Ultrasound-Guided Needle Study Report

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Section 1: Introduction

Ultrasound-guided regional anesthesia relies on real-time imaging to guide needle placement and requires coordinated bimanual motor control, with one hand manipulating the probe and the other advancing the needle. Trainees are traditionally instructed to hold the needle in their dominant hand. However, limited empirical evidence exists to support this convention.

This study investigates how hand hand arrangement, participant characteristics, and repeated practice attempts influence the time required to reach the target. The experiment used a replicated cross-over design with 20 participants completing 10 attempts under each hand arrangement.

Given the repeated-measures design and individual variability, a **linear mixed-effects model** (LLM) with participant-level random intercepts was used.

Section 2: Data Description and Data

The study consisted of 20 participants, each completing 10 attempts under two hand arrangements, yielding 400 total observations. The primary outcome was the time (in seconds) to reach the target. A cross-over repeated-measures design was used so that each participant served as their own control. Participant-level demographic and background variables were recorded to assess their contribution to performance differences.

Section 3: Exploratory Data Analysis (EDA)

Exploratory analysis examined the distribution of completion times, learning trends across attempts, and raw differences between hand arrangements. Given the repeated-measures structure, a linear mixed-effects model with participant-level random intercepts was used. To further examine skill acquisition, an exponential learning model was used to estimate when performance improvements plateaued.

Section 4: Results

4.1 Distribution of times

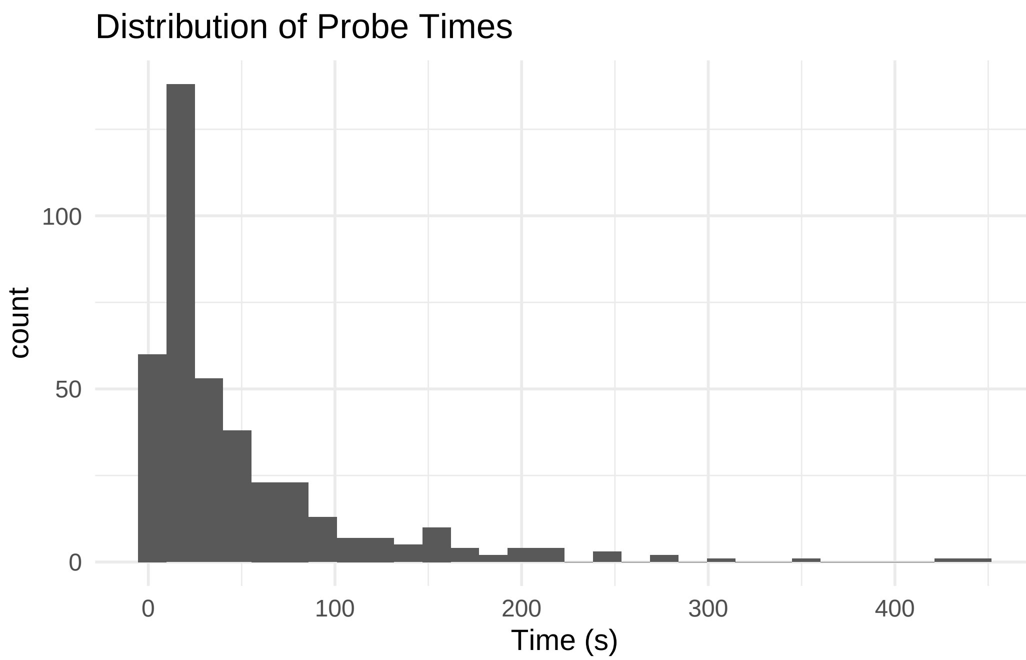
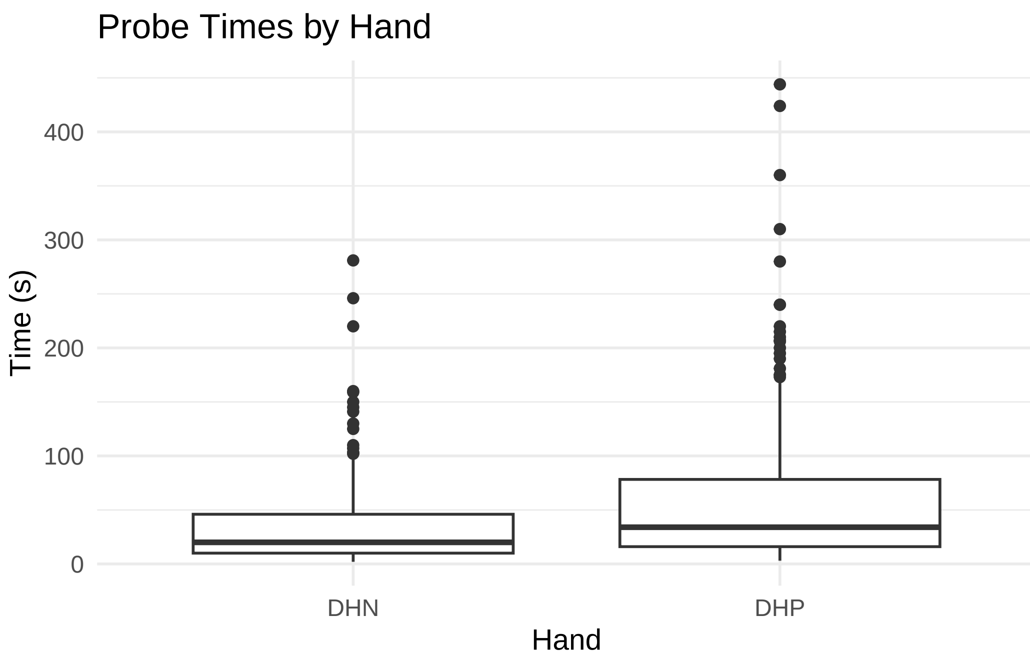


