```
# Install CRAN packages if missing
packages <- c("dplyr", "ggplot2", "lme4", "emmeans","car","ARTool","rstatix","effectsize","effsize")

installed <- rownames(installed.packages())
for (p in packages) {
  if (!(p %in% installed)) {
    install.packages(p, dependencies = TRUE)
  }
}

# Load them after installation
lapply(packages, library, character.only = TRUE)

```

```
Attaching package: ‘dplyr’


The following objects are masked from ‘package:stats’:

    filter, lag


The following objects are masked from ‘package:base’:

    intersect, setdiff, setequal, union


Loading required package: Matrix

Welcome to emmeans.
Caution: You lose important information if you filter this package's results.
See '? untidy'

Loading required package: carData


Attaching package: ‘car’
```

Data Import & Cleaning

We load the experimental run table (`run_table.csv`), inspect its structure, and remove missing values.
We also check the number of runs per treatment combination to ensure balanced data.

⚠️ In a later step, we must report failed runs (e.g., "X out of N failed due to Y") instead of silently removing them.

```
# Load the CSV
df <- read.csv("run_table.csv")

# Check structure
str(df)

# Basic cleaning: remove NAs
df <- na.omit(df)

# Summary of missing values
colSums(is.na(df))

# Check number of runs per treatment combination
df %>% count(gc_strategy, workload, jdk)

# Count failed runs before NA removal
failed_runs <- sum(is.na(df))
total_runs <- nrow(df) + failed_runs
cat("Failed runs:", failed_runs, "out of", total_runs, "\n")

```

1. 'dplyr' · 'stats' · 'graphics' · 'grDevices' · 'utils' · 'datasets' · 'methods' · 'base'
2. 'ggplot2' · 'dplyr' · 'stats' · 'graphics' · 'grDevices' · 'utils' · 'datasets' · 'methods' · 'base'
3. 'lme4' · 'Matrix' · 'ggplot2' · 'dplyr' · 'stats' · 'graphics' · 'grDevices' · 'utils' · 'datasets' · 'methods' · 'base'
4. 'emmeans' · 'lme4' · 'Matrix' · 'ggplot2' · 'dplyr' · 'stats' · 'graphics' · 'grDevices' · 'utils' · 'datasets' · 'methods' · 'base'
5. 'car' · 'carData' · 'emmeans' · 'lme4' · 'Matrix' · 'ggplot2' · 'dplyr' · 'stats' · 'graphics' · 'grDevices' · 'utils' · 'datasets' · 'methods' · 'base'
6. 'ARTool' · 'car' · 'carData' · 'emmeans' · 'lme4' · 'Matrix' · 'ggplot2' · 'dplyr' · 'stats' · 'graphics' · 'grDevices' · 'utils' · 'datasets' · 'methods' · 'base'
7. 'rstatix' · 'ARTool' · 'car' · 'carData' · 'emmeans' · 'lme4' · 'Matrix' · 'ggplot2' · 'dplyr' · 'stats' · 'graphics' · 'grDevices' · 'utils' · 'datasets' · 'methods' · 'base'
8. 'effectsize' · 'rstatix' · 'ARTool' · 'car' · 'carData' · 'emmeans' · 'lme4' · 'Matrix' · 'ggplot2' · 'dplyr' · 'stats' · 'graphics' · 'grDevices' · 'utils' · 'datasets' · 'methods' · 'base'
9. 'effsize' · 'effectsize' · 'rstatix' · 'ARTool' · 'car' · 'carData' · 'emmeans' · 'lme4' · 'Matrix' · 'ggplot2' · 'dplyr' · 'stats' · 'graphics' · 'grDevices' · 'utils' · 'datasets' · 'methods' · 'base'

```
'data.frame':	216 obs. of  12 variables:
 $ X__run_id     : chr  "run_0_repetition_0" "run_1_repetition_0" "run_2_repetition_0" "run_3_repetition_0" ...
 $ X__done       : chr  "DONE" "DONE" "DONE" "DONE" ...
 $ subject       : chr  "dacapo" "dacapo" "dacapo" "dacapo" ...
 $ gc_strategy   : chr  "SerialGC" "SerialGC" "SerialGC" "SerialGC" ...
 $ workload      : chr  "light" "light" "medium" "medium" ...
 $ jdk           : chr  "oraclejdk11" "openjdk17" "oraclejdk11" "openjdk17" ...
 $ energy_joules : num  3.58 2.57 7.66 8.98 9.51 ...
 $ execution_time: num  0.327 0.338 0.649 0.71 1.036 ...
 $ power_watts   : num  10.96 7.61 11.81 12.64 9.18 ...
 $ exit_code     : int  0 0 0 0 0 0 0 0 0 0 ...
 $ X             : int  1 2 3 4 5 6 7 8 9 10 ...
 $ X.1           : chr  "/Users/rahilsharma/Desktop/Green-Lab/Mock-Server/gc_energy_experiment/experiments/gc_energy_experiment/run_0_repetition_0" "/Users/rahilsharma/Deskto
```

