Picture Naming Analysis

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1 Reading the Data File

2 Reading File

```
> pic = read.csv("CompiledPictureNaming_Degraded.csv", header = TRUE, sep = ",")
> pic_mainvariables = pic[, c(2,3,22,26,28,31,33,36,37,8)]
> colnames(pic_mainvariables) = c("Subject", "Session", "Trial", "Object",
+                   "PictureType", "RT", "ObjectNo",  "Accuracy",
+                   "InvalidTrial", "ItemCount")
>
```

3 Excluding Subjects

```
> ## we exclude some subjects from all further RT analyses here
> library(dplyr)
> numitems = group_by(pic_mainvariables, Subject, ItemCount)%>%
+     summarise(count = n())
> ## each subject has 201 items: see how many in each condition
>
> numitems_sub_type = group_by(pic_mainvariables, Subject, PictureType, ItemCount)%>%
+     summarise(count = n())
> agg_sub = group_by(pic_mainvariables, Subject)%>%
+     summarise_at(vars(Accuracy), mean)
> #which(agg_sub$Accuracy < 0.51) -- no subject scored less than 50%
```

4 Separating Intact and Degaraded

```
> #separating out full and degraded trials
>
> pic_intact_orig = pic_mainvariables %>% filter(PictureType == "FullPicture")
> pic_degraded_orig = pic_mainvariables %>% filter(PictureType == "DegradedPicture")
> ## removing error trials separately for intact and degraded
> pic_intact = pic_intact_orig %>% filter(InvalidTrial == "0" &
```

```
+                                        Accuracy == "1")
> ## removes 14.6% trials
> pic_degraded = pic_degraded_orig %>% filter(InvalidTrial == "0" &
+                                        Accuracy == "1")
> ## removes 16.07% trials
```

5 Making the z-scores

```
> library(dplyr)
> pic_firsttrim_intact = pic_intact %>% filter( RT > 250 & RT < 5000)
> # removes 0.24% trials
> pic_firsttrim_degraded = pic_degraded %>% filter( RT > 250 & RT < 5000)
> # removes 0.49% trials
```

For Intact

```
> ### FOR INTACT PICTURES
> ## aggregate per subject all IVs and DVs
> meanRT_intact = group_by(pic_firsttrim_intact, Subject) %>%
+   summarise_at(vars(RT), mean)
> colnames(meanRT_intact) = c("Subject", "MeanRT")
> sdRT_intact = group_by(pic_firsttrim_intact, Subject) %>%
+   summarise_at(vars(RT), sd)
> colnames(sdRT_intact) = c("Subject", "sdRT")
> RT_agg = merge(meanRT_intact, sdRT_intact, by = "Subject")
> ## merge aggregate info with long data
> pic_z_intact = merge(pic_firsttrim_intact, RT_agg, by = "Subject", all.x = T)
> ## person and grand-mean centered scores using original and aggregate
> library(dplyr)
> pic_z_intact = pic_z_intact %>% mutate(zRT = (RT - MeanRT)/sdRT)
> ## checking: subject level means should be zero
>
> sub_pic = group_by(pic_z_intact, Subject) %>%
+   summarise_at(vars(zRT), mean)
>
> #write.csv(pic_z, file="pic_z.csv")
```

For Degraded

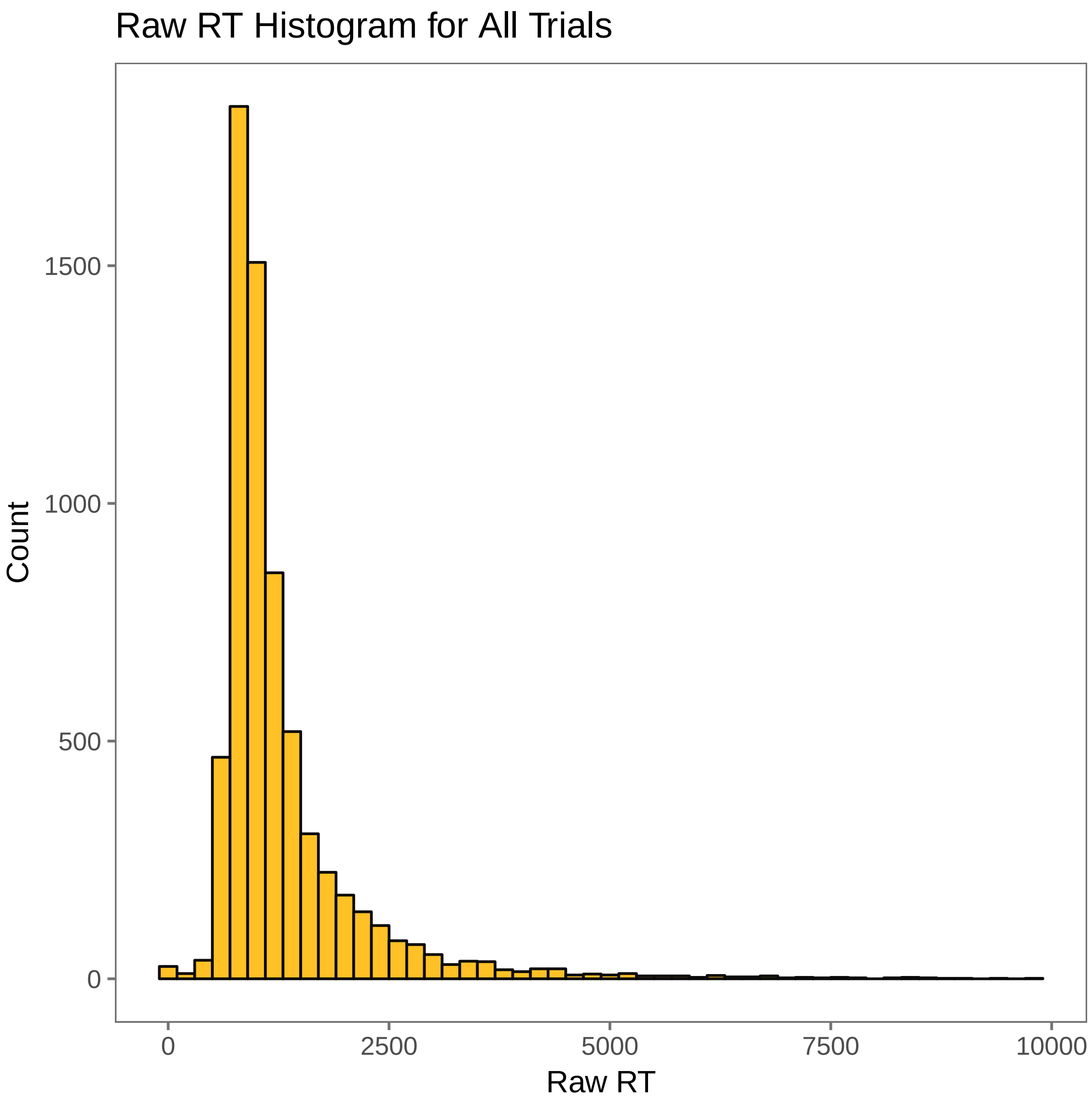
```
> ### FOR DEGRADED PICTURES
> ## aggregate per subject all IVs and DVs
> meanRT_degraded = group_by(pic_firsttrim_degraded, Subject) %>%
+   summarise_at(vars(RT), mean)
> colnames(meanRT_degraded) = c("Subject", "MeanRT")
```

```
> sdRT_degraded = group_by(pic_firsttrim_degraded, Subject) %>%
+   summarise_at(vars(RT), sd)
> colnames(sdRT_degraded) = c("Subject", "sdRT")
> RT_agg = merge(meanRT_degraded, sdRT_degraded, by = "Subject")
> ## merge aggregate info with long data
> pic_z_degraded = merge(pic_firsttrim_degraded, RT_agg, by = "Subject", all.x = T)
> ## person and grand-mean centered scores using original and aggregate
> library(dplyr)
> pic_z_degraded = pic_z_degraded %>% mutate(zRT = (RT - MeanRT)/sdRT)
> ## checking: subject level means should be zero
>
> sub_pic = group_by(pic_z_degraded, Subject) %>%
+   summarise_at(vars(zRT), mean)
>
> #write.csv(pic_z, file="pic_z.csv")
```

6 Histograms for raw and z-RT

Raw RT

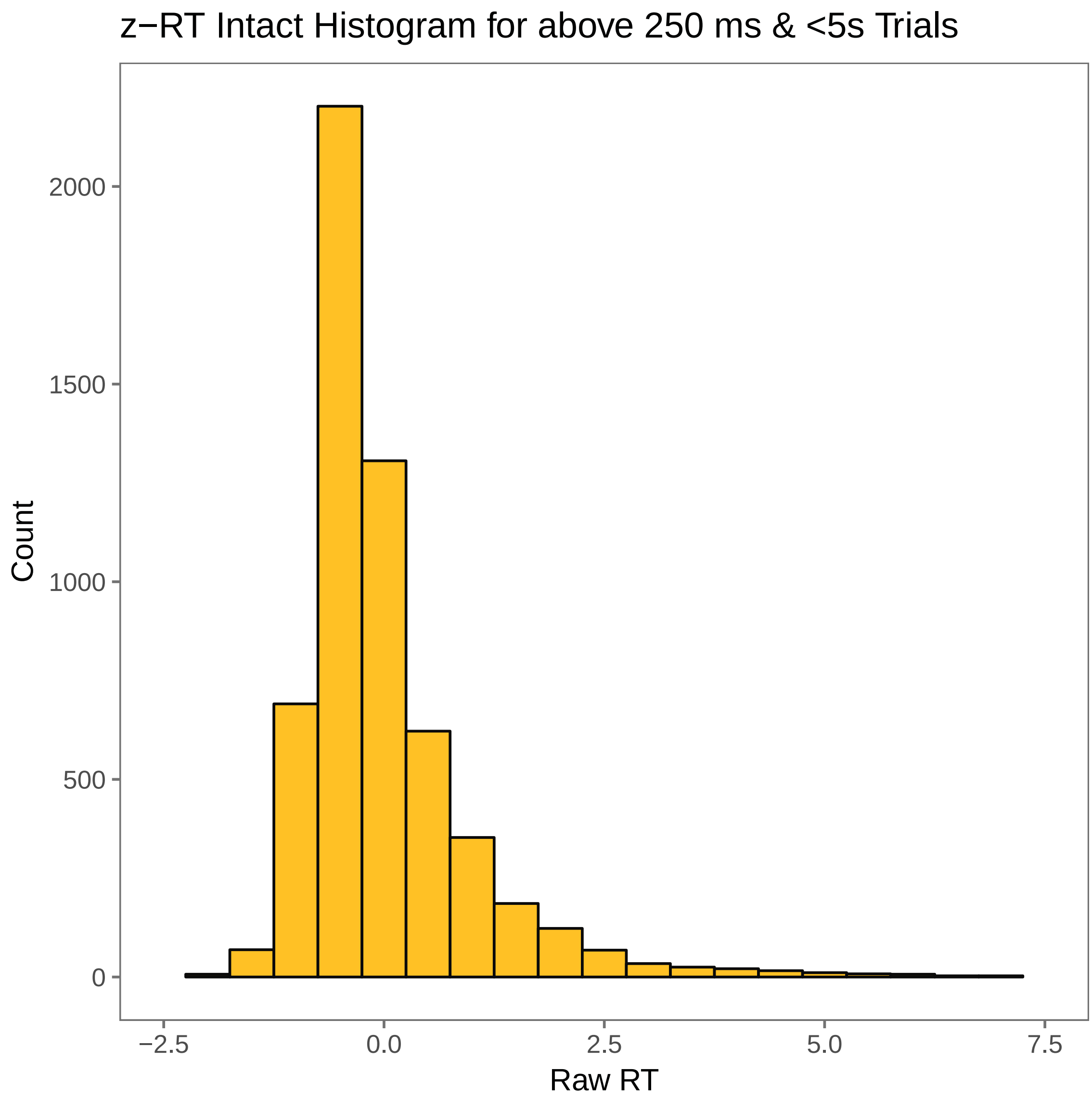
```
> library(ggplot2)
> library(ggthemes)
> ggplot(pic_degraded_orig, aes(x = RT))+
+ geom_histogram(binwidth = 200, color = "gray4", fill = "goldenrod1")+
+     theme_few()+
+   xlab("Raw RT") + ylab("Count") +
+   ggtitle("Raw RT Histogram for All Trials")
```



