Qingyuan Gao

1 Problem Statement

The primary problems in RECS survey study are detecting who the electricity-dependent medical device households are, measuring power outage risks in electricity-dependent medical device households and understanding electricity-dependent medical device HHs' energy insecurity or resilience.

2 Literature Review

2.1 Electricity Dependent Medical Device (EDMD)

Previous studies suggest that people have been receiving medical care at home over the years, which also contributes to the growing trend of medical device household use.

Care at home has seen major growth in recent years influenced by changes in patient demographics, economic factors and technological advances. The FDA (Food and Drug Administration) considers home care devices as the fastest growing segment of MD (medical device) industry.

Most household-use medical devices consume electricity to function, and these electricity dependent medical devices (EDMD) play an important role in household medical care. According to U.S. department of Health & Human Services, over 3 million Medicare beneficiaries rely on electricity-dependent durable medical and assistive equipment and devices, such as ventilators, to live independently in their homes.

2.2 Energy Security and Resilience Problems in EDMD Households

One of the most concerning problems in the use of EDMD is energy security and resilience, especially under severe weather conditions. Power outage threatens the health of patients relying on their EDMD, and some patients have to pay for the high bills resulting from EDMD use.

According to Administration for Strategic Preparedness and Response (ASPR) and the Centers for Medicare and Medicaid Services (CMS), there are a total of 66,496,126 people beneficiaries receiving home health services from electricity-dependent durable medical and assistive equipment (DME) and devices.

Many of the DME users are defined as medical vulnerable people, including those reliant on electricity for independence (e.g. electric wheelchairs, mobility scooters etc), as well as those reliant on electricity for survival (e.g. those with ventilators, oxygen concentrators, reliance on exceptional temperature stability or other critical at-home medical devices). A much larger subset of the population may additionally be considered electricity vulnerable, such as those susceptible to heat/cold, or with limited mobility to leave home in a blackout.

Severe weather and other emergencies, especially those with prolonged power outages, can be life-threatening for these individuals. Many may rapidly seek assistance from emergency medical services (EMS), and or overwhelm hospitals and shelters when seeking access to care or secure power. Others may shelter in place, as they are unable to evacuate safely without assistance, putting their lives at risk. This leads to severe surges in healthcare demand and stress on public health, health care, emergency management, and first responder systems and shelters, and commonly leads to increases in adverse health outcomes for at-risk individuals impacted by the event.

2.3 Research on the EDMD Energy Security & Resilience Problems

To date, the literature on the impact of power outages on health has primarily been focused on hospital settings and has failed to examine the geographic regions at the highest risk for the consequences of extreme weather and power outages among individuals reliant on medical devices in their own households. As for historical research, stable electricity supply or contingency for loss of supply remains a knowledge gap. Obstacles to accessing home battery storage will need to be addressed with prioritized solutions to ensure that electricity-dependent, medically vulnerable populations can safely withstand a power outage.

Brown et.al stated that low-income households with high utility bills have to make trade-offs between meeting alternative critical household expenditures. Paying for food, medical care, telecommunications, and shelter are often sacrificed to make timely utility bill payments. These trade-offs create a negative feedback loop that traps families in an enduring cycle of poverty. Electricity termination can have health and safety consequences, which can be particularly serious for the elderly and young children, and for those needing medical equipment. Problems associated with high energy burdens often include adverse health effects. This will intern increase their risk of catching diseases, thus worsening their financial state. In-depth studies in U.S. cities and an analysis conducted at the U.S. Census Division level revealed that certain demographic populations are more likely to be energy insecure, including households of color, those without a college education, and the chronically underemployed. Brown et.al found that poverty is the strongest determinant of energy burden. Particular combinations of vulnerabilities – such as living in low-income, female-headed households with children – are associated with particularly high energy burdens. Health related consequences are the second most common energy vulnerability issues after Service disconnection/bill delinquencies, which are the most frequent issues. As energy-burden vulnerabilities increase, in number, health-related consequences become more common. Adam X. Andresen et.al revealed that many households did not receive assistance, whether financial or other tangible resources. There is a significant difference in power outage length between high-income and low-income households in Phoenix. Households owning medical devices have many more outages than those not owning medical devices. Households owning generators have many more outages than those not owning one. Households owning homes have many more outages than those renting homes. Spurlock et.al found that high disaster counts and high DME populations were found scattered throughout the southeastern US, with coastal counties exhibiting higher concentrations of both. Molinari et.al discovered that the highest proportion of electricity-dependent persons was identified in the South (~39%), while the North Central region had the largest proportion of rural living electricity-dependent individuals (~28%) More than three-fourths of the electricity-dependent population lived in MSAs, which were defined as urban.

To cope with the energy insecurity and resilience problems in EDMD households, energy security technologies and policies need to adjust to meet the needs of the home health care community. Policy barriers should be replaced with incentives and programs that make solar and battery storage adoption easier. Gaps in preparedness and response are endangering an already vulnerable population and must be addressed. The technology to improve resiliency and energy independence exists, and it needs to be made more accessible to those who could most benefit from resilient and reliable emergency power options

3 Summary of Data

The study used the 2020 Residential Energy Consumption Survey (RECS) dataset. The survey dataset included data from 17,942 households, of which 2,257 households are medical device households, taking up a proportion of 14.09%, with 1020 fields of variables. Summary tables and plots were derived to explore the heterogeneities of household features and energy consumption patterns between medical device households/non-medical device households. This section mainly focuses on the major factors influencing the energy consumption patterns and the medical conditions of households, ranging from geographic to demographic features.

