Multilevel Modeling Summative

Anonymous Marking Code: Z0195806

2024-03-27

Contents

Part 1 Introduction

1.1 Background of Multisite Trials

1.1.1 Definition of Multisite Trials

Multisite trials are a type of clinical research study where the intervention being tested is administered across multiple sites or locations. These trials are particularly valuable in assessing the effectiveness of an intervention in a broader, more diverse population. By including a variety of settings, such as different hospitals, clinics, or communities, multisite trials can provide more generalizable results, ensuring that the findings are not specific to a single location or population (Youth Endowment Fund 2024).

1.1.2 Relevance for assessing the effectiveness of an intervention

1. **Generalizability**: Multisite trials enhance the external validity of the study findings. By testing the intervention across various demographic and geographic settings, the results are more likely to be applicable to a wider population.
2. **Variability and Robustness**: These trials capture the variability across different sites, which can include differences in implementation, participant characteristics, and contextual factors. This variability helps in assessing the robustness of the intervention's effectiveness.
3. **Standardization vs. Adaptation**: Multisite trials can explore the balance between the standardization of the intervention (to ensure fidelity) and its adaptation to different settings (to ensure relevance). This balance is crucial for interventions that aim to be scaled up or replicated in diverse contexts.
4. **Statistical Power**: Conducting a trial across multiple sites often allows for a larger sample size, which increases the statistical power of the study. This is particularly important for detecting small to moderate effects of interventions.
5. **Complex Interventions**: Many interventions, especially in healthcare, are complex and multifaceted. Multisite trials can provide insights into how different components of the intervention perform across various settings.
6. **Healthcare System Insights**: For interventions implemented in healthcare settings, multisite trials can offer valuable insights into how different healthcare systems or practices impact the effectiveness of the intervention.

1.1.3 Bias of Multisite Trials

Multisite trials enhance the relevance of findings but face challenges like selection bias, variability in implementation, and contextual influences, which can skew results. Mitigating these requires careful site selection, standardization across sites, and statistical techniques like multilevel modeling to ensure the trials' findings are both robust and widely applicable.

1.1.4 Pros and Cons of Multisite Trials

Multisite trials offer enhanced generalizability and statistical power due to their diverse and large participant pools, and can be more resource-efficient through shared infrastructure. However, they also face challenges such as logistical complexities, variability in intervention implementation, regulatory hurdles, potential site-specific biases, and data integration issues. Balancing these pros and cons requires careful planning, standardization of protocols, and sophisticated statistical methods to ensure the reliability and applicability of the findings across varied settings (Mudaranthakam et al. 2021).

1.2 Intro to the MST Dataset

1.2.1 Read the Dataset

```
# ------------------------------------------------------
## clear the environment var area
# rm(list = ls())
## clear all plots
# graphics.off()
## clear the console area
```

```
# cat("\014")
# ------------------------------------------------------------
# install.packages("gridExtra")
# ------------------------------------------------------------
require(lme4)
require(lmerTest)
require(ggplot2)
require(sjPlot)
```

Download the dataset "MST" only once from GitHub and save it to csv files.

```
# MST <-
#   read.csv(
#     "https://andygolightly.github.io/teaching/MATH43515/summative/andy.csv",
#     header = TRUE
#   )
# write.csv(MST, "MST.csv")
MST = read.csv("./MST.csv")
dim(MST)
```

```
## [1] 200  10
```

```
head(MST)
```

```
##   X ID Hospital Responset1 Responset2 Responset3 Trt Experience Gender Size
## 1 1  1        1          1         36         38         38   1        6.8      1    0
## 2 2  2        2          1         35         39         39   1        9.1      1    0
## 3 3  3        3          1         46         41         41   0        6.0      1    0
## 4 4  4        4          1         31         31         40   1        3.7      0    0
## 5 5  5        5          1         36         36         39   1       12.1      1    0
## 6 6  6        6          1         29         33         36   1       15.8      0    0
```

```
## Show three line table MST with sjPlot::tab_df
# tab_df(MST[1:5, ])
```

The MST dataset encompasses data from a longitudinal multisite trial assessing a stress-coping training program's effectiveness for nurses in 20 hospitals' Accident and Emergency (A&E) departments. It comprises 200 entries across 9 columns, detailing anonymized nurse identifiers (ID), hospital IDs, treatment assignment (Trt) with 0 indicating control and 1 indicating receipt of the training program, nurse experience in years, gender (0 for male, 1 for female), and A&E department size (0 for small, 1 for large). The dataset tracks the program's impact on job-related stress through post-test stress scores (Responset1, Responset2, Responset3) measured at 1, 2, and 3 months post-training, respectively, on a scale from 0 (no stress) to 100 (maximum stress), providing a multifaceted view of the intervention's short-term effects on nurse stress levels across diverse hospital settings.