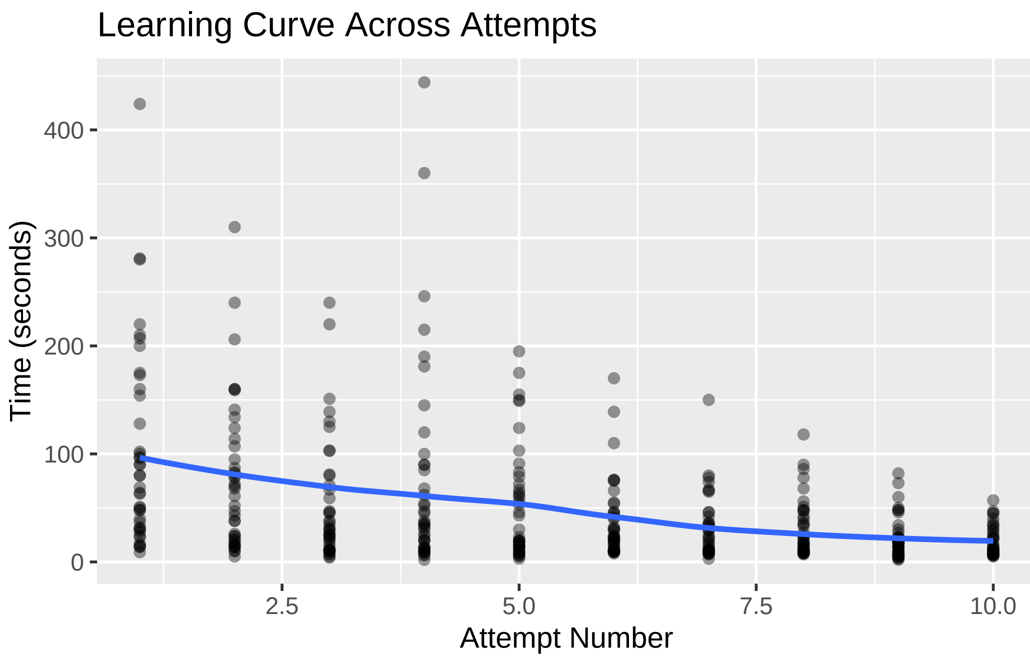
Figure 1 displays the distribution of probe completion times across all participants and trials. The distribution is strongly right-skewed, with the majority of times falling below approximately 60 s. A long tail extends toward higher values, including several extreme outliers above 200 s and even beyond 400s. This indicates that while most trials were completed quickly, occasional attempts took substantially longer.