3.1 Spatial Distribution

The spatial distribution of medical device households/non-medical-device households are different, in terms of Census regions and states.

Medical device/Census region	MIDWEST	NORTHEAST	SOUTH	WEST
1	536	468	971	637
0	3250	3143	5368	3892
Percentage of medical device households	14.2	13.0	15.3	14.1

Table 3.1 Number of households by Census region

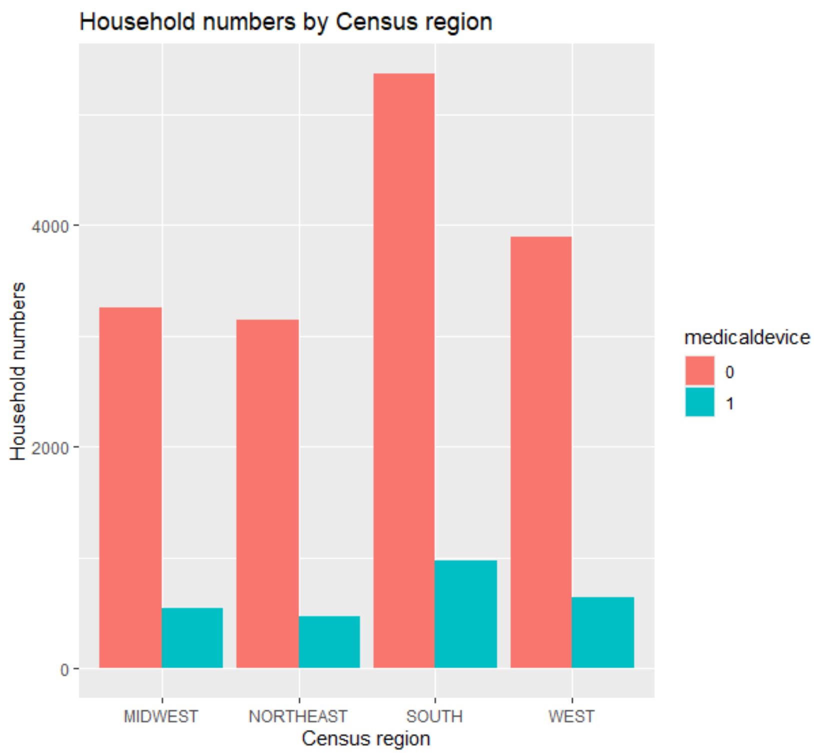

Figure 3.1 Number of households by Census region

REGIONC	*MEDICALDEV* 0	*MEDICALDEV* 1	***Total***
MIDWEST	3250 20.8 %	536 20.5 %	3786 20.7 %
NORTHEAST	3143 20.1 %	468 17.9 %	3611 19.8 %
SOUTH	5368 34.3 %	971 37.2 %	6339 34.7 %
WEST	3892 24.9 %	637 24.4 %	4529 24.8 %
Total	15653 100 %	2612 100 %	18265 100 %

$\chi^2=10.913 \cdot df=3 \cdot Cramer's\ V=0.024 \cdot p=0.012$

Table 3.2 Cross table of household numbers and Census regions

More households in the South Census region tend to have medical devices at home, while less households in the Northeast Census region tend to have medical devices at home. From the cross-table Chi-square test, there is a significant difference in medical device use for households in different Census regions.

Similarly, conduct cross-table analysis for the number of households and states. The full table is in the Appendix A.

From the cross-table, there are significantly more medical device households in California, New York and Texas than other states. However, considering the rate of using medical devices compared to the total household numbers, Arizona, Iowa, Idaho, Kentucky have larger percentage of medical device user households, while the rate of medical device users in CA, NY and TX is rather low. There is a significant difference in medical device use for households in different states.

3.2 Number of Household Members

The demographic features of medical device households/non-medical-device households are different in many dimensions. One of the most important factors is the size of the household.

