Be Well Program: Baseline And 6 Months Post Program Measurements Analysis

The Data

Variable list:

1. HbA1C: hba1c
2. Fasting Blood Glucose: fast_blood_gluc
3. Blood Pressure (Systolic): blood_press_sys
4. Weight
5. BMI
6. LDL
7. Triglycerides (indicators 13, 14, 17, 18, 20, 22, 25)
8. Vegetable Dervings : pa_21
9. Fruit Servings :pa_22
10. Soda Consumption: pa_23
11. Sugar-Sweetened Beverages Consumption: pa_24
12. Attitudes Toward Healthy Foods : healthy_eating_important

We will be renaming the time points in the 'time' variable as follows only for more convenience when analyzing the data:

'1' for baseline measurement

'2' for the end of program assessment

'3' for the 6-month mark after the program

'4' for the 12-month mark after the program

'5' for the 24-month mark after the program

In this analysis, we will only be focusing on the baseline and 6 months after the program measurements.

```
## `summarise()` has grouped output by 'record_id'. You can override using the
## `.groups` argument.
```

Quick Inventory Check

The data has been filtered to include only: - People who have data for both baseline and EOP - Observations, for each health metric, that were recorded in both baseline and EOP. (Eg: if someone had only baseline triglycerides levels recorded, that observation is disregarded in this analysis by being turned into NA)

Total sample size:

```
## [1] 156
```

Sample size for high participation:

```
## [1] 102
```

Plots and Graphs

Distributions of The Variables

In assessing the health program's impact, distribution plots were generated for key variables, combining data from both Time 1 (baseline) and Time 3 (6 months after the program). This approach offers a comprehensive view of participant characteristics, facilitating a nuanced understanding of the program's potential influence. The distribution plots can aid in visually narrating the dataset's overall evolution, laying the groundwork for further detailed explorations of specific variables across the program's timeline.

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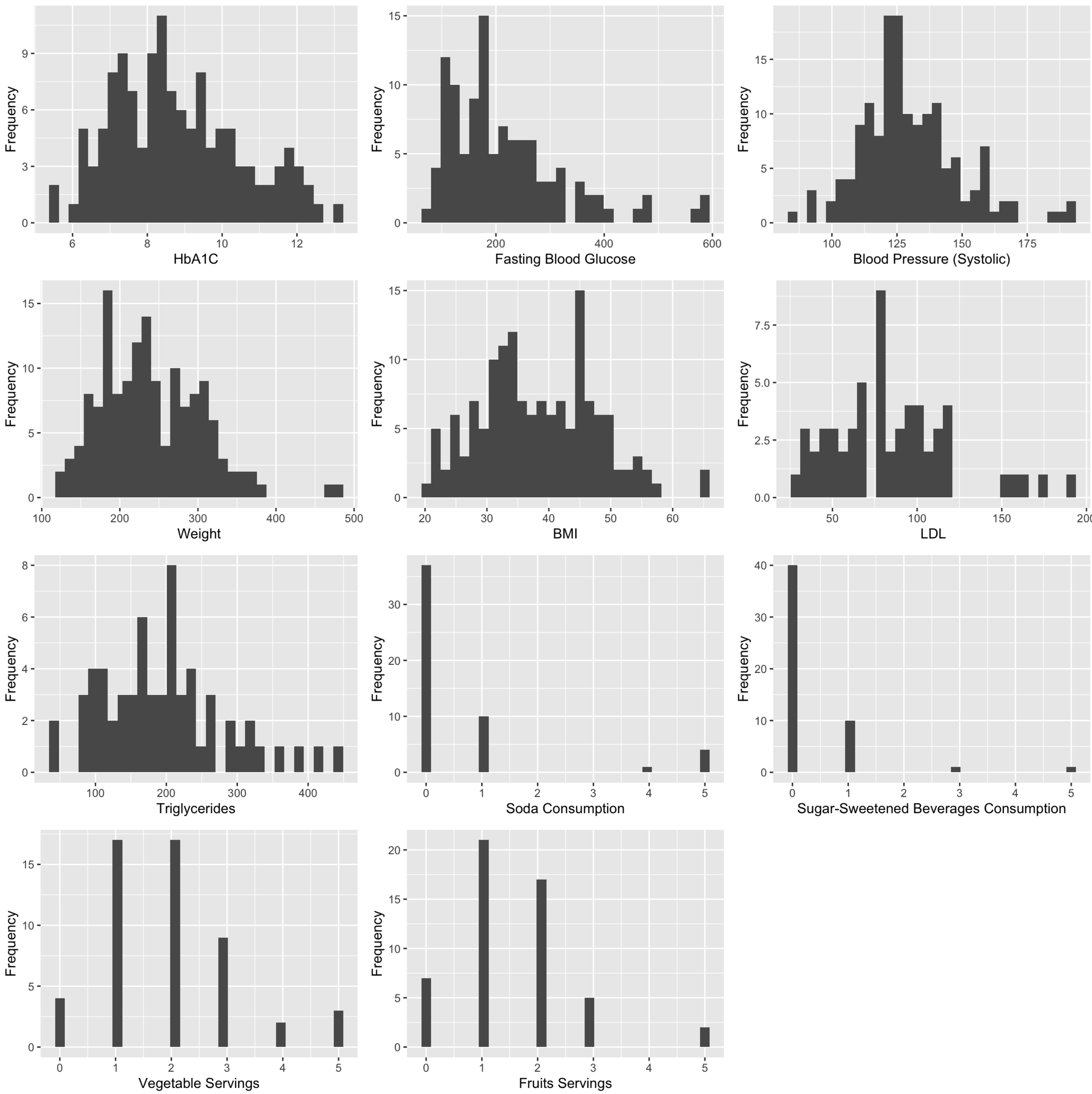
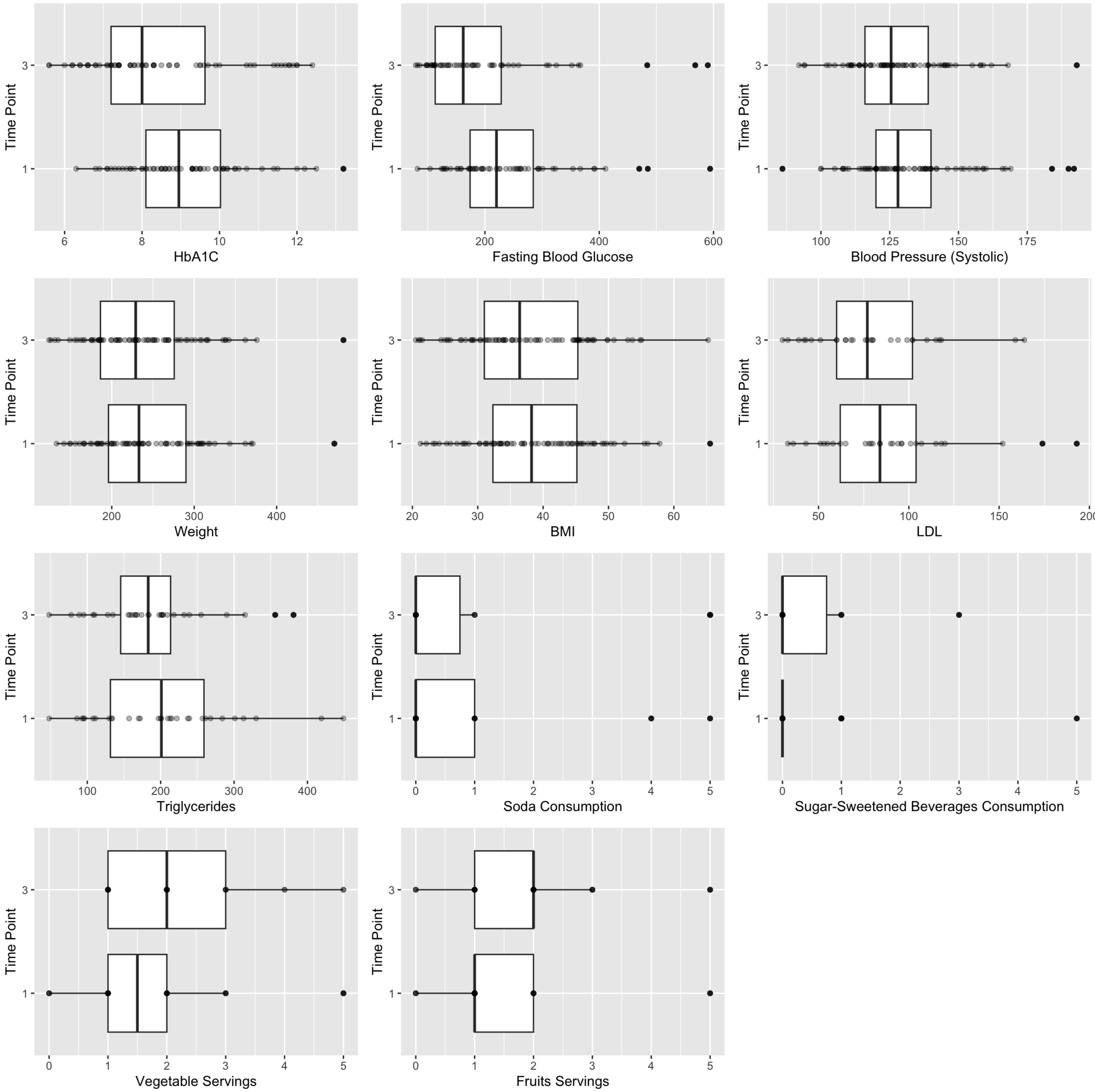