z RT

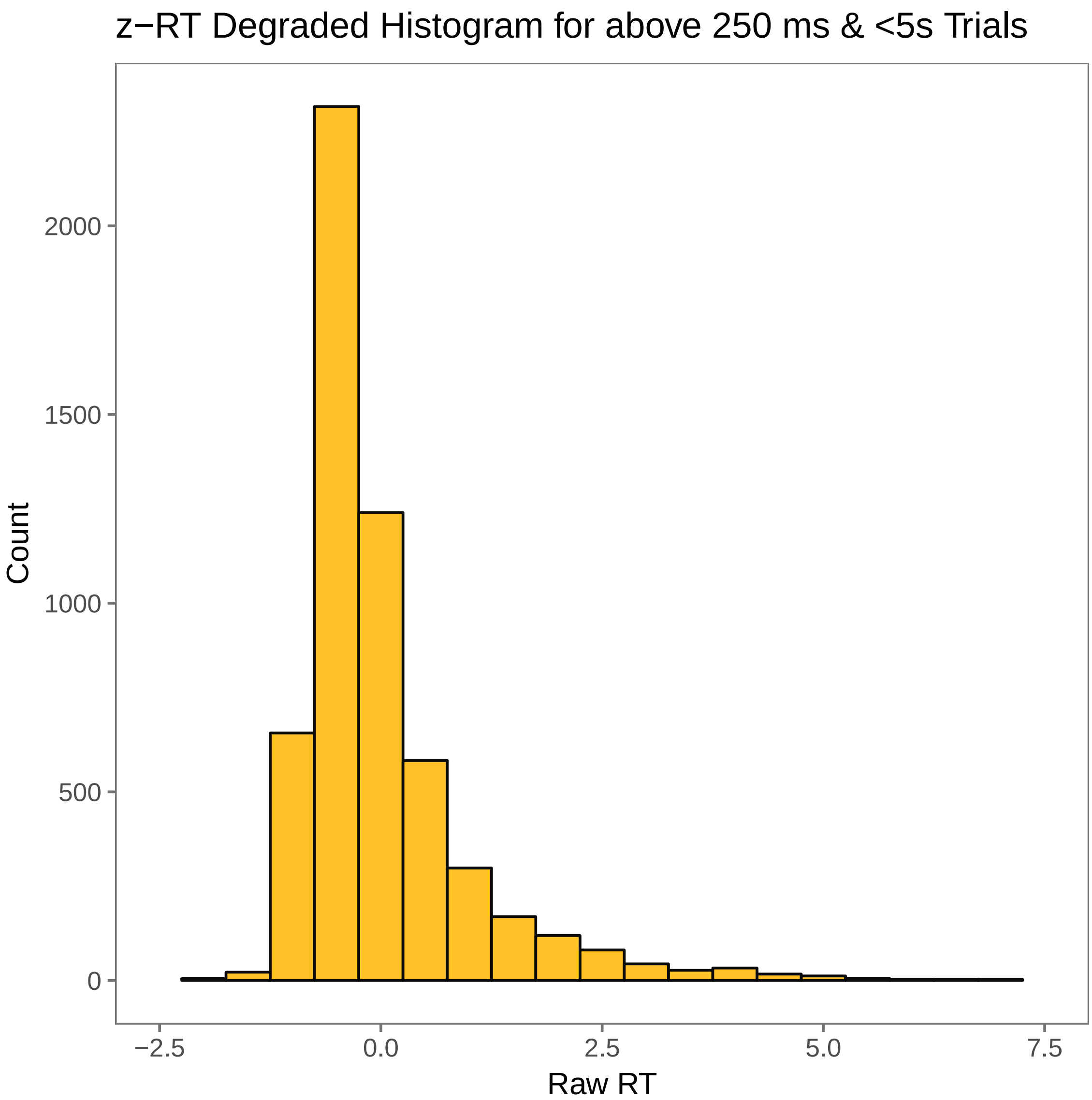
Intact

```
> ggplot(pic_z_intact, aes(x = zRT))+
+ geom_histogram(binwidth = 0.5, color = "gray4", fill = "goldenrod1")+
+     theme_few()+
+   xlim(-2.5,7.5)+
+   xlab("Raw RT") + ylab("Count") +
+   ggtitle("z-RT Intact Histogram for above 250 ms & <5s Trials")
```



Degraded

```
> ggplot(pic_z_degraded, aes(x = zRT))+
+ geom_histogram(binwidth = 0.5, color = "gray4", fill = "goldenrod1")+
+     theme_few()+
+   xlim(-2.5,7.5)+
+   xlab("Raw RT") + ylab("Count") +
+   ggtitle("z-RT Degraded Histogram for above 250 ms & <5s Trials")
```



Trimming zRT

```
> ## trimming above and below 3 s.d.
> pic_intact_trimmed = pic_z_intact %>% filter(zRT < 3 & zRT > -3)
> pic_degraded_trimmed = pic_z_degraded %>% filter(zRT < 3 & zRT > -3)
```

7 Repeat z-scoring after trimming

7.1 For Intact

```
> library(dplyr)
> ## aggregate per subject all IVs and DVs
> meanRT_trim_intact = group_by(pic_intact_trimmed, Subject) %>%
+   summarise_at(vars(RT), mean)
> colnames(meanRT_trim_intact) = c("Subject", "MeanRT_trim")
> sdRT_trim_intact = group_by(pic_intact_trimmed, Subject) %>%
+   summarise_at(vars(RT), sd)
> colnames(sdRT_trim_intact) = c("Subject", "sdRT_trim")
> RT_agg_trim = merge(meanRT_trim_intact, sdRT_trim_intact, by = "Subject")
> ## merge aggregate info with long data
> new_intact_z = merge(pic_intact_trimmed, RT_agg_trim, by = "Subject", all.x = T)
> ## person and grand-mean centered scores using original and aggregate
> library(dplyr)
> new_intact_z = new_intact_z %>% mutate(zRT_trim = (RT - MeanRT_trim)/sdRT_trim)
> ## checking: subject level means should be zero
>
> sub_pic = group_by(new_intact_z, Subject) %>%
+   summarise_at(vars(zRT_trim), mean)
>
> #write.csv(new_intact_z, file="final_pic_z.csv")
```

7.2 For Degraded

```
> library(dplyr)
> ## aggregate per subject all IVs and DVs
> meanRT_trim_degraded = group_by(pic_degraded_trimmed, Subject) %>%
+   summarise_at(vars(RT), mean)
> colnames(meanRT_trim_degraded) = c("Subject", "MeanRT_trim")
> sdRT_trim_degraded = group_by(pic_degraded_trimmed, Subject) %>%
+   summarise_at(vars(RT), sd)
> colnames(sdRT_trim_degraded) = c("Subject", "sdRT_trim")
> RT_agg_trim = merge(meanRT_trim_degraded, sdRT_trim_degraded, by = "Subject")
> ## merge aggregate info with long data
> new_degraded_z = merge(pic_degraded_trimmed, RT_agg_trim, by = "Subject", all.x = T)
> ## person and grand-mean centered scores using original and aggregate
> library(dplyr)
> new_degraded_z = new_degraded_z %>%
+     mutate(zRT_trim = (RT - MeanRT_trim)/sdRT_trim)
> ## checking: subject level means should be zero
>
> sub_pic = group_by(new_degraded_z, Subject) %>%
+   summarise_at(vars(zRT_trim), mean)
>
> #write.csv(new_intact_z, file="final_pic_z.csv")
```

8 Combining Separate z

```
> main_intact = new_intact_z[,c(1,3,4,5,6,7,8,16)]
> main_degraded = new_degraded_z[,c(1,3, 4,5, 6,7,8,16)]
>   final_pic_z = rbind(main_intact, main_degraded)
> final_pic_z = final_pic_z[order(final_pic_z$Subject),]
```

9 z-Scoring a different way

```
> pic_valid = pic_mainvariables %>% filter(InvalidTrial == "0" &
+                                     Accuracy == "1")
> pic_firsttrim = pic_valid %>% filter( RT > 250 & RT < 5000)
> meanRT = group_by(pic_firsttrim, Subject) %>%
+   summarise_at(vars(RT), mean)
> colnames(meanRT) = c("Subject", "MeanRT")
> sdRT = group_by(pic_firsttrim, Subject) %>%
+   summarise_at(vars(RT), sd)
> colnames(sdRT) = c("Subject", "sdRT")
> RT_agg = merge(meanRT, sdRT, by = "Subject")
> ## merge aggregate info with long data
> pic_z = merge(pic_firsttrim, RT_agg, by = "Subject", all.x = T)
> ## person and grand-mean centered scores using original and aggregate
> library(dplyr)
> pic_z = pic_z %>% mutate(zRT = (RT - MeanRT)/sdRT)
> ## checking: subject level means should be zero
>
> sub_pic = group_by(pic_z, Subject) %>%
+   summarise_at(vars(zRT), mean)
> pic_trimmed = pic_z %>% filter(zRT < 3 & zRT > -3)
> #### REPEATING Z SCORING ########
>
> ## aggregate per subject all IVs and DVs
> meanRT_trim = group_by(pic_trimmed, Subject) %>%
+   summarise_at(vars(RT), mean)
> colnames(meanRT_trim) = c("Subject", "MeanRT_trim")
> sdRT_trim = group_by(pic_trimmed, Subject) %>%
+   summarise_at(vars(RT), sd)
> colnames(sdRT_trim) = c("Subject", "sdRT_trim")
> RT_agg_trim = merge(meanRT_trim, sdRT_trim, by = "Subject")
> ## merge aggregate info with long data
> new_z = merge(pic_trimmed, RT_agg_trim, by = "Subject", all.x = T)
> ## person and grand-mean centered scores using original and aggregate
> library(dplyr)
> new_z = new_z %>% mutate(zRT_trim = (RT - MeanRT_trim)/sdRT_trim)
> ## checking: subject level means should be zero
>
```

```
> sub_pic = group_by(new_z, Subject) %>%
+   summarise_at(vars(zRT_trim), mean)
```

10 Aggregating RTs and Accuracy

```
> library(dplyr)
> agg_pic_validRT = group_by(new_z, Subject, PictureType)%>%
+     summarise_at(vars(Accuracy, zRT), mean)
> agg_pic_validRT$Subject ← as.factor(agg_pic_validRT$Subject)
> agg_pic_validRT$PictureType ← as.factor(agg_pic_validRT$PictureType)
> pic_RT_aov ← aov(zRT ~ PictureType + Error(Subject/PictureType),
+                  data = agg_pic_validRT )
> summary(pic_RT_aov)
```

```
Error: Subject
          Df  Sum Sq  Mean Sq F value Pr(>F)
Residuals 66 0.08475 0.001284

Error: Subject:PictureType
            Df Sum Sq Mean Sq F value   Pr(>F)
PictureType  1  2.898  2.8977   81.86 3.58e-13 ***
Residuals   66  2.336  0.0354
---
Signif. codes:  0 âĂŸ***âĂŹ 0.001 âĂŸ**âĂŹ 0.01 âĂŸ*âĂŹ 0.05 âĂŸ.âĂŹ 0.1 âĂŸ âĂŹ 1
```

```
> pic_acc_aov ← aov(Accuracy ~ PictureType + Error(Subject/PictureType),
+                   data = agg_pic_validRT)
> summary(pic_acc_aov)
```

