level proxy variables that can be easily extracted from routinely collected clinical and sociodemographic data in the EHR. The variables included for NAM recommended domains were: 1.) race and ethnicity, which was extracted at individual-level from EHR; 2.) education, which is also proxy for health literacy, was extracted at neighborhood-level; 3.) financial resource strain was extracted as poverty and access to healthy food at neighborhood-level; 4.) stress and depression were denoted by the presence of mood disorders at individual-level from EHR; 5.) physical activity opportunities were extracted at neighborhood-level; 6.) tobacco and alcohol status was extracted at individual-level from EHR; 7.) social connections and isolation were measured by marital status at individual-level in EHR and neighborhood-level social capital; 8.) intimate partner violence was measured by neighborhood-level domestic violence injury rates.

As the LIGHT^2 program was focused on nurse-led care coordination for healthcare utilization and chronic disease management, we adjusted for health resource utilization, nurse care manager contacts, and the number of comorbidities. Additionally, as LIGHT^2 program was solely based in primary care clinics, we examined driving time to the primary care clinic from each patient's geocoded residential address. As baseline cardiometabolic measures, including body mass index (BMI), are used by clinicians for CVD risk stratification, we adjusted for baseline values of cardiometabolic measures.

We included basic demographic data such as age, sex, race/ethnicity, as well as smoking status, alcohol status, and geocoded residential addresses from the EHR. We extracted the total number of comorbidities, nurse care manager contacts, and presence or absence of a mood disorder reported as of the last day of intervention based on the International Classification of Diseases, Ninth Revision, Clinical Modification diagnosis codes (ICD 9 codes). We defined high-resource healthcare utilizers as individuals with 4 or more emergency room visits, or 2 or more inpatient encounters in the previous 12 months. The patient's residential address and primary care physician's (PCP) clinic addresses were geocoded using ArcGIS Online World Geocoding Service.[29] If a patient was seen at 2 or more primary care clinic locations during the intervention period, we coded the distance to the clinic as missing to avoid misattributions. For calculating the travel distance to the closest grocery store from patients' geocoded address, supermarket locations were obtained from the Reference USA US Businesses dataset.[30, 31] The neighborhood-level poverty was extracted using the percentage of population < 200% federal poverty level (FPL) and was extracted at census-tract level, and the percentage of the population without high school diploma was determined at census block group-level.[32] Neighborhood social capital for patients' ZIP-code level was assessed using the number of civic or social organizations per capita, obtained by summarizing data from the 2017 US Census Bureau ZIP code Business Patterns.[33] Domestic violence injury rates were extracted at the ZIP-code level of the patient's geocoded address. To assess opportunities for physical activity, we generated WalkScore™ values for each patient's census block.[34] The visual assessment found that the WalkScore™ dataset did not represent physical activity opportunities in areas with networks of unpaved trails such as our local county and rural areas; hence, we excluded these measures. See Additional File1 for a detailed description of methods used for determining neighborhood-level social risks in our analysis.

Statistical methods

After adjusting for covariates, we examined post-intervention HbA1C, LDL, and BP controlling for pre-intervention values (from before the July 1, 2013 nurse-led care coordination start date to after the end of the project in June 2015). Dataset was created with de-identified records for each patient containing their clinical and sociodemographic information and geocoded residential addresses. Geocoded residential addresses of patients were used to extract neighborhood-level variables. Data analysis was conducted between November 2019 and October 2020. We fitted a separate generalized linear model (GLM) for each of these measures as the dependent variable. We adjusted for covariates, including pre-intervention measures and pre-intervention body mass index (BMI). The GLM model assumptions were checked. Using the Pearson correlation between continuous variables, we chose one variable from each group of variables. Variance Inflation Factors (VIF) were calculated as 1/ (type I tolerance) of the GLM model for categorical variables, and cutoff point of 5 was used. The overall fit of the models was assessed using the coefficient of determinations (R^2). We report statistical significance at $p < 0.05$. Results were generated using SAS software.