1.2.2 Identify the variables at each level

Considerations for "Size" Placement: It is no longer true that other variables are identified as different hierarchies. However, it is worth discussing whether the Size is placed on the Nurse level or the Hospital level. Based on my observations of the Hospital and Size columns in the dataset, there is only one possible Size value for each hospital. For the study's focus on the intervention's impact on stress responses, placing

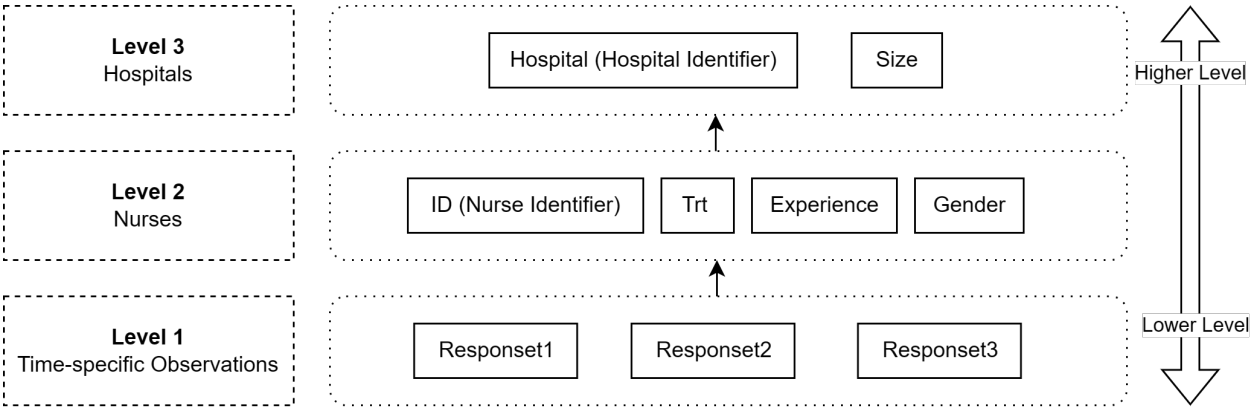


Figure 1: Variables at each level

Size at Level 3 is generally more suitable. This approach recognizes department size as a contextual factor at the hospital level that may influence the stress-coping intervention's effectiveness across different settings. It allows the study to explore how the broader environmental and organizational context, such as the scale of A&E departments, moderates the treatment outcomes, providing insights into adapting the intervention for varied hospital environments to enhance its efficacy.

1.2.3 Aims of Multilevel Modeling

The study aims to determine whether the experimental intervention, a stress-coping training program, significantly reduces job-related stress among nurses in A&E departments post-test. Additionally, it seeks to explore how the intervention's impact on stress levels changes over time, providing insights into the sustainability and temporal dynamics of the program's effectiveness.

1.3 Exploratory Data Analysis

1.3.1 Check missing values and imputation

```
# Check if there are any missing values in the entire dataset
any_na <- any(is.na(MST))
print(paste("Are there any missing values in the dataset? ", any_na))
```

```
## [1] "Are there any missing values in the dataset?  FALSE"
```

```
remove(any_na)
```