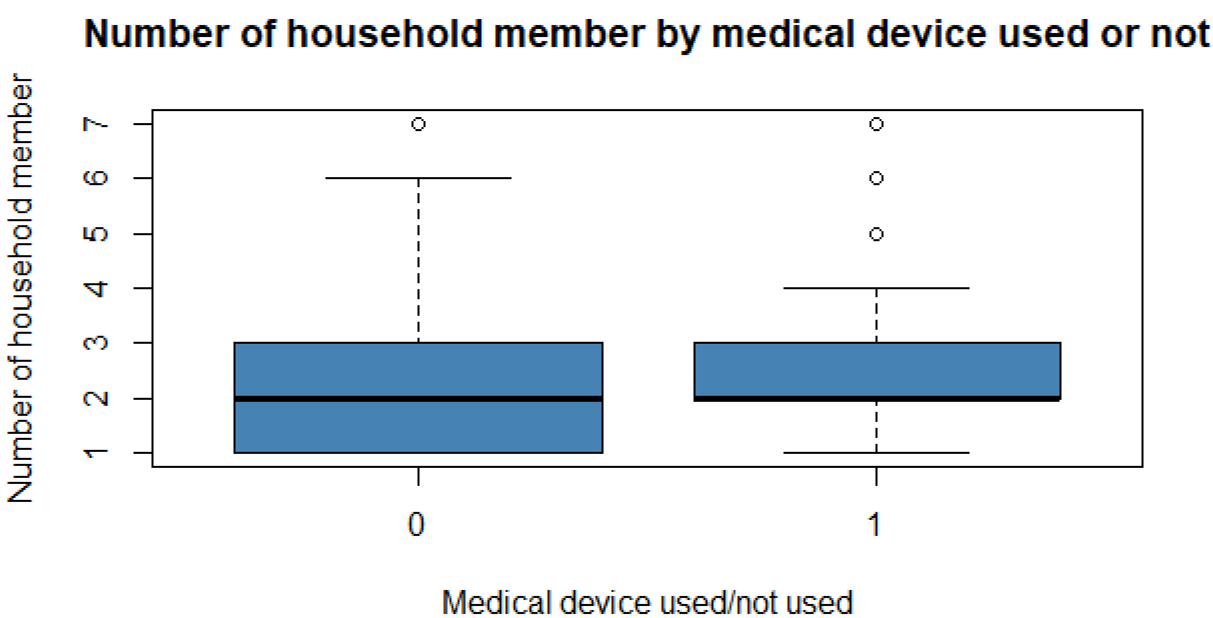

Figure 3.2 Number of household members by medical device/ non-medical-device households

From Figure 3.2, The proportion of single person households is less in households using medical devices, indicating that single person tends not to use medical devices at home. Most households using medical devices have 2 household members. Households using medical devices generally have less than 4 household members, while larger households generally tend not to use medical devices at home.

3.3 Household income level

INCOMELEVEL	MEDICALDEV 0	MEDICALDEV 1	Total
1	459 3 %	60 2.3 %	519 2.9 %
2	182 1.2 %	29 1.1 %	211 1.2 %
3	204 1.3 %	37 1.4 %	241 1.3 %
4	343 2.2 %	62 2.4 %	405 2.3 %
5	287 1.9 %	54 2.1 %	341 1.9 %
6	457 3 %	99 3.9 %	556 3.1 %
7	683 4.4 %	131 5.1 %	814 4.5 %
8	631 4.1 %	115 4.5 %	746 4.2 %
9	743 4.8 %	121 4.7 %	864 4.8 %
10	679 4.4 %	102 4 %	781 4.4 %
11	1134 7.4 %	179 7 %	1313 7.3 %
12	1267 8.2 %	201 7.9 %	1468 8.2 %
13	1656 10.8 %	296 11.6 %	1952 10.9 %
14	1998 13 %	322 12.6 %	2320 12.9 %
15	2258 14.7 %	400 15.6 %	2658 14.8 %
16	2404 15.6 %	349 13.6 %	2753 15.3 %
Total	15385 100 %	2557 100 %	17942 100 %

$\chi^2=23.561 \cdot df=15 \cdot Cramer's\ V=0.036 \cdot p=0.073$

Table 3.3 Cross table of household numbers and income level

The data is measured in annual gross income, divided into 16 levels from lower than 5,000$ to higher than 150,000 $. From the cross-table, there is significant difference between the income level of medical device HHs and non-medical device HHs. The biggest difference is that non-medical device HHs have a greater proportion of high-income families, with income more than 15,0000$ a year.

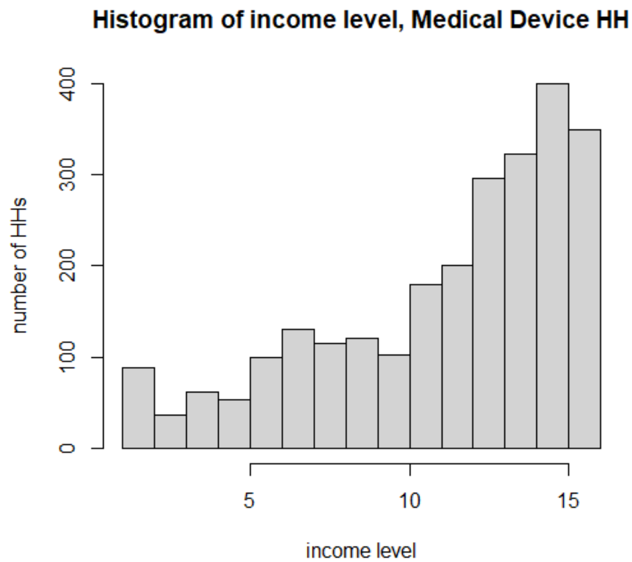

Figure 3.3 Histogram of income level of medical device HHs

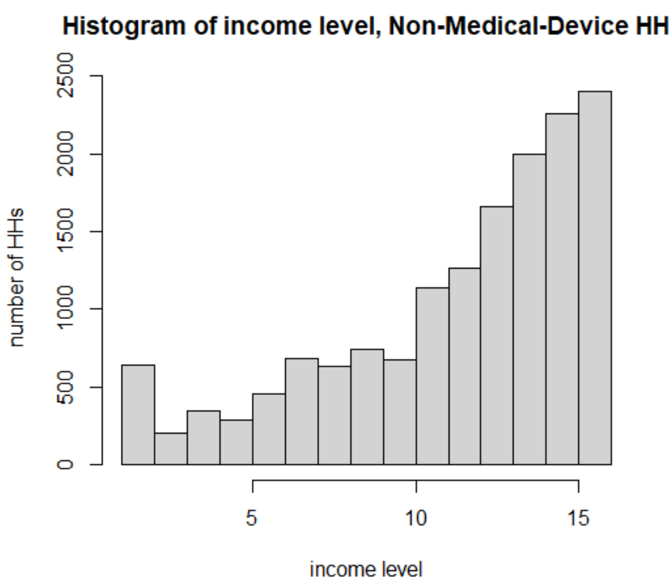

Figure 3.4 Histogram of income level of non-medical-device HHs

3.4 Electricity Consumption

From the literature review, the energy consumption patterns should vary for different types of households.

