

# 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(2,3,22,26,28,31,33,36,37,38)]
> 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 Degraded

```
> #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_firstttrim_intact = pic_intact %>% filter( RT > 250 & RT < 5000)
> # removes 0.24% trials
> pic_firstttrim_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_firstttrim_intact, Subject) %>%
+   summarise_at(vars(RT), mean)
> colnames(meanRT_intact) = c("Subject", "MeanRT")
> sdRT_intact = group_by(pic_firstttrim_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_firstttrim_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_firstttrim_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

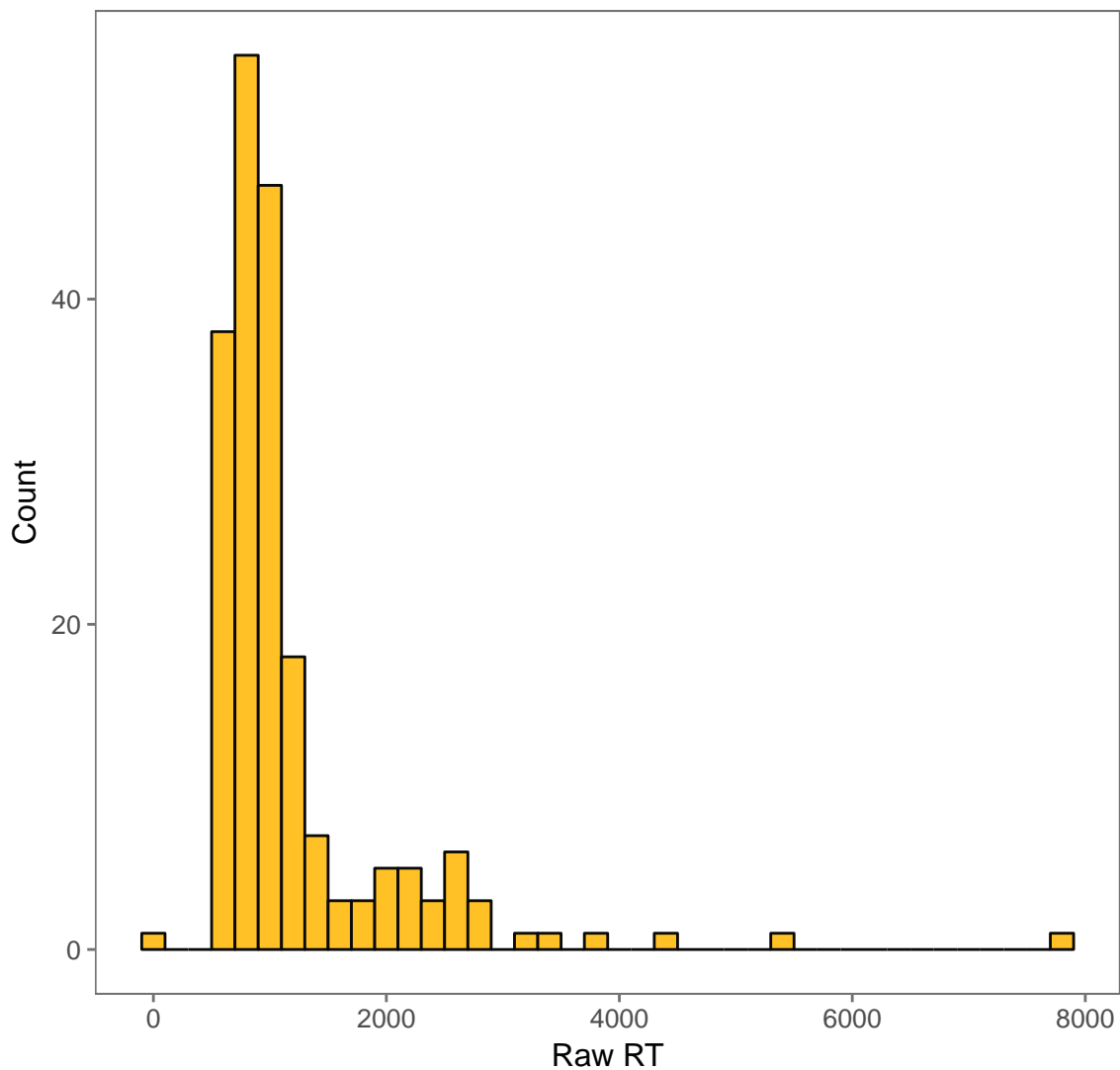
### Raw RT

```

> 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")

```

Raw RT Histogram for All Trials

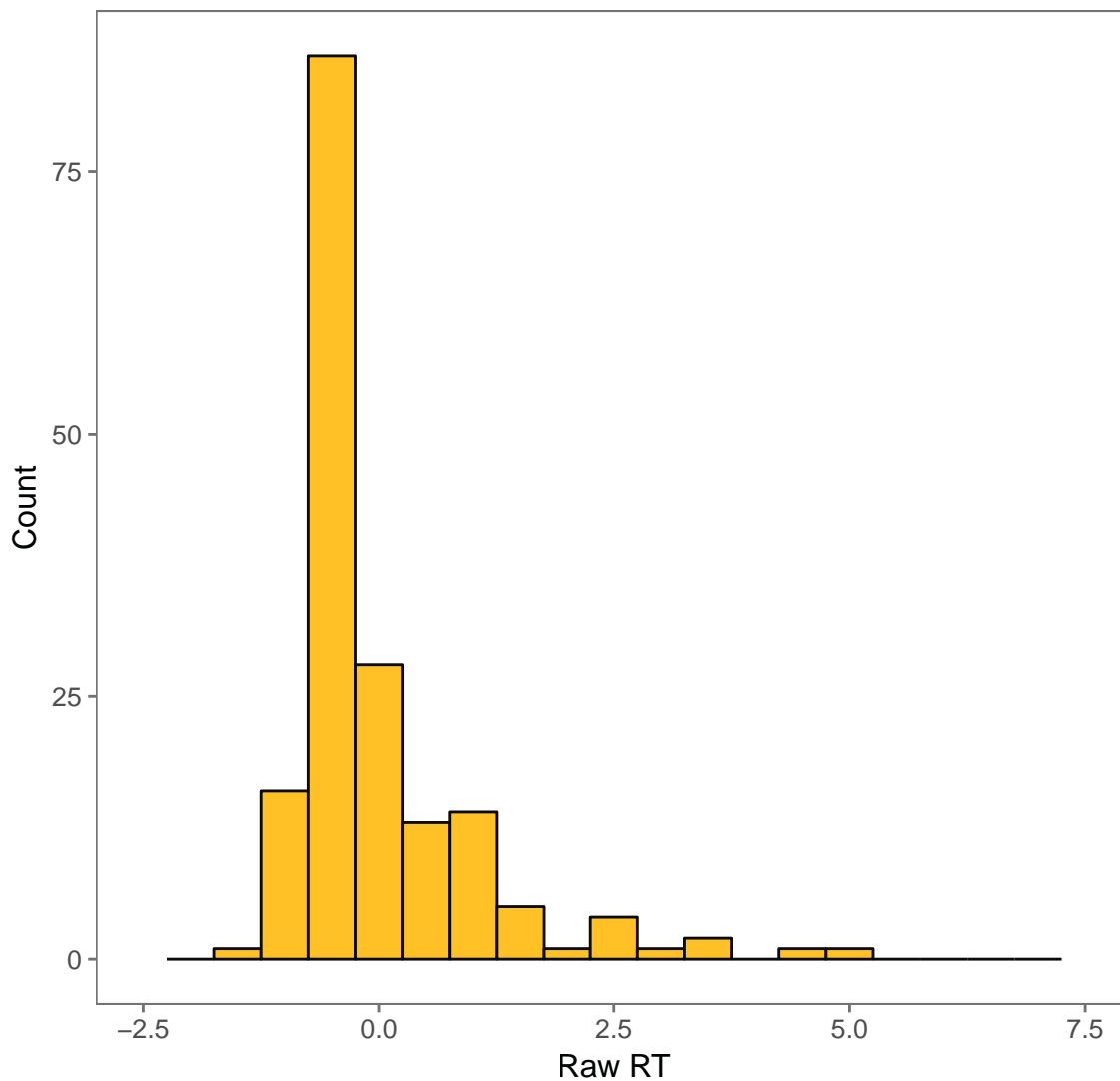


**z RT**

**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")
```