Model 1: Included covariates readily available in the clinical chart: age, gender, race/ethnicity, marital status, smoking status, alcohol use, healthcare utilization 12 months before the study's start date, pre-intervention cardiometabolic measure levels, pre-intervention BMI, presence of mood disorder, total number of chronic health conditions, and total number of nurse care manager contacts during the study period. Significant interactions between the covariates and the pre-intervention values were included in the model.

Model 2

Included the covariates in Model 1 and also included neighborhood-level measures of poverty, education, social capital, and domestic violence injury rates.

Model 3

Included the covariates in Model 2 and added physical determinants of access to healthy food (grocery store) and healthcare (PCP clinic location) from the patient's geocoded address.

Parsimonious Model

We used a backward-selection technique to remove non-significant factors step-by-step to obtain a parsimonious model with only significant factors.

At the census block group level, we noted collinearity among the percentage of the population below 200% of the FPL and the Area Deprivation Index.[35] Thus, we included only the percentage of the population below 200% of the FPL in our models. We dichotomized driving time to PCP clinic location to 30 minutes or less, and over 30 minutes, as Health Professional Shortage Area (HPSA) designation utilizes driving time of more than 30 to 40 minutes to the nearest source of care as one of the scoring criteria.[36] Based on frequency distributions and outliers, we represented the percentage of the population without a high school diploma and the number of nurse care manager contacts as categorical variables by quartiles.

Sensitivity analysis

We performed 2 additional analyses for each outcome: 1) We fit a mixed-effects model to test for random variability across clinics. 2) We fit a mixed-effects model to test for random variability across all included patients' census tracts (137 census tracts). Various area-level measures included in our analyses were associated with different geographic areas; hence an overall nested analysis was not possible.

Results

Of 8593 eligible participants in the LIGHT[2] cohort, 6378 participants had at least 1 cardiometabolic measure reported both before and after the intervention. Figure 1 Flow Diagram illustrates the derivation of participants for each measure. The cohort description is included in Table 1. Because our cohort was primarily White, non-Hispanic ethnicity (86.3%), we dichotomized the race/ethnicity variable.

Table 1 Characteristics of the study sample (N = 6378)

Variable	Total
Demographics	
Age (mean, SD)	62.67(18.5)
Sex [frequency(percentage)]	
Female	3928(61.59)
Male	2450(38.41)
Race [frequency (percentage)]	
White non-Hispanic	5507(86.34)
Other	871(13.66)
Marital status [frequency (percentage)]	
Married	2746(43.05)
Other	892(13.99)
Single	1622(25.43)
Widowed	1118(17.53)
Cardiometabolic measures (mean, SD)	
Pre-intervention LDL- cholesterol (mg/dL)	106.26(31.55)
Post-intervention LDL- cholesterol (mg/dL)	99.41(36.22)
Pre-intervention HbA1C (percentage)	6.94(1.43)
Post-intervention HbA1C (percentage)	7.09(1.53)
Pre-intervention systolic BP (mm of Hg)	132.74 (14.17)
Post-intervention systolic BP (mm of Hg)	131.14(17.61)
Pre-intervention diastolic BP (mm of Hg)	75.83(7.64)
Post-intervention diastolic BP (mm of Hg)	75.05(9.69)
Neighborhood characteristics	
Percentage of population below 200% of the FPL (mean, SD) for patient's census-tract	36.14(14.30)
Percentage of population that did not graduate from high school for patient's census-block group [frequency (percentage)]	
Quartile 1: <3.17%	2049(32.13)
Quartile 2: 3.17–8.79%	1519(23.82)