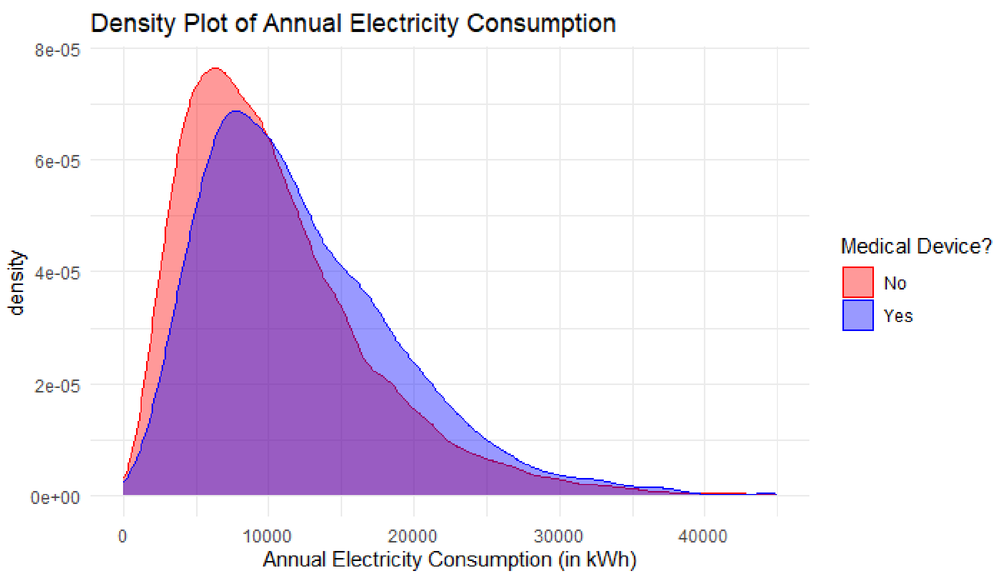

Figure 3.5 Density plot of annual electricity consumption for the 2 types of households

It is observed that there is a larger proportion of high electricity consumption in medical device households, especially those whose annual electricity consumption is larger than 10,000 kWh. In terms of distribution, there is a large proportion of households consuming about 10,000 kWh in the non-medical-device households, while the energy consumption pattern of the medical device households is more evenly distributed.

4 Statistics Tests

To measure the different patterns of power consumption and power outage risks in the 2 types of households, formal statistics tests were derived. In general, there are 2 levels of the independent variable, which is the type of the household. The dependent variable could have many levels, or categories, corresponding to the variables like power outage reasons in the dataset. Below are the tests implemented on the dataset.

A 2x2 chi-square test is used when there are two levels of the independent variable & two levels of the dependent variable, and a Chi-square test is used in cases with more than two categories. Under rare circumstances, there are less than 5 frequencies of variables in a cell of the cross table, then a Fisher's test should be used.

In most cases, the independent and dependent variables are both categorized. If the dependent variables are continuous and normally distributed, such as the electricity consumption and costs, a one-way ANOVA should be tested.

If the dependent variable is ordinal, such as the education level, then a Kruskal Wallis test should be conducted.

In some special cases, Wilcoxon signed rank sum test is used to test the difference between continuous data.

Below is the summary of statistics test conducted between the medical device households and non-medical device households, on several important variables.

Table 4.1 Statistics tests for important variables

Variable	Test Type	p-value	Conclusion: significant/insignificant difference between 2 types of HHs	% in Medical Device HHS	% in non-medical -device HHs
Number of household members	Kruskal-Wallis	0.000	significant		
Census Regions	Chi-square	0.012	significant		
States	Chi-square	0.000	significant		
KWH used in other appliances (except for charging electric vehicles)	Wilcoxon	0.000	significant		

Variable	Test Type	p-value	Conclusion: significant/insignificant difference between 2 types of HHs	% in Medical Device HHS	% in non-medical -device HHs
KWH used in charging electric vehicles	Wilcoxon	0.941	insignificant		
Heating Degree Days	Wilcoxon	0.618	insignificant		
Cooling Degree Days	Wilcoxon	0.658	insignificant		
Backup generator	Chi-square	0.000	significant	20.5%	14.8%
Power outage	Chi-square	0.000	significant	19.8%	17.7%
Housing type	Chi-square	0.000	significant		
Number of elderly people	Kruskal Wallis	0.000	significant		
Frequency of foregoing basic necessity	Chi-square	0.000	significant		

Variable	Test Type	p-value	Conclusion: significant/insignificant difference between 2 types of HHs	% in Medical Device HHS	% in non-medical -device HHs
Frequency of keeping home at unhealthy temperature	Chi-square	0.000	significant		
Frequency of receiving disconnection notice	Chi-square	0.000	significant		
Receive energy assistance	Chi-square	0.005	significant	19.7%	13.5%
Medical attention is needed because home is too hot	Chi-square	0.000	significant	0.9%	0.3%
Medical attention is needed because home is too cold	Chi-square	0.000	significant	1.5%	0.5%
Urban type(Urban)	Chi-square	0.000	Significant	62.1%	68%
Rent or own home(own)	Chi-square	0.000	Significant	77.3%	72%
Education	Kruskal Wallis	0.000	Significant		
Employment	Chi-square	0.000	Significant		

Besides, the reasons for power outage were also tested.