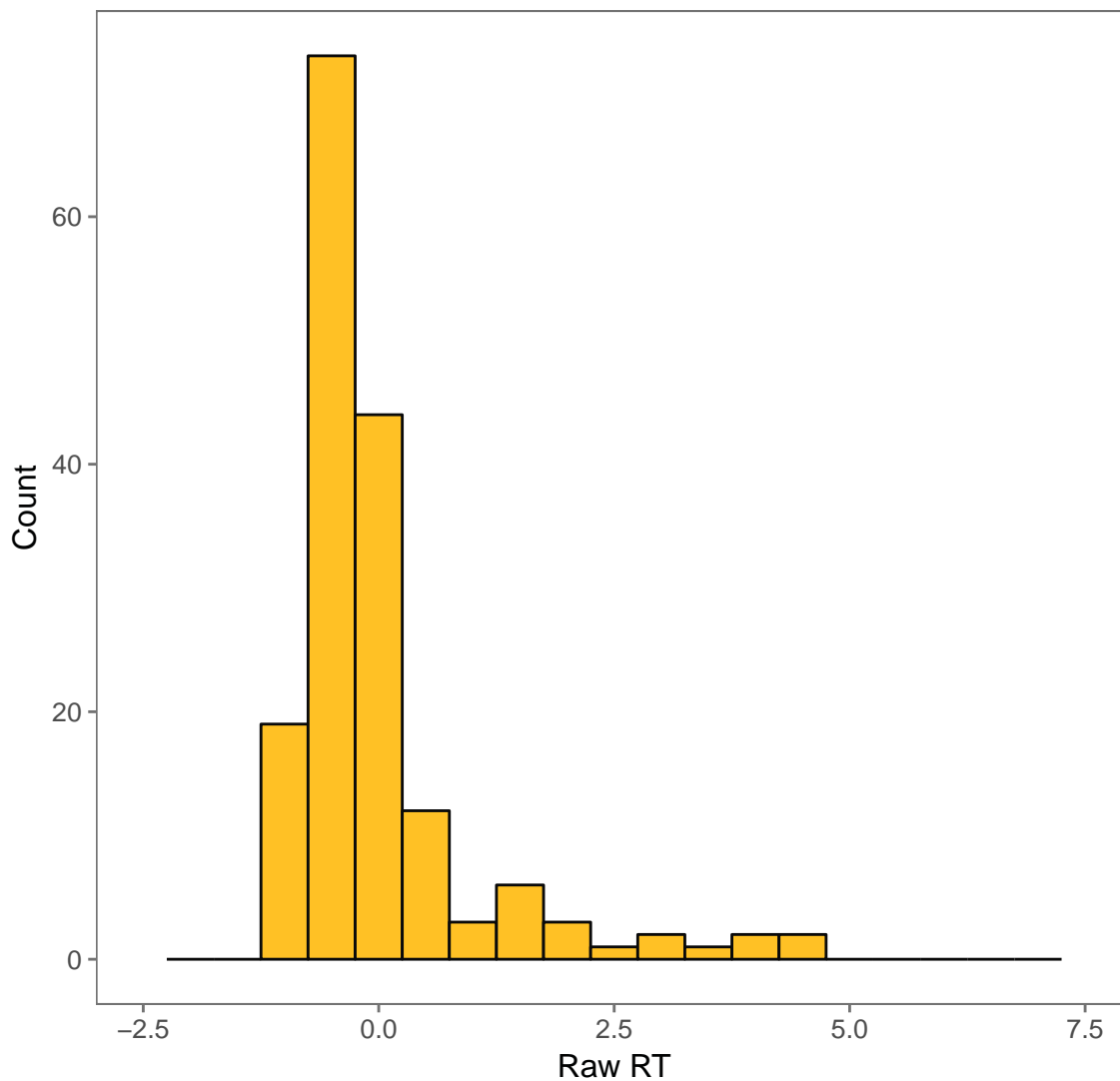
z-RT Intact Histogram for above 250 ms & <5s Trials



#### 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")
```

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  1 0.009747 0.009747
```

```
Error: Subject:PictureType
      Df  Sum Sq Mean Sq F value Pr(>F)
PictureType  1 0.01703 0.01703    0.16  0.757
Residuals    1 0.10618 0.10618
```

```
> 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  1      0      0
```

```
Error: Subject:PictureType
      Df Sum Sq Mean Sq F value Pr(>F)
PictureType  1      0      0
Residuals    1      0      0
```

## 11 Plotting Accuracy and RT

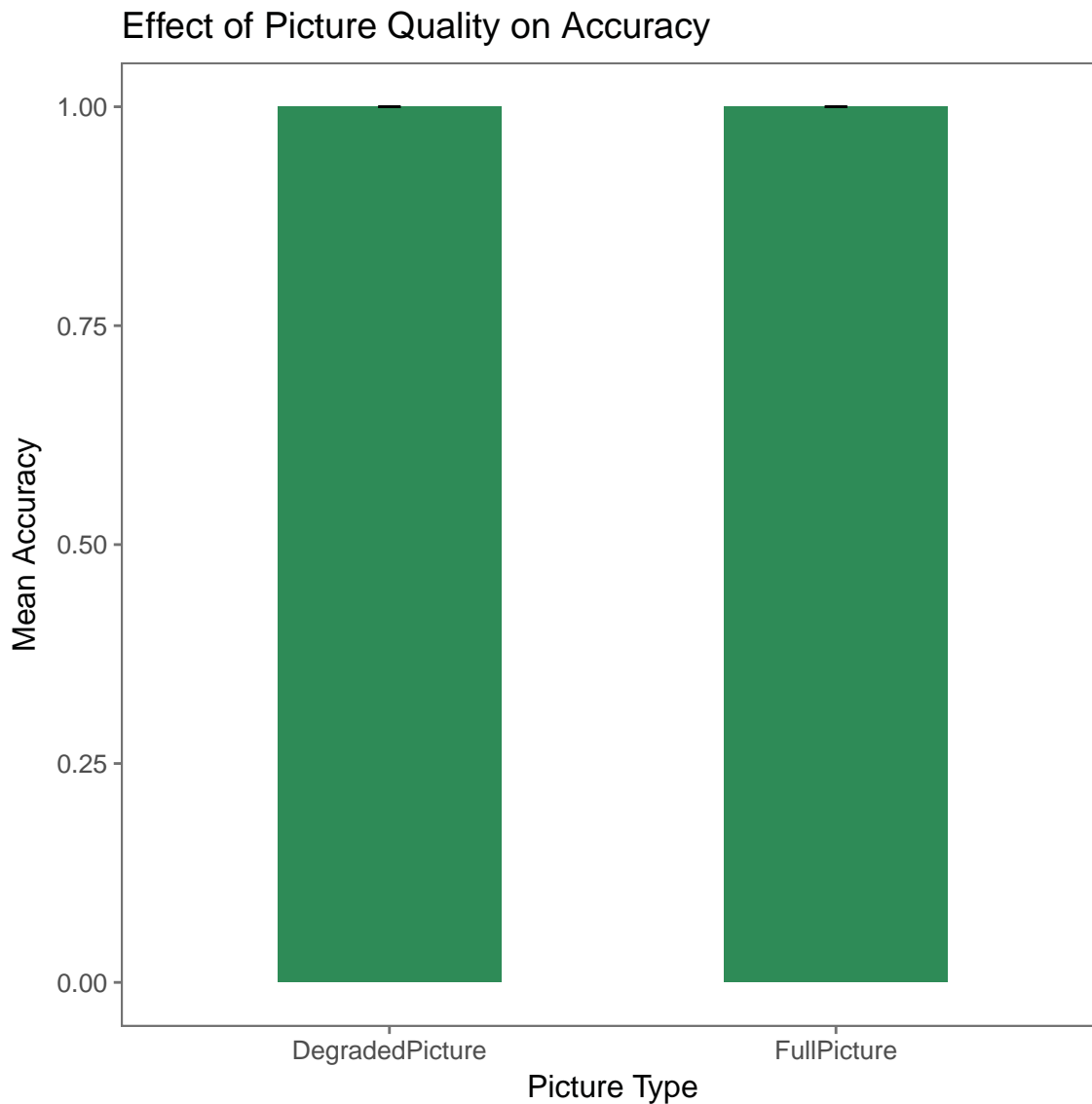
### Plotting Accuracy

```
> 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")