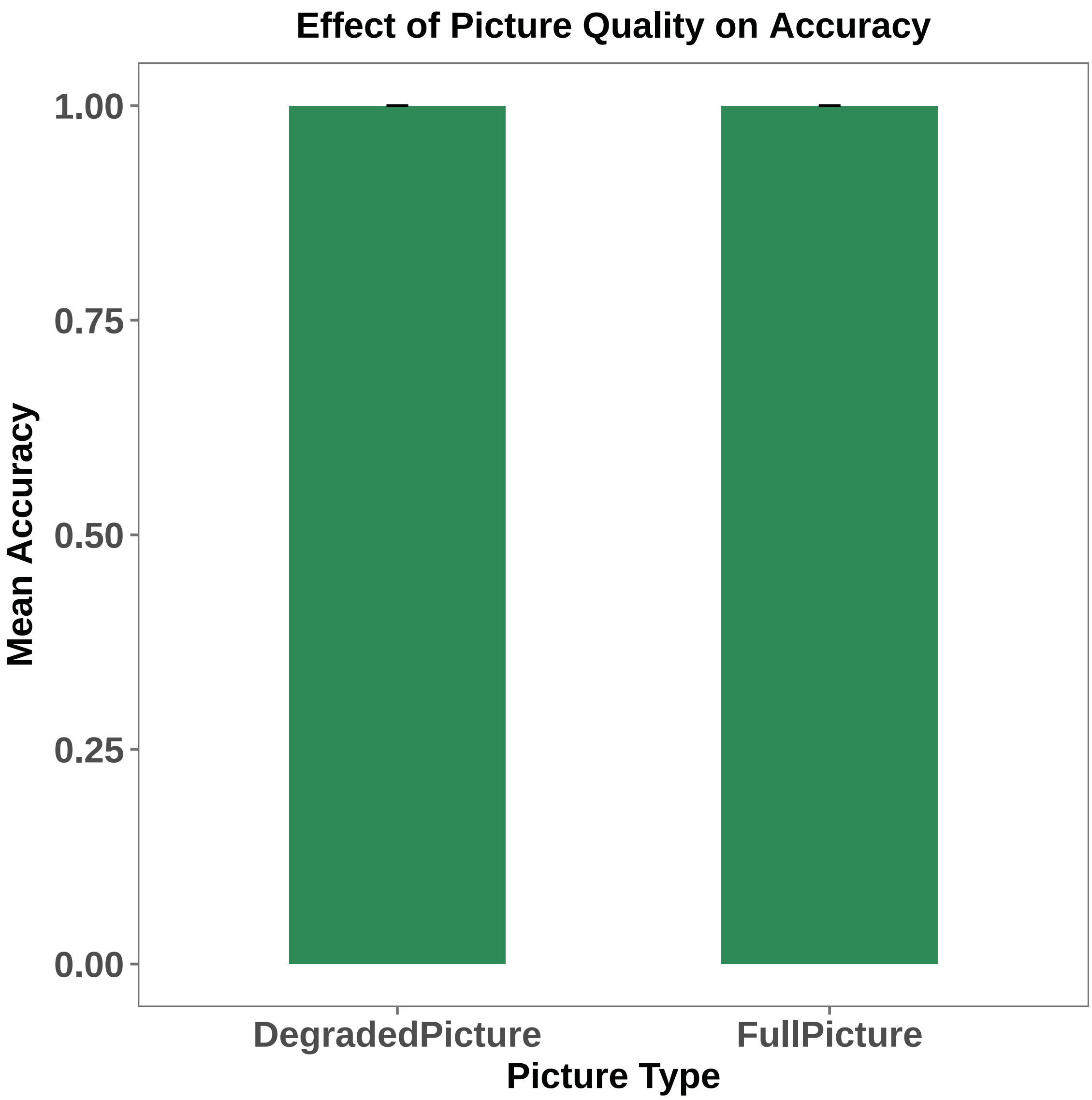
```
Error: Subject
          Df    Sum Sq   Mean Sq F value Pr(>F)
Residuals 66 2.636e-28 3.994e-30

Error: Subject:PictureType
            Df    Sum Sq   Mean Sq F value Pr(>F)
PictureType  1 3.990e-30 3.994e-30       1  0.321
Residuals   66 2.636e-28 3.994e-30
```

11 Plotting Accuracy and RT

Plotting Accuracy

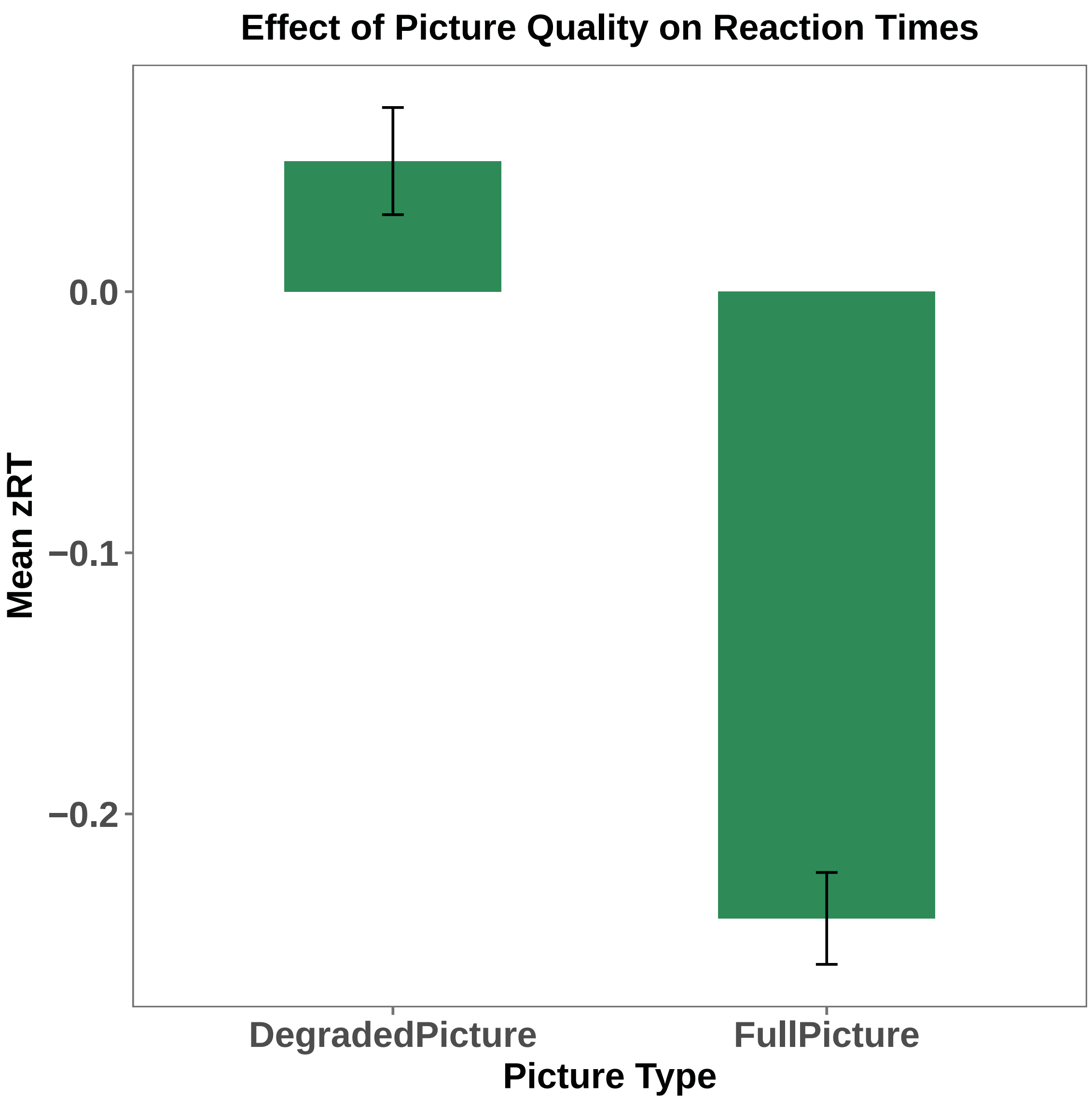
```
> library(Rmisc)
> agg_pic_plot_rmisc = summarySE(new_z,
```

```
+                         measurevar = "Accuracy",
+                         groupvars = c("PictureType"))
> ggplot(agg_pic_plot_rmisc, aes(x = PictureType, y = Accuracy))+
+  geom_bar(stat = "identity", position = "dodge", width = 0.5, fill = "seagreen")+
+   geom_errorbar(aes(ymin = Accuracy - ci, ymax = Accuracy + ci),
+                 width=.05, position=position_dodge(.5)) +
+   theme_few()+
+   xlab("Picture Type") + ylab("Mean Accuracy") +
+   ggtitle("Effect of Picture Quality on Accuracy") +
+     theme(axis.text = element_text(face = "bold", size = rel(1.2)),
+           axis.title = element_text(face = "bold", size = rel(1.2)),
+           legend.title = element_text(face = "bold", size = rel(1.2)),
+           plot.title = element_text(face = "bold", size = rel(1.2), hjust = .5))
```




```
> agg_pic_validRT_plot_rmisc = summarySE(new_z,
+                          measurevar = "zRT",
+                          groupvars = c("PictureType"))
> agg_pic_validRT_plot_rmisc$zRT = round(agg_pic_validRT_plot_rmisc$zRT, digits = 2)
> ggplot(agg_pic_validRT_plot_rmisc, aes(x = PictureType, y = zRT))+
+  geom_bar(stat = "identity", position = "dodge", width = 0.5, fill = "seagreen")+
+   geom_errorbar(aes(ymin = zRT - ci, ymax = zRT + ci),
+                 width=.05, position=position_dodge(.5)) +
+   theme_few()+
+   xlab("Picture Type") + ylab("Mean zRT") +
+   ggtitle("Effect of Picture Quality on Reaction Times") +
```

```
+      theme(axis.text = element_text(face = "bold", size = rel(1.2)),
+            axis.title = element_text(face = "bold", size = rel(1.2)),
+            legend.title = element_text(face = "bold", size = rel(1.2)),
+            plot.title = element_text(face = "bold", size = rel(1.2), hjust = .5))
```



12 Fetching AoA data and Merging

```
> AoA ← read.csv("AoA_51715_words.csv", header = TRUE, sep = ",")
```

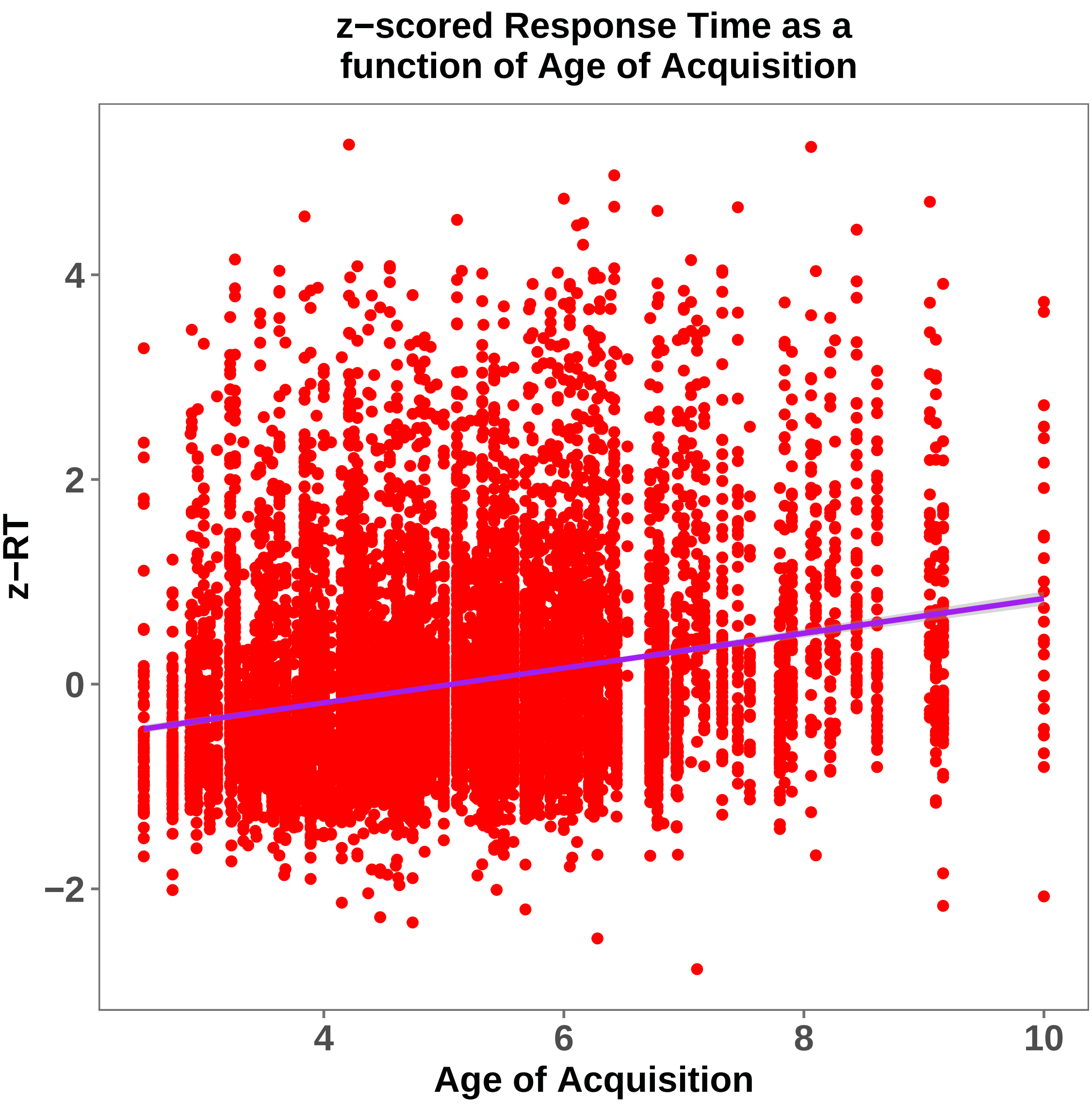
```
> ### final_pic_z combines z-scores from separately z-scored intact and degraded
```

```
> pic_withAoA_z = merge(final_pic_z, AoA, by = "Object")
> pic_withAoA_z = pic_withAoA_z[, c(1:8, 18)]
> pic_withAoA_z = pic_withAoA_z[order(pic_withAoA_z$Subject),]
> ### ALSO MERGING WITH THE COMBINED Z SCORING DATA SET : new_z
>
> new_z_AoA = merge(new_z, AoA, by = "Object")
> new_z_AoA = new_z_AoA[, c(1:17, 26)]
> new_z_AoA = new_z_AoA[order(new_z_AoA$Subject),]
```