X__run_id: 0 X__done: 0 subject: 0 gc_strategy: 0 workload: 0 jdk: 0 energy_joules: 0 execution_time: 0 power_watts: 0 exit_code: 0 X: 0 X.1: 0

A data.frame: 18 × 4

gc_strategy	workload	jdk	n
<chr>	<chr>	<chr>	<int>
G1GC	heavy	openjdk17	12
G1GC	heavy	oraclejdk11	12
G1GC	light	openjdk17	12
G1GC	light	oraclejdk11	12
G1GC	medium	openjdk17	12
G1GC	medium	oraclejdk11	12
ParallelGC	heavy	openjdk17	12
ParallelGC	heavy	oraclejdk11	12
ParallelGC	light	openjdk17	12
ParallelGC	light	oraclejdk11	12
ParallelGC	medium	openjdk17	12
ParallelGC	medium	oraclejdk11	12
SerialGC	heavy	openjdk17	12
SerialGC	heavy	oraclejdk11	12
SerialGC	light	openjdk17	12
SerialGC	light	oraclejdk11	12
SerialGC	medium	openjdk17	12
SerialGC	medium	oraclejdk11	12

```
Failed runs: 0 out of 216
```

Descriptive Statistics & Visualization

We compute the mean, standard deviation, and 95% confidence intervals for energy consumption across GC, workload, and JDK combinations.

We also visualize distributions using boxplots and interaction plots to identify trends and possible outliers.

```
# Descriptive statistics
df %>%
  group_by(gc_strategy, workload, jdk) %>%
  summarise(
    mean_energy = mean(energy_joules),
    sd_energy   = sd(energy_joules),
    ci_low      = mean_energy - qt(0.975, n()-1) * sd_energy/sqrt(n()),
    ci_high     = mean_energy + qt(0.975, n()-1) * sd_energy/sqrt(n()),
    .groups = "drop"
  )

# Boxplots
ggplot(df, aes(x = gc_strategy, y = energy_joules, fill = gc_strategy)) +
  geom_boxplot() +
  facet_wrap(~workload) +
  theme_minimal()

# Interaction plot
interaction.plot(df$gc_strategy, df$workload, df$energy_joules)


# Identify outliers in energy consumption
outliers <- boxplot.stats(df$energy_joules)$out
outliers

# Inspect which runs are outliers
df %>% filter(energy_joules %in% outliers)

outliers <- boxplot.stats(df$energy_joules)$out
print(outliers)