1.3.2 Summary Statistics

```
# Summary statistics for continuous variables
summary(MST$Experience)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   1.700   5.675   7.250   8.387  10.700  27.800
```

```r
summary(MST$Responset1)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   29.00   36.00   39.00   38.94   42.00   48.00
```

```r
summary(MST$Responset2)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    31.0    37.0    40.0    39.7    42.0    47.0
```

```r
summary(MST$Responset3)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   33.00   38.00   40.00   40.23   43.00   48.00
```

```r
# Load the necessary libraries
library(gridExtra)

# Frequency counts for categorical variables
# Bar chart for Treatment Groups
bar.Trt <- ggplot(data = MST, aes(factor(Trt))) +
  geom_bar(fill="lightblue") +
  labs(x="Treatment Group", y="Count", title="Treatment Group Distribution")

# Bar chart for Gender
bar.Gender <- ggplot(data = MST, aes(factor(Gender))) +
  geom_bar(fill="green") +
  labs(x="Gender", y="Count", title="Gender Distribution")

# Bar chart for Department Size
bar.Size <- ggplot(data = MST, aes(factor(Size))) +
  geom_bar(fill="pink") +
  labs(x="Department Size", y="Count", title="A&E Department Size Distribution")

# Bar chart for Hospital
bar.Hospital <- ggplot(data = MST, aes(factor(Hospital))) +
  geom_bar(fill="gray") +
  labs(x="Hospital", y="Count", title="Hospital Distribution")


grid.arrange(bar.Trt, bar.Gender, bar.Size, bar.Hospital, ncol = 2)
```


```
remove(bar.Trt, bar.Gender, bar.Size, bar.Size, bar.Hospital)
```

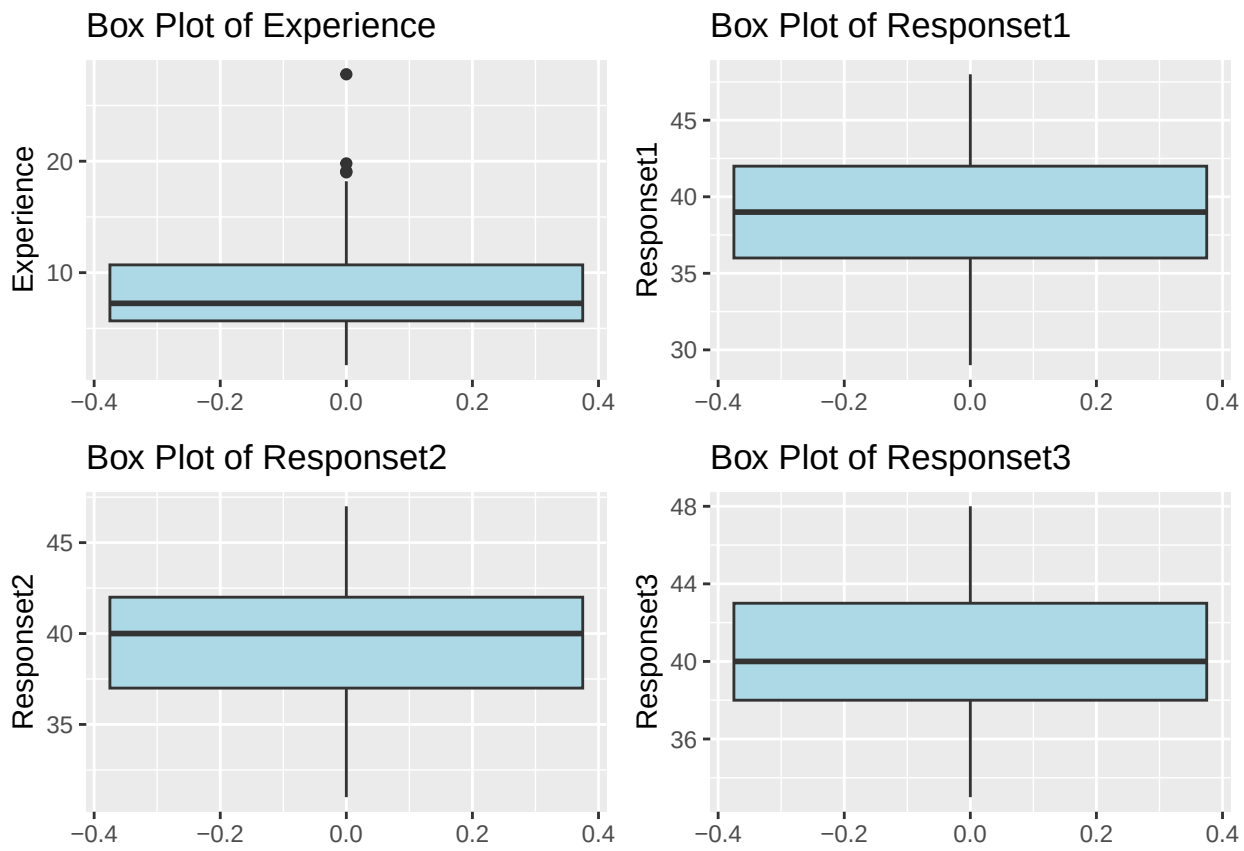
```
## Warning in remove(bar.Trt, bar.Gender, bar.Size, bar.Size, bar.Hospital):
## object 'bar.Size' not found
```