13 Actual Plots

zRT and AoA

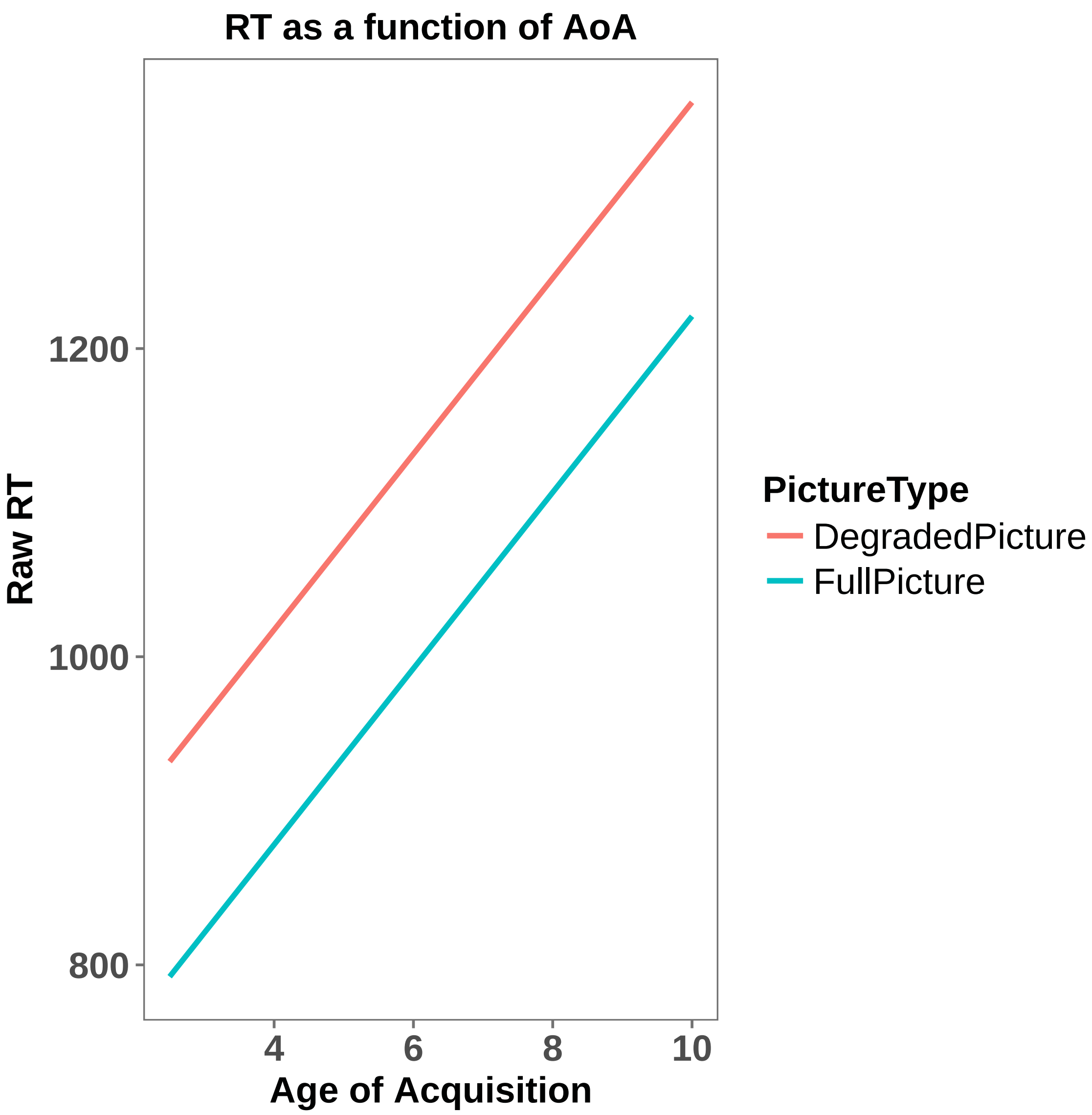
```
> ggplot(new_z_AoA, aes(x = AoA_Kup_lem, y = zRT_trim))+
+  geom_point(color = "red")+
+   geom_smooth(method = "lm", color = "purple")+
+  theme_few()+
+   xlab("Age of Acquisition") + ylab("z-RT") +
+   ggtitle("z-scored Response Time as a\n function of Age of Acquisition")+
+     theme(axis.text = element_text(face = "bold", size = rel(1.2)),
+           axis.title = element_text(face = "bold", size = rel(1.2)),
+           legend.title = element_text(face = "bold", size = rel(1.2)),
+           plot.title = element_text(face = "bold", size = rel(1.2), hjust = .5))
```



Raw Plot by Picture Type

```
> ggplot(new_z_AoA, aes(x = AoA_Kup_lem, y = RT,
+                          group = PictureType, color = PictureType))+
+   #geom_point(aes(color = PictureType))+
+    geom_smooth(method = "lm", se = FALSE)+
+   theme_few()+
+    xlab("Age of Acquisition") + ylab("Raw RT") +
+    ggtitle("RT as a function of AoA") +
+      theme(axis.text = element_text(face = "bold", size = rel(1.2)),
```

```
+           axis.title = element_text(face = "bold", size = rel(1.2)),
+           legend.title = element_text(face = "bold", size = rel(1.2)),
+           legend.text = element_text(size = rel(1.2)),
+           plot.title = element_text(face = "bold", size = rel(1.2), hjust = .5))
>
```



14 Regressions

```
> library(lme4)
> m0 = lmer (data = new_z_AoA , zRT_trim ~ AoA_Kup_lem +
```

```
+               (1|Subject) + (1|Trial) + (1|ObjectNo))
> summary(m0)
```

```
Linear mixed model fit by REML ['lmerMod']
Formula: zRT_trim ~ AoA_Kup_lem + (1 | Subject) + (1 | Trial) + (1 | ObjectNo)
   Data: new_z_AoA

REML criterion at convergence: 28691.9

Scaled residuals:
    Min      1Q  Median      3Q     Max
-4.6189 -0.6062 -0.1865  0.3792  4.8338

Random effects:
 Groups   Name        Variance Std.Dev.
 ObjectNo (Intercept) 0.263405 0.5132
 Trial    (Intercept) 0.006724 0.0820
 Subject  (Intercept) 0.000000 0.0000
 Residual             0.719304 0.8481
Number of obs: 11160, groups:  ObjectNo, 200; Trial, 200; Subject, 67

Fixed effects:
            Estimate Std. Error t value
(Intercept) -0.87775    0.14204  -6.180
AoA_Kup_lem  0.18678    0.02642   7.069

Correlation of Fixed Effects:
            (Intr)
AoA_Kup_lem -0.964
```

```
> m1 = lmer (data = new_z_AoA, RT ~ AoA_Kup_lem*PictureType +
+               (1|Subject)+ (1|Trial) + (1|ObjectNo))
> summary(m1)
```

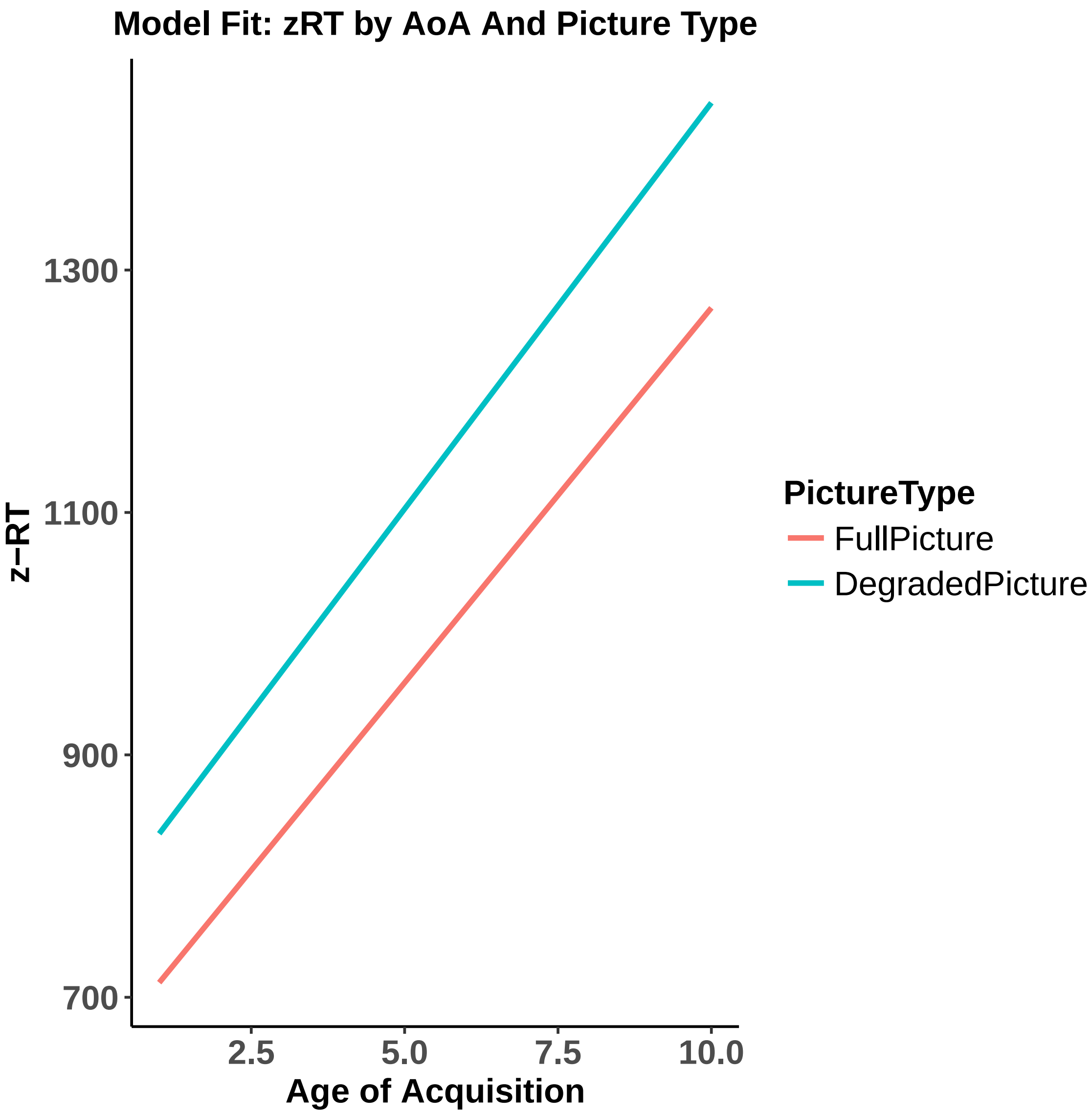
```
Linear mixed model fit by REML ['lmerMod']
Formula: RT ~ AoA_Kup_lem * PictureType + (1 | Subject) + (1 | Trial) +
    (1 | ObjectNo)
   Data: new_z_AoA

REML criterion at convergence: 159318.9

Scaled residuals:
    Min      1Q  Median      3Q     Max
-3.2602 -0.5810 -0.1638  0.3449  6.8369

Random effects:
 Groups   Name        Variance Std.Dev.
 ObjectNo (Intercept) 30288.6  174.0
```

```
 Trial     (Intercept)   829.3   28.8
 Subject   (Intercept) 21944.7  148.1
 Residual              85533.3  292.5
Number of obs: 11160, groups:  ObjectNo, 200; Trial, 200; Subject, 67

Fixed effects:
                                   Estimate Std. Error t value
(Intercept)                         767.958     52.833  14.536
AoA_Kup_lem                          67.005      9.254   7.240
PictureTypeFullPicture             -117.704     22.123  -5.320
AoA_Kup_lem:PictureTypeFullPicture   -5.148      4.222  -1.219

Correlation of Fixed Effects:
            (Intr) AA_Kp_ PctTFP
AoA_Kup_lem -0.906
PctrTypFllP -0.223  0.237
AA_Kp_:PTFP  0.218 -0.246 -0.968
```