```

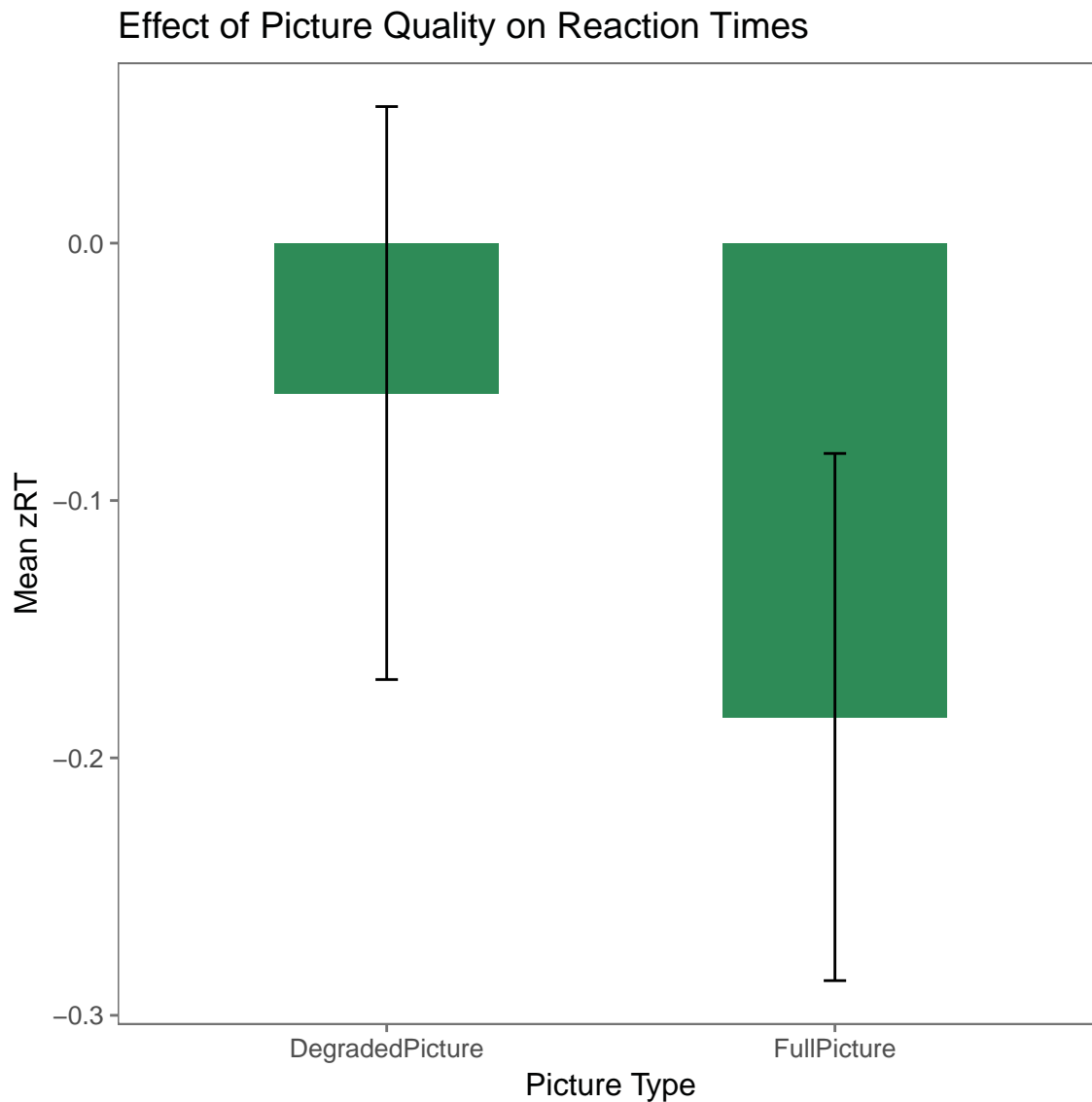


```

> agg_pic_validRT_plot_rmisc = summarySE(new_z,
+   measurevar = "zRT",
+   groupvars = c("PictureType"))