1.3.3 Distribution Analysis

```
# List of variable names to plot
variables_to_plot <-
  c("Experience", "Responset1", "Responset2", "Responset3")

# Initialize lists to store the plots
hist_plots <- list()
box_plots <- list()

# Loop through each variable and create histograms and box plots
for (i in 1:length(variables_to_plot)) {
  var <- variables_to_plot[i]

  # Histogram with Density Plot
  hist_plots[[i]] <- ggplot(MST, aes_string(x = var)) +
    geom_histogram(
      aes(y = ..density..),
```

```
      binwidth = 1,
      color = "black",
      fill = "skyblue"
    ) +
    geom_density(alpha = .2, fill = "#FF6666") +
    ggtitle(paste("Distribution of", var)) +
    xlab(var) +
    ylab("Density")

  # Box Plot
  box_plots[[i]] <- ggplot(MST, aes_string(y = var)) +
    geom_boxplot(fill = "lightblue") +
    ggtitle(paste("Box Plot of", var)) +
    ylab(var)
}

# Arrange the histograms in a 4-graph plot
grid.arrange(grobs = hist_plots, ncol = 2)
```

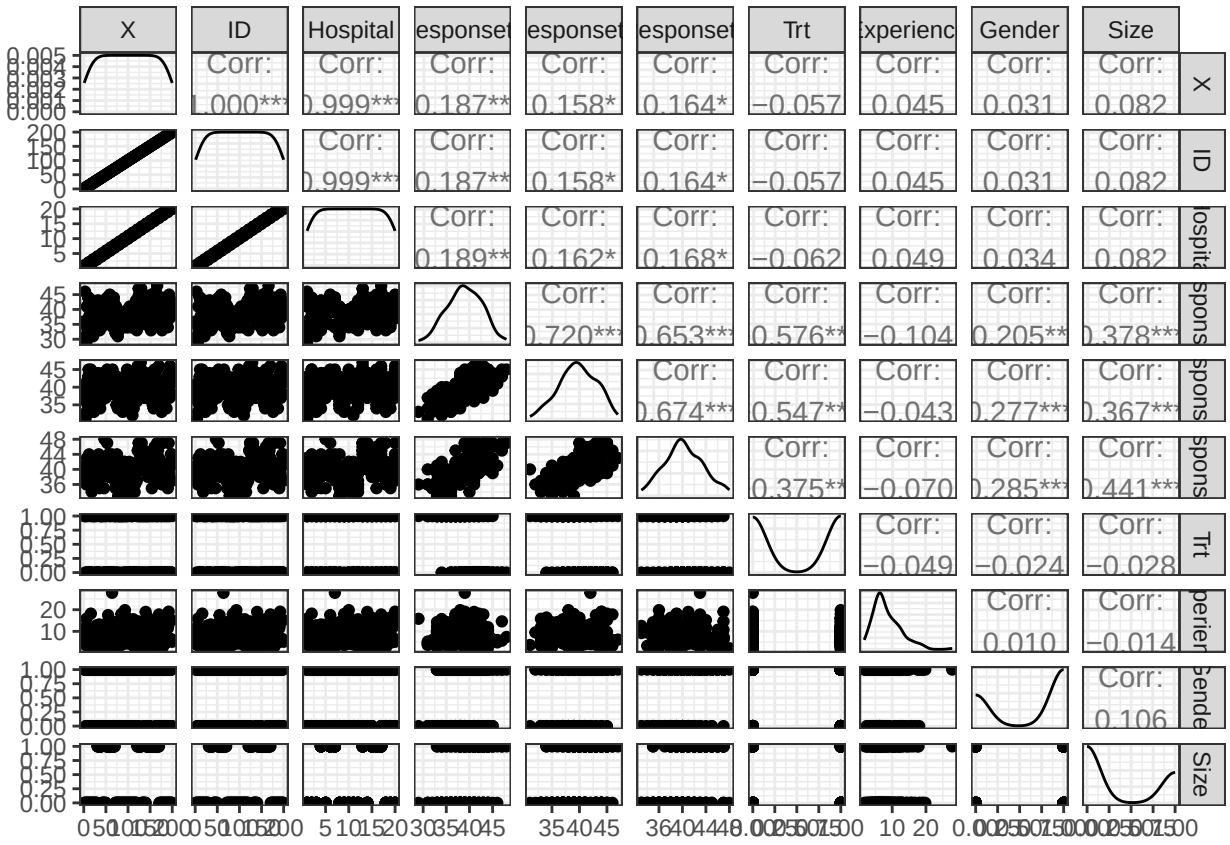

```
# Arrange the box plots in a 4-graph plot
grid.arrange(grobs = box_plots, ncol = 2)
```




```
remove(hist_plots, box_plots, variables_to_plot, i, var)
```