15 Plotting Model Fits

AOA and Picture Type

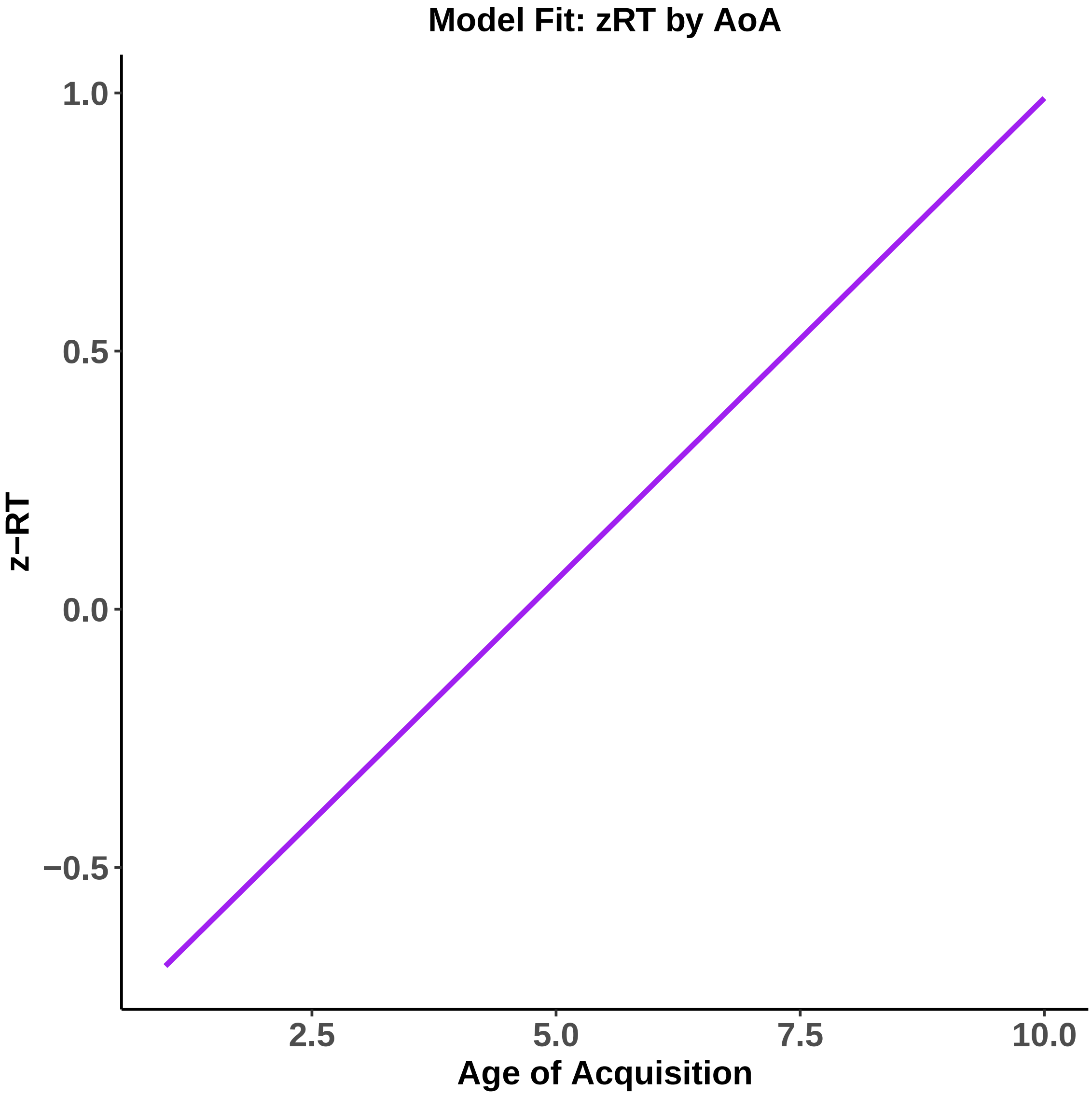
```
> fixed.frame ←
+   data.frame(expand.grid(AoA_Kup_lem = seq(1,10,0.5),
+              PictureType = c("FullPicture","DegradedPicture"))) %>%
+   mutate(pred = predict(m1, newdata = ., re.form = NA))
> fixed.frame %>%
+   mutate(AoA = AoA_Kup_lem) %>%
+   ggplot(aes(x = AoA, y = pred, color = PictureType)) +
+     geom_line(size = 1) +
+     xlab("Age of Acquisition") + ylab ("z-RT")+
+   ggtitle("Model Fit: zRT by AoA And Picture Type")+
+ theme_classic() +
+     theme(axis.text = element_text(face = "bold", size = rel(1.2)),
+           axis.title = element_text(face = "bold", size = rel(1.2)),
+           legend.title = element_text(face = "bold", size = rel(1.2)),
+           legend.text = element_text(size = rel(1.2)),
+           plot.title = element_text(face = "bold", size = rel(1.2), hjust = .5))
```



AOA Only

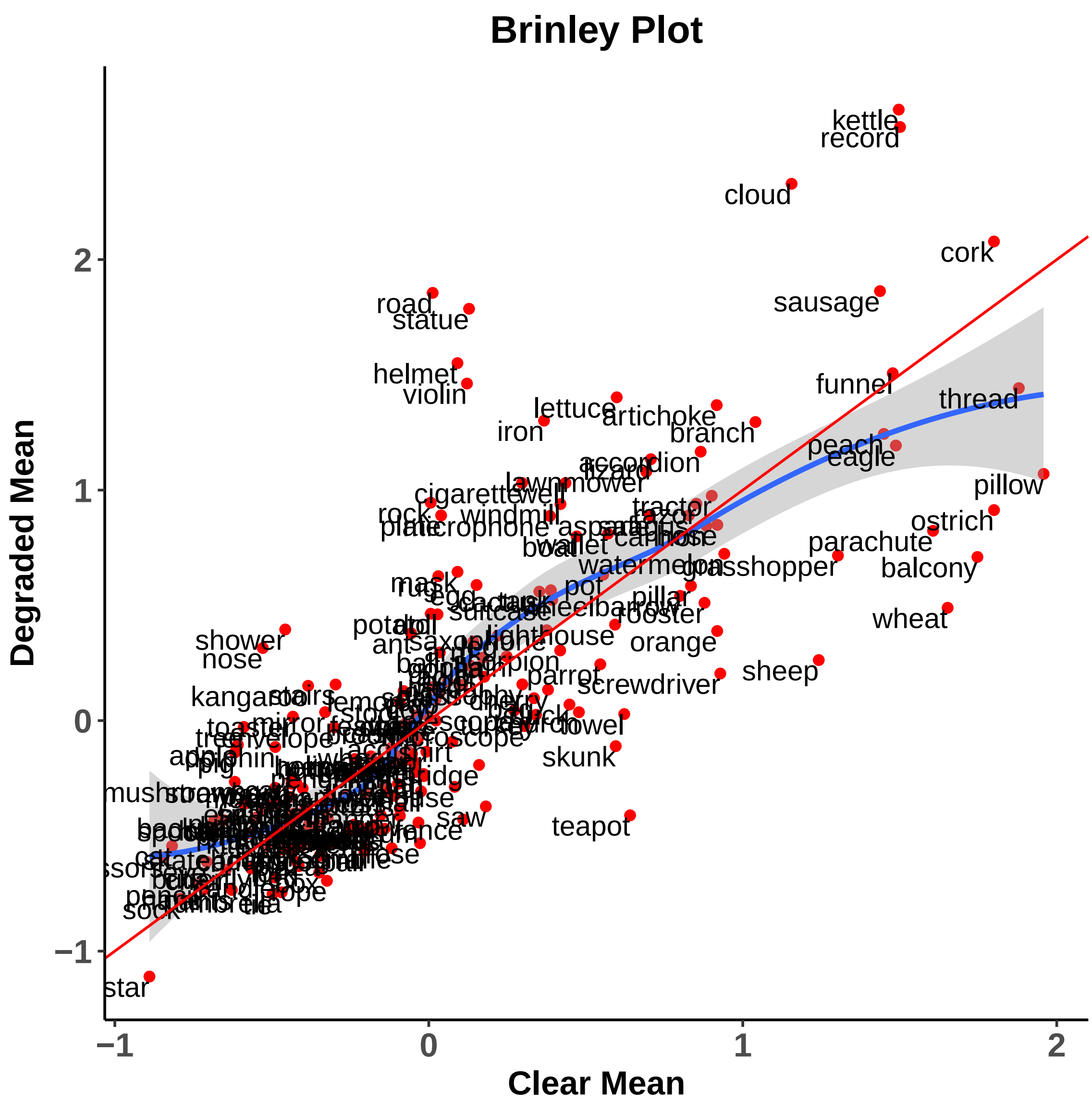
```
> fixed.frame ←
+   data.frame(expand.grid(AoA_Kup_lem = seq(1,10,0.5))) %>%
+   mutate(pred = predict(m0, newdata = ., re.form = NA))
> fixed.frame %>%
+   mutate(AoA = AoA_Kup_lem) %>%
+   ggplot(aes(x = AoA, y = pred)) +
+       geom_line(size = 1, color = "purple") +
+     xlab("Age of Acquisition") + ylab ("z-RT")+
```

```
+   ggtitle("Model Fit: zRT by AoA")+
+ theme_classic()  +
+     theme(axis.text = element_text(face = "bold", size = rel(1.2)),
+           axis.title = element_text(face = "bold", size = rel(1.2)),
+           legend.title = element_text(face = "bold", size = rel(1.2)),
+           legend.text = element_text(size = rel(1.2)),
+           plot.title = element_text(face = "bold", size = rel(1.2), hjust = .5))
```



16 Brinley Plot

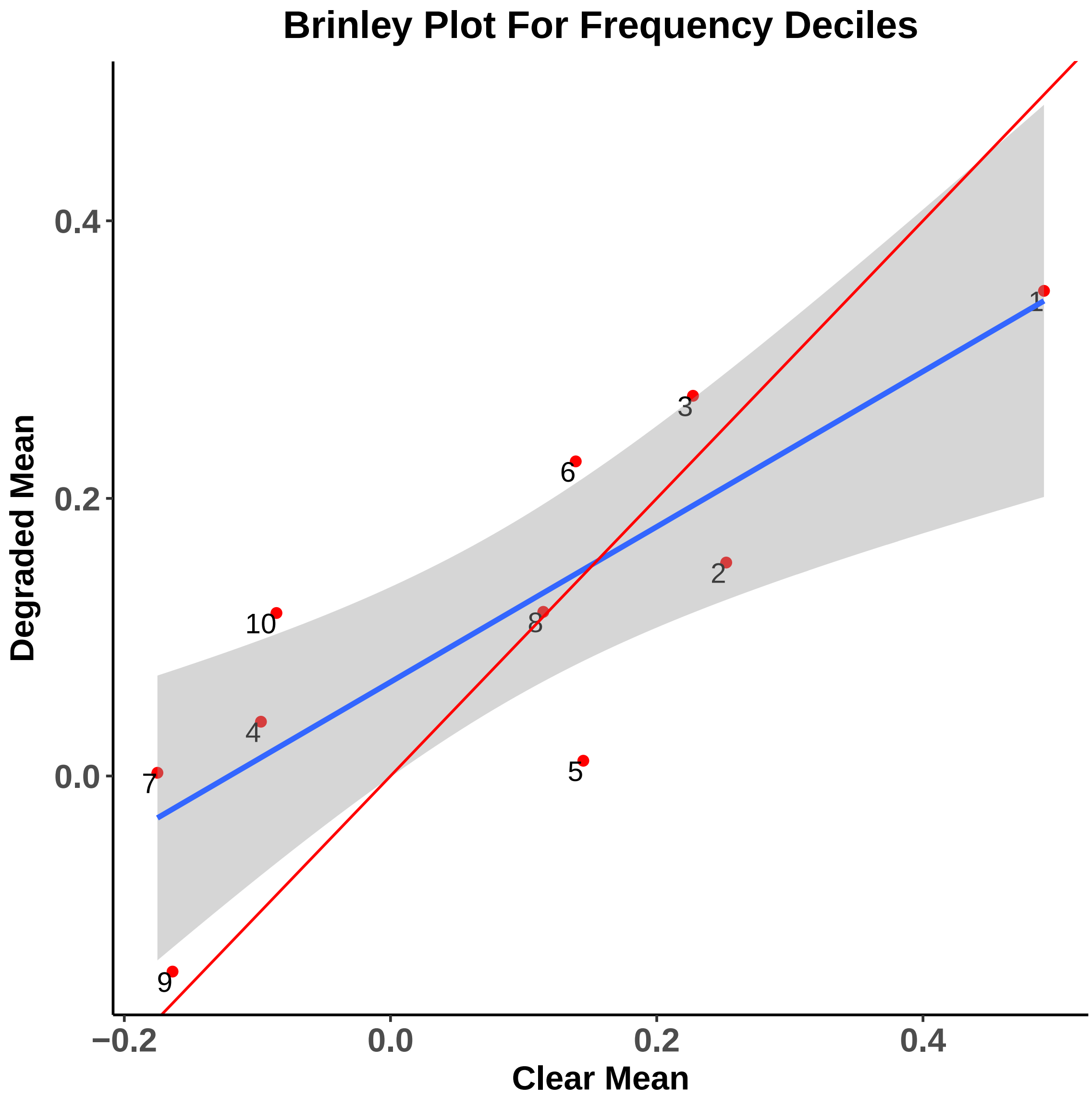
```
> #item_acc contains zRT for degraded and full pictures for each item
> item_brinley = group_by(final_pic_z, Object, PictureType )%>%
+     summarise_at(vars( zRT_trim), mean)
> library(tidyr)
> wide_item = item_brinley %>%
+   spread(PictureType, zRT_trim)
> # Now, we plot these in a brinley plot
> library(ggplot2)
> library(ggthemes)
>   ggplot(wide_item, aes(x = FullPicture, y = DegradedPicture, label = Object)) +
+     geom_point(color = "red")+
+     geom_smooth(method = "loess")+
+         geom_text(aes(label=Object, vjust = 1, hjust = 1))+
+     geom_abline(slope = 1, intercept = 0, color = "red")+
+     xlab("Clear Mean") + ylab ("Degraded Mean")+
+   ggtitle("Brinley Plot")+
+ theme_classic() +
+     theme(axis.text = element_text(face = "bold", size = rel(1.2)),
+           axis.title = element_text(face = "bold", size = rel(1.2)),
+           legend.title = element_text(face = "bold", size = rel(1.2)),
+           plot.title = element_text(face = "bold", size = rel(1.4), hjust = .5))
>
```