```

```
> 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")
```



## 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

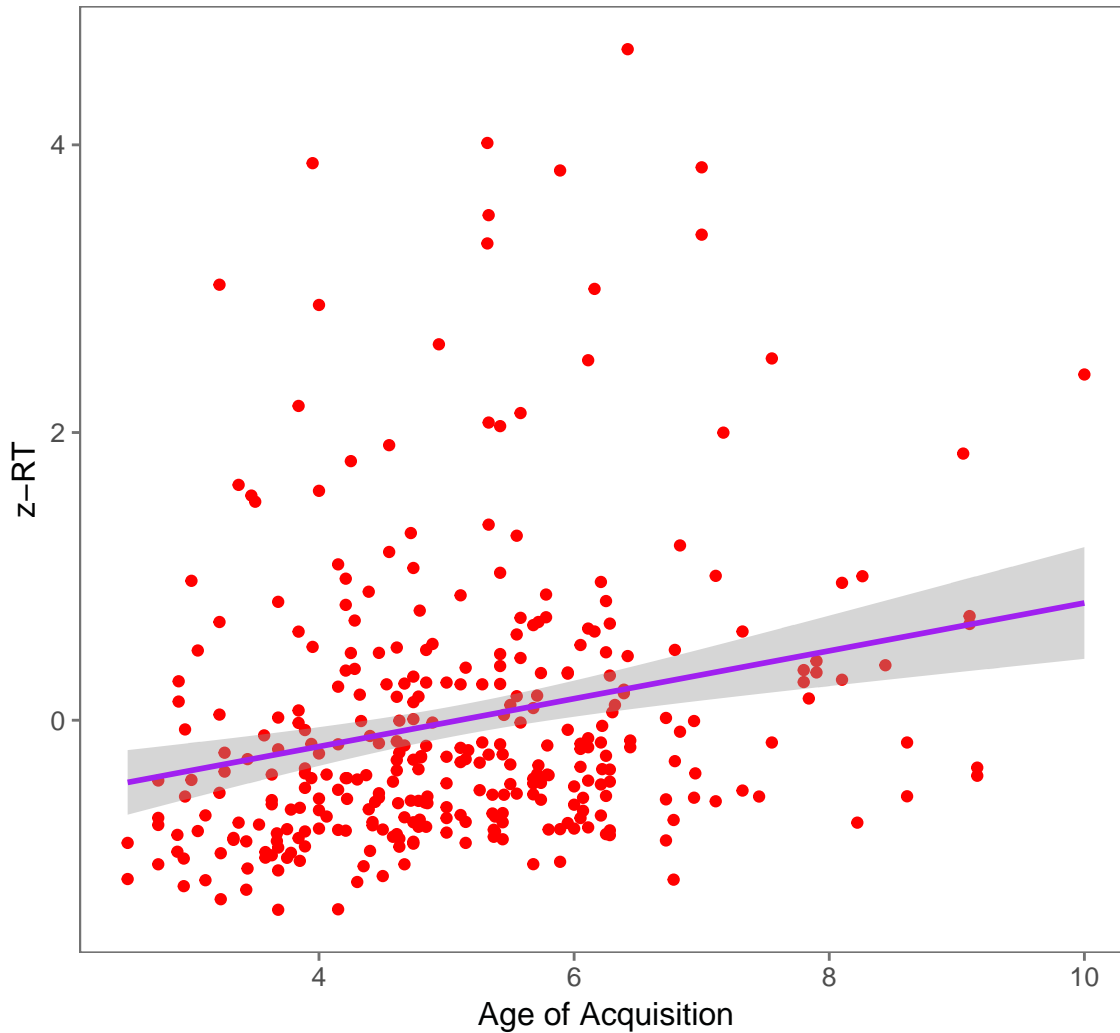
### zRT and AoA

```

> 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")

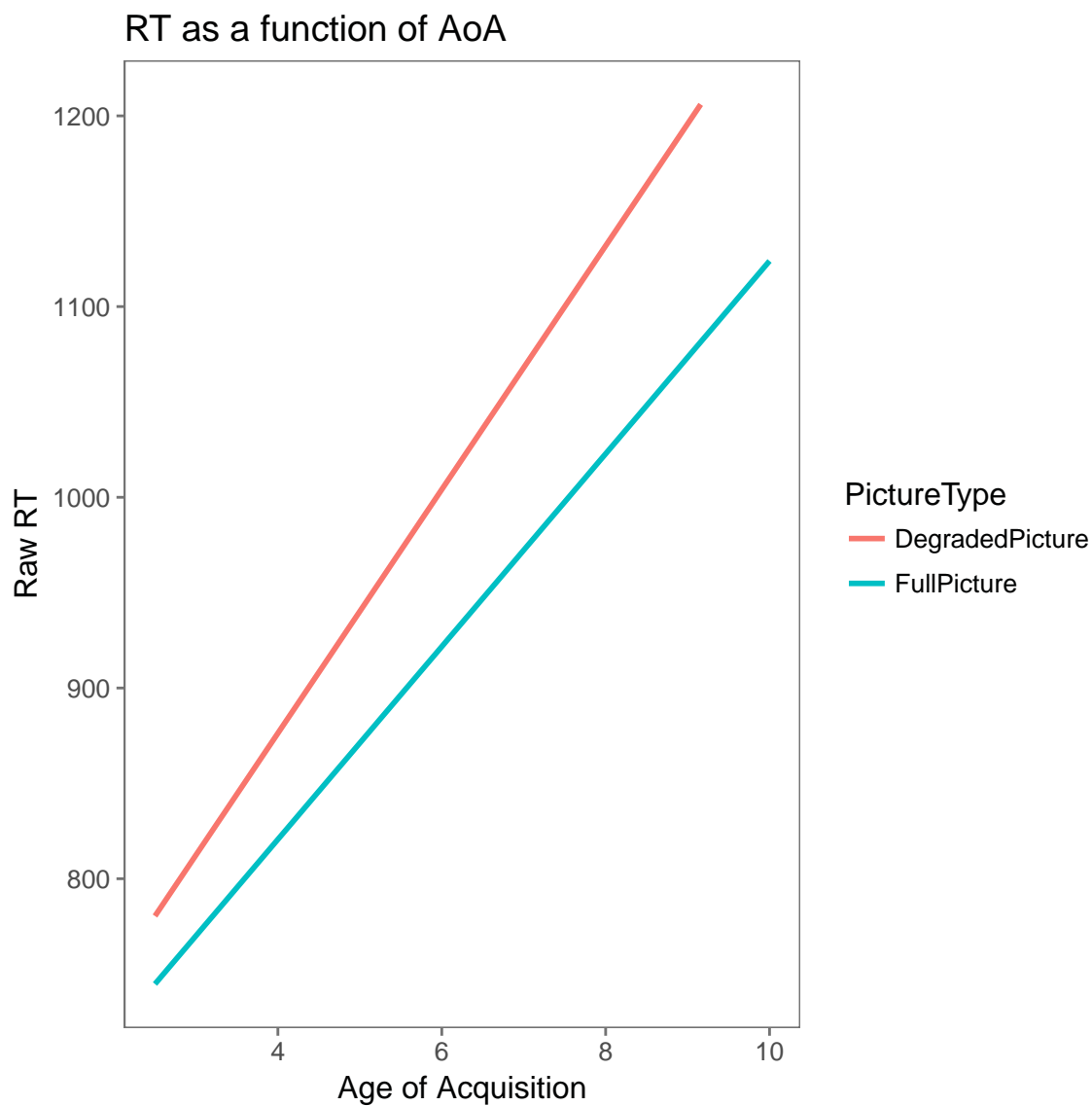
```

### z-scored Response Time as a function of Age of Acquisition



### 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")
```



## 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: 902.2

Scaled residuals:

Min	1Q	Median	3Q	Max
-1.6243	-0.4958	-0.2064	0.2625	4.1129

Random effects:

Groups	Name	Variance	Std.Dev.
Trial	(Intercept)	2.321e-15	4.818e-08
ObjectNo	(Intercept)	3.933e-01	6.272e-01
Subject	(Intercept)	0.000e+00	0.000e+00
Residual		5.581e-01	7.470e-01

Number of obs: 331, groups: Trial, 194; ObjectNo, 188; Subject, 2

Fixed effects:

	Estimate	Std. Error	t value
(Intercept)	-0.85831	0.23537	-3.647
AoA_Kup_lem	0.17028	0.04436	3.839

Correlation of Fixed Effects:

	(Intr)
AoA_Kup_lem	-0.965

```
> 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: 4671

Scaled residuals:

Min	1Q	Median	3Q	Max
-1.6446	-0.5015	-0.1844	0.2408	3.7344

Random effects:

Groups	Name	Variance	Std.Dev.
Trial	(Intercept)	3.150e-09	5.613e-05
ObjectNo	(Intercept)	3.998e+04	1.999e+02
Subject	(Intercept)	2.151e+03	4.637e+01
Residual		5.474e+04	2.340e+02

Number of obs: 331, groups: Trial, 194; ObjectNo, 188; Subject, 2

Fixed effects:

	Estimate	Std. Error	t value
(Intercept)	623.59	99.52	6.266
AoA_Kup_lem	64.73	17.90	3.617
PictureTypeFullPicture	-16.88	103.80	-0.163
AoA_Kup_lem:PictureTypeFullPicture	-11.48	19.73	-0.582

Correlation of Fixed Effects:

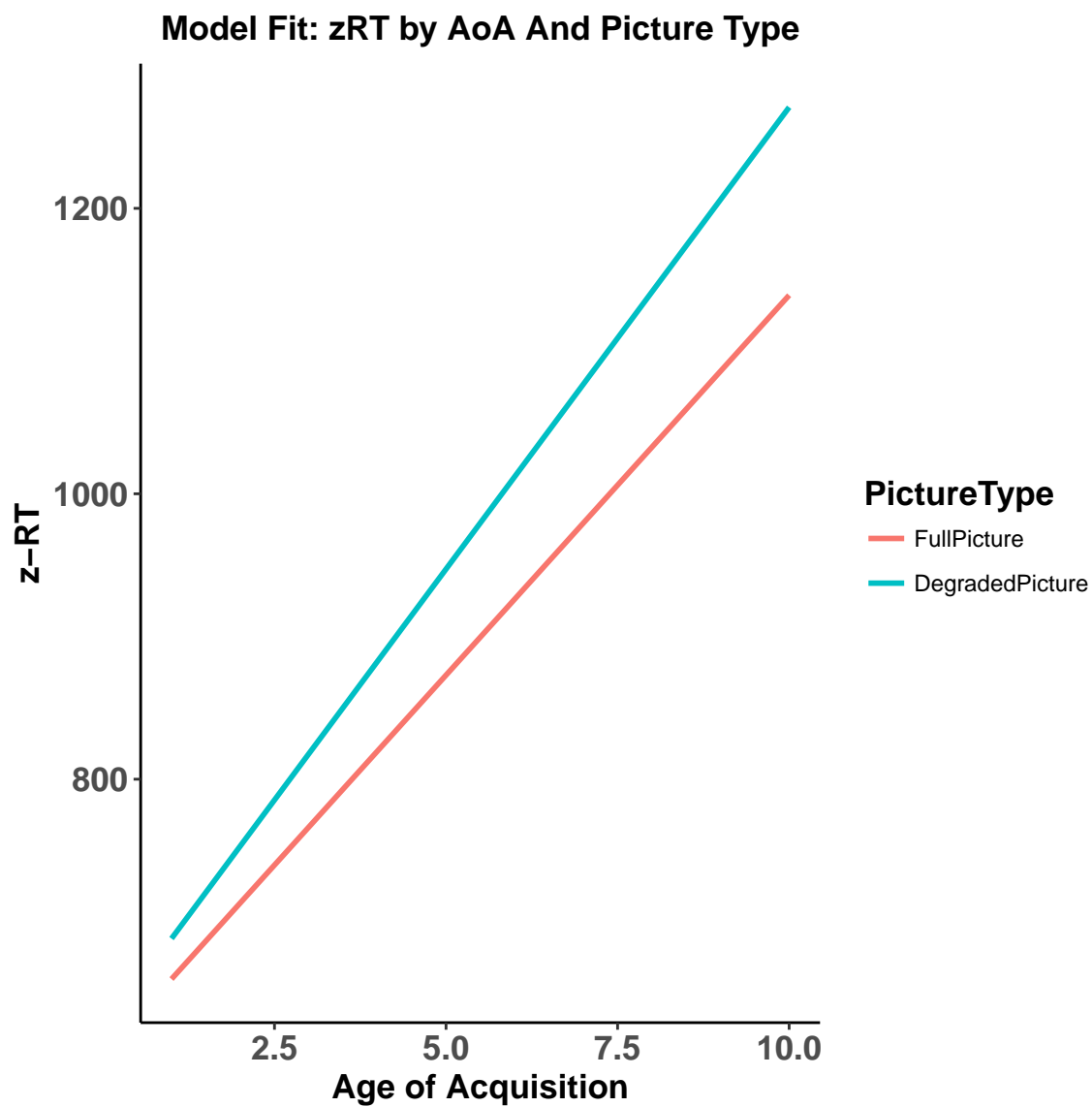
	(Intr)	AA_Kp_	PctTFP
AoA_Kup_lem	-0.913		
PctrTypFl1P	-0.575	0.595	
AA_Kp_:PTFP	0.563	-0.621	-0.967