```

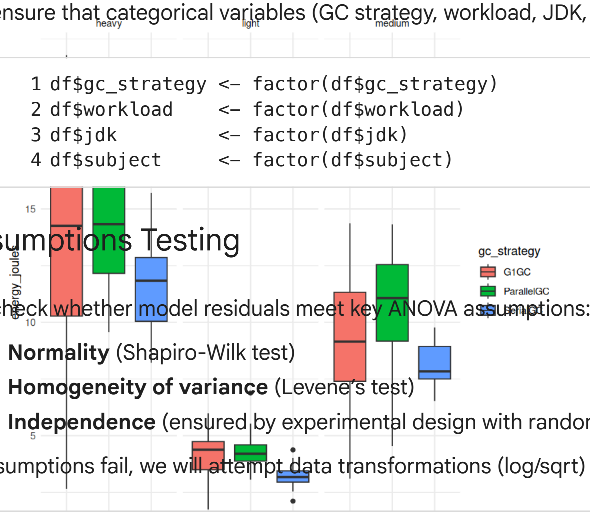
A tibble: 18 × 7

gc_strategy	workload	jdk	mean_energy	sd_energy	ci_low	ci_high
<chr>	<chr>	<chr>	<dbl>	<dbl>	<dbl>	<dbl>
G1GC	heavy	openjdk17	15.370162	4.3996477	12.574760	18.165565
G1GC	heavy	oraclejdk11	11.477760	4.9121901	8.356703	14.598816
G1GC	light	openjdk17	4.190206	1.2493240	3.396423	4.983989
G1GC	light	oraclejdk11	3.982909	0.9971837	3.349328	4.616489
G1GC	medium	openjdk17	9.603073	3.0567949	7.660878	11.545268
G1GC	medium	oraclejdk11	8.954945	3.4731396	6.748217	11.161672
ParallelGC	heavy	openjdk17	14.674603	2.7285167	12.940986	16.408220
ParallelGC	heavy	oraclejdk11	13.853493	2.9230599	11.996269	15.710717
ParallelGC	light	openjdk17	4.096408	0.6394977	3.690090	4.502725
ParallelGC	light	oraclejdk11	4.545249	0.9721383	3.927582	5.162916
ParallelGC	medium	openjdk17	10.468336	2.7424103	8.725892	12.210781
ParallelGC	medium	oraclejdk11	10.718180	2.1917966	9.325579	12.110781
SerialGC	heavy	openjdk17	11.125027	1.9343769	9.895982	12.354071
SerialGC	heavy	oraclejdk11	12.203132	2.0193407	10.920105	13.486160
SerialGC	light	openjdk17	3.189427	0.4188336	2.923323	3.455551
SerialGC	light	oraclejdk11	3.209871	0.6046521	2.825693	3.594048
SerialGC	medium	openjdk17	8.220377	0.9042711	7.645830	8.794923
SerialGC	medium	oraclejdk11	7.952360	0.8858042	7.389546	8.515173

Boxplots showed a few potential outliers, but none were flagged as extreme by boxplot.stats. Therefore, no runs were excluded

Data Preparation

We ensure that categorical variables (GC strategy, workload, JDK, subject) are properly treated as factors for analysis.




```
df$gc_strategy <- factor(df$gc_strategy)
df$workload    <- factor(df$workload)
df$jdk         <- factor(df$jdk)
df$subject     <- factor(df$subject)
```

Assumptions Testing

We check whether model residuals meet key ANOVA assumptions:

- **Normality** (Shapiro-Wilk test)
- **Homogeneity of variance** (Levene's test)
- **Independence** (ensured by experimental design with randomization and cooldowns).

If assumptions fail, we will attempt data transformations (log/sqrt) before switching to non-parametric methods.

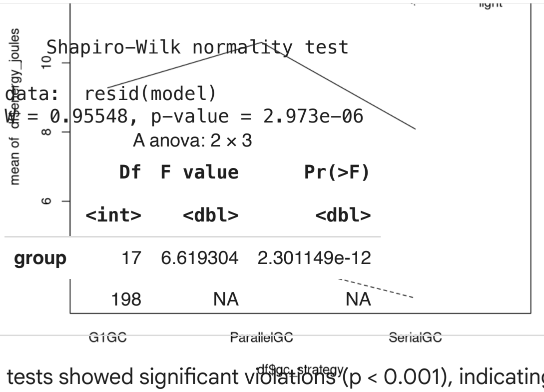
```
# Fit linear model for residuals check
model <- lm(energy_joules ~ gc_strategy * workload * jdk, data=df)

# Normality test on residuals
shapiro.test(resid(model))

# Homogeneity of variance (Levene's test)
leveneTest(energy_joules ~ gc_strategy * workload * jdk, data=df)

# Independence: assumed from randomization protocol

```




```
	Shapiro-Wilk normality test

data:  resid(model)
W = 0.95548, p-value = 2.973e-06
```

A anova: 2 × 3

	Df	F value	Pr(>F)
	<int>	<dbl>	<dbl>
group	17	6.619304	2.301149e-12
	198	NA	NA

Both tests showed significant violations ($p < 0.001$), indicating the ANOVA assumptions are not satisfied.
Therefore, we attempted a log-transformation before considering non-parametric methods.