Variable	Test Type	p-value	Conclusion: significant/insignificant difference between 2 types of HHs	% in Medical Device HHS	% in non-medical -device HHs
Reasons for power outage	Fisher’s	0.138	insignificant		
Natural disasters/weathers vs no power outage	Fisher’s	0.024	significant		
Unable to pay bills vs no power outage	Fisher’s	0.464	insignificant		
utility had planned or unplanned outage	Fisher’s	0.146	insignificant		

Table 4.2 Statistics tests of reasons for power outage

5 Latent Class Analysis (LCA)

A Latent Class Model (LCM) is built to detect the underlying groups of different households, with regard to their need for energy assistance, their frequencies of suffering from power outage problems, their energy consumption and housing status. Covariates of the LCM are demographic variables ranging from income level to education level.

The name and meaning of the outcome & covariate variables are listed below

Variable name	Variable meaning	Variable type
regionc	Census region, 1=Midwest,2=Northeast,3=South,4=West	Outcome variable
Uatyp10	Urban type, 1=urban cluster, 2=rural,3= urban	Outcome variable
typhuq	Type of housing unit, 1 Mobile home 2 Single-family house detached from any other house 3 Single-family house attached to one or more other houses (for example: duplex, row house, or townhome) 4 Apartment in a building with 2 to 4 units 5 Apartment in a building with 5 or more units	Outcome variable
backup	Backup generator, 1=have backup generator 0=does not have backup generator	Outcome variable
powerout	Experienced power outage last year/not	Outcome variable
energyasst	Received energy assistance/not	Outcome variable
hotma	Medical attention needed too hot/not	Outcome variable
coldma	Medical attention needed too cold/not	Outcome variable
scaleb	Frequency of reducing or forgoing basic necessities due to home energy bill, 3 Almost every month 2 Some months 1 1 or 2 months 0 Never	Outcome variable
scaleg	Frequency of keeping home at unhealthy temperature 3 Almost every month 2 Some months 1 1 or 2 months 0 Never	Outcome variable

scalee	Frequency of receiving disconnection notice 3 Almost every month 2 Some months 1 1 or 2 months 0 Never	Outcome variable
kwh	Total electricity use (taking the log)	Outcome variable

Table 5.1 List of outcome variables

Variable name	Variable meaning	Variable type
employhh	Respondent employment status 1 Employed full-time 2 Employed part-time 3 Retired 4 Not employed	Covariate variable
education	Education level, 1 Less than high school diploma or GED 2 High school diploma or GED 3 Some college or Associate's degree 4 Bachelor's degree 5 Master's, Professional, or Doctoral degree	Covariate variable
moneypy	Household income level(1-16)	Covarate variable
nhsldmem	Number of household members	Covariate variable
Numadult2	Number of elderly people	Covariate variable

Table 5.2 List of covariate variables

The LCM is estimated by the poLCA package in R, where the BIC criterion is used to determine the number of latent classes.

Number of latent classes	BIC
2	35840
3	35339
4	35252
5	35505

Table 5.3 The information criterion of different number of latent classes

The BIC value reaches the minimum at 4 latent classes. Therefore, the best number of latent classes should be 4.