Frequency
HbA1C
6 8 10 12
0 3 6 9
Fasting Blood Glucose
200 400 600
0 5 10 15
Blood Pressure (Systolic)
100 125 150 175
0 5 10 15
Weight
100 200 300 400 500
0 5 10 15
BMI
20 30 40 50 60
0 5 10 15
LDL
50 100 150 200
0.0 2.5 5.0 7.5
Triglycerides
100 200 300 400
0 2 4 6 8
Soda Consumption
0 1 2 3 4 5
0 10 20 30
Sugar-Sweetened Beverages Consumption
0 1 2 3 4 5
0 10 20 30 40
Vegetable Servings
0 1 2 3 4 5
0 5 10 15
Fruits Servings
0 1 2 3 4 5
0 5 10 15 20

Box Plots: The Distribution of Each Variable at Each Time Point:



The box plots reaffirm the trends observed in mean values, with the addition of quartiles trends, offering a detailed portrayal of the data distribution.

One noteworthy observation from the box plots is the reduction in extreme outliers at 6 months after the program compared to the baseline. These outliers, indicative of poorer health conditions, appear to diminish post-program participation. This reduction underscores a potential mitigation of severe health issues among participants, aligning with the overarching goal of the health program.

This visual confirmation strengthens our earlier findings and reinforces the notion that the health program may be instrumental in fostering healthier conditions among participants.

The Distribution of Rates of Change in the Variables Before and 6 months after the program

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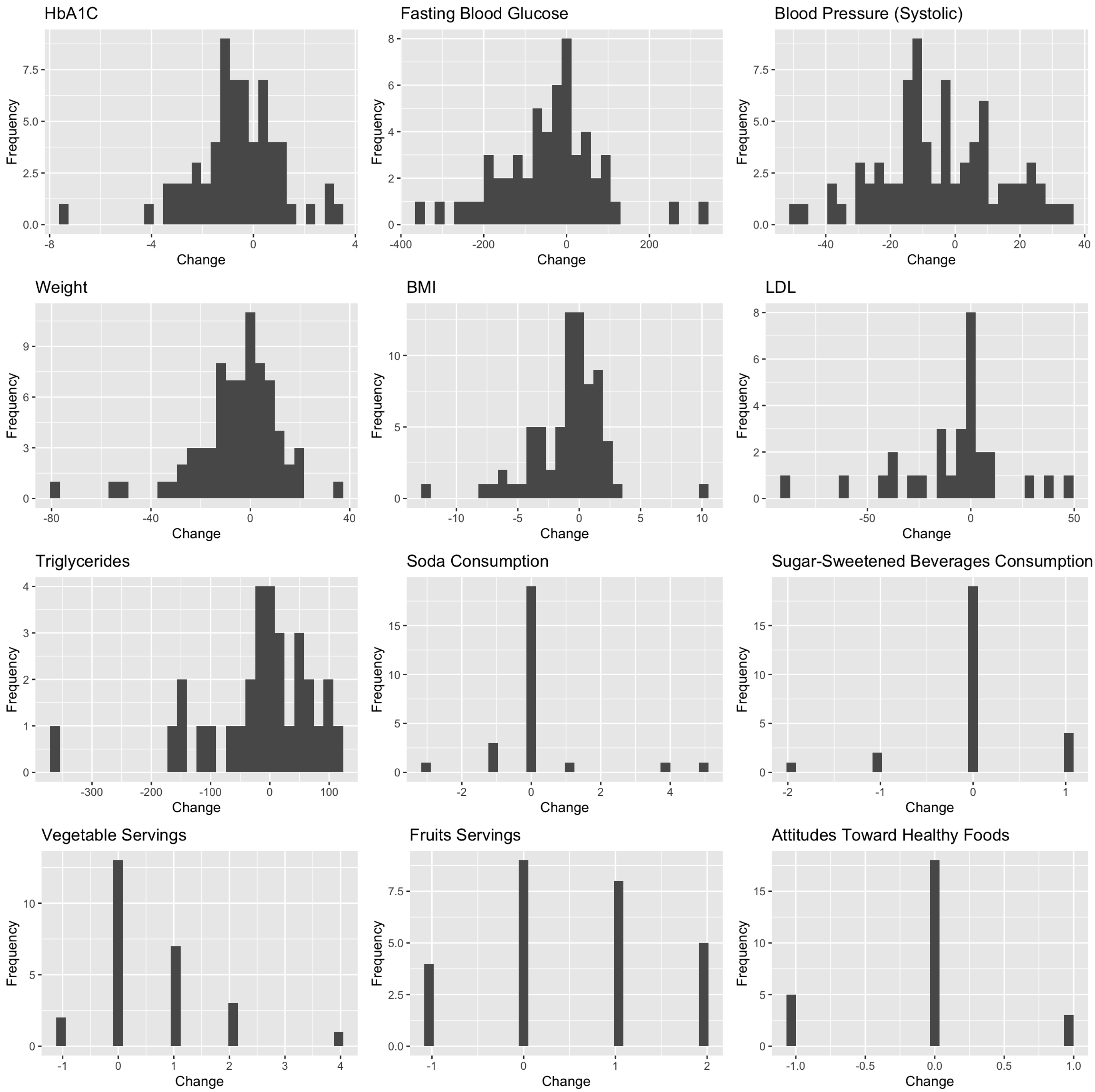

This analysis reveals a favorable trend, with the majority of variables showcasing decreases rather than increases.

For health attributes that we aim to decrease, such as HbA1c and blood sugar levels, the prevalence and extremity of decreases in the rates of change are particularly encouraging. Although there are instances of participants recording higher measurements in certain health attributes, there are also even more notable decreases observed in the majority of variables.