4.2 Hand Arrangement Effect



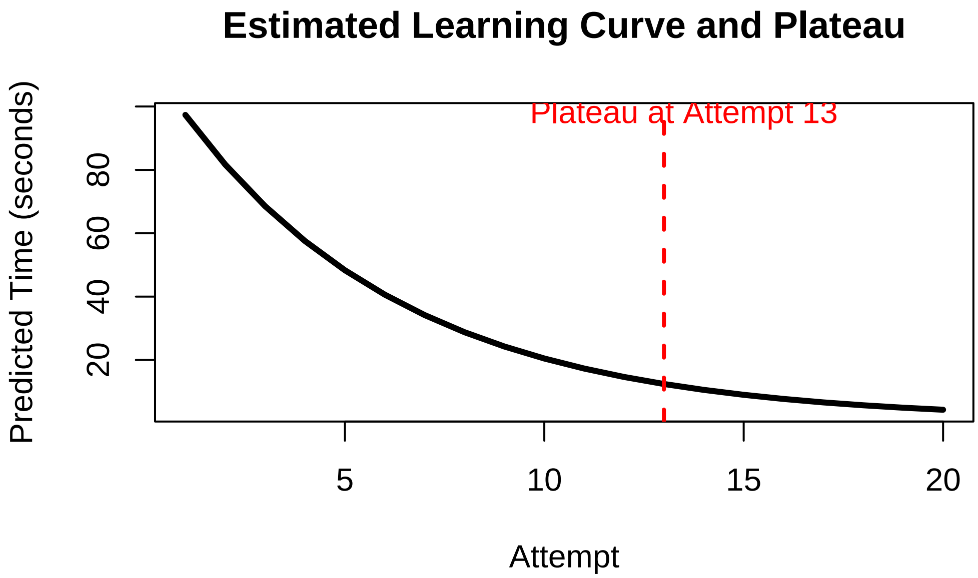
Hand arrangement had a strong and statistically significant effect on task performance. Using the probe in the dominant hand resulted in an average increase of approximately 27 seconds in completion time compared to the alternative arrangement ($p < 0.001$). This indicates that the traditionally taught configuration was consistently more efficient for participants.

4.3 Learning Effect Across Attempts



A pronounced learning effect was observed across attempts. Each additional attempt was associated with an average reduction of approximately 8.5 seconds in task completion time ($p < 0.001$), demonstrating rapid skill acquisition with repeated practice. This effect was consistent across participants and hand arrangements.