Quartile 3: 8.79–14.06%	1325(20.77)
Quartile 4 > 14.06%	1485(23.28)
Domestic violence injury rates (per 1,000) for patient zip codes, 2011–2015 (mean, SD)	0.39(0.37)
Distance to nearest grocery store from patient's geocoded address (miles)	3.42(3.69)
Civic and Social Associations Rate per 100,000 population (mean, SD)	13.10(4.9)
Health characteristics	
Number of comorbidities	4.89(4.23)
Pre-intervention body mass index (kg/m^2)	30.35(7.71)
Current smoking [frequency (percentage)]	
Yes	1455(22.81)
No	4810(75.42)
Missing	113(1.77)
High-risk alcohol use [frequency (percentage)]	
Yes	110(1.72)
Unknown	6368(98.28)
Presence of mood disorder [frequency (percentage)]	
Yes	1475(23.13)
Unknown	4903(76.87)
Total number of nurse care manager contacts during the study period [frequency (percentage)]	
Quartile 1: <5	1504(23.58)
Quartile 2: 5–10	1489(23.35)
Quartile 3: 11–21	1745(27.36)
Quartile 4: >22	1640(25.71)
High vs low healthcare resource utilizer [frequency (percentage)]	
High utilizer	778(12.2)
Low utilizer	5600(87.8)
Travel time to PCP office from geocoded addresses [frequency (percentage)]	
<=30 minutes	4004(62.78)

> 30 minutes	1331(20.87)
Unknown	1043 (16.35)
SD = standard deviation, LDL = low density lipoprotein cholesterol, HbA1C = glycosylated hemoglobin, BP = blood pressure, FPL = Federal poverty level, PCP = primary care provider	

We had LDL cholesterol outcomes for 2377 participants, HbA1C for 1290 participants, and BP outcomes for 4619 participants. The results of all models were consistent. The final parsimonious models showed significant worsening of LDL-cholesterol associated with higher pre-intervention LDL-cholesterol levels (β 0.56, 95% CI 0.52 to 0.60, $p < 0.001$), significant worsening of HbA1C associated with higher pre-intervention HbA1C levels (main effect β 0.51, 95% CI 0.43 to 0.59, $p < 0.001$), significant deterioration of systolic and diastolic BP with higher pre-intervention systolic BP (main effect β 0.95, 95% CI 0.83 to 1.08, $p < 0.001$), and higher pre-intervention diastolic BP (main effect β 0.83, 95% CI 0.75 to 0.91, $p < 0.001$), respectively. LDL-cholesterol worsened for women compared to men (β 7.76, 95% CI 5.21 to 10.32, $p < 0.001$). There was a significant interaction between pre-intervention HbA1C and gender (main effect β -1.29, 95% CI -1.95 to -0.62, $p < 0.001$; interaction effect β 0.19, 95% CI 0.09 to 0.28, $p < .001$), with HbA1C worsening if the pre-intervention HbA1C is more than 6.8% in women compared to men (S3 Figure). The interaction between gender and pre-intervention systolic BP levels (main effect β -7.86, 95% CI -15.55 to -0.17 $p = 0.045$; interaction effect β 0.06, 95% CI 0.002 to 0.12, $p = 0.043$) indicates worsening trend in systolic BP for women compared to men with pre-intervention systolic BP level > 131 mm Hg. All other associations were inconsistent across all cardiometabolic measures. The coefficient of determinations (R^2) did not change significantly with the addition of neighborhood-level variables. See Table 2, 3, 4 for results from parsimonious models for LDL- cholesterol, HbA1C, and systolic BP outcomes and Additional Table 1 for results from the parsimonious model for diastolic BP outcome. See Additional Tables 2–5 Table for detailed models for all measures and R^2 for all models.

Table 2

Results of Parsimonious model for LDL cholesterol outcome (R2 = 0.29)

Parameter	**Adjusted β (95% Confidence Limits)**	**P-value**
Intercept	68.66 (57.87, 79.44)	< 0.001
Pre-intervention BMI	-0.19 (-0.35, -0.02)	0.02
Pre-intervention LDL	0.56 (0.52, 0.60)	< 0.001
Female (ref = male)	7.76 (5.21, 10.32)	< 0.001
Non-White race (ref = White)	-3.43 (-7.24, 0.38)	0.077
Age	-0.26 (-0.36, -0.17)	< 0.001
Number of comorbidities	-0.47 (-0.79, -0.15)	0.004
Percentage of area population below 200% of the FPL	-0.14 (-0.23, -0.05)	0.002
Domestic violence injury hospitalization rate (per 1,000 population)	-5.78 (-9.24, -2.33)	0.001

LDL = low density lipoprotein, BMI = body mass index (kg/m^2), ref = reference category, FPL = Federal poverty level; R^2 = coefficient of determinations