This asymmetry in the distribution suggests that, on the whole, participants are experiencing improvements in key health indicators rather than deteriorations.

Summary Tables

These concise and generalized tables offer convenient summaries of the aforementioned graphs, encapsulating both the mean values of the variables and their respective distributions.

The Means of Each Variable Before and 6 months after the program:

Variables legend:

fast_blood_gluc: Fasting Blood Glucose

blood_press_sys: Blood Pressure (Systolic)

pa_23: Soda Consumption

pa_24: Sugar-Sweetened Beverages Consumption

pa_21: Vegetable Servings

pa_22: Fruits Servings

healthy_eating_important: Attitudes Toward Healthy Foods

time	hba1c	fast_blood_gluc	blood_press_sys	weight	bmi	ldl	triglycerides	pa_23	pa_24	pa_21	pa_22
1	9.12	239.66	132.45	242.77	38.63	89.24	204.81	0.58	0.35	1.65	1.27
3	8.50	194.93	127.88	237.30	37.75	80.45	187.32	0.73	0.35	2.23	1.81

The Standard Deviations of Each Variable Before and 6 months after the program:

time	hba1c	fast_blood_gluc	blood_press_sys	weight	bmi	ldl	triglycerides	pa_23	pa_24	pa_21	pa_22
1	1.46	102.07	20.21	63.87	9.28	37.82	95.69	1.24	1.02	1.20	1.00
3	1.87	113.62	17.87	66.00	9.49	34.12	76.72	1.61	0.69	1.21	1.13

Comparison Graphs Between Participation Levels

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## `geom_smooth()` using formula = 'y ~ x'
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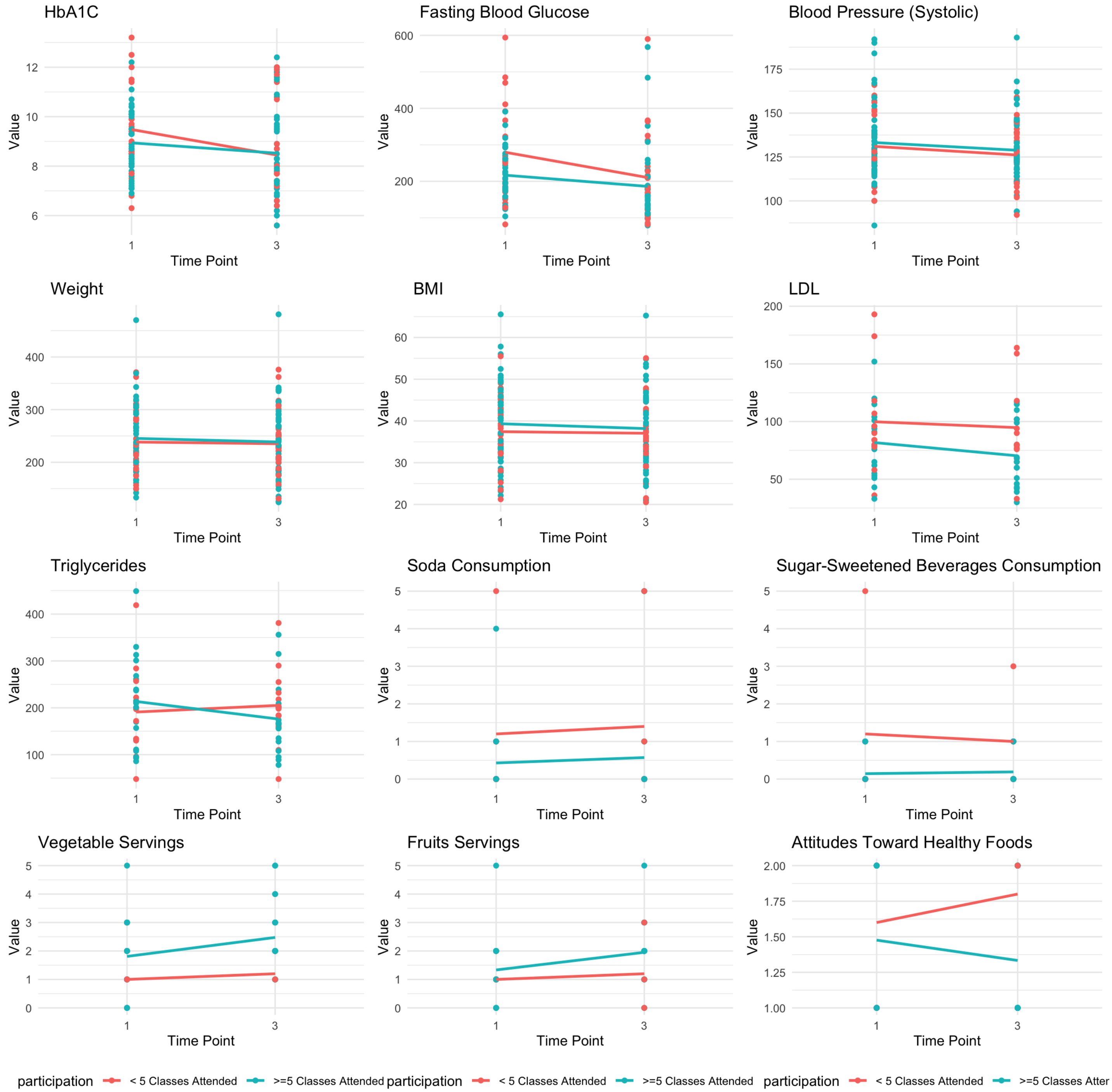


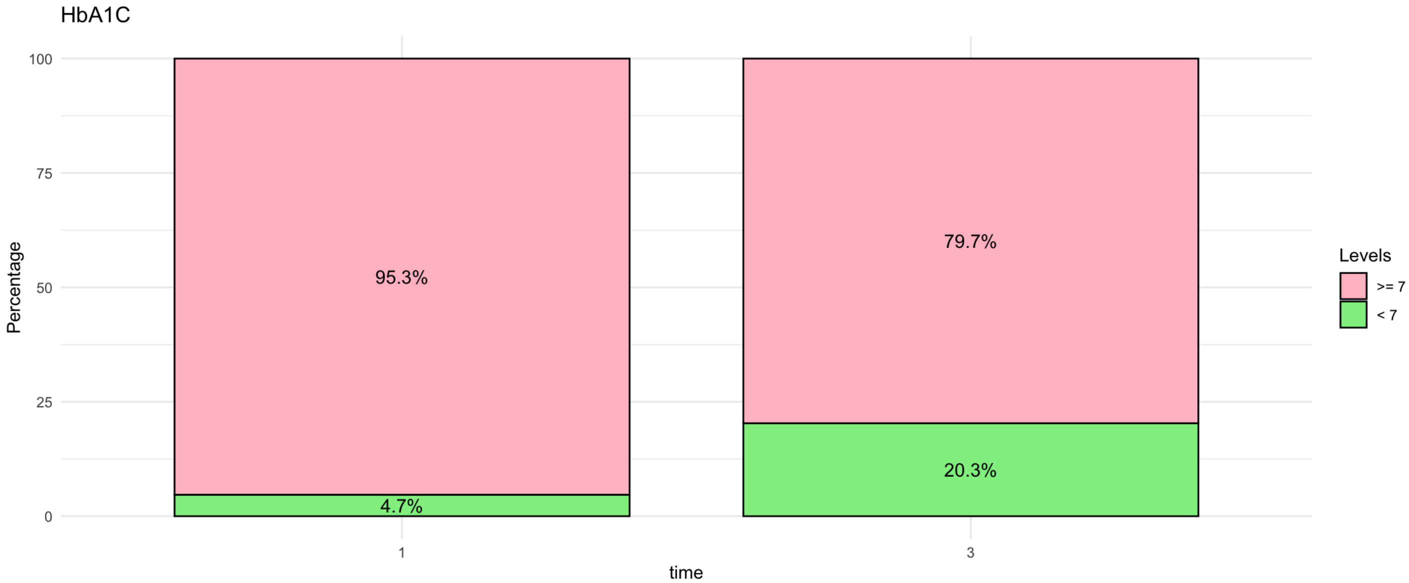
Investigating With Thresholds

This section will visualize the number of people, if observed, whose certain health metrics are under or over (and equal to) a certain threshold at baseline and 6 months after the program. We will be using bar graphs for this purpose. Due to the nature of the function used in creating these graphs, there will be p-values and equations at the top of the graphs. This information will not be one of our focus points because this analysis only involves data visualization and not predictive modeling.