Frequency Decile Brinley Plot

```
> item_elp = read.csv("DegradedItems_ELP.csv", header = TRUE, sep = ",")
> item_elp_brinley = merge(item_elp, item_brinley, by  = c("Object"))
> # 398 rows: dropped wheelbarrow
>
> item_elp_brinley$Decile = ntile(item_elp_brinley$Log_Freq_HAL, 10)
> elp_decile_data = group_by(item_elp_brinley, Decile, PictureType) %>%
+   summarize_at(vars(zRT_trim), mean)
> library(tidyr)
```

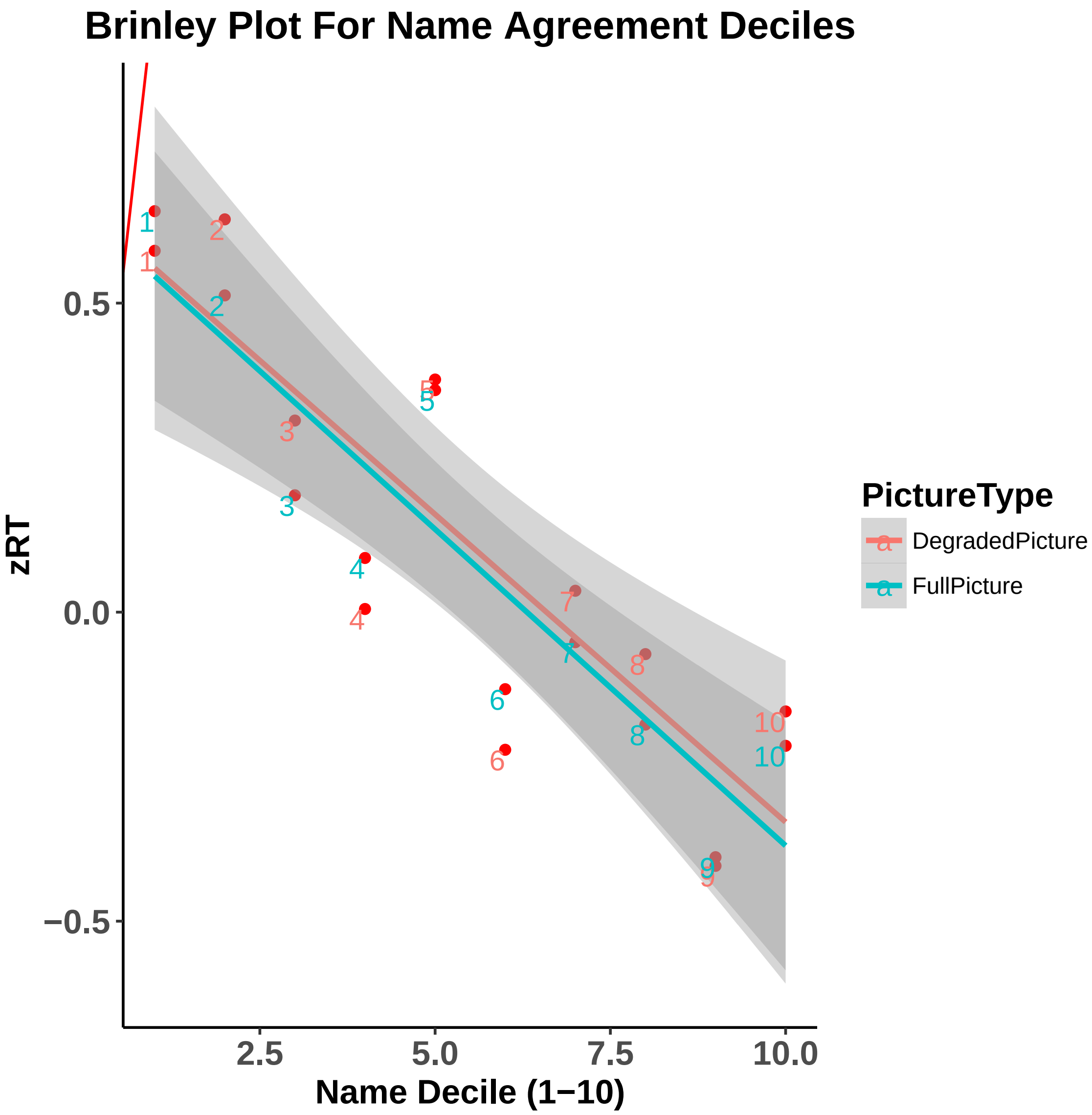
```
> elp_decile_wide = elp_decile_data %>%
+   spread(PictureType, zRT_trim)
> # Now, we plot these in a brinley plot
> library(ggplot2)
> library(ggthemes)
>   ggplot(elp_decile_wide, aes(x = FullPicture, y = DegradedPicture)) +
+     geom_point(color = "red")+
+                  geom_text(aes(label=Decile, vjust = 1, hjust = 1))+
+     geom_smooth(method = "lm")+
+     geom_abline(slope = 1, intercept = 0, color = "red")+
+     xlab("Clear Mean") + ylab ("Degraded Mean")+
+  #    xlim(-0.5,0.5)+
+   ggtitle("Brinley Plot For Frequency Deciles")+
+ theme_classic() +
+     theme(axis.text = element_text(face = "bold", size = rel(1.2)),
+           axis.title = element_text(face = "bold", size = rel(1.2)),
+           legend.title = element_text(face = "bold", size = rel(1.2)),
+           plot.title = element_text(face = "bold", size = rel(1.4), hjust = .5))
>
```



H-Statistic Decile Brinley Plot

```
> marcnorms = read.csv("590MarcNorms.csv", header = TRUE, sep = ",")
>   ## lower H statistic means greater name agreement. So we reverse code
>   marcnorms$NameAgreement = 3.19 - marcnorms$H.statistic
>   # Thus, higher NameAgreement, means higher name agreement
>
> item_marc_brinley = merge(marcnorms, item_brinley, by  = c("Object"))
> # 390 rows: dropped castle, pillow, radio, shower, tank: used anti_join
>
```

```
> item_marc_brinley$Decile = ntile(item_marc_brinley$NameAgreement, 10)
> marc_decile_data = group_by(item_marc_brinley, Decile, PictureType) %>%
+   summarize_at(vars(zRT_trim), mean)
> library(tidyr)
> marc_decile_wide = marc_decile_data %>%
+   spread(PictureType, zRT_trim)
> # Now, we plot these in a brinley plot
> library(ggplot2)
> library(ggthemes)
>   ggplot(marc_decile_data, aes(x = Decile, y = zRT_trim,
+                               group = PictureType, color = PictureType)) +
+     geom_point(color = "red")+
+     geom_smooth(method = "lm")+
+            geom_text(aes(label=Decile, vjust = 1, hjust = 1))+
+     geom_abline(slope = 1, intercept = 0, color = "red")+
+     xlab("Name Decile (1-10)") + ylab ("zRT")+
+    # xlim(-0.6,0.5)+
+   ggtitle("Brinley Plot For Name Agreement Deciles")+
+ theme_classic() +
+     theme(axis.text = element_text(face = "bold", size = rel(1.2)),
+           axis.title = element_text(face = "bold", size = rel(1.2)),
+           legend.title = element_text(face = "bold", size = rel(1.2)),
+           plot.title = element_text(face = "bold", size = rel(1.4), hjust = .5))
>
```



17 Picture Variables

We first create a combined excel file with ALL the relevant variables, so that we can run a regression model eventually.

Combining

```
> marc590 = read.csv("590MarcNorms.csv", header = TRUE, sep = ",")
> ipnp = read.csv("IPNPnorms.csv", header = TRUE, sep = ",")
> ipnp = ipnp[,c(2,3, 5)]
> multipic = read.csv("MultipicNorms.csv", header = TRUE, sep = ",")
```

```
> item_elp = read.csv("DegradedItems_ELP.csv", header = TRUE, sep = ",")
> multipic = multipic[,c(3,11)]
> AoA_main = AoA[,c(1,11)]
> item_all = Reduce(function(x, y) merge(x, y, all=TRUE),
+                   list(marc590, ipnp, item_elp, multipic, AoA_main))
> items = read.csv("Degraded_ItemList.csv", header = TRUE, sep = ",")
> item_final = dplyr::inner_join(items, item_all)
> ## this file currently has many duplicates so we remove these in excel
> ## note that some objects had multiple values for Visual Complexity, in
> ## which case a mean value was chosen.
> write.csv(item_final, file = "item_duplicates.csv")
```

Variable Correlations

```
> item_descriptives = read.csv("item_finaldescriptives.csv",
+                              header = TRUE, sep = ",")
> x = item_descriptives[complete.cases(item_descriptives),]
> cor_table = Hmisc::rcorr(as.matrix(x[,c(4,7,8,10,11,12)]))
> cor_table
```

```
                  H.statistic Syllables Length Log_Freq_HAL VISUAL_COMPLEXITY
H.statistic              1.00      0.09   0.12        -0.18              0.02
Syllables                0.09      1.00   0.82        -0.52              0.15
Length                   0.12      0.82   1.00        -0.57              0.12
Log_Freq_HAL            -0.18     -0.52  -0.57         1.00             -0.16
VISUAL_COMPLEXITY        0.02      0.15   0.12        -0.16              1.00
AoA_Kup_lem              0.29      0.44   0.45        -0.45              0.18
                  AoA_Kup_lem
H.statistic              0.29
Syllables                0.44
Length                   0.45
Log_Freq_HAL            -0.45
VISUAL_COMPLEXITY        0.18
AoA_Kup_lem              1.00

n= 189


P
                  H.statistic Syllables Length Log_Freq_HAL VISUAL_COMPLEXITY
H.statistic                   0.2252    0.0972 0.0113       0.7568
Syllables         0.2252                0.0000 0.0000       0.0390
Length            0.0972      0.0000           0.0000       0.1149
Log_Freq_HAL      0.0113      0.0000    0.0000              0.0242
VISUAL_COMPLEXITY 0.7568      0.0390    0.1149 0.0242
AoA_Kup_lem       0.0000      0.0000    0.0000 0.0000       0.0110
                  AoA_Kup_lem
```

```
H.statistic         0.0000
Syllables           0.0000
Length              0.0000
Log_Freq_HAL        0.0000
VISUAL_COMPLEXITY 0.0110
AoA_Kup_lem
```

Merging with Experiment Data

```
> ## final data is in pic_withAoA_z (for separate z-scoring) and in new_z_AOA for combin
> ## need to merge with item_descriptives
>
> final_pic_data_1 = merge(pic_withAoA_z, item_descriptives, by = "Object")
> final_pic_data_1= final_pic_data_1[order(final_pic_data_1$Subject),]
> final_pic_data_2 = merge(new_z_AoA, item_descriptives, by = "Object")
> final_pic_data_2= final_pic_data_2[order(final_pic_data_2$Subject),]
>
```