Data Transformation Attempt (Log)

Since the Shapiro-Wilk and Levene's tests showed that assumptions of normality and equal variance are violated, we attempt a simple log-transformation of the energy values.

The results still indicated strong violations of normality ($p < 1e-9$) and homogeneity ($p \approx 0.006$).
Thus, transformation did not resolve assumption issues, and we proceed with ART (non-parametric factorial ANOVA).

```
# Apply log transformation to the dependent variable
df$log_energy <- log(df$energy_joules)

# Check assumptions again with transformed data
log_model <- lm(log_energy ~ gc_strategy * workload * jdk, data=df)

# Shapiro-Wilk test for normality on residuals
shapiro.test(resid(log_model))

# Levene’s test for homogeneity of variance
leveneTest(log_energy ~ gc_strategy * workload * jdk, data=df)

```

```
	Shapiro-Wilk normality test

data:  resid(log_model)
W = 0.91183, p-value = 5.084e-10
```

A anova: 2 × 3

	Df	F value	Pr(>F)
	<int>	<dbl>	<dbl>
group	17	2.176071	0.005905881
	198	NA	NA

Log-transformation did not resolve assumption violations (normality and homogeneity still violated). Therefore, we proceed with non-parametric ART for hypothesis testing.

Hypothesis Testing (Parametric, for comparison)

Although assumptions were not satisfied, we still ran a mixed-effects ANOVA to provide a comparison.
Results showed workload as the dominant factor ($F \approx 265$, $p < 1e\text{-}50$) and GC strategy also significant ($F \approx 13.5$, $p < 0.001$).
However, due to violated assumptions, these results should be interpreted with caution and are presented as supplementary.

```r
# Mixed-effects ANOVA: subject as random effect
anova_model <- lmer(energy_joules ~ gc_strategy * workload * jdk + (1|subject), data=df)

anova(anova_model)

# Post-hoc Tukey HSD
emmeans(anova_model, pairwise ~ gc_strategy | workload)


# Example: adjust p-values from Tukey comparisons
tukey_results <- emmeans(anova_model, pairwise ~ gc_strategy | workload)
tukey_df <- as.data.frame(tukey_results$contrasts)

# Apply Benjamini-Hochberg correction
tukey_df$p.adjusted <- p.adjust(tukey_df$p.value, method = "BH")
tukey_df


```

A anova: 7 × 4

	npar	Sum Sq	Mean Sq	F value
	<int>	<dbl>	<dbl>	<dbl>
gc_strategy	2	157.96009	78.980043	13.4734016
workload	2	3111.92855	1555.964274	265.4358085
jdk	1	10.87962	10.879618	1.8559811
gc_strategy:workload	4	18.80326	4.700816	0.8019239
gc_strategy:jdk	2	35.61363	17.806817	3.0377091
workload:jdk	2	16.57793	8.288965	1.4140351
gc_strategy:workload:jdk	4	43.64785	10.911962	1.8614987

```
NOTE: Results may be misleading due to involvement in interactions

$emmeans
workload = heavy:
 gc_strategy emmean   SE df lower.CL upper.CL
 G1GC         13.42 0.52 61    12.38    14.46
 ParallelGC   14.26 0.52 61    13.22    15.30
 SerialGC     11.66 0.52 61    10.62    12.70

workload = light:
 gc_strategy emmean   SE df lower.CL upper.CL
 G1GC          4.09 0.52 61     3.05     5.13
 ParallelGC    4.32 0.52 61     3.28     5.36
 SerialGC      3.20 0.52 61     2.16     4.24

workload = medium:
 gc_strategy emmean   SE df lower.CL upper.CL
 G1GC          9.28 0.52 61     8.24    10.32
 ParallelGC   10.59 0.52 61     9.55    11.63
 SerialGC      8.09 0.52 61     7.05     9.13

Results are averaged over the levels of: jdk
Degrees-of-freedom method: kenward-roger
Confidence level used: 0.95

$contrasts
workload = heavy:
```

Hypothesis Testing (Non-Parametric, ART)

Given that both raw and log-transformed data violated assumptions,
we applied the Aligned Rank Transform (ART) for factorial ANOVA.