The data sets used to generate these graphs will be them same ones used for the mean plots to ensure consistent samples sizes for the 2 time points.

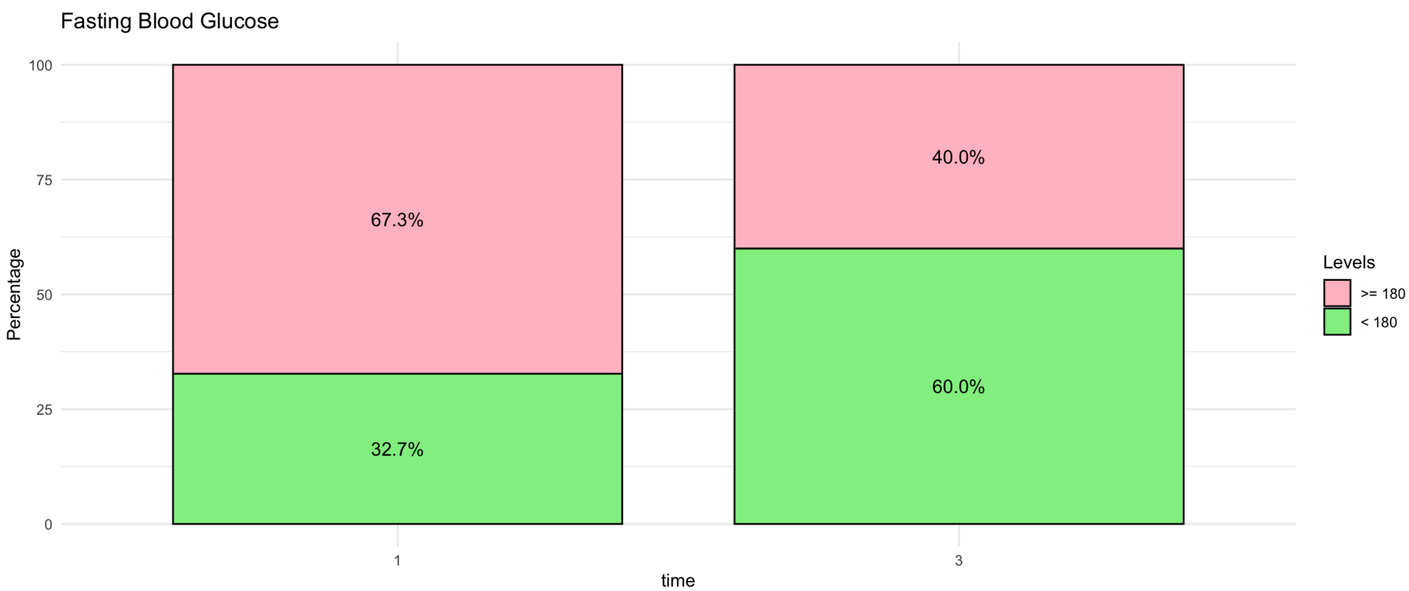
HbA1c

```
## `summarise()` has grouped output by 'time'. You can override using the
## `.groups` argument.
```



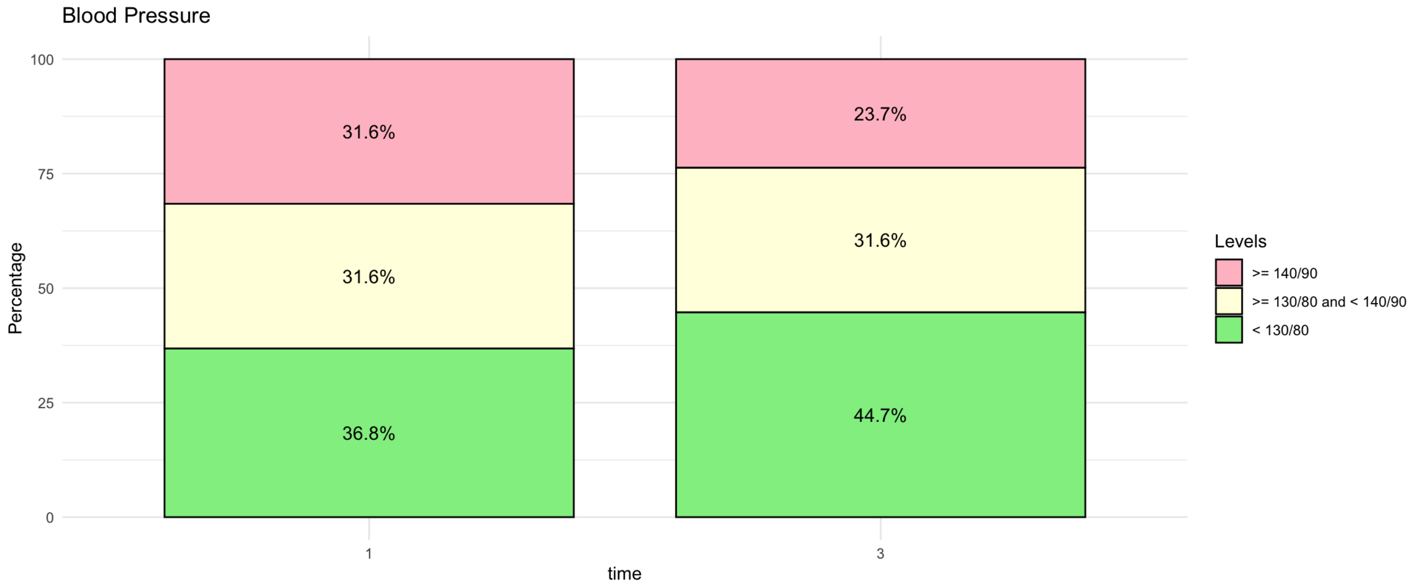
Fasting Blood Glucose

```
## `summarise()` has grouped output by 'time'. You can override using the
## `.groups` argument.
```



Blood Pressure

```
## `summarise()` has grouped output by 'time'. You can override using the
## `.groups` argument.
```



Note: 130/80 is the threshold for diabetics with pre-existing cardiovascular risk.