Table 3
Results of Parsimonious model for HbA1C outcome (R2 = 0.39)

Parameter	Adjusted β (95% Confidence Limits)	P-value
Intercept	3.73 (2.93, 4.53)	< 0.001
Pre-intervention HbA1C	0.51 (0.43, 0.59)	< 0.001
Female (ref = male)	-1.29 (-1.95, -0.62)	< 0.001
Pre-intervention HbA1C*female sex	0.19 (0.09, 0.28)	< 0.001
Non-White race (ref = White)	-1.16 (-1.94, -0.37)	0.004
Pre-intervention HbA1C*non-White race	0.14 (0.03, 0.25)	0.01
Age	-0.006 (-0.012, -0.00001)	0.05
Current smoker (ref = No)		
Yes	-0.20 (-0.38, -0.017)	0.03
Unknown	-0.58 (-1.16, -0003)	0.05
Civic and Social Associations Rate (per 100,000 population)	0.01 (-0.0008,0.026)	0.06
Distance to nearest grocery store from patient’s geocoded address in miles	0.01 (-0.007, 0.03)	0.25
HbA1C = hemoglobin A1C; ref = reference category, R^2 = coefficient of determinations		

Table 4
Results of Parsimonious model for Systolic BP (R2 = 0.43)

Parameter	Adjusted β (95% Confidence Limits)	P-value
Intercept	-3.68 (-19.70, 12.34)	0.65
Pre-intervention BMI	0.096 (0.04, 0.15)	< 0.001
Pre-intervention SBP	0.95(0.83, 1.08)	< 0.001
Female (ref = Male)	-7.86 (-15.55, -0.17)	0.045
Pre-intervention SBP*female sex	0.06 (0.002, 0.12)	0.043
Age	0.38 (0.17, 0.60)	< 0.001
Pre-intervention SBP*age	-0.003 (-0.004, -0.0008)	0.003
Number of comorbidities	0.10 (0.009, 0.19)	0.03
Percentage of area population below 200% of the FPL	0.30 (0.18, 0.43)	< 0.001
Pre-intervention DBP*Percentage of area population below 200% of the FPL	-0.004 (-005, -0.002)	< 0.001
Domestic violence injury hospitalization rate (per 1,000)	2.21 (1.16, 3.26)	< 0.001

BMI = body mass index (kg/m^2), SBP = systolic blood pressure, FPL = Federal poverty level, DBP = diastolic blood pressure R^2 = coefficient of determinations

Sensitivity Analysis

The results from both the mixed-effects model for clinics and census tracts show no significant changes in the parameter estimates for significant associations. Additional tables 6–9 give the solution to the random effect of clinics and the variability. The intra-class correlation coefficient (ICC) for census tract levels for LDL-cholesterol was 0.019, for HbA1C was 0.048, for systolic BP was 0.005, and for diastolic BP was 0.02. Using census tract levels as random effects did not change associations significantly. The ICC for mixed models when controlling for pre-intervention values and all other variables was even smaller (for example, for LDL it was 0.007).

Discussion

In predominantly white suburban and rural participants from a two-year nurse-led care coordination program, we found higher pre-intervention cardiometabolic measures were associated with worsening post-intervention levels. Additionally, we found women's LDL-cholesterol worsened compared to men, and women with high pre-intervention HbA1C (> 6.8%) and BP (> 131 mm Hg systolic BP) got worse compared to men despite clinic-based, nurse-led care coordination. Individuals with uncontrolled cardiometabolic disorders, especially women, may benefit from additional disease management support outside clinic walls. While there were some inconsistent findings across outcomes, the addition of neighborhood-level risks based on geocoded residential addresses did not significantly change associations or fit of models compared to models based on variables that are routinely available in clinical charts.