18 HLMs

z-RT

Basic Variables

```
> library(lme4)
> p0 = lmer(data = final_pic_data_2, zRT_trim ~ 1 + (1|Subject) + (1|Trial))
> summary(p0)
```

```
Linear mixed model fit by REML ['lmerMod']
Formula: zRT_trim ~ 1 + (1 | Subject) + (1 | Trial)
   Data: final_pic_data_2

REML criterion at convergence: 31605.2

Scaled residuals:
    Min      1Q  Median      3Q     Max
-2.7837 -0.6804 -0.2809  0.3861  5.2946

Random effects:
 Groups   Name        Variance Std.Dev.
 Trial    (Intercept) 0.004772 0.06908
 Subject  (Intercept) 0.000000 0.00000
 Residual             0.989354 0.99466
Number of obs: 11160, groups:  Trial, 200; Subject, 67

Fixed effects:
```

```
                Estimate Std. Error t value
(Intercept) -3.714e-05  1.061e-02  -0.004
```

```
> reghelper::ICC(p0)
```

```
[1] 0.004800118
```

```
> p1 = lmer(data = final_pic_data_2, zRT_trim ~ H.statistic +
+              (1|Subject) + (1|Trial))
> summary(p1)
```

```
Linear mixed model fit by REML ['lmerMod']
Formula: zRT_trim ~ H.statistic + (1 | Subject) + (1 | Trial)
   Data: final_pic_data_2

REML criterion at convergence: 30199.9

Scaled residuals:
    Min      1Q  Median      3Q     Max
-3.3107 -0.6525 -0.2513  0.3866  5.1231

Random effects:
 Groups   Name        Variance Std.Dev.
 Trial    (Intercept) 0.004064 0.06375
 Subject  (Intercept) 0.000000 0.00000
 Residual             0.923454 0.96096
Number of obs: 10929, groups:  Trial, 200; Subject, 67

Fixed effects:
            Estimate Std. Error t value
(Intercept) -0.27124    0.01415  -19.17
H.statistic  0.38713    0.01433   27.01

Correlation of Fixed Effects:
            (Intr)
H.statistic -0.690
```

```
> p2 = lmer(data = final_pic_data_2, zRT_trim ~ H.statistic + VISUAL_COMPLEXITY +
+              (1|Subject) + (1|Trial))
> summary(p2)
```

```
Linear mixed model fit by REML ['lmerMod']
Formula: zRT_trim ~ H.statistic + VISUAL_COMPLEXITY + (1 | Subject) +
    (1 | Trial)
   Data: final_pic_data_2

REML criterion at convergence: 30098.9
```

```
Scaled residuals:
    Min      1Q  Median      3Q     Max
-3.2988 -0.6510 -0.2511  0.3870  5.0474

Random effects:
 Groups   Name        Variance Std.Dev.
 Trial    (Intercept) 0.004042 0.06357
 Subject  (Intercept) 0.000000 0.00000
 Residual             0.914499 0.95629
Number of obs: 10929, groups:  Trial, 200; Subject, 67

Fixed effects:
                  Estimate Std. Error t value
(Intercept)       -0.72479    0.04589  -15.79
H.statistic        0.38602    0.01426   27.06
VISUAL_COMPLEXITY  0.17770    0.01711   10.38

Correlation of Fixed Effects:
            (Intr) H.stts
H.statistic -0.205
VISUAL_COMP -0.952 -0.008
```

```
> p3 = lmer(data = final_pic_data_2, zRT_trim ~ H.statistic + VISUAL_COMPLEXITY +
+                              Length +
+             (1|Subject) + (1|Trial))
> summary(p3)
```

```
Linear mixed model fit by REML ['lmerMod']
Formula: zRT_trim ~ H.statistic + VISUAL_COMPLEXITY + Length + (1 | Subject) +
    (1 | Trial)
   Data: final_pic_data_2

REML criterion at convergence: 29807.4

Scaled residuals:
    Min      1Q  Median      3Q     Max
-3.2729 -0.6463 -0.2454  0.3864  5.0869

Random effects:
 Groups   Name        Variance Std.Dev.
 Trial    (Intercept) 0.003865 0.06217
 Subject  (Intercept) 0.000000 0.00000
 Residual             0.902688 0.95010
Number of obs: 10872, groups:  Trial, 200; Subject, 67

Fixed effects:
                   Estimate Std. Error t value
```

```
(Intercept)        -0.927954   0.049997  -18.560
H.statistic         0.369696   0.014250   25.943
VISUAL_COMPLEXITY   0.154383   0.017132    9.011
Length              0.049105   0.004717   10.411

Correlation of Fixed Effects:
            (Intr) H.stts VISUAL
H.statistic -0.152
VISUAL_COMP -0.819  0.006
Length      -0.408 -0.090 -0.110
```

Adding Degradation

```
> p4 = lmer(data = final_pic_data_2, zRT_trim ~ H.statistic + VISUAL_COMPLEXITY +
+                            Length + PictureType +
+              (1|Subject) + (1|Trial))
> summary(p4)
```

```
Linear mixed model fit by REML ['lmerMod']
Formula: zRT_trim ~ H.statistic + VISUAL_COMPLEXITY + Length + PictureType +
    (1 | Subject) + (1 | Trial)
   Data: final_pic_data_2

REML criterion at convergence: 29344.9

Scaled residuals:
    Min      1Q  Median      3Q     Max
-3.1427 -0.6435 -0.2384  0.3829  5.0910

Random effects:
 Groups   Name        Variance Std.Dev.
 Trial    (Intercept) 0.003463 0.05885
 Subject  (Intercept) 0.000000 0.00000
 Residual             0.864861 0.92998
Number of obs: 10872, groups:  Trial, 200; Subject, 67

Fixed effects:
                        Estimate Std. Error t value
(Intercept)            -0.730839   0.049744 -14.692
H.statistic             0.373762   0.013948  26.796
VISUAL_COMPLEXITY       0.155670   0.016768   9.284
Length                  0.048449   0.004616  10.495
PictureTypeFullPicture -0.391044   0.017869 -21.884

Correlation of Fixed Effects:
            (Intr) H.stts VISUAL Length
H.statistic -0.147
```

```
VISUAL_COMP -0.805  0.006
Length      -0.402 -0.090 -0.110
PctrTypFllP -0.181 -0.013 -0.004  0.007
```

Adding Freq and AoA

```
> p5 = lmer(data = final_pic_data_2, zRT_trim ~ H.statistic + VISUAL_COMPLEXITY +
+                          Length + PictureType + AoA_Kup_lem.x +
+             (1|Subject) + (1|Trial))
> summary(p5)
```

```
Linear mixed model fit by REML ['lmerMod']
Formula: zRT_trim ~ H.statistic + VISUAL_COMPLEXITY + Length + PictureType +
    AoA_Kup_lem.x + (1 | Subject) + (1 | Trial)
   Data: final_pic_data_2

REML criterion at convergence: 29131.2

Scaled residuals:
    Min      1Q  Median      3Q     Max
-3.4813 -0.6338 -0.2400  0.3792  5.2123

Random effects:
 Groups   Name        Variance Std.Dev.
 Trial    (Intercept) 0.003768 0.06138
 Subject  (Intercept) 0.000000 0.00000
 Residual             0.847179 0.92042
Number of obs: 10872, groups:  Trial, 200; Subject, 67

Fixed effects:
                       Estimate Std. Error t value
(Intercept)           -0.998418   0.052405 -19.052
H.statistic            0.321216   0.014246  22.548
VISUAL_COMPLEXITY      0.119761   0.016771   7.141
Length                 0.014862   0.005091   2.919
PictureTypeFullPicture -0.394522   0.017689 -22.303
AoA_Kup_lem.x          0.115094   0.007692  14.963

Correlation of Fixed Effects:
            (Intr) H.stts VISUAL Length PctTFP
H.statistic -0.050
VISUAL_COMP -0.700  0.041
Length      -0.189  0.031 -0.034
PctrTypFllP -0.166 -0.010 -0.002  0.012
AoA_Kp_lm.x -0.341 -0.246 -0.143 -0.441 -0.013
```

```
> p6 = lmer(data = final_pic_data_2, zRT_trim ~ H.statistic + VISUAL_COMPLEXITY +
```

```
+                            Length + PictureType*Log_Freq_HAL +
+             (1|Subject) + (1|Trial))
> summary(p6)
```

```
Linear mixed model fit by REML ['lmerMod']
Formula: zRT_trim ~ H.statistic + VISUAL_COMPLEXITY + Length + PictureType *
    Log_Freq_HAL + (1 | Subject) + (1 | Trial)
   Data: final_pic_data_2

REML criterion at convergence: 29351.7

Scaled residuals:
    Min      1Q  Median      3Q     Max
-3.1563 -0.6421 -0.2401  0.3839  5.1024

Random effects:
 Groups   Name        Variance Std.Dev.
 Trial    (Intercept) 0.003377 0.05811
 Subject  (Intercept) 0.000000 0.00000
 Residual             0.864431 0.92975
Number of obs: 10872, groups:  Trial, 200; Subject, 67

Fixed effects:
                                  Estimate Std. Error t value
(Intercept)                      -0.500783   0.113074  -4.429
H.statistic                       0.367515   0.014116  26.035
VISUAL_COMPLEXITY                 0.149661   0.016895   8.858
Length                            0.039866   0.005507   7.239
PictureTypeFullPicture           -0.356375   0.104489  -3.411
Log_Freq_HAL                     -0.018858   0.009520  -1.981
PictureTypeFullPicture:Log_Freq_HAL -0.003971   0.011897  -0.334

Correlation of Fixed Effects:
            (Intr) H.stts VISUAL Length PctTFP L_F_HA
H.statistic -0.185
VISUAL_COMP -0.448  0.025
Length      -0.568  0.011 -0.023
PctrTypFllP -0.474  0.001  0.001  0.003
Log_Frq_HAL -0.888  0.122  0.097  0.421  0.630
PTFP:L_F_HA  0.468 -0.004 -0.002 -0.003 -0.985 -0.641
```

```
> p7 = lmer(data = final_pic_data_2, zRT_trim ~ H.statistic + VISUAL_COMPLEXITY +
+                         Length + PictureType + AoA_Kup_lem.x + Log_Freq_HAL +
+             (1|Subject) + (1|Trial))
> summary(p7)
```

```
Linear mixed model fit by REML ['lmerMod']
Formula: zRT_trim ~ H.statistic + VISUAL_COMPLEXITY + Length + PictureType +
```

```
    AoA_Kup_lem.x + Log_Freq_HAL + (1 | Subject) + (1 | Trial)
   Data: final_pic_data_2

REML criterion at convergence: 29138.9

Scaled residuals:
    Min      1Q  Median      3Q     Max
-3.4776 -0.6337 -0.2396  0.3792  5.2131

Random effects:
 Groups   Name        Variance  Std.Dev.
 Trial    (Intercept) 3.785e-03 6.152e-02
 Subject  (Intercept) 8.179e-16 2.860e-08
 Residual             8.472e-01 9.204e-01
Number of obs: 10872, groups:  Trial, 200; Subject, 67

Fixed effects:
                        Estimate Std. Error t value
(Intercept)            -1.044919   0.106079  -9.850
H.statistic             0.321929   0.014317  22.486
VISUAL_COMPLEXITY       0.120559   0.016846   7.156
Length                  0.016139   0.005687   2.838
PictureTypeFullPicture -0.394604   0.017690 -22.306
AoA_Kup_lem.x           0.115993   0.007896  14.690
Log_Freq_HAL            0.003746   0.007430   0.504

Correlation of Fixed Effects:
            (Intr) H.stts VISUAL Length PctTFP AA_K_.
H.statistic -0.111
VISUAL_COMP -0.426  0.050
Length      -0.471  0.071  0.011
PctrTypFllP -0.074 -0.010 -0.002  0.006
AoA_Kp_lm.x -0.360 -0.216 -0.118 -0.284 -0.015
Log_Frq_HAL -0.869  0.099  0.094  0.446 -0.009  0.226
```