## 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)),
+           plot.title = element_text(face = "bold", size = rel(1.2), hjust = .5))
```

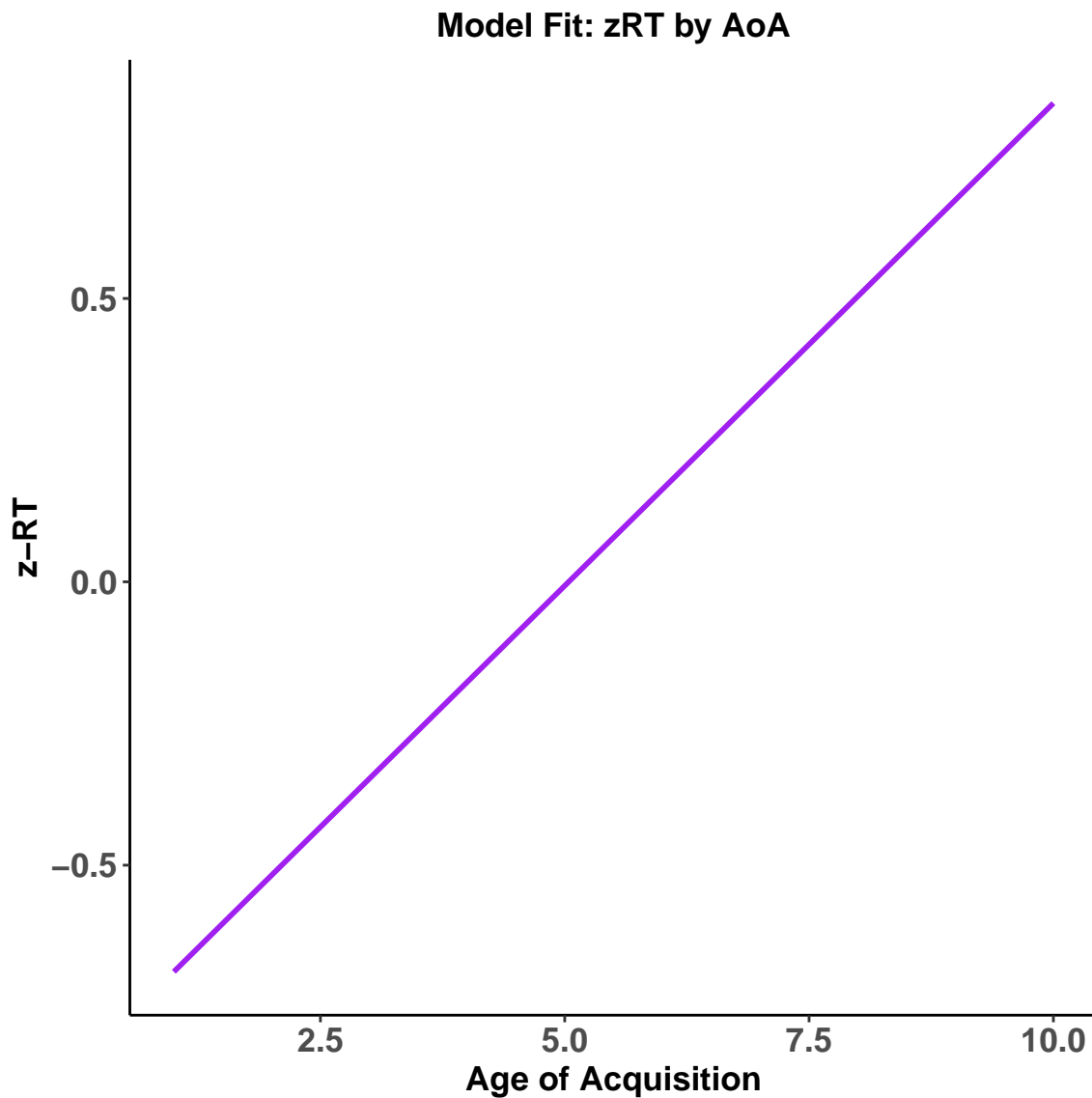




### AOA Only

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



## 16 Brinley Plot

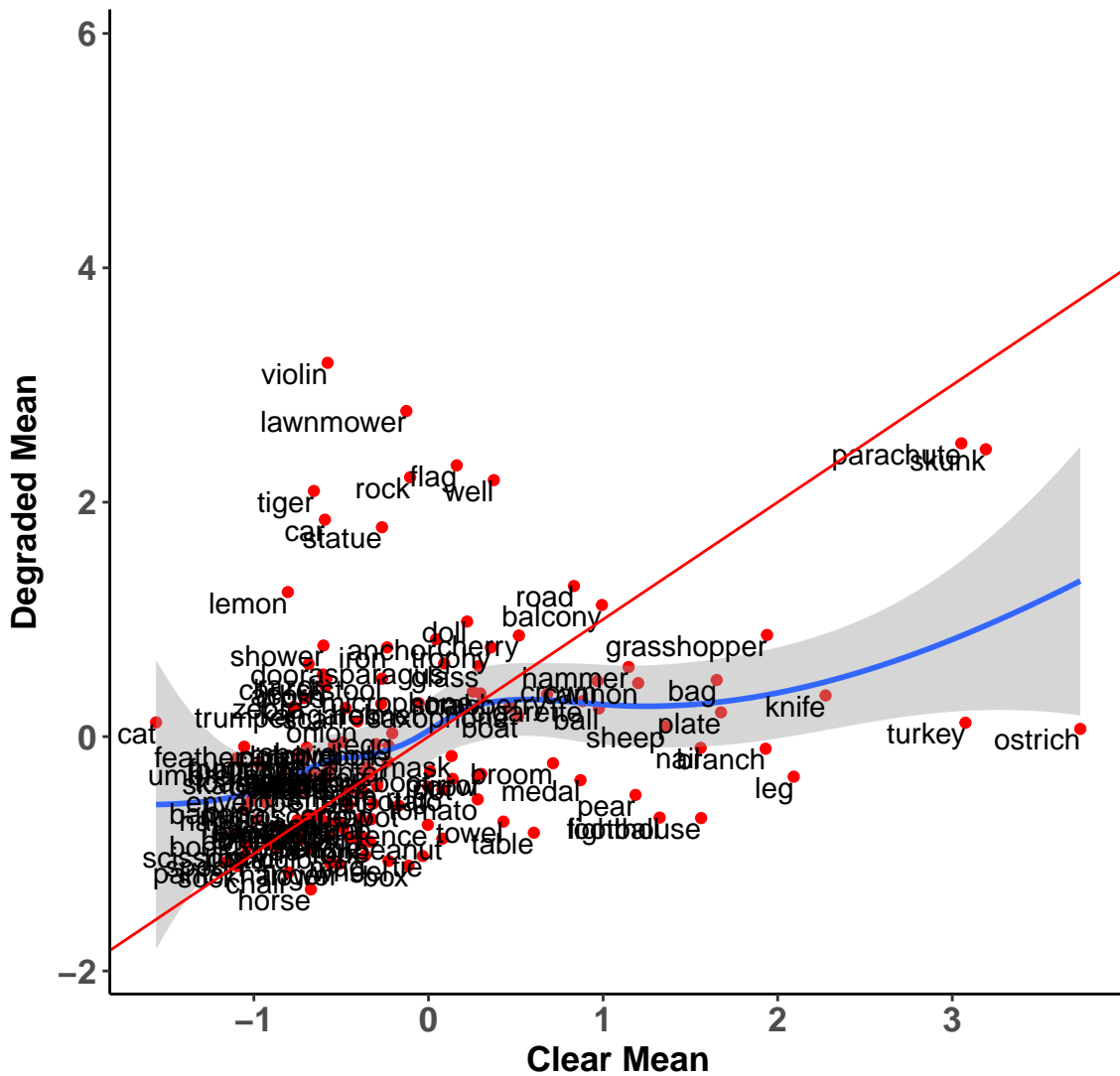
```
> #item_acc contains zRT for degraded and full pictures for each item
```