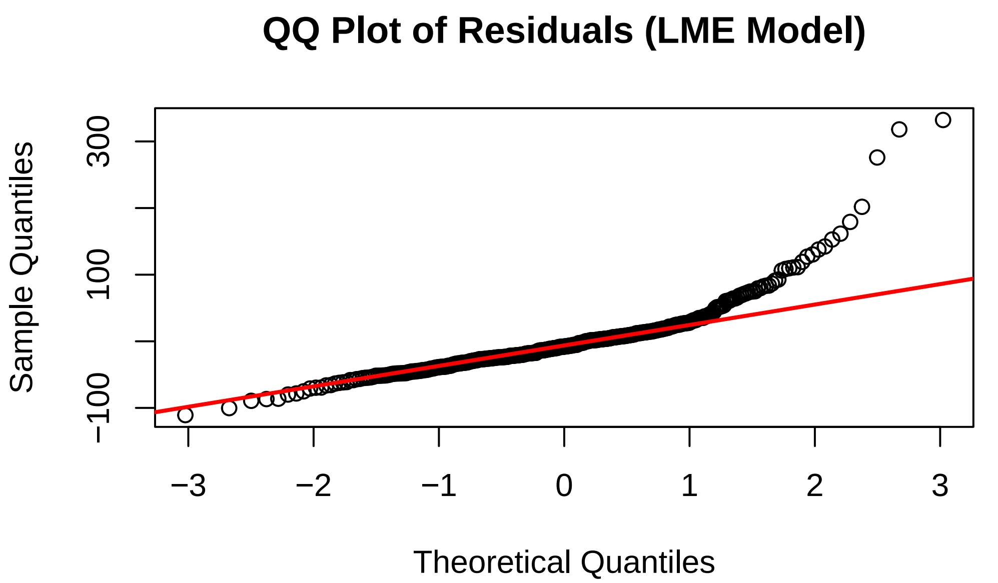
4.4 Learning Plateau & Predicted time

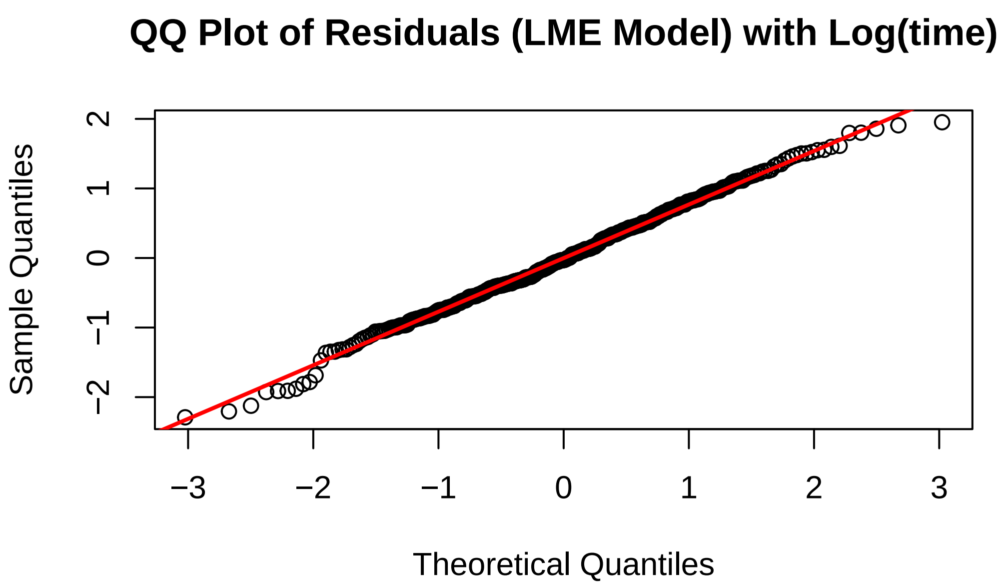


Metric	Time (seconds)	Interpretation
Theoretical asymptotic time ( )	1.00	Theoretical minimum under infinite practice
Predicted time at plateau (Attempt 13)	12.40	Stable, achievable proficiency benchmark

An exponential learning model was fitted to identify performance stabilization. Using a two-second improvement threshold to define negligible gains, performance plateaued at approximately 13 attempts, beyond which additional practice produced minimal time reductions. Although the model's asymptote represents a theoretical minimum (1 second), the predicted plateau time (~12.5 s) provides a more realistic and clinically meaningful proficiency benchmark, indicating that trainees achieve stable performance after approximately 13 attempts.

Diagnostic check: QQ Plot





Residual diagnostics indicated right-skewness in the primary linear mixed-effects model. A log-transformed sensitivity analysis improved normality, while the direction and significance of key predictors remained unchanged, indicating that the main conclusions are robust to distributional assumptions.

Section 5: Discussion

This study demonstrates that both hand arrangement and practice repetition significantly influence performance in an ultrasound-guided needle task. Participants were substantially slower when using the probe in their dominant hand, validating traditional instructional practices and affirming that alternative hand arrangements may not be more efficient during early training. A strong learning effect was observed, with rapid improvements over initial attempts and performance stabilizing after approximately 13 repetitions. Demographic and background variables contributed minimally to performance differences, emphasizing that practice and task configuration are the primary drivers of skill acquisition.

The plateau occurs when the rate of change between attempts becomes negligible.
We define the plateau as the point where predicted improvements fall below 2 second **improvement**.

Section 6: Implications for Training

The findings have direct implications for clinical education. Training programs should reconsider emphasizing dominant-hand probe use, particularly during early skill acquisition. Structured repetition is essential, and trainees should complete at least **13 supervised attempts under each hand arrangement** before proficiency is evaluated. Awareness of individual baseline variability may further help instructors tailor feedback and expectations.

Section 7: Conclusion

This study identified hand arrangement and repeated practice as the dominant predictors of performance in an ultrasound-guided needle task. Following traditional instruction, using the probe in the dominant hand resulted in significantly slower completion times. Rapid learning occurred over early attempts and plateaued after approximately 13 trials, suggesting that structured repetition may be more important than hand dominance during early training.