The estimation result of the LCM is listed below

```
## Conditional item response (column) probabilities,
##  by outcome variable, for each class (row)
##
## $nominal_regionc1
##            Pr(1)  Pr(2)  Pr(3)  Pr(4)
## class 1:  0.1644 0.1584 0.4625 0.2147
## class 2:  0.2105 0.1862 0.2790 0.3243
## class 3:  0.2612 0.2605 0.2506 0.2276
## class 4:  0.2016 0.1362 0.5096 0.1526
##
## $nominal_uatyp101
##            Pr(1)  Pr(2)  Pr(3)
## class 1:  0.1119 0.1995 0.6886
## class 2:  0.1029 0.0797 0.8174
```

```
## class 3:  0.1849 0.0932 0.7219
## class 4:  0.1459 0.6267 0.2275
##
## $nominal_typehuq1
##            Pr(1)  Pr(2)  Pr(3)  Pr(4)  Pr(5)
## class 1:  0.1515 0.5381 0.1236 0.0870 0.0998
## class 2:  0.0000 0.8574 0.1096 0.0056 0.0274
## class 3:  0.0622 0.2366 0.1478 0.1835 0.3699
## class 4:  0.1055 0.8939 0.0006 0.0000 0.0000
##
## $nominal_backup1
##            Pr(1)  Pr(2)
## class 1:  0.8767 0.1233
## class 2:  0.8488 0.1512
## class 3:  0.9050 0.0950
## class 4:  0.5894 0.4106
##
## $nominal_powerout1
##            Pr(1)  Pr(2)
## class 1:  0.7397 0.2603
## class 2:  0.8588 0.1412
## class 3:  0.8755 0.1245
## class 4:  0.7268 0.2732
##
## $nominal_energyasst1
##            Pr(1)  Pr(2)
## class 1:  0.7524 0.2476
## class 2:  0.9855 0.0145
## class 3:  0.9117 0.0883
## class 4:  0.9916 0.0084
```

```
## $nominal_hotma1
##             Pr(1)  Pr(2)
## class 1:  0.9581 0.0419
## class 2:  0.9979 0.0021
## class 3:  1.0000 0.0000
## class 4:  1.0000 0.0000
##
## $nominal_coldma1
##             Pr(1)  Pr(2)
## class 1:  0.9299 0.0701
## class 2:  0.9991 0.0009
## class 3:  0.9964 0.0036
## class 4:  1.0000 0.0000
##
## $ordinal_scaleb1
##             Pr(1)  Pr(2)  Pr(3)  Pr(4)
## class 1:  0.1938 0.2526 0.3639 0.1897
## class 2:  0.9787 0.0000 0.0000 0.0213
## class 3:  0.8624 0.0290 0.0754 0.0332
## class 4:  0.9334 0.0093 0.0233 0.0340
##
## $ordinal_scaleg1
##             Pr(1)  Pr(2)  Pr(3)  Pr(4)
```

```
## class 1:  0.6315 0.0886 0.1841 0.0958
## class 2:  0.9848 0.0039 0.0036 0.0077
## class 3:  0.9102 0.0266 0.0357 0.0275
## class 4:  0.9793 0.0065 0.0031 0.0112
##
## $ordinal_scalee1
##             Pr(1)  Pr(2)  Pr(3)  Pr(4)
## class 1:  0.4906 0.0862 0.1878 0.2353
## class 2:  0.9764 0.0000 0.0037 0.0199
## class 3:  0.9730 0.0046 0.0146 0.0078
## class 4:  0.9782 0.0000 0.0020 0.0199
##
## $continuous_kwh1
##             Pr(1)  Pr(2)  Pr(3)  Pr(4)  Pr(5)  Pr(6) Pr(7)
## class 1:  0.0000 0.0000 0.0199 0.2648 0.6172 0.0981 0.000
## class 2:  0.0000 0.0000 0.0037 0.2300 0.6883 0.0769 0.001
## class 3:  0.0000 0.0051 0.1333 0.7273 0.1343 0.0000 0.000
## class 4:  0.0015 0.0000 0.0009 0.1580 0.6746 0.1650 0.000
##
## Estimated class population shares
##  0.2049 0.3777 0.1535 0.2639
##
## Predicted class memberships (by modal posterior prob.)
##  0.201 0.3993 0.1443 0.2554
```

Table 5.4 LCM model result

The covariate variables and their coefficients of different latent classes are listed below

```
## =========================================================
## Fit for 4 latent classes:
## =========================================================
## 2 / 1
##                      Coefficient  Std. error  t value  Pr(>|t|)
## (Intercept)             -8.25749     0.77107  -10.709     0.000
## nominal_employhh1        0.07976     0.09637    0.828     0.408
## ordinal_education1       0.40945     0.09250    4.427     0.000
## ordinal_moneypy1         0.57109     0.04374   13.055     0.000
## count_nhsldmem1         -0.32394     0.06887   -4.704     0.000
## count_numadult21         1.01278     0.12710    7.968     0.000
## =========================================================
## 3 / 1
##                      Coefficient  Std. error  t value  Pr(>|t|)
## (Intercept)              1.12266     0.58310    1.925     0.054
## nominal_employhh1       -0.18641     0.11155   -1.671     0.095
## ordinal_education1       0.09549     0.09780    0.976     0.329
## ordinal_moneypy1         0.16916     0.03416    4.951     0.000
## count_nhsldmem1         -1.86974     0.15513  -12.053     0.000
## count_numadult21         0.65250     0.15578    4.189     0.000
## =========================================================
## 4 / 1
##                      Coefficient  Std. error  t value  Pr(>|t|)
## (Intercept)             -3.55190     0.52835   -6.723     0.000
## nominal_employhh1        0.01246     0.09253    0.135     0.893
## ordinal_education1      -0.05649     0.08706   -0.649     0.517
## ordinal_moneypy1         0.36132     0.03095   11.674     0.000
## count_nhsldmem1         -0.53392     0.07287   -7.327     0.000
## count_numadult21         1.01127     0.12033    8.404     0.000
```

Table 5.5 Coefficients of covariate variables

From the LCM results, there are 4 latent classes of households, in terms of regions, house types, energy assistance and medical vulnerability. Class 1 is for urban households with single houses, which forgo their basic necessities, consuming high level of electricity, but undergoing low probability of power outage, accounting for 21% of total households. Class 2 is for urban single households with high electricity consumption and high probability of power outage risks, which accounts for 38% of the total households. Class 3 is for urban apartments households with low kwh consumption but high probability of power outage, taking up 15% of the total households. Class 4 is for rural single house families with high kwh and low risks of power outage, taking up 26% of the population. Note that, compared with the urban classes, the rural class has a larger vulnerability to severe weather conditions and disasters as they tend to buy fewer backup generators.

The covariate variables impact the conditional probability that one household become to a latent class differently. As is observed from the coefficients, an increasing number of family members suggests less probability that the household belongs to class 2, indicating that urban single households with high electricity consumption and large power outage risks are more likely to be small families. Similarly, people with better employment status are less likely to belong to urban apartment households. People with higher education levels are less likely to live in rural houses.