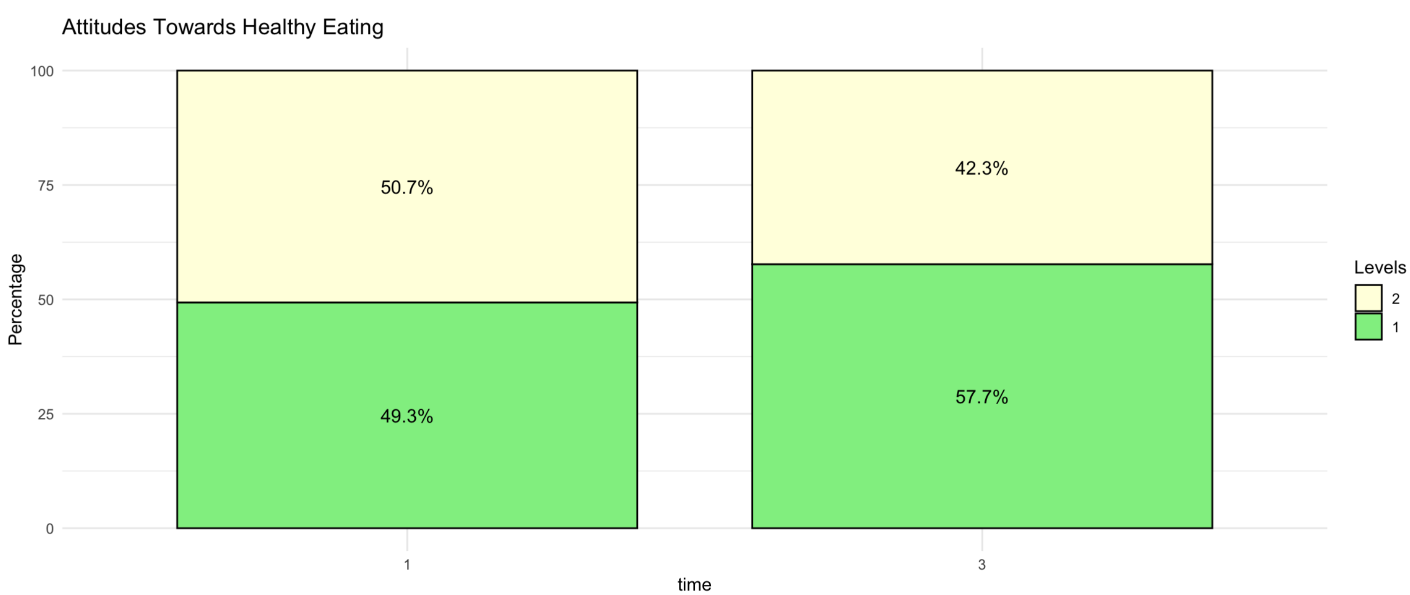
All three graphs depict a positive indication that the program potentially contributed to an increase in the proportion of individuals whose health metrics align with healthier thresholds.

Attitudes Toward Healthy Foods

We have delved into various health attributes and dietary intake variables, uncovering notable trends and shifts. As we pivot our focus, the next step involves examining a variable that captures individuals' perspectives on healthy eating.

Given that "Attitude Towards Healthy Eating" is represented by only two values, a transition to a visual representation, such as a bar graph, becomes particularly relevant. This graphical approach allows us to illustrate the proportions of each attitude value both at the baseline and the End-of-Program (EOP) marks. By doing so, we aim to provide a clear and insightful depiction of how participants' attitudes toward healthy foods may have evolved after the health program.

```
## `summarise()` has grouped output by 'time'. You can override using the
## `.groups` argument.
```



Comparison Between Participation Levels (Number of Classes Attended)

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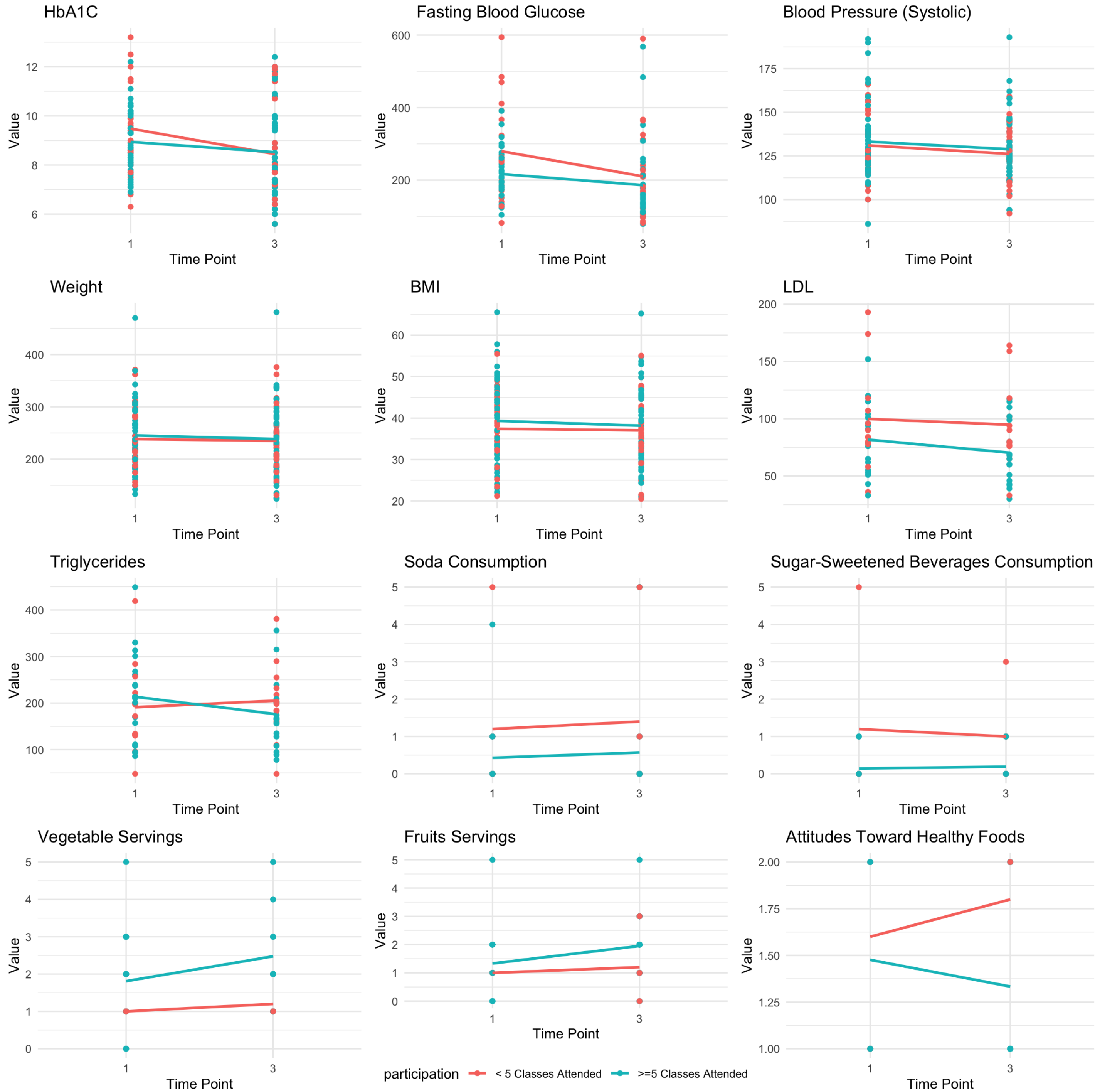

Linear Mixed Effects Models

The models aim to provide rates of change in the response variable from the baseline to the target time point.

We have chosen to treat the 'time' variable as a categorical factor rather than a numeric variable, even though it has been transformed into sequential numbers (1, 2, 3, 4, 5), for several reasons. First, our decision is rooted in the recognition that the rates of change in the response variables over time may not be linear and continuous. Representing 'time' as a numeric variable could potentially mislead by implying a linear relationship between time points and response changes that might not accurately reflect the underlying dynamics.