Appendix

2.1 Dataset Preview

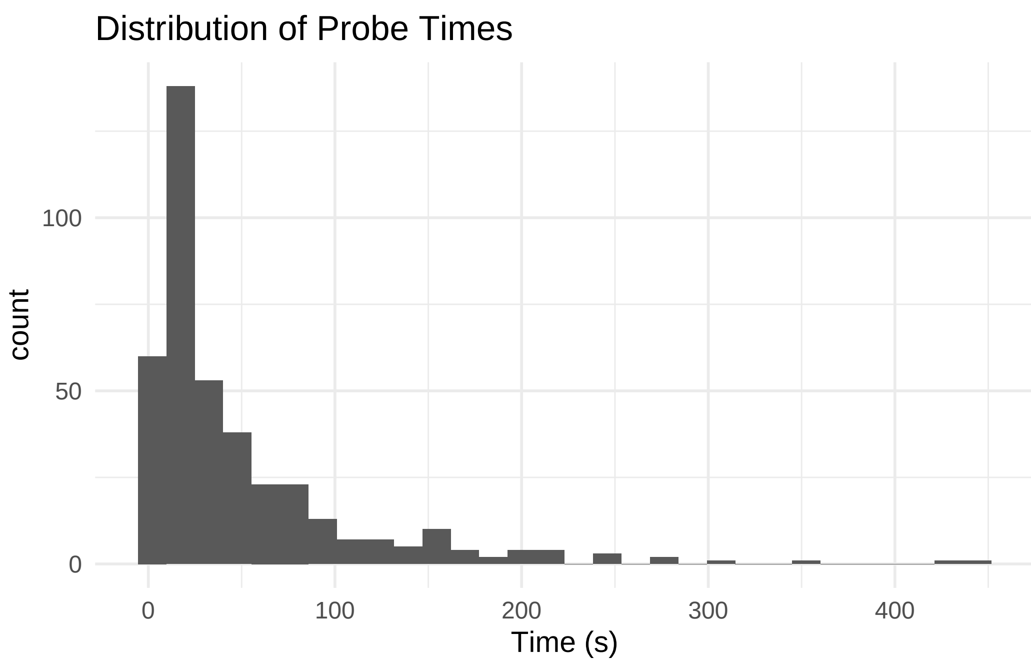
Table 2.1.1: First 6 Rows of the Probe Times Dataset

```r
library(tidyverse)
library(lme4)
library(lmerTest)
library(ggplot2)

# Display first 6 rows of the dataset
df_red <- df %>%
  select(id, hand, attempt, time)

head(df_red)
```

id	hand	attempt	time
1	DHP	1	97
1	DHP	2	78
1	DHP	3	46
1	DHP	4	52
1	DHP	5	62
1	DHP	6	76

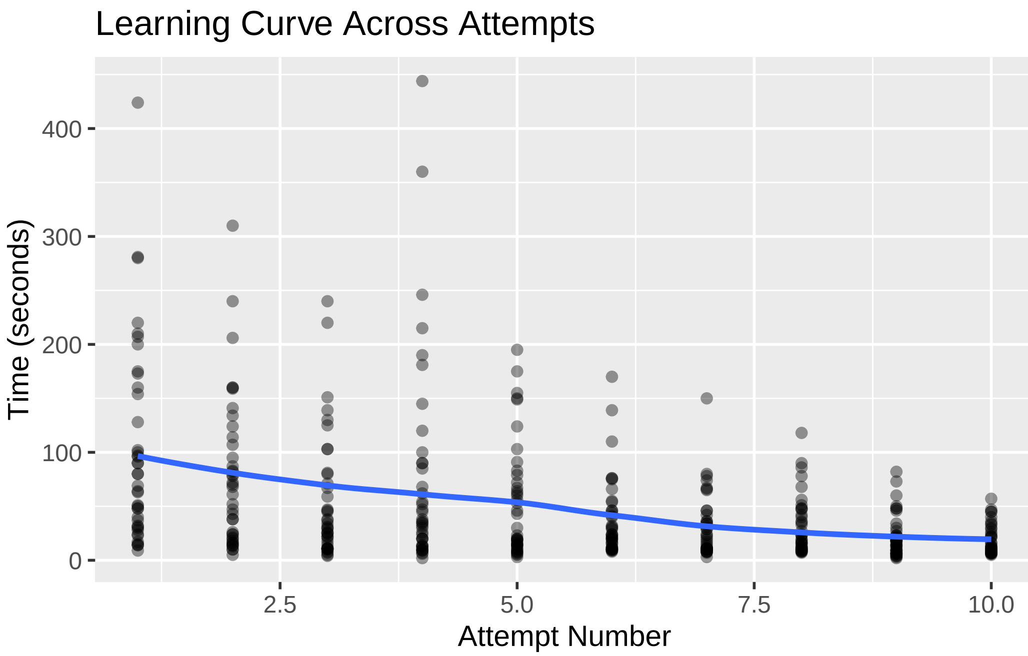
3.1.1: Distribution of times to reach target

```r
library(ggplot2)

ggplot(df, aes(time)) +
  geom_histogram(bins = 30) +
  theme_minimal() +
  labs(title = "Distribution of Probe Times", x = "Time (s)")
```