6 Structural Equation Modeling (SEM)

Incorporating the significant factors in the statistics tests and the latent class analysis of these households, an SEM model with latent variables of energy assistance levels and medical vulnerability levels is derived, where the energy assistance level is assumed to impact the energy assistance program enrollment, the frequency of forgoing necessities and the reasons of power outage, while the medical vulnerability level is assumed to impact the frequency of people keeping their house under unhealthy temperatures whether too hot or too cold.

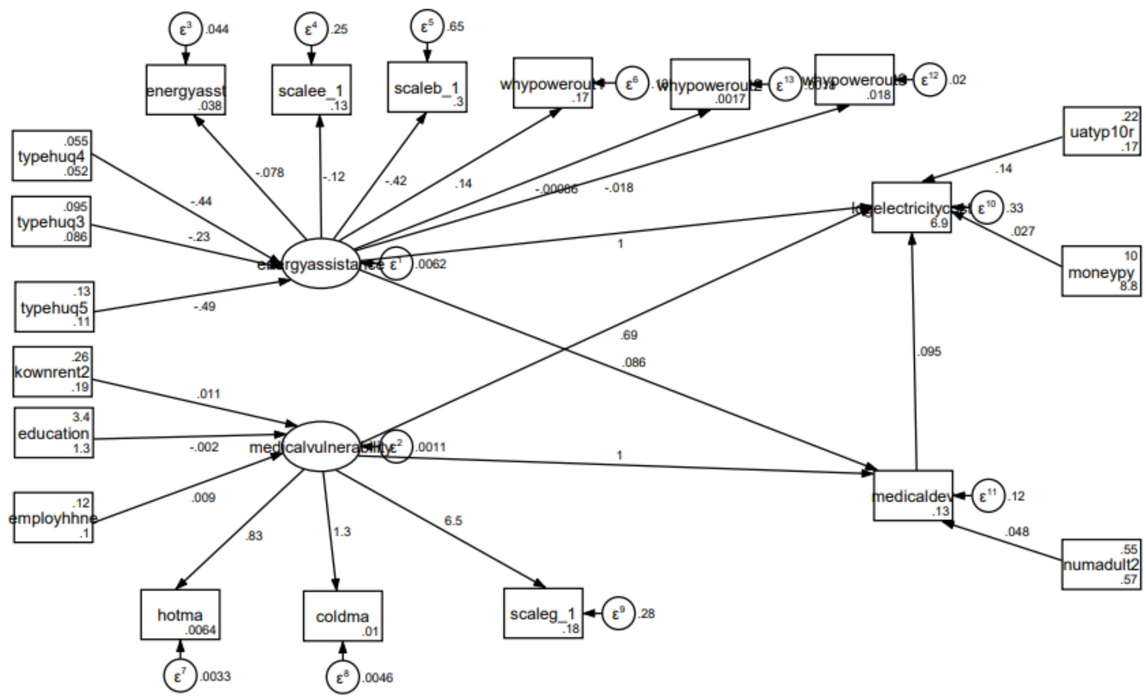

Figure 6.1 SEM path diagram and coefficients values

	Coefficient	OIM std. err.	z	P>|z|	[95% conf.	interval]
Structural						
logelectricitycost						
medicaldev	.0952435	.0130463	7.30	0.000	.0696732	.1208139
energyassistance	1	(constrained)				
medicalvulnerability	.6819326	.2132004	3.20	0.001	.2640675	1.099798
uatyp10r	.1367136	.0106842	12.80	0.000	.115773	.1576543
moneypy	.0270906	.0016003	16.93	0.000	.0239541	.030227
_cons	6.880145	.018147	379.13	0.000	6.844577	6.915712
medicaldev						
energyassistance	.0899511	.0144178	6.24	0.000	.0616927	.1182095
medicalvulnerability	1	(constrained)				
numadult2	.0481637	.0034441	13.98	0.000	.0414134	.0549141
_cons	.1293967	.0038806	33.34	0.000	.1217909	.1370026
energyassistance						
typehuq3	-.2268793	.0137086	-16.55	0.000	-.2537476	-.2000109
typehuq4	-.4351466	.0178523	-24.37	0.000	-.4701365	-.4001567
typehuq5	-.4899451	.0139999	-35.00	0.000	-.5173844	-.4625059
medicalvulnerability						
employhhne	.0091292	.0015816	5.77	0.000	.0060293	.012229
education	-.0020026	.00041	-4.88	0.000	-.0028062	-.0011991
kownrent2	.0107231	.0014889	7.20	0.000	.0078049	.0136412
Measurement						
energyasst						
energyassistance	-.0774377	.0096443	-8.03	0.000	-.0963401	-.0585353
_cons	.0375606	.0018498	20.31	0.000	.0339352	.0411861
scalee_1						
energyassistance	-.1158683	.0227475	-5.09	0.000	-.1604526	-.0712841
_cons	.1287215	.0044159	29.15	0.000	.1200664	.1373765
scaleb_1						
energyassistance	-.4242838	.0345874	-12.27	0.000	-.4920738	-.3564938
_cons	.2952965	.0069285	42.62	0.000	.2817169	.3088762
whypowerout1						
energyassistance	.1433045	.0156285	9.17	0.000	.1126732	.1739357
_cons	.1724032	.0031469	54.79	0.000	.1662354	.1785709
whypowerout3						
energyassistance	-.0178184	.0055994	-3.18	0.001	-.028793	-.0068439
_cons	.0180177	.0011974	15.05	0.000	.015671	.0203645
whypowerout2						
energyassistance	-.0008309	.0017237	-0.48	0.630	-.0042094	.0025475
_cons	.0016951	.0003638	4.66	0.000	.0009821	.0024081
hotma						
medicalvulnerability	.8221375	.0951634	8.64	0.000	.6356206	1.008654
_cons	.0064524	.0010841	5.95	0.000	.0043275	.0085772
coldma						
medicalvulnerability	1.268145	.1473093	8.61	0.000	.9794237	1.556866
_cons	.0101027	.001614	6.26	0.000	.0069394	.013266
scaleg_1						
medicalvulnerability	6.436285	.7476568	8.61	0.000	4.970905	7.901665
_cons	.1817334	.0087931	20.67	0.000	.1644992	.1989675