Secondly, treating 'time' categorically helps avoid extrapolation or interpolation beyond the provided time points. Using 'time' as a factor acknowledges that the observations at our specific time points are the only reliable data we have, and we should refrain from assuming relationships outside these intervals. This approach can be helpful in maintaining the integrity of our findings and prevent unwarranted assumptions about the program's effects at unobserved time points.

In our model, we will have time points 1 and 2 for baseline and EOP. The summaries of our models will be presented in forms of tables that include the following columns that we will be analyzing further with each variable: - effect: this column indicates whether a variable is a fixed or random effect. In our analysis, the investigated variables will be the fixed effect and the participant id will be the random effect, accounting for the relationship between different observations of the same participant. - term: the coefficient, or in this case, the time point (baseline and EOP as Intercept and time2) - estimate: the average difference in the investigated variable between baseline and EOP - p.value: suggests whether there is evidence that the observed change is based on pure chance or potential effects from the program.

Interaction Terms and Their General Interpretations

- 'time' and 'participation': the `participation` variable was derived from the `classes_attended` variable, with values categorized as '>=5 Classes Attended' and '<5 Classes Attended'. The interaction term between the `time` variable and the `participation` variable captures whether the effect of time on the outcome differs depending on the level of participation in the program. A significant interaction would imply that the relationship between time and the outcome varies depending on the level of participation.
- 'time' and 'classes_attended': the interaction term between the `time` variable and the `classes_attended` variable quantifies whether the effect of time on the outcome changes based on the number of classes attended. Essentially, it examines whether individuals who attended more classes experienced different changes in their outcomes over time compared to those who attended fewer classes.

The p-values associated with these interaction terms indicate the strength of evidence for these relationship; lower p-values suggest stronger evidence for an interaction effect between each pair of variables.

P-Value Scale:

For convenience, we can refer to this P-Value scale when determining if an observed trend statistically has strong evidence or is possibly due to random chance.

$p < 0.001$: Extremely strong evidence.

$0.001 \leq p < 0.01$: Very strong evidence.

$0.01 \leq p < 0.05$: Strong evidence.

$0.05 \leq p < 0.1$: Moderate evidence.

$p \geq 0.1$: Not considered statistically significant.

HbA1C

effect	group	term	estimate	std.error	t-value	df	p.value
fixed	NA	(Intercept)	9.4809524	0.3664324	25.873672	102.14	0.000000
fixed	NA	time3	-1.0333333	0.3798817	-2.720145	62.00	0.008456
fixed	NA	participation>=5 Classes Attended	-0.5390919	0.4470434	-1.205905	102.14	0.230640
fixed	NA	time3:participation>=5 Classes Attended	0.6147287	0.4634514	1.326415	62.00	0.189568
random	record_id	sd__(Intercept)	1.1421343	NA	NA	NA	NA

$$\text{Score} = 9.901 - 0.957 \times \text{time2} \qquad \text{(for participation} < 5 \text{ classes attended)}$$
$$\text{Score} = 9.783 - 1.001 \times \text{time2} \qquad \text{(for participation} \geq 5 \text{ classes attended)}$$
$$\text{p-value (interaction)} = 0.285$$

The p-value suggests that the interaction effect between “time2” and “classes attended” may not reliably contribute to explaining the variation in the outcome (score) compared to the main effects of time2 and classes attended alone.

Fasting Blood Glucose

effect	group	term	estimate	std.error	t-value	df	p.value
fixed	NA	(Intercept)	279.61500	23.81219	11.742513	94.86842	0.000000
fixed	NA	time3	-69.26500	27.30533	-2.536684	53.00000	0.014171
fixed	NA	participation>=5 Classes Attended	-62.78071	29.85017	-2.103195	94.86842	0.038095
fixed	NA	time3:participation>=5 Classes Attended	38.54500	34.22904	1.126091	53.00000	0.265201
random	record_id	sd__(Intercept)	62.32657	NA	NA	NA	NA

$$\text{Fasting Blood Glucose} = 245.974 - 47.370 \times \text{time2} - 1.727 \times \text{classes\_attended}$$
$$+ 0.853 \times \text{time2} \times \text{classes\_attended}$$
$$\text{p-value (interaction)} = 0.790$$

The p-value suggests that the interaction effect between “time2” and “classes attended” may not reliably contribute to explaining the variation in fasting blood glucose compared to the main effects of time2 and classes attended alone.

Blood Pressure (Systolic)

effect	group	term	estimate	std.error	t-value	df	p.value
fixed	NA	(Intercept)	131.0370370	3.688767	35.5232572	116.546	0.000000
fixed	NA	time3	-4.8888889	3.616106	-1.3519759	74.000	0.180501
fixed	NA	participation>=5 Classes Attended	2.1874528	4.593990	0.4761553	116.546	0.634855
fixed	NA	time3:participation>=5 Classes Attended	0.5011338	4.503498	0.1112766	74.000	0.911698
random	record_id	sd__(Intercept)	13.8152129	NA	NA	NA	NA

Weight

effect	group	term	estimate	std.error	t-value	df	p.value
fixed	NA	(Intercept)	238.370370	12.575432	18.9552423	74.67416	0.000000
fixed	NA	time3	-3.185185	3.396617	-0.9377523	72.00001	0.351507
fixed	NA	participation>=5 Classes Attended	6.927502	15.779377	0.4390225	74.67416	0.661913
fixed	NA	time3:participation>=5 Classes Attended	-3.602049	4.262000	-0.8451545	72.00001	0.400824
random	record_id	sd__(Intercept)	64.141024	NA	NA	NA	NA

BMI

effect	group	term	estimate	std.error	t-value	df	p.value
fixed	NA	(Intercept)	37.4285185	1.8134628	20.6392531	74.63312	0.000000
fixed	NA	time3	-0.3814815	0.5730434	-0.6657113	71.00000	0.507753
fixed	NA	participation>=5 Classes Attended	1.9043076	2.2845001	0.8335774	74.63312	0.407179
fixed	NA	time3:participation>=5 Classes Attended	-0.7828663	0.7218883	-1.0844701	71.00000	0.281825
random	record_id	sd__(Intercept)	9.1847901	NA	NA	NA	NA

LDL

effect	group	term	estimate	std.error	t-value	df	p.value
fixed	NA	(Intercept)	99.833333	10.104612	9.8799773	36.61006	0.000000
fixed	NA	time3	-5.083333	7.966565	-0.6380835	27.00000	0.528794
fixed	NA	participation>=5 Classes Attended	-18.068628	13.197576	-1.3690869	36.61006	0.179314
fixed	NA	time3:participation>=5 Classes Attended	-6.328431	10.405085	-0.6082056	27.00000	0.548134
random	record_id	sd__(Intercept)	29.059270	NA	NA	NA	NA

Triglycerides

effect	group	term	estimate	std.error	t-value	df	p.value
fixed	NA	(Intercept)	191.00000	25.17938	7.5855706	49.93491	0.000000
fixed	NA	time3	14.25000	27.53926	0.5174431	29.00000	0.608772
fixed	NA	participation>=5 Classes Attended	22.52632	32.16245	0.7003917	49.93491	0.486933
fixed	NA	time3:participation>=5 Classes Attended	-51.77632	35.17680	-1.4718882	29.00000	0.151821
random	record_id	sd__(Intercept)	55.29513	NA	NA	NA	NA