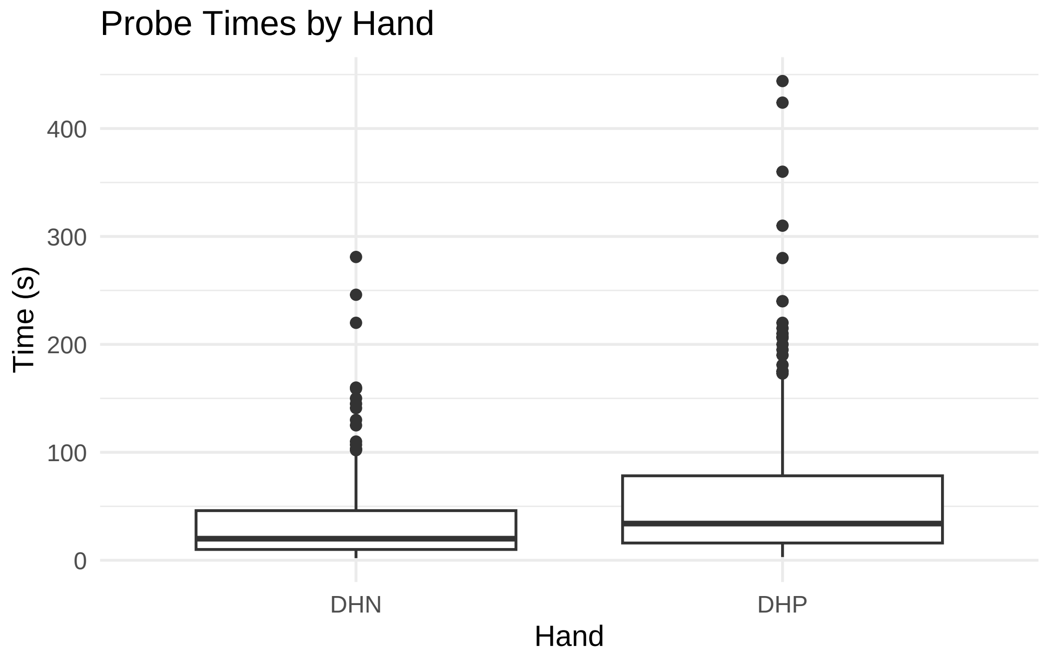
3.1.2: Learning Curve Across Attempts

```r
ggplot(df,aes(attempt,time))+
  geom_point(alpha=0.4)+
  geom_smooth(se = FALSE) +
  labs(title="Learning Curve Across Attempts",
       x = "Attempt Number", y="Time (seconds)")
```



3.1.3 Boxplots By Hand Arrangements: DHP vs DHN

```
library(ggplot2)
ggplot(df, aes(hand, time)) +
  geom_boxplot() +
  theme_minimal() +
  labs(title = "Probe Times by Hand", x = "Hand", y = "Time (s)")
```



4.1

```
library(lme4)

model <- lmer(time~hand+attempt+DOMINANCE+GENDER+AGE+BACKGROUND+STARTING.ARRANGEMENT+SUBJECTI
summary(model)
```