Results confirmed:

- **GC strategy**: significant (F ≈ 24.3, p [illegible])
- **Workload**: dominant effect (F ≈ 265, p < 1e-56)
- **JDK**: not significant (p ≈ 0.09)
- **GC × workload interaction**: borderline (p ≈ 0.058)

We therefore base our main conclusions on these ART results.

```
1 art_model <- art(energy_joules ~ gc_strategy * workload * jdk + (1|subject), data=df)
2 anova(art_model)
```

```
 ParallelGC - SerialGC    2.600 0.699 195   3.720  0.0008

workload = light:
 contrast              estimate    SE  df t.ratio p.value
 G1GC - ParallelGC       -0.234 0.699 195  -0.335  0.9400
 G1GC - SerialGC          0.887 0.699 195   1.269  0.4144
 ParallelGC - SerialGC    1.121 0.699 195   1.604  0.2463

workload = medium:
 contrast              estimate    SE  df t.ratio p.value
 G1GC - ParallelGC       -1.314 0.699 195  -1.880  0.1471
 G1GC - SerialGC          1.193 0.699 195   1.706  0.2054
 ParallelGC - SerialGC    2.507 0.699 195   3.587  0.0012

Results are averaged over the levels of: jdk
```

```
Results are averaged over the levels of: jdk
Degrees-of-freedom method: kenward-roger
P value adjustment: tukey method for comparing a family of 3 estimates
NOTE: Results may be misleading due to involvement in interactions
```

A anova.art: 7 × 5

	Term	F	Df	Df.res	Pr(>F)
	<chr>	<dbl>	<dbl>	<dbl>	<dbl>
gc_strategy	gc_strategy	24.341860	2	195	3.654175e-10
workload	workload	265.174416	2	195	2.371648e-56
jdk	jdk	2.881885	1	195	9.117637e-02
gc_strategy:workload	gc_strategy:workload	2.327720	4	195	5.765203e-02
gc_strategy:jdk	gc_strategy:jdk	4.368306	2	195	1.393604e-02
workload:jdk	workload:jdk	1.715447	2	195	1.825865e-01
gc_strategy:workload:jdk	gc_strategy:workload:jdk	2.024419	4	195	9.251673e-02

A summary_emm: 9 × 8

								p.adjusted
	<fct>	<fct>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>
								0.510107108
2	G1GC - SerialGC	heavy	1.7598815	0.6989232	195	2.5179900	0.0335814422	0.100744327
								0.005518166
4	G1GC - ParallelGC	light	-0.2342712	0.6989232	195	-0.3351888	0.9399692137	0.939969214
								0.510107108
6	ParallelGC - SerialGC	light	1.1211747	0.6989232	195	1.6041459	0.2463069145	0.369460372
7	G1GC - ParallelGC	medium	-1.3142492	0.6989232	195	-1.8803916	0.1470940800	0.330961680
8	G1GC - SerialGC	medium	1.1926408	0.6989232	195	1.7063976	0.2053624344	0.369460372
9	ParallelGC - SerialGC	medium	2.5068900	0.6989232	195	3.5867891	0.0012262591	0.005518166

Effect Size

We compute Cohen's d for pairwise comparisons of GC strategies.
This complements p-values by quantifying the *practical significance* of differences (small ≈ 0.2, medium ≈ 0.5, large ≈ 0.8).

⚠️ For non-parametric cases, Cliff's delta should also be computed.

```
strategies <- unique(df$gc_strategy)

# Generate all pairwise Cohen's d
pairwise_d <- combn(strategies, 2, simplify = FALSE, FUN = function(groups) {
  d <- cohens_d(energy_joules ~ gc_strategy,
                data = df %>% filter(gc_strategy %in% groups))
  d$comparison <- paste(groups, collapse = " vs ")
  d
})

pairwise_d <- do.call(rbind, pairwise_d)
print(pairwise_d)

# Cliff's delta between groups (example GC1 vs GC2)
cliff.delta(energy_joules ~ gc_strategy, data = df)


```