```

> 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))
>

```

## Brinley Plot



## Frequency Decile Brinley Plot

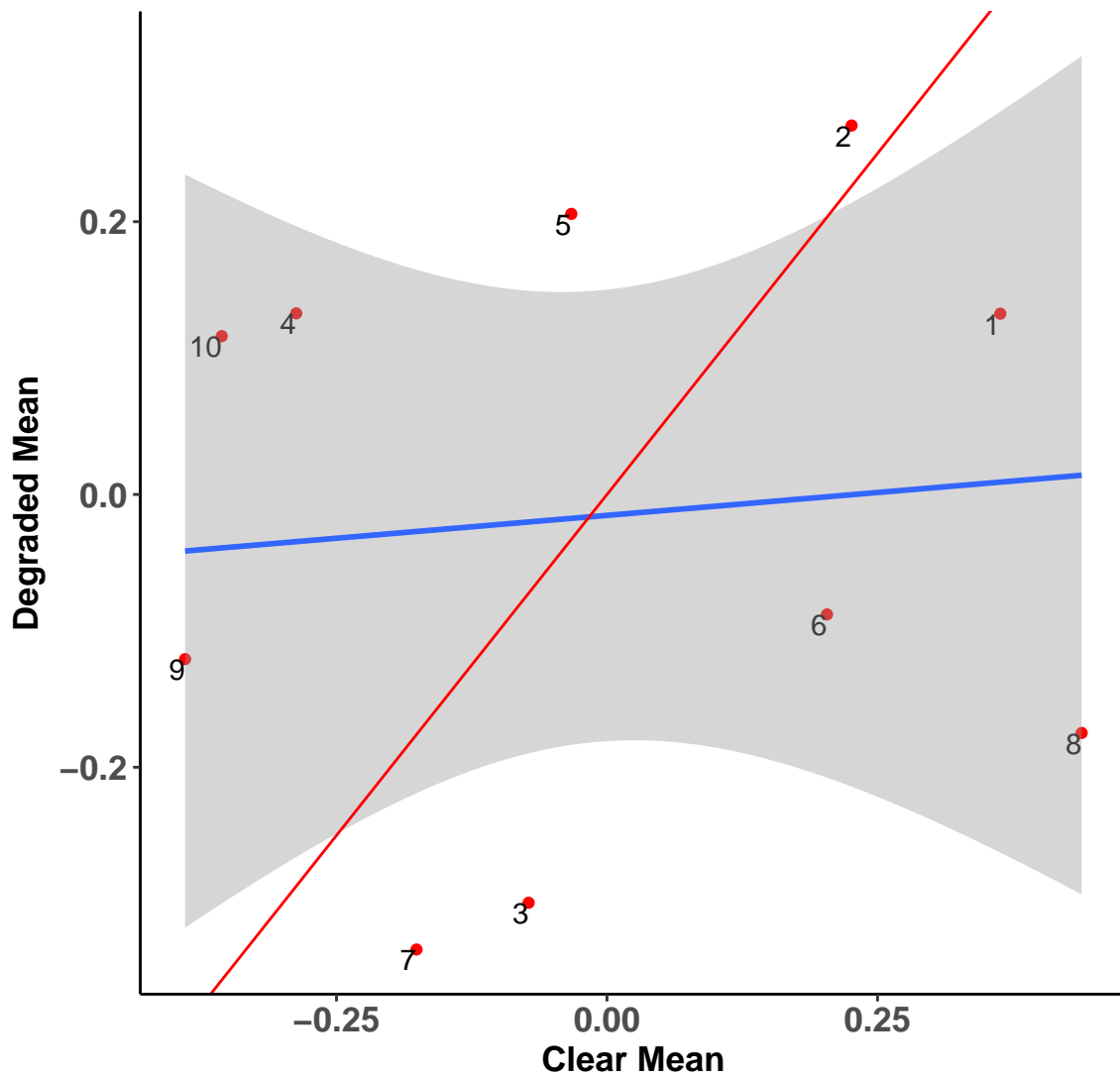
```
> item_elp = read.csv("DegradedItems_ELP.csv", header = TRUE, sep = ",")
> item_elp_brinley = merge(item_elp, item_brinley, by = c("Object"))
> # 398 rows: dropped wheelbarrow
>
> item_elp_brinley$Decile = ntile(item_elp_brinley$Log_Freq_HAL, 10)
> elp_decile_data = group_by(item_elp_brinley, Decile, 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))
>

```

## Brinley Plot For Frequency Deciles



## H-Statistic Decile Brinley Plot

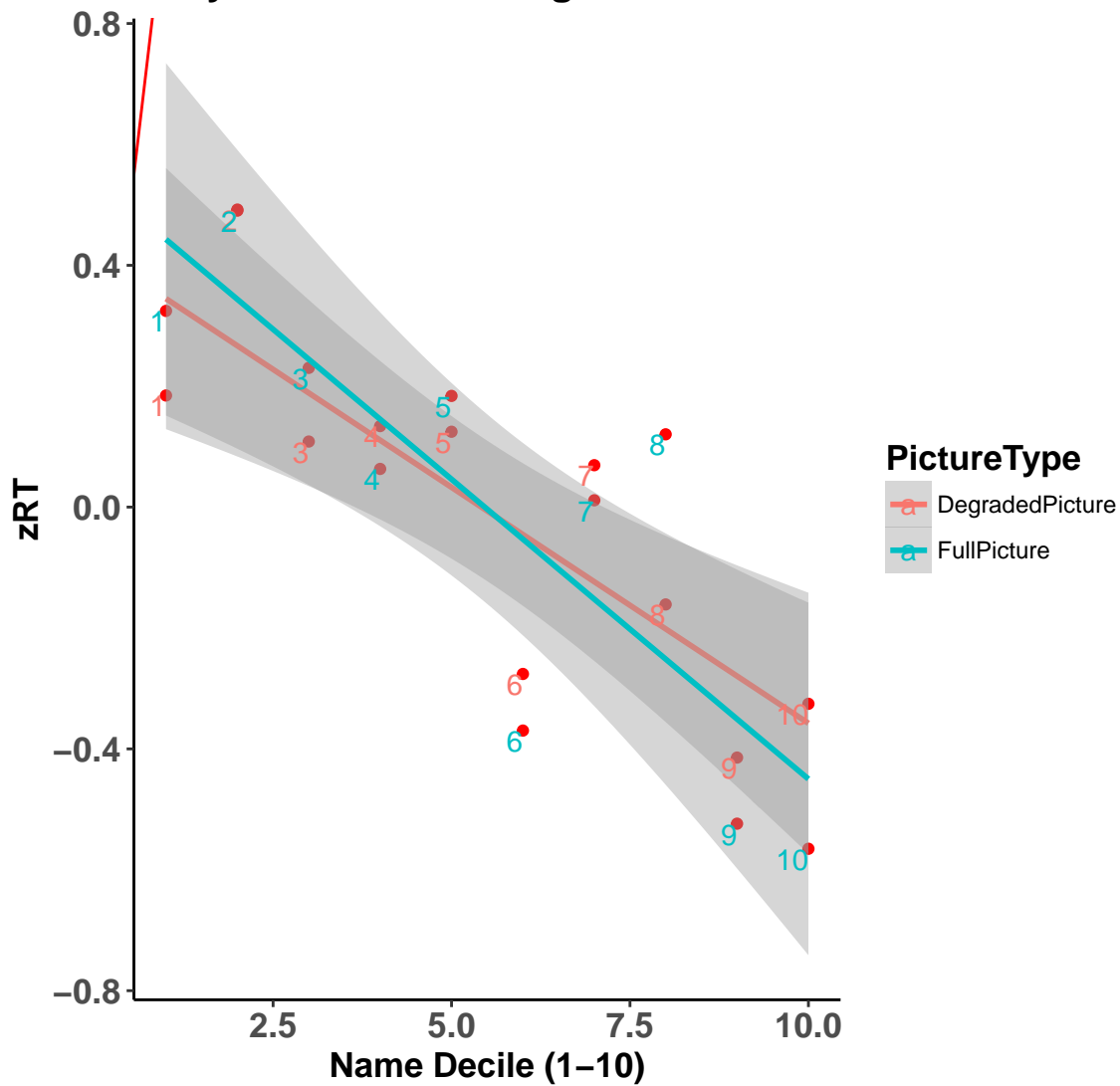
```
> marcnorms = read.csv("590MarcNorms.csv", header = TRUE, sep = ",")
> ## lower H statistic means greater name agreement. So we reverse code
> marcnorms$NameAgreement = 3.19 - marcnorms$H.statistic
> # Thus, higher NameAgreement, means higher name agreement
>
> item_marc_brinley = merge(marcnorms, 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))
>

```

## Brinley Plot For Name Agreement Deciles



## 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)]))

```

## 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: 941.3

```

```

Scaled residuals:
    Min       1Q   Median       3Q      Max
-1.3198 -0.6707 -0.2770  0.3324  4.6720

Random effects:
 Groups   Name                Variance Std.Dev.
 Trial    (Intercept) 1.902e-14 1.379e-07
 Subject (Intercept) 1.650e-17 4.062e-09
 Residual                    9.970e-01 9.985e-01
Number of obs: 331, groups: Trial, 194; Subject, 2

Fixed effects:
              Estimate Std. Error t value
(Intercept) -2.140e-16  5.488e-02      0

```

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

```
[1] 1.909888e-14
```

```

> 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: 898.8

Scaled residuals:
    Min       1Q   Median       3Q      Max
-1.5335 -0.6192 -0.2566  0.3692  4.7985

Random effects:
 Groups   Name                Variance Std.Dev.
 Trial    (Intercept) 3.977e-16 1.994e-08
 Subject (Intercept) 0.000e+00 0.000e+00
 Residual                    9.233e-01 9.609e-01
Number of obs: 324, groups: Trial, 194; Subject, 2

Fixed effects:
              Estimate Std. Error t value
(Intercept) -0.29512      0.07880  -3.745
H.statistic  0.40618      0.08233   4.934

Correlation of Fixed Effects:
      (Intr)

```

```
H.statistic -0.736
```

```
> 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: 890.6
```

```
Scaled residuals:
```

Min	1Q	Median	3Q	Max
-1.8611	-0.6455	-0.2541	0.3393	4.6702

```
Random effects:
```

Groups	Name	Variance	Std.Dev.
Trial	(Intercept)	3.789e-14	1.947e-07
Subject	(Intercept)	0.000e+00	0.000e+00
Residual		8.952e-01	9.462e-01

```
Number of obs: 324, groups: Trial, 194; Subject, 2
```

```
Fixed effects:
```

	Estimate	Std. Error	t value
(Intercept)	-1.13305	0.26332	-4.303
H.statistic	0.40842	0.08107	5.038
VISUAL_COMPLEXITY	0.32844	0.09863	3.330