Our results differ from a few previous studies that have shown nurse case management improves diabetes and hypertension control.[37, 38] Our results may be different from previous studies as nurses in the LIGHT^2 program provided care coordination and as-needed chronic disease education during clinic visits. Most other studies of nurse-led interventions included additional case management or disease management components delivered during and in between clinic visits. [37–39]. Individuals with higher baseline cardiometabolic measures may need additional support between clinic visits to address social and behavioral contexts not captured by EHR or neighborhood-level variables. Gender is the only socially stratifying factor present in > 50% of our cohort.[40] Our findings of worsening cardiometabolic outcomes in women compared to men may indicate the presence of additional psychosocial contexts that limit women's ability to benefit from solely clinic-based interventions.[41–44] Further research to understand and address these associations with their contextual causes may help tailor clinic and community-based healthcare resources.

Strengths of our study

Our study is the first study to examine the interaction of baseline cardiometabolic risk factors with clinical factors and neighborhood-level risks to identify individuals who may get less benefit or not benefit from solely clinic-based care coordination for CVD prevention. We included variables widely available in clinical charts and neighborhood-level social risks based on patients' residential addresses to avoid burdening PCPs with additional individual social and behavioral risk screenings.[15, 16] In addition to variables accounting for the NAM recommended social and behavioral domains, our study included 1 factor associated with each of 5 key areas of social determinants of health included in the place-based organizing framework developed by Healthy People 2020, namely, economic stability, education, social and community context, neighborhood environment, and healthcare.[45, 46]

Weaknesses of our Study

We acknowledge several limitations. First, the cohort consists of Medicaid, Medicare, or dual-eligible beneficiaries of predominantly white, non-Hispanic ethnicity from Midwestern primary care clinics, which may limit the generalizability of our findings. Second, physical activity is one of the primary CVD risk factors, but we could not identify reliable neighborhood-level measures of physical activity opportunities for our cohort of suburban and rural participants.[47, 48] Third, though burdensome, individual-level social and behavior risks, rather than neighborhood-level risks, can improve the ability to predict which patients may benefit from supplementary community-based interventions.[49–51] Lastly, we acknowledge that the LIGHT^2 care coordination program focused on super-utilizers and reducing care fragmentation rather than reducing health disparities.[22]

Conclusions

We found higher cardiometabolic measures and gender were commonly associated with worsening cardiometabolic outcomes in predominantly White suburban and rural participants from a clinic-based care coordination program. Further research to understand the contextual causes for these associations may aid tailoring of healthcare resources for disease management support between clinic visits. Addition of neighborhood-level risks based on patients' residential address did not change estimates of associations beyond routinely collected clinical and sociodemographic data in EHR.

Abbreviations

CVD
Cardiovascular Disease
EHR
Electronic Health Record
LIGHT^2
Leveraging Information Technology to Guide High Tech, High Touch Care
STROBE
Strengthening the Reporting of Observational Studies in Epidemiology
CMS
Centers for Medicare and Medicaid Services
AHRQ
Agency of Healthcare Research and Quality
HbA1C
hemoglobin A1C
BP
Blood Pressure, and
LDL-cholesterol
low density-lipoprotein cholesterol
NAM
National Academy of Medicine (NAM)
BMI
Body Mass Index
PCP
Primary Care Physician
FPL

Federal Poverty Level
GLM
Generalized Linear Model
VIF
Variance Inflation Factors
ICC
Intra-class correlation coefficient

Declarations

Ethics Approval and Consent to participate: The University of Missouri institutional review board determined the LIGHT^2 program to be a quality improvement activity not requiring institutional review board review. As it was deemed quality improvement activity, patient consents were not collected.

Consent to Publish: Not Applicable. Consent to publish not collected as it was quality improvement project and manuscript does not report any details on individuals.

Availability of data and materials: The datasets generated and/or analyzed during the current study are not publicly available because they contain confidential clinical data as well as variables that would allow a user to discern the identity of a participant. The datasets are available from the corresponding author on reasonable request.

Competing interests: None of the authors report any conflicts of interests

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Authors' contributions

Concept and design: SJP

Acquisition, analysis, or interpretation of data: SJP, MG, AJ, YW, JCP, DHJ, DRM, REF, RLK.

Drafting of the manuscript: SJP, MG

Critical revision of the manuscript for important intellectual content: All authors.