1.3.4 Correlations

```
# Correlation between two varibales with GGpairs
library("GGally")
ggpairs(MST)+theme_bw()
```



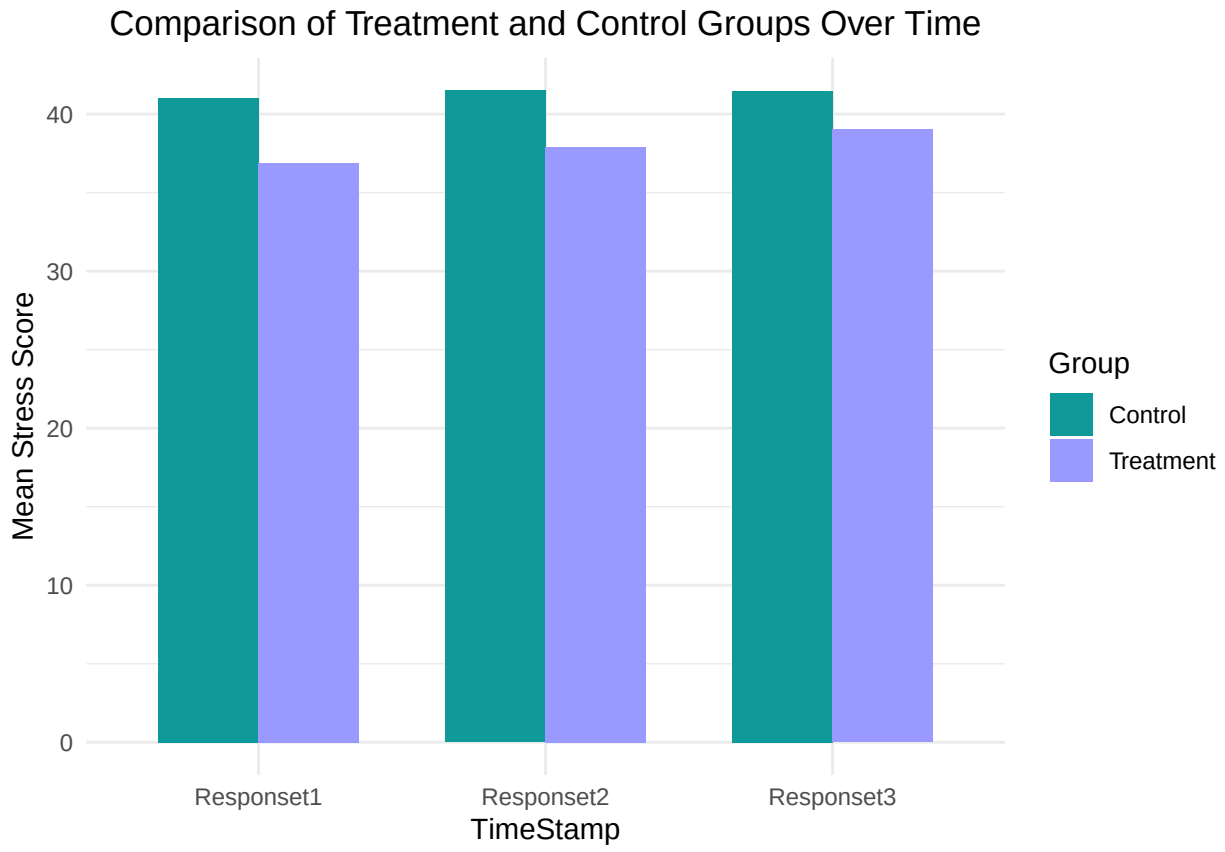
1.3.5 Treatment and Control Group Comparison

```
# Reshape data to "long format" for easier plotting
library(tidyr)
```

```
##
## Attaching package: 'tidyr'

## The following objects are masked from 'package:Matrix':
##
##     expand, pack, unpack
```

```
MST_long <-
  pivot_longer(
    MST,
    cols = starts_with("Responset"),
    names_to = "TimeStamp",
    values_to = "StressScore"
  )

# Convert TimeStamp to a factor for ordered plotting
MST_long$TimeStamp <-
  factor(MST_long$TimeStamp,
         levels = c("Responset1", "Responset2", "Responset3"))
```

```r
# Create a bar plot comparing treatment and control groups over time
ggplot(MST_long, aes(x = TimeStamp, y = StressScore, fill = factor(Trt))) +
  geom_bar(
    stat = "summary",
    fun = "mean",
    position = "dodge",
    width = 0.7
  ) +
  scale_fill_manual(
    values = c("#0F9999", "#9999FF"),
    labels = c("Control", "Treatment")
  ) +
  labs(title = "Comparison of Treatment and Control Groups Over Time",
       x = "TimeStamp",
       y = "Mean Stress Score",
       fill = "Group") +
  theme_minimal() +
  theme(plot.title = element_text(hjust = 0.5))  # Center the plot title
```