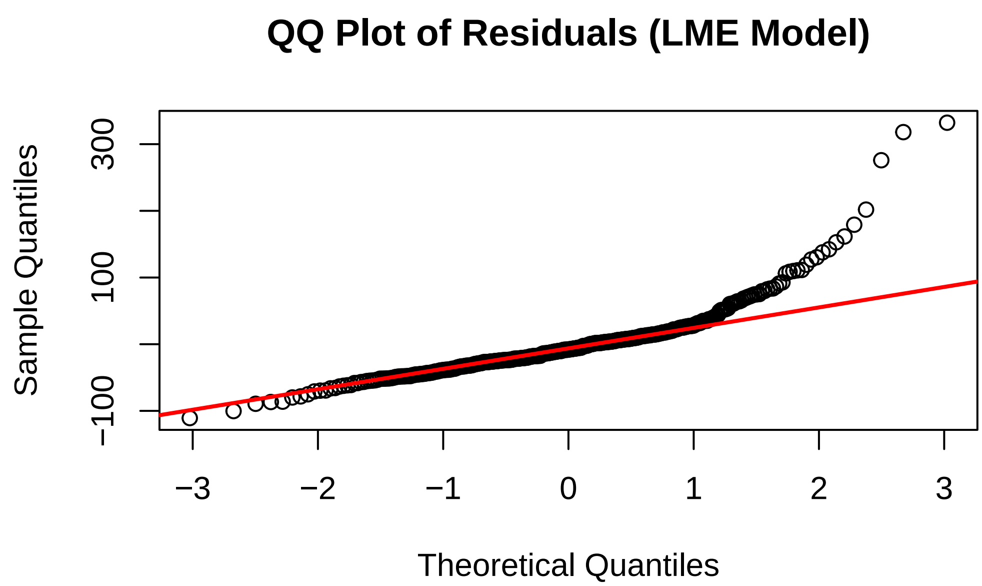
```
Linear mixed model fit by REML. t-tests use Satterthwaite's method [
lmerModLmerTest]
Formula: time ~ hand + attempt + DOMINANCE + GENDER + AGE + BACKGROUND +
    STARTING.ARRANGEMENT + SUBJECTIVE.EASIER + (1 | id)
   Data: df

REML criterion at convergence: 4256.9

Scaled residuals:
    Min      1Q  Median      3Q     Max
-2.1302 -0.5176 -0.1503  0.2787  6.3889

Random effects:
 Groups   Name        Variance Std.Dev.
```

```
 id       (Intercept)  344.4   18.56
 Residual             2703.7   52.00
Number of obs: 400, groups:  id, 20

Fixed effects:
                        Estimate Std. Error       df t value Pr(>|t|)
(Intercept)              87.8306    36.0192  12.6052   2.438   0.0304 *
handDHP                  27.3700     5.1997 378.0000   5.264 2.37e-07 ***
attempt                  -8.4818     0.9051 378.0000  -9.371  < 2e-16 ***
DOMINANCER              -32.3687    15.8909  12.0000  -2.037   0.0643 .
GENDERM                 -21.5642    16.9821  12.0000  -1.270   0.2282
AGE                       0.6211     0.7917  12.0000   0.784   0.4480
BACKGROUNDORDERLY         7.2648    14.3503  12.0000   0.506   0.6219
BACKGROUNDSTUDENT        31.7964    19.7891  12.0000   1.607   0.1341
STARTING.ARRANGEMENTDHP   4.2946    11.2468  12.0000   0.382   0.7092
SUBJECTIVE.EASIERDHP      4.8933    12.9535  12.0000   0.378   0.7122
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:
            (Intr) hndDHP attmpt DOMINA GENDER AGE    BACKGROUNDO BACKGROUNDS
handDHP     -0.072
attempt     -0.138  0.000
DOMINANCER  -0.391  0.000  0.000
GENDERM     -0.451  0.000  0.000  0.454
AGE         -0.829  0.000  0.000 -0.039  0.114
BACKGROUNDO -0.340  0.000  0.000 -0.264 -0.345  0.443
BACKGROUNDS -0.155  0.000  0.000 -0.382 -0.489  0.382  0.584
STARTING.AR -0.428  0.000  0.000  0.065  0.397  0.262 -0.002      -0.165
SUBJECTIVE. -0.417  0.000  0.000  0.203  0.524  0.150  0.092      -0.128
            STARTI
handDHP
attempt
DOMINANCER
GENDERM
AGE
BACKGROUNDO
BACKGROUNDS
STARTING.AR
SUBJECTIVE.  0.163
```

5.1: Diagnostic check

5.1.1

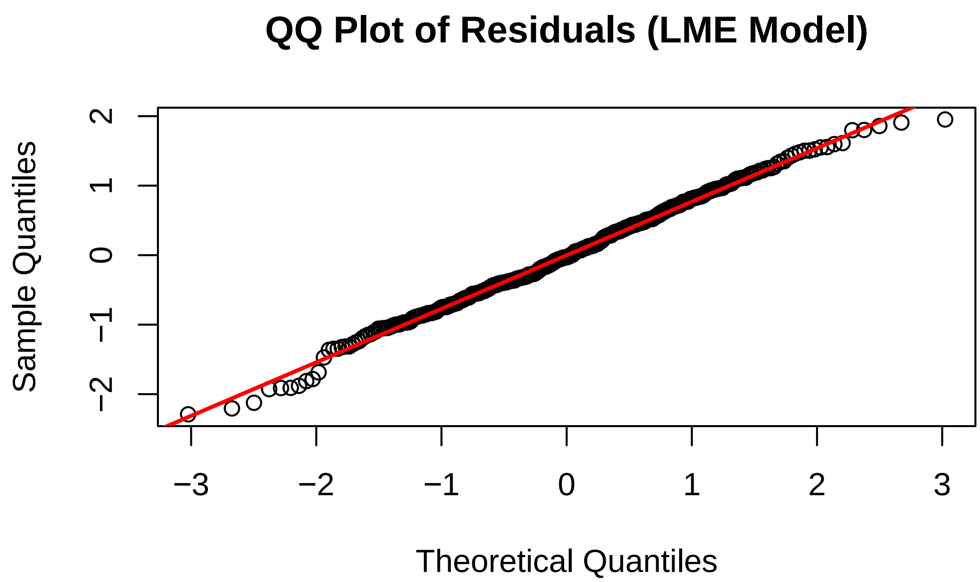
```r
## QQ plot for model
resid_lmer <- resid(model)

qqnorm(resid_lmer, main="QQ Plot of Residuals (LME Model)")
qqline(resid_lmer, col="red",lwd=2)
```