Soda Consumption

effect	group	term	estimate	std.error	t-value	df	p.value
fixed	NA	(Intercept)	1.2000000	0.6399405	1.8751744	39.70789	0.068136
fixed	NA	time3	0.2000000	0.6669047	0.2998929	24.00000	0.766841
fixed	NA	participation>=5 Classes Attended	-0.7714286	0.7120600	-1.0833758	39.70789	0.285176
fixed	NA	time3:participation>=5 Classes Attended	-0.0571429	0.7420631	-0.0770054	24.00000	0.939258
random	record_id	sd__(Intercept)	0.9673233	NA	NA	NA	NA

Sugar-Sweetened Beverages Consumption

effect	group	term	estimate	std.error	t-value	df	p.value
fixed	NA	(Intercept)	1.2000000	0.3571270	3.3601493	32.78022	0.001990
fixed	NA	time3	-0.2000000	0.2850787	-0.7015608	24.00000	0.489701
fixed	NA	participation>=5 Classes Attended	-1.0571429	0.3973742	-2.6603206	32.78022	0.011988
fixed	NA	time3:participation>=5 Classes Attended	0.2476190	0.3172062	0.7806248	24.00000	0.442655
random	record_id	sd__(Intercept)	0.6591842	NA	NA	NA	NA

Vegetable Servings

effect	group	term	estimate	std.error	t-value	df	p.value
fixed	NA	(Intercept)	1.0000000	0.5134694	1.9475358	36.3562	0.059225
fixed	NA	time3	0.2000000	0.4784233	0.4180398	24.0000	0.679635
fixed	NA	participation>=5 Classes Attended	0.8095238	0.5713360	1.4168963	36.3562	0.165026
fixed	NA	time3:participation>=5 Classes Attended	0.4666667	0.5323403	0.8766322	24.0000	0.389377
random	record_id	sd__(Intercept)	0.8637313	NA	NA	NA	NA

Fruits Servings

effect	group	term	estimate	std.error	t-value	df	p.value
fixed	NA	(Intercept)	1.0000000	0.4761786	2.1000525	36.43087	0.042710
fixed	NA	time3	0.2000000	0.4449006	0.4495387	24.00000	0.657077
fixed	NA	participation>=5 Classes Attended	0.3333333	0.5298426	0.6291177	36.43087	0.533197
fixed	NA	time3:participation>=5 Classes Attended	0.4190476	0.4950396	0.8464931	24.00000	0.405639
random	record_id	sd__(Intercept)	0.7993053	NA	NA	NA	NA

Interaction Term with Numerical Variable ‘classes_attended’

The interaction between time and classes_attended suggests that the effect of time on the outcome variable varies depending on the number of classes attended.

HbA1C

effect	group	term	estimate	std.error	t-value	df	p.value
fixed	NA	(Intercept)	9.6913491	0.3892280	24.898902	102.6917	0.000000
fixed	NA	time3	-1.0764822	0.4061721	-2.650311	62.0000	0.010192
fixed	NA	classes_attended	-0.0825368	0.0473753	-1.742190	102.6917	0.084469

effect	group	term	estimate	std.error	t-value	df	p.value
fixed	NA	time3:classes_attended	0.0657542	0.0494377	1.330042	62.0000	0.188377
random	record_id	sd__(Intercept)	1.1258301	NA	NA	NA	NA

$$\text{HbA1c} = 9.9013 - 0.9568 \times \text{time2} - 0.1183 \times \text{classes\_attended} + 0.0439 \times \text{time2} \times \text{classes\_attended}$$

$$\text{p-value (interaction)} = 0.285$$

For people who attended more classes, the change in the HbA1c over time is slightly more positive compared to those who attended fewer classes. However, the p-value associated with this interaction term (0.285) suggests that this effect is not statistically significant. Therefore, we do not have sufficient evidence to conclude that the relationship between time and HbA1c differs significantly based on the number of classes attended.

Fasting Blood Glucose

effect	group	term	estimate	std.error	t-value	df	p.value
fixed	NA	(Intercept)	285.469615	25.804533	11.062770	94.81574	0.000000
fixed	NA	time3	-73.707686	29.569565	-2.492688	53.00000	0.015838
fixed	NA	classes_attended	-6.700343	3.136817	-2.136032	94.81574	0.035252
fixed	NA	time3:classes_attended	4.237826	3.594497	1.178976	53.00000	0.243673
random	record_id	sd__(Intercept)	62.381812	NA	NA	NA	NA

$$\text{Fasting Blood Glucose} = 245.97 - 47.37 \times \text{time2} - 1.73 \times \text{classes\_attended} + 0.85 \times \text{time2} \times \text{classes\_attended}$$

$$\text{p-value (interaction)} = 0.79$$

For individuals with different levels of class attendance, there appears to be no significant difference in the change of fasting blood glucose over time. The interaction term's p-value of 0.79 indicates that the effect of class attendance on the change in fasting blood glucose over time is not statistically significant.

Blood Pressure (Systolic)

effect	group	term	estimate	std.error	t-value	df	p.value
fixed	NA	(Intercept)	129.9390131	3.9270597	33.0881178	116.7322	0.000000
fixed	NA	time3	-4.4860726	3.8575193	-1.1629424	74.0000	0.248589
fixed	NA	classes_attended	0.3774951	0.4901273	0.7701980	116.7322	0.442738
fixed	NA	time3:classes_attended	-0.0119970	0.4814481	-0.0249186	74.0000	0.980187
random	record_id	sd__(Intercept)	13.7623835	NA	NA	NA	NA

$$\text{Systolic Blood Pressure} = 129.26 - 0.42 \times \text{time2} + 0.50 \times \text{classes\_attended} - 0.89 \times \text{time2} \times \text{classes\_attended}$$

$$\text{p-value (interaction)} = 0.033$$

For individuals who attended more classes, the change in systolic blood pressure over time is slightly more negative compared to those who attended fewer classes. The interaction between time and classes attended has a statistically significant effect on systolic blood pressure, with a p-value of 0.033. This suggests that the relationship between time and systolic blood pressure differs significantly based on the number of classes attended.

Weight

effect	group	term	estimate	std.error	t-value	df	p.value
fixed	NA	(Intercept)	243.3186249	13.4573901	18.0806697	74.67106	0.000000
fixed	NA	time3	-2.9330020	3.6327613	-0.8073754	72.00001	0.422110
fixed	NA	classes_attended	-0.0840129	1.7015045	-0.0493757	74.67106	0.960752
fixed	NA	time3:classes_attended	-0.3891467	0.4593134	-0.8472356	72.00001	0.399671
random	record_id	sd__(Intercept)	64.1774316	NA	NA	NA	NA

$$\text{Weight} = 235.36 - 0.06 \times \text{time2} + 0.56 \times \text{classes\_attended}$$
$$- 0.28 \times \text{time2} \times \text{classes\_attended}$$
$$\text{p-value (interaction)} = 0.309$$

The change in weight over time is not statistically significant, as indicated by the p-value of 0.979 for the main effect of time. Similarly, the interaction between time and classes attended, with a p-value of 0.309, is also not statistically significant. This suggests that the relationship between time, classes attended, and weight is not significantly different across different levels of class attendance.

BMI

effect	group	term	estimate	std.error	t-value	df	p.value
fixed	NA	(Intercept)	38.3359292	1.9468120	19.6916442	74.62873	0.000000
fixed	NA	time3	-0.4193798	0.6148176	-0.6821207	71.00000	0.497382
fixed	NA	classes_attended	0.0449625	0.2461870	0.1826354	74.62873	0.855579
fixed	NA	time3:classes_attended	-0.0699901	0.0777477	-0.9002208	71.00000	0.371046
random	record_id	sd__(Intercept)	9.2138743	NA	NA	NA	NA

$$\text{BMI} = 37.45 + 0.23 \times \text{time2} + 0.14 \times \text{classes\_attended}$$
$$- 0.07 \times \text{time2} \times \text{classes\_attended}$$
$$\text{p-value (interaction)} = 0.167$$

The change in BMI over time is not statistically significant, as indicated by the p-value of 0.518 for the main effect of time. The interaction between time and classes attended also does not show statistical significance with a p-value of 0.167. This suggests that the relationship between time, classes attended, and BMI is not significantly different across different levels of class attendance.