Table 6.2 Summary of the SEM estimation

7 Conclusions

Some important conclusions from the data analysis and modeling are:

1) Energy assistance and medical vulnerability level contribute to the chance that a household use electricity dependent medical device. They increase the expense on electricity both directly and indirectly through the use of medical devices.
2) The rural households tend to have higher electricity costs, but fewer backup generators. Policies should be driven to secure their resilience to extreme weather and disasters, especially for those using medical devices in rural houses.
3) Apartment buildings with more units tend to receive less energy assistance, so the energy assistance program should pay attention to medical device user households living in apartments with more units.
4) People owning houses suffer more from medical vulnerabilities than people renting houses.
5) Households with higher education levels tend to suffer less from medical vulnerabilities.
6) People not employed suffer more from medical vulnerabilities and tend to keep their housing at unhealthy temperatures.

Future work on this study might look into the specific energy assistance programs the medical device households enrolled in, and how they benefit from it or need more assistance from policies.

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Appendix: Cross table test of number of households and states

state_postal	*MEDICALDEV*		***Total***
	0	1	
AK	259 1.7 %	52 2 %	311 1.7 %
AL	196 1.3 %	43 1.6 %	239 1.3 %
AR	202 1.3 %	63 2.4 %	265 1.5 %
AZ	420 2.7 %	69 2.6 %	489 2.7 %
CA	1003 6.4 %	136 5.2 %	1139 6.2 %
CO	312 2 %	46 1.8 %	358 2 %
CT	253 1.6 %	34 1.3 %	287 1.6 %
DC	202 1.3 %	17 0.7 %	219 1.2 %
DE	119 0.8 %	23 0.9 %	142 0.8 %
FL	559 3.6 %	90 3.4 %	649 3.6 %
GA	356 2.3 %	57 2.2 %	413 2.3 %
HI	250 1.6 %	28 1.1 %	278 1.5 %
IA	230 1.5 %	53 2 %	283 1.5 %
ID	215 1.4 %	52 2 %	267 1.5 %
IL	469 3 %	54 2.1 %	523 2.9 %

IN	326 2.1 %	67 2.6 %	393 2.2 %
KS	174 1.1 %	31 1.2 %	205 1.1 %
KY	344 2.2 %	79 3 %	423 2.3 %
LA	252 1.6 %	55 2.1 %	307 1.7 %
MA	473 3 %	72 2.8 %	545 3 %
MD	305 1.9 %	52 2 %	357 2 %
ME	196 1.3 %	25 1 %	221 1.2 %
MI	329 2.1 %	54 2.1 %	383 2.1 %
MN	286 1.8 %	39 1.5 %	325 1.8 %
MO	247 1.6 %	45 1.7 %	292 1.6 %
MS	136 0.9 %	27 1 %	163 0.9 %
MT	148 0.9 %	21 0.8 %	169 0.9 %
NC	401 2.6 %	73 2.8 %	474 2.6 %
ND	279 1.8 %	46 1.8 %	325 1.8 %
NE	163 1 %	23 0.9 %	186 1 %
NH	150 1 %	25 1 %	175 1 %

NJ	399 2.5 %	52 2 %	451 2.5 %
NM	149 1 %	28 1.1 %	177 1 %
NV	193 1.2 %	36 1.4 %	229 1.3 %
NY	762 4.9 %	126 4.8 %	888 4.9 %
OH	291 1.9 %	44 1.7 %	335 1.8 %
OK	194 1.2 %	35 1.3 %	229 1.3 %
OR	263 1.7 %	45 1.7 %	308 1.7 %
PA	530 3.4 %	83 3.2 %	613 3.4 %
RI	164 1 %	25 1 %	189 1 %
SC	279 1.8 %	50 1.9 %	329 1.8 %
SD	148 0.9 %	33 1.3 %	181 1 %
TN	412 2.6 %	81 3.1 %	493 2.7 %
TX	869 5.6 %	134 5.1 %	1003 5.5 %
UT	155 1 %	30 1.1 %	185 1 %
VA	382 2.4 %	60 2.3 %	442 2.4 %
VT	216 1.4 %	26 1 %	242 1.3 %

WA	377 2.4 %	54 2.1 %	431 2.4 %
WI	308 2 %	47 1.8 %	355 1.9 %
WV	160 1 %	32 1.2 %	192 1.1 %
WY	148 0.9 %	40 1.5 %	188 1 %
Total	15653 100 %	2612 100 %	18265 100 %

χ^2*=101.305 · df=50 · Cramer's V=0.074 · p=0.000*