5.1.2 LMM With Log Time As The Response Variable

```r
model_log <- lmer(
  log(time) ~ hand + attempt + DOMINANCE + GENDER + AGE +
              BACKGROUND + STARTING.ARRANGEMENT + SUBJECTIVE.EASIER +
              (1 | id),
  data = df
)
resid_log <- resid(model_log)
```

```r
qqnorm(resid_log, main="QQ Plot of Residuals (LME Model)")
qqline(resid_log, col="red",lwd=2)
```



6.1.1 Fitting model

```r
library(minpack.lm)

exp_model <- nlsLM(
  time ~ alpha + beta * exp(-lambda * attempt),
  data = df,
  start = list(alpha = 40, beta = 80, lambda = 0.25),
  lower = c(1, 0, 0),    # alpha > 0, beta > 0, lambda > 0
  control = nls.lm.control(maxiter = 200)
)
```

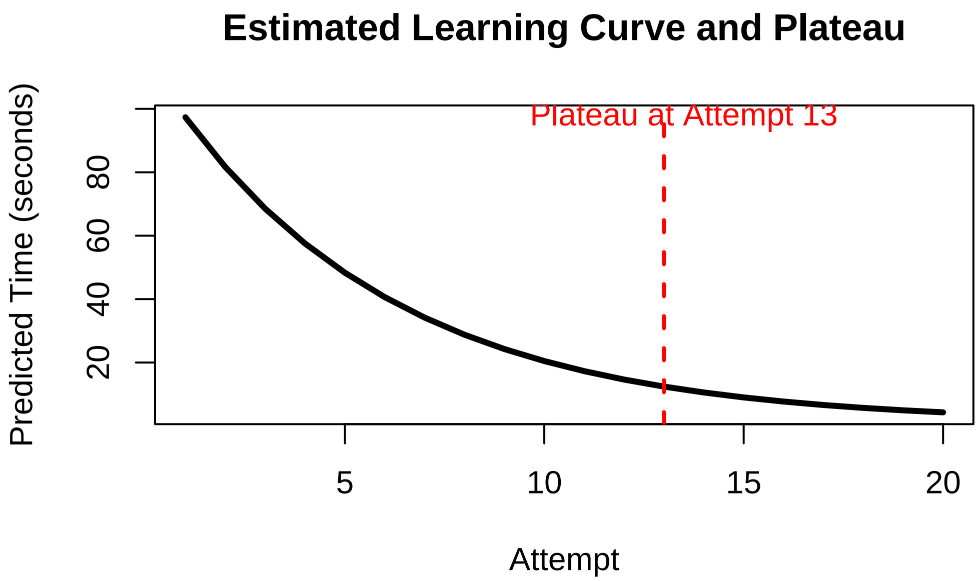
6.2.1 Plateau attempt number

```
# Extract parameters
alpha <- coef(exp_model)['alpha']
beta <- coef(exp_model)['beta']
lambda <- coef(exp_model)['lambda']

# Finding the improvement after attempt k:
# k is given by the formula: predicted_time(k) - predicted_time(k+1)
delta_k <- function(k){
  (alpha+beta*exp(-lambda*k))-(alpha+beta*exp(-lambda*(k+1)))
}

threshold <- 2
plateau_attempt <- which(delta_k(1:20) < threshold)[1]
plateau_attempt
```

```
[1] 13
```

6.2.2 Plot of Predicted Learning Curve & Time at attempt 13

```
attempt_vals <- 1:20
pred <- alpha+beta*exp(-lambda*attempt_vals)

plot(attempt_vals,pred,type="l",lwd=3,
     xlab="Attempt",ylab="Predicted Time (seconds)",
     main = "Estimated Learning Curve and Plateau")

abline(v = plateau_attempt,col="red",lwd=2,lty=2)
text(plateau_attempt+0.5,max(pred),
     paste("Plateau at Attempt",plateau_attempt),
     col="red")
```




```r
time_at_plateau <- alpha + beta * exp(-lambda * plateau_attempt)
time_at_plateau
```

```
   alpha
12.41927
```

References

1. UCLA. (2024). *Introduction to Linear Mixed Models.* Stats.oarc.ucla.edu. https://stats.oarc.ucla.edu/other/mult-pkg/introduction-to-linear-mixed-models/

2. "NlsLM Function - RDocumentation."*Rdocumentation.org*, 2023,

   www.rdocumentation.org/packages/minpack.lm/versions/1.2-4/topics/nlsLM. Accessed 15 Dec. 2025.