1.3.6 Temporal Trends

```r
# Plotting temporal trends
ggplot(MST_long,
```

```
      aes(
        x = TimeStamp,
        y = StressScore,
        group = Trt,
        color = factor(Trt)
      )) +
geom_line(stat = "summary", fun.y = "mean") +
geom_point(stat = "summary", fun.y = "mean", size = 3) +
scale_color_manual(
  values = c("#60F999", "#123456"),
  labels = c("Control", "Treatment")
) +
labels(
  title = "Temporal Trends in Stress Scores",
  x = "TimeStamp",
  y = "Mean Stress Score",
  color = "Group"
) +
theme_minimal() +
theme(plot.title = element_text(hjust = 0.5))  # Center the plot title
```

1.3.7 Categorical Variable Analysis

```
# Scatterplot of Experience vs. StressScore, colored by Treatment Group
ggplot(MST_long, aes(x = Experience, y = StressScore, color = factor(Trt))) +
  geom_point(alpha = 0.6) +
  scale_color_manual(
    values = c("orange", "purple"),
    labels = c("Control", "Treatment")
  ) +
  facet_wrap( ~ TimeStamp) +  # Optional: To separate plots by time points
  labs(
    title = "Experience vs. Stress Score by Treatment Group",
    x = "Experience (Years)",
    y = "Stress Score",
    color = "Group"
  ) +
  theme_minimal() +
  theme(plot.title = element_text(hjust = 0.5))  # Center the plot title
```

Part 2 Methods

Part 3 Analysis

Part 4 Discussion of results

Word Count

```
# install.packages("devtools")
# devtools::install_github("benmarwick/wordcountaddin",
#                          type = "source", dependencies = TRUE)
require(wordcountaddin)
word_count()
```

```
## [1] 879
```

```
text_stats()
```

Method	koRpus	stringi
Word count	879	817
Character count	6091	6153
Sentence count	76	Not available
Reading time	4.4 minutes	4.1 minutes

References

Mudaranthakam, Dinesh Pal, Alexandra Brown, Elizabeth Kerling, Susan E. Carlson, Christina J. Valentine, and Byron Gajewski. 2021. "The Successful Synchronized Orchestration of an Investigator-Initiated Multicenter Trial Using a Clinical Trial Management System and Team Approach: Design and Utility Study." *JMIR Formative Research* 5 (12): e30368. https://doi.org/10.2196/30368.

Youth Endowment Fund. 2024. "Multi-Site Trials." https://youthendowmentfund.org.uk/multi-site-trials/.