Statistical analysis: MG, YW, SJP

Administrative, technical, or material support: AJ

Supervision: RLK, REF, DRM

All authors have read and approved the final manuscript

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Figures

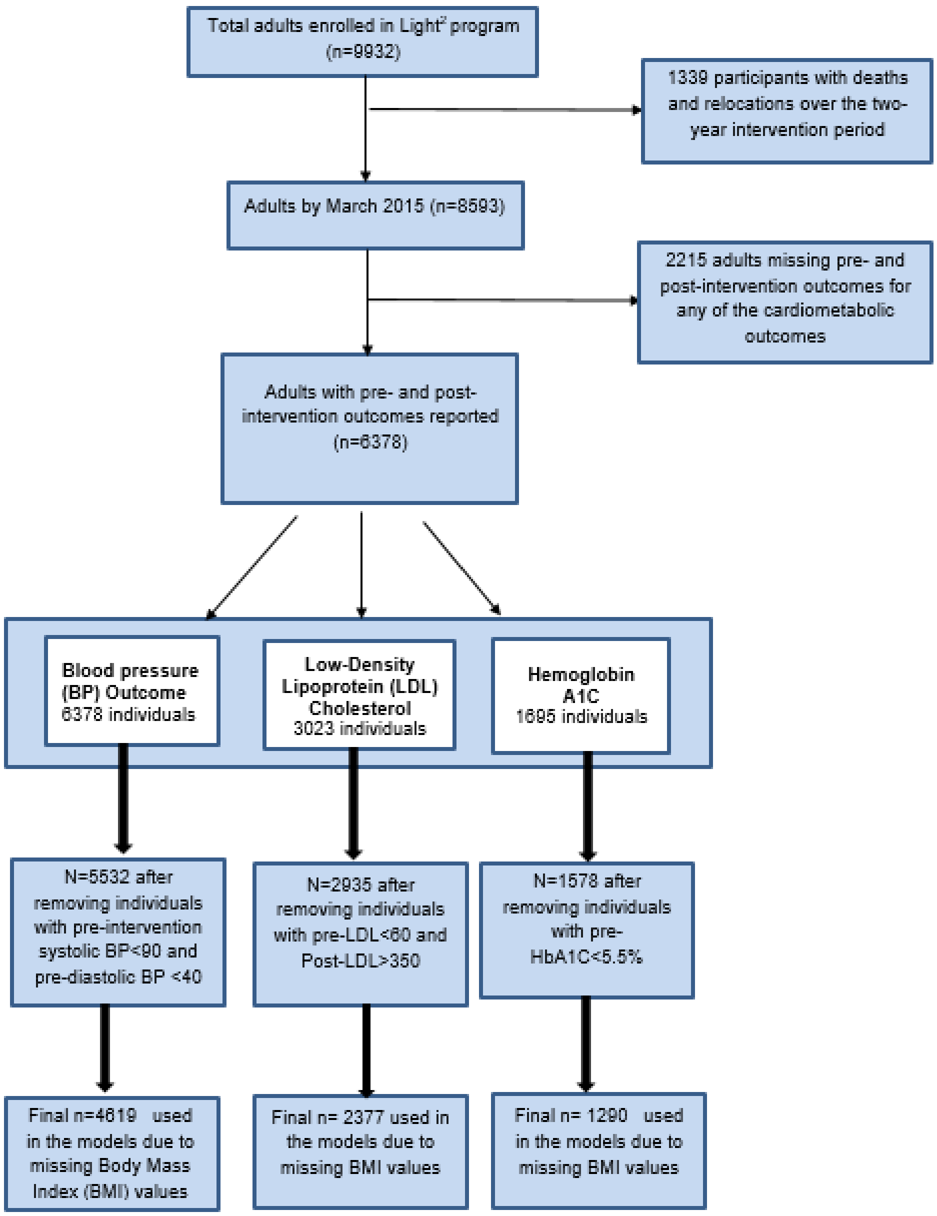

Figure 1

Flow diagram of participants Flow diagram of Leveraging Information Technology to Guide High Tech, High Touch Care (LIGHT2) program participants and final number of participants included in analysis for each cardiometabolic measure

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