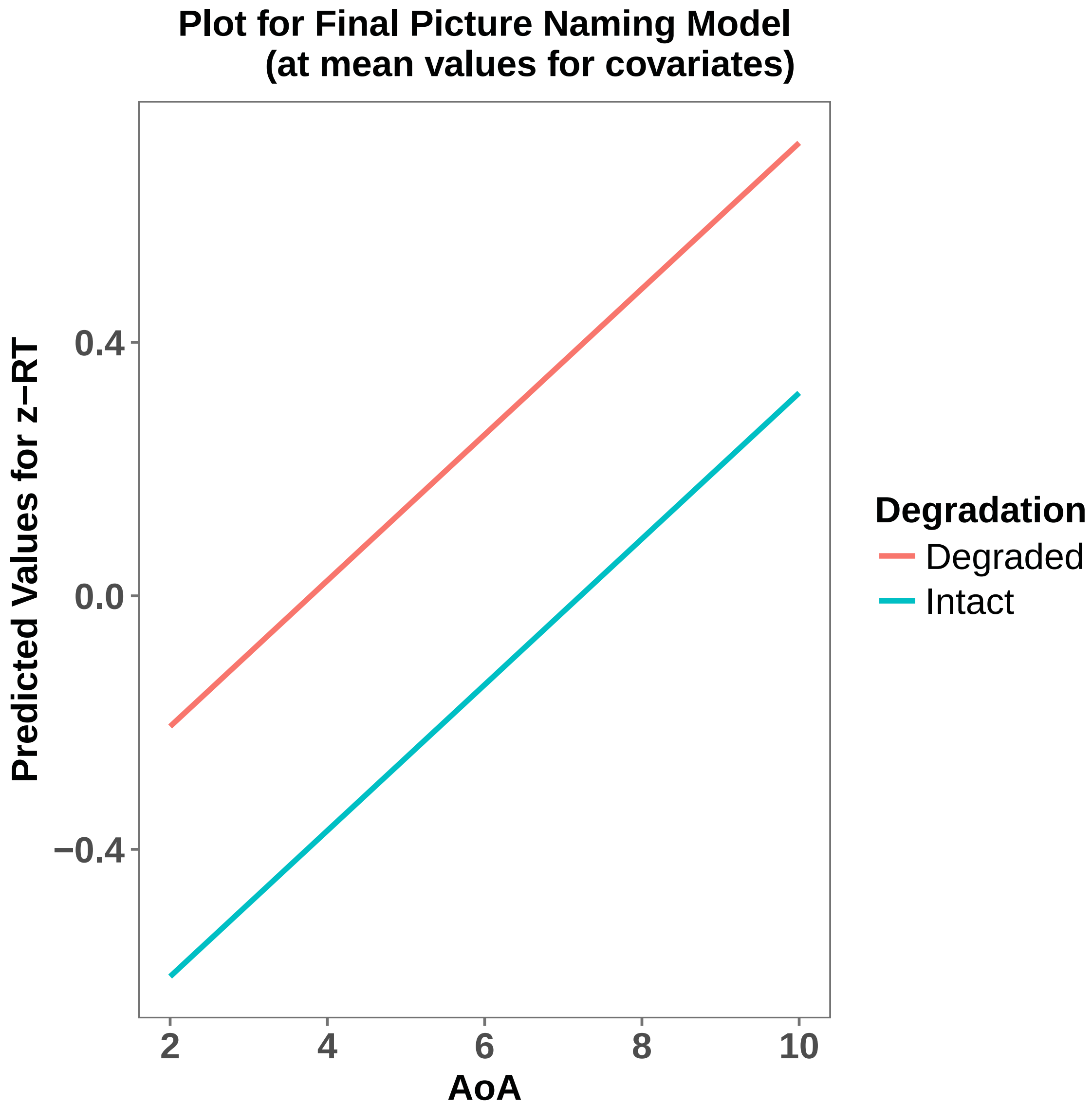
```
> ## interaction models: not sig: tried all 2-ways and 3-ways
>
> p8 = lmer(data = final_pic_data_2, zRT_trim ~ H.statistic + VISUAL_COMPLEXITY +
+                              Length + PictureType*AoA_Kup_lem.x*Log_Freq_HAL +
+               (1|Subject) + (1|Trial))
> summary(p8)
```

```
Linear mixed model fit by REML ['lmerMod']
Formula: zRT_trim ~ H.statistic + VISUAL_COMPLEXITY + Length + PictureType *
    AoA_Kup_lem.x * Log_Freq_HAL + (1 | Subject) + (1 | Trial)
   Data: final_pic_data_2

REML criterion at convergence: 29167.7
```

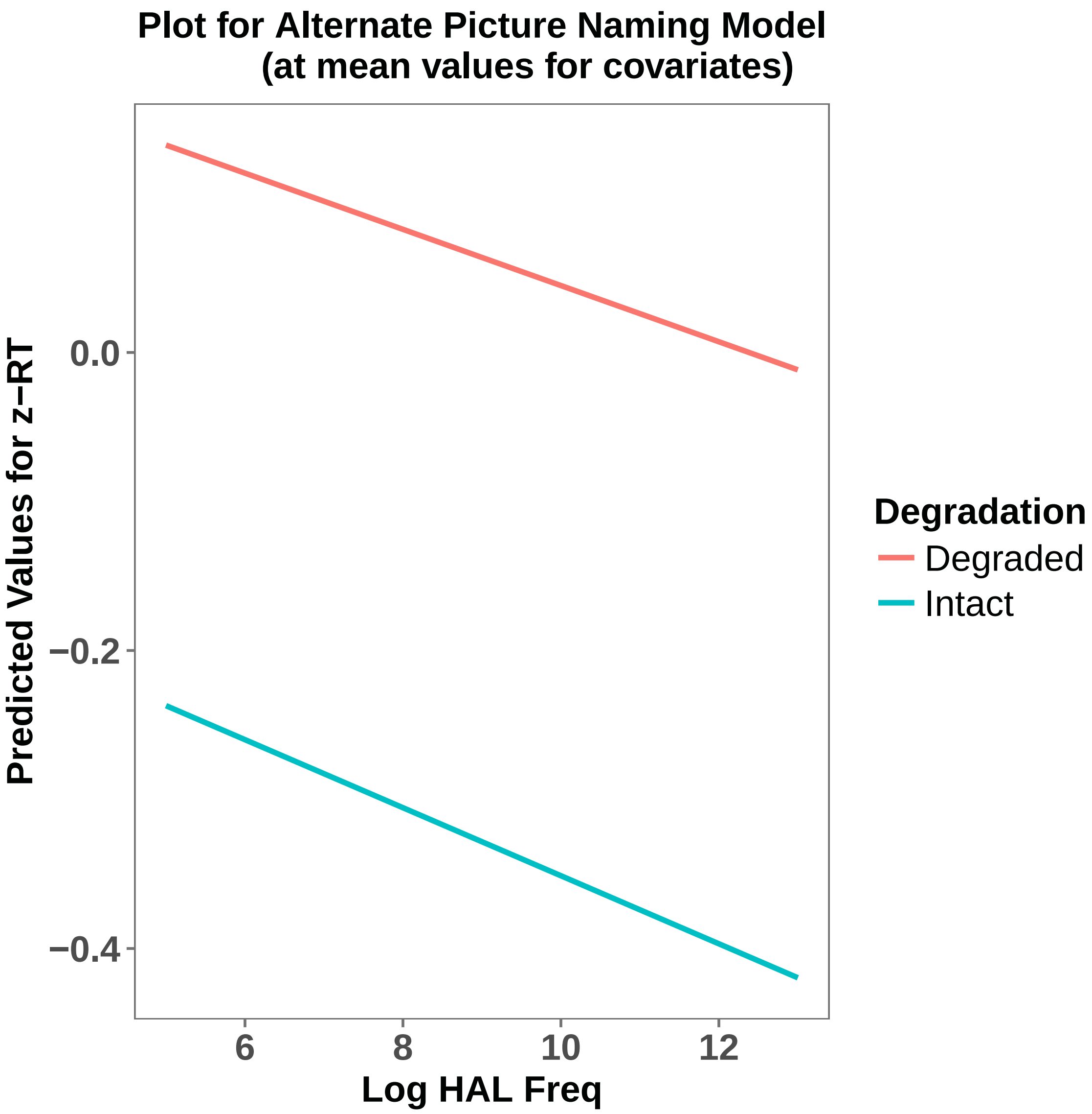
```
Scaled residuals:
    Min      1Q  Median      3Q     Max
-3.5262 -0.6330 -0.2391  0.3779  5.2098

Random effects:
 Groups   Name        Variance  Std.Dev.
 Trial    (Intercept) 3.774e-03 6.143e-02
 Subject  (Intercept) 7.698e-82 2.774e-41
 Residual             8.474e-01 9.206e-01
Number of obs: 10872, groups:  Trial, 200; Subject, 67

Fixed effects:
                                                 Estimate Std. Error t value
(Intercept)                                     -1.185054   0.296370  -3.999
H.statistic                                      0.322331   0.014340  22.479
VISUAL_COMPLEXITY                                0.120844   0.016857   7.169
Length                                           0.016029   0.005697   2.813
PictureTypeFullPicture                          -0.156380   0.397388  -0.394
AoA_Kup_lem.x                                    0.134836   0.053656   2.513
Log_Freq_HAL                                     0.014647   0.033055   0.443
PictureTypeFullPicture:AoA_Kup_lem.x            -0.030035   0.073017  -0.411
PictureTypeFullPicture:Log_Freq_HAL             -0.017471   0.045259  -0.386
AoA_Kup_lem.x:Log_Freq_HAL                      -0.001160   0.006397  -0.181
PictureTypeFullPicture:AoA_Kup_lem.x:Log_Freq_HAL  0.001513   0.008727   0.173

Correlation of Fixed Effects:
            (Intr) H.stts VISUAL Length PctTFP AA_Kp_. L_F_HA PcTFP:AA_K_.
H.statistic -0.070
VISUAL_COMP -0.173  0.051
Length      -0.125  0.068  0.010
PctrTypFllP -0.709  0.000  0.002 -0.014
AoA_Kp_lm.x -0.921 -0.001  0.003 -0.089  0.696
Log_Frq_HAL -0.970  0.052  0.041  0.055  0.711  0.953
PcTFP:AA_K_.  0.683  0.003  0.000  0.015 -0.957 -0.730  -0.703
PTFP:L_F_HA   0.695  0.003  0.000  0.012 -0.981 -0.700  -0.725  0.963
AA_K_.:L_F_   0.889 -0.029 -0.019  0.047 -0.664 -0.978  -0.952  0.716
PTFP:AA_K_.: -0.650 -0.007 -0.003 -0.013  0.912  0.715   0.697 -0.979
            PTFP:L AA_K_.:
H.statistic
VISUAL_COMP
Length
PctrTypFllP
AoA_Kp_lm.x
Log_Frq_HAL
PcTFP:AA_K_.
PTFP:L_F_HA
AA_K_.:L_F_   0.696
```

```
PTFP:AA_K_.:  -0.956  -0.731
```

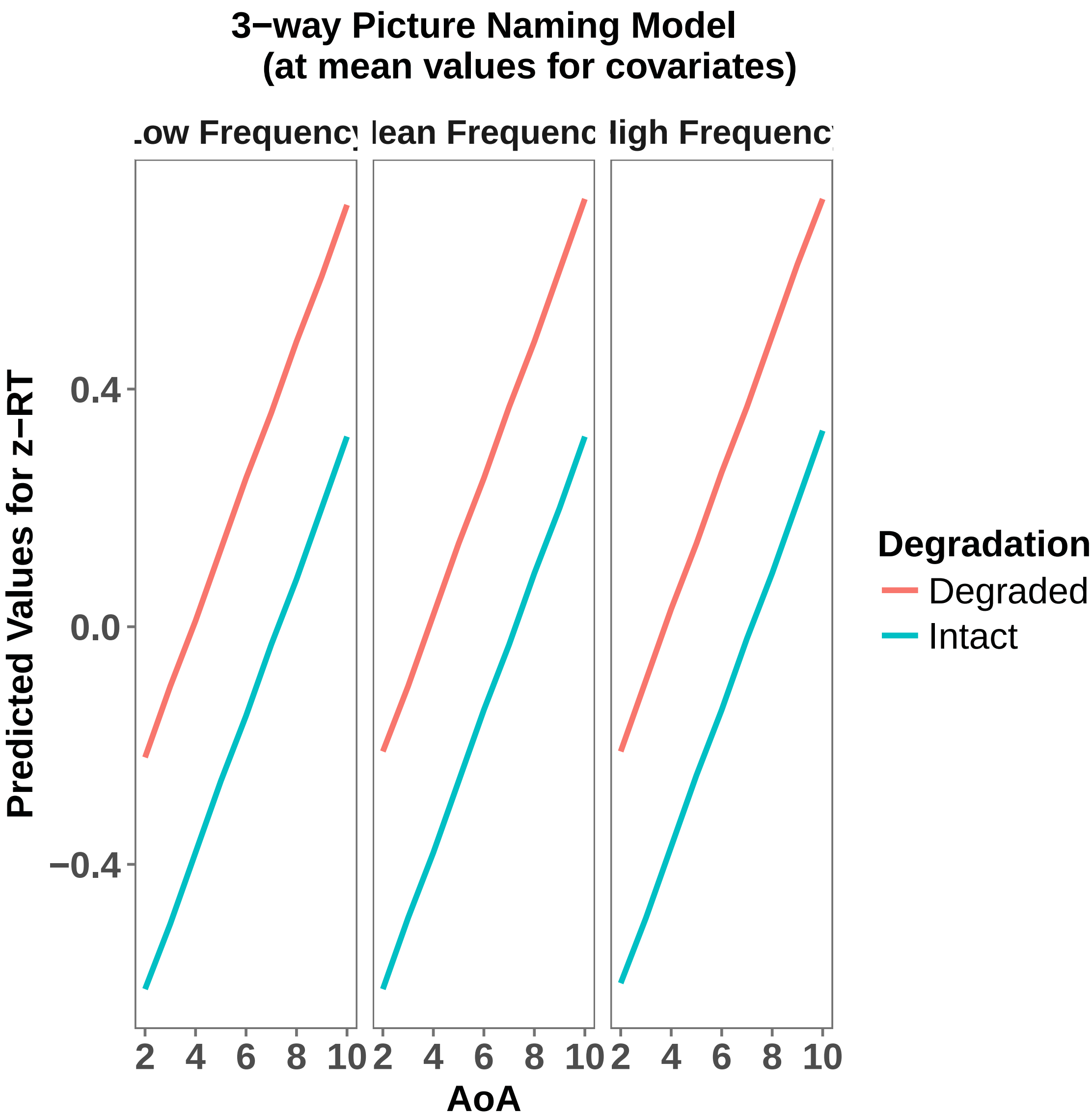
19 Plotting Final Model: p5



20 Plotting Final Model: p6



21 Plotting Final Model: p7



22 Plotting Final Model: p8