LDL

effect	group	term	estimate	std.error	t-value	df	p.value
fixed	NA	(Intercept)	101.9665057	10.964189	9.2999585	36.66411	0.000000
fixed	NA	time3	-6.2482791	8.666202	-0.7209940	27.00000	0.477110

effect	group	term	estimate	std.error	t-value	df	p.value
fixed	NA	classes_attended	-1.9525326	1.353493	-1.4425875	36.66411	0.157626
fixed	NA	time3:classes_attended	-0.3904757	1.069814	-0.3649939	27.00000	0.717959
random	record_id	sd__(Intercept)	29.0784808	NA	NA	NA	NA

$$\text{LDL} = 81.65 - 2.81 \times \text{time2} + 0.21 \times \text{classes\_attended} - 0.24 \times \text{time2} \times \text{classes\_attended}$$

$$\text{p-value (interaction)} = 0.852$$

The change in LDL cholesterol levels over time is not statistically significant, as evidenced by the p-value of 0.761 for the main effect of time. Similarly, the interaction between time and classes attended also lacks statistical significance with a p-value of 0.852. This indicates that the relationship between time, classes attended, and LDL cholesterol levels is not significantly different across different levels of class attendance.

Triglycerides

effect	group	term	estimate	std.error	t-value	df	p.value
fixed	NA	(Intercept)	176.101425	27.079262	6.5031841	49.72917	0.000000
fixed	NA	time3	22.999319	29.469891	0.7804345	29.00000	0.441459
fixed	NA	classes_attended	4.217326	3.253881	1.2960912	49.72917	0.200927
fixed	NA	time3:classes_attended	-5.947767	3.541142	-1.6796184	29.00000	0.103775
random	record_id	sd__(Intercept)	55.401518	NA	NA	NA	NA

$$\text{Triglycerides} = 226.58 - 33.18 \times \text{time2} - 0.61 \times \text{classes\_attended} - 2.05 \times \text{time2} \times \text{classes\_attended}$$

$$\text{p-value (interaction)} = 0.595$$

The change in triglyceride levels over time is not statistically significant, with a p-value of 0.258 for the main effect of time. Additionally, there is no significant interaction effect between time and classes attended on triglyceride levels, as indicated by a p-value of 0.595. This suggests that the relationship between time, classes attended, and triglyceride levels does not vary significantly based on the number of classes attended.

Soda Consumption

effect	group	term	estimate	std.error	t-value	df	p.value
fixed	NA	(Intercept)	1.2585139	0.6588029	1.9103043	39.71996	0.063333
fixed	NA	time3	0.1377709	0.6868160	0.2005936	24.00000	0.842707
fixed	NA	classes_attended	-0.0820433	0.0717500	-1.1434613	39.71996	0.259692
fixed	NA	time3:classes_attended	0.0019350	0.0748009	0.0258685	24.00000	0.979576
random	record_id	sd__(Intercept)	0.9666458	NA	NA	NA	NA

$$\text{Soda Consumption} = 1.64 - 1.19 \times \text{time2} - 0.11 \times \text{classes\_attended} \\ + 0.09 \times \text{time2} \times \text{classes\_attended}$$

$$\text{p-value (interaction)} = 0.020$$

The change in soda consumption over time is statistically significant, with a p-value of 0.0005 for the main effect of time. Additionally, there is a significant interaction effect between time and classes attended on soda consumption, as indicated by a p-value of 0.020. This suggests that the relationship between time, classes attended, and soda consumption varies significantly based on the number of classes attended.

Sugar-Sweetened Beverages Consumption

effect	group	term	estimate	std.error	t-value	df	p.value
fixed	NA	(Intercept)	1.1772446	0.3734242	3.1525665	32.48382	0.003471
fixed	NA	time3	-0.2089783	0.2934987	-0.7120246	24.00000	0.483314
fixed	NA	classes_attended	-0.1000387	0.0406695	-2.4597966	32.48382	0.019401
fixed	NA	time3:classes_attended	0.0251548	0.0319648	0.7869520	24.00000	0.439013
random	record_id	sd__(Intercept)	0.6741210	NA	NA	NA	NA

$$\text{Sugar-Sweetened Beverages Consumption} = 1.78 - 1.33 \times \text{time2} - 0.13 \times \text{classes\_attended} \\ + 0.11 \times \text{time2} \times \text{classes\_attended}$$

$$\text{p-value (interaction)} = 0.004$$

The change in sugar-sweetened beverages consumption over time is statistically significant, with a p-value of 0.0002 for the main effect of time. Additionally, there is a significant interaction effect between time and classes attended on sugar-sweetened beverages consumption, as indicated by a p-value of 0.004. This suggests that the relationship between time, classes attended, and sugar-sweetened beverages consumption varies significantly based on the number of classes attended.

Vegetable Servings

effect	group	term	estimate	std.error	t-value	df	p.value
fixed	NA	(Intercept)	0.6346749	0.5111689	1.2416149	37.72372	0.222043
fixed	NA	time3	0.4643963	0.4998343	0.9291005	24.00000	0.362088
fixed	NA	classes_attended	0.1226780	0.0556712	2.2036161	37.72372	0.033730
fixed	NA	time3:classes_attended	0.0135449	0.0544368	0.2488187	24.00000	0.805618
random	record_id	sd__(Intercept)	0.8019101	NA	NA	NA	NA

$$\text{Vegetable Servings} = 1.41 + 0.59 \times \text{time2} + 0.03 \times \text{classes\_attended} \\ + 0.04 \times \text{time2} \times \text{classes\_attended}$$

$$\text{p-value (interaction)} = 0.230$$

The change in vegetable servings over time is statistically significant, with a p-value of 0.043 for the main effect of time. However, the interaction effect between time and classes attended on vegetable servings is not statistically significant, with a p-value of 0.230. This suggests that while there is a significant overall change in vegetable servings over time, the relationship between time, classes attended, and vegetable servings does not differ significantly based on the number of classes attended.

Fruits Servings

effect	group	term	estimate	std.error	t-value	df	p.value
fixed	NA	(Intercept)	1.0007740	0.4895193	2.0444015	36.37907	0.048202
fixed	NA	time3	0.1478328	0.4564934	0.3238444	24.00000	0.748861
fixed	NA	classes_attended	0.0323142	0.0533134	0.6061188	36.37907	0.548199
fixed	NA	time3:classes_attended	0.0470201	0.0497165	0.9457643	24.00000	0.353694
random	record_id	sd__(Intercept)	0.7991405	NA	NA	NA	NA

$$\text{Fruit Servings} = 1.48 + 0.18 \times \text{time2} - 0.02 \times \text{classes\_attended} + 0.03 \times \text{time2} \times \text{classes\_attended}$$

$$\text{p-value (interaction)} = 0.469$$

The change in fruit servings over time is not statistically significant, with a p-value of 0.593 for the main effect of time. Similarly, the interaction effect between time and classes attended on fruit servings is also not statistically significant, with a p-value of 0.469. This suggests that neither time nor classes attended significantly affect the number of fruit servings consumed, and there is no significant interaction effect between these variables on fruit servings.