```
Correlation of Fixed Effects:
```

	(Intr)	H.stts
H.statistic	-0.225	
VISUAL_COMP	-0.956	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: 886
```

```
Scaled residuals:
```

	Min	1Q	Median	3Q	Max
	-1.7925	-0.6436	-0.2362	0.3303	4.6801

Random effects:

Groups	Name	Variance	Std.Dev.
Trial	(Intercept)	9.578e-15	9.787e-08
Subject	(Intercept)	0.000e+00	0.000e+00
Residual		8.854e-01	9.410e-01

Number of obs: 322, groups: Trial, 194; Subject, 2

Fixed effects:

	Estimate	Std. Error	t value
(Intercept)	-1.20170	0.28649	-4.195
H.statistic	0.39734	0.08117	4.895
VISUAL_COMPLEXITY	0.31314	0.09894	3.165
Length	0.02014	0.02720	0.740

Correlation of Fixed Effects:

	(Intr)	H.stts	VISUAL
H.statistic	-0.166		
VISUAL_COMP	-0.823	0.023	
Length	-0.402	-0.101	-0.115

## 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: 887.1

Scaled residuals:

	Min	1Q	Median	3Q	Max
	-1.7272	-0.6113	-0.2336	0.2995	4.7512

Random effects:

Groups	Name	Variance	Std.Dev.
Trial	(Intercept)	0.0000	0.0000
Subject	(Intercept)	0.0000	0.0000
Residual		0.8837	0.9401

Number of obs: 322, groups: Trial, 194; Subject, 2

```
Fixed effects:
              Estimate Std. Error t value
(Intercept)   -1.14370    0.28983  -3.946
H.statistic    0.39789    0.08109   4.907
VISUAL_COMPLEXITY 0.31598    0.09887   3.196
Length         0.02063    0.02718   0.759
PictureTypeFullPicture -0.13331    0.10485  -1.271
```

```
Correlation of Fixed Effects:
              (Intr) H.stts VISUAL Length
H.statistic  -0.164
VISUAL_COMP  -0.809  0.024
Length        -0.395 -0.101 -0.114
PctrTypFl1p  -0.157 -0.005 -0.023 -0.014
```

### 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: 885.1

```
Scaled residuals:
      Min       1Q   Median       3Q      Max
-1.6010 -0.6109 -0.2359  0.2399  4.7227
```

```
Random effects:
 Groups   Name      Variance Std.Dev.
Trial    (Intercept) 0.0000   0.0000
Subject  (Intercept) 0.0000   0.0000
Residual              0.8689   0.9321
Number of obs: 322, groups: Trial, 194; Subject, 2
```

```
Fixed effects:
              Estimate Std. Error t value
(Intercept)   -1.38556    0.30286  -4.575
H.statistic    0.34283    0.08330   4.115
VISUAL_COMPLEXITY 0.27637    0.09928   2.784
Length        -0.01333    0.03011  -0.443
```

PictureTypeFullPicture	-0.13785	0.10398	-1.326
AoA_Kup_lem.x	0.11209	0.04429	2.531

Correlation of Fixed Effects:

	(Intr)	H.stts	VISUAL	Length	PctTFP
H.statistic	-0.067				
VISUAL_COMP	-0.709	0.064			
Length	-0.195	0.029	-0.031		
PctrTypFl1P	-0.144	-0.001	-0.020	-0.005	
AoA_Kp_lm.x	-0.316	-0.261	-0.158	-0.446	-0.017

```
> 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: 893.7

Scaled residuals:

Min	1Q	Median	3Q	Max
-1.6372	-0.6217	-0.2486	0.3201	4.6314

Random effects:

Groups	Name	Variance	Std.Dev.
Trial	(Intercept)	0.0000	0.000
Subject	(Intercept)	0.0000	0.000
Residual		0.8855	0.941

Number of obs: 322, groups: Trial, 194; Subject, 2

Fixed effects:

	Estimate	Std. Error	t value
(Intercept)	-1.43706	0.64485	-2.229
H.statistic	0.39291	0.08276	4.747
VISUAL_COMPLEXITY	0.31273	0.09943	3.145
Length	0.01841	0.03212	0.573
PictureTypeFullPicture	0.56499	0.61053	0.925
Log_Freq_HAL	0.03652	0.05488	0.665
PictureTypeFullPicture:Log_Freq_HAL	-0.08053	0.06936	-1.161

Correlation of Fixed Effects:

	(Intr)	H.stts	VISUAL	Length	PctTFP	L_F_HA
H.statistic	-0.203					
VISUAL_COMP	-0.425	0.042				

```

Length      -0.552  0.019 -0.046
PctrTypFllP -0.462 -0.036 -0.024 -0.016
Log_Frq_HAL -0.882  0.125  0.059  0.400  0.629
PTFP:L_F_HA  0.457  0.036  0.020  0.014 -0.985 -0.638

```

```

> 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: 889.4

Scaled residuals:

Min	1Q	Median	3Q	Max
-1.6191	-0.6083	-0.2269	0.2406	4.7529

Random effects:

Groups	Name	Variance	Std.Dev.
Trial	(Intercept)	0.000	0.0000
Subject	(Intercept)	0.000	0.0000
Residual		0.871	0.9333

Number of obs: 322, groups: Trial, 194; Subject, 2

Fixed effects:

	Estimate	Std. Error	t value
(Intercept)	-1.629719	0.605799	-2.690
H.statistic	0.348053	0.084157	4.136
VISUAL_COMPLEXITY	0.279125	0.099583	2.803
Length	-0.006661	0.033375	-0.200
PictureTypeFullPicture	-0.138100	0.104114	-1.326
AoA_Kup_lem.x	0.116724	0.045448	2.568
Log_Freq_HAL	0.019991	0.042939	0.466

Correlation of Fixed Effects:

	(Intr)	H.stts	VISUAL	Length	PctTFP	AA_K_.
H.statistic	-0.149					
VISUAL_COMP	-0.405	0.071				
Length	-0.460	0.083	-0.002			
PctrTypFllP	-0.068	-0.001	-0.020	-0.007		
AoA_Kp_lm.x	-0.344	-0.223	-0.141	-0.299	-0.018	
Log_Frq_HAL	-0.866	0.133	0.059	0.429	-0.005	0.219

```

> ## 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: 901.4

Scaled residuals:

Min	1Q	Median	3Q	Max
-1.6619	-0.6018	-0.2170	0.2844	4.5915

Random effects:

Groups	Name	Variance	Std.Dev.
Trial	(Intercept)	0.0000	0.0000
Subject	(Intercept)	0.0000	0.0000
Residual		0.8702	0.9328

Number of obs: 322, groups: Trial, 194; Subject, 2

Fixed effects:

	Estimate	Std. Error	t value
(Intercept)	-1.375405	1.786295	-0.770
H.statistic	0.349809	0.084224	4.153
VISUAL_COMPLEXITY	0.278261	0.099590	2.794
Length	-0.006813	0.033492	-0.203
PictureTypeFullPicture	-1.040222	2.311075	-0.450
AoA_Kup_lem.x	-0.039750	0.329624	-0.121
Log_Freq_HAL	-0.042611	0.198919	-0.214
PictureTypeFullPicture:AoA_Kup_lem.x	0.381178	0.421325	0.905
PictureTypeFullPicture:Log_Freq_HAL	0.173746	0.262260	0.662
AoA_Kup_lem.x:Log_Freq_HAL	0.025173	0.038607	0.652
PictureTypeFullPicture:AoA_Kup_lem.x:Log_Freq_HAL	-0.058926	0.050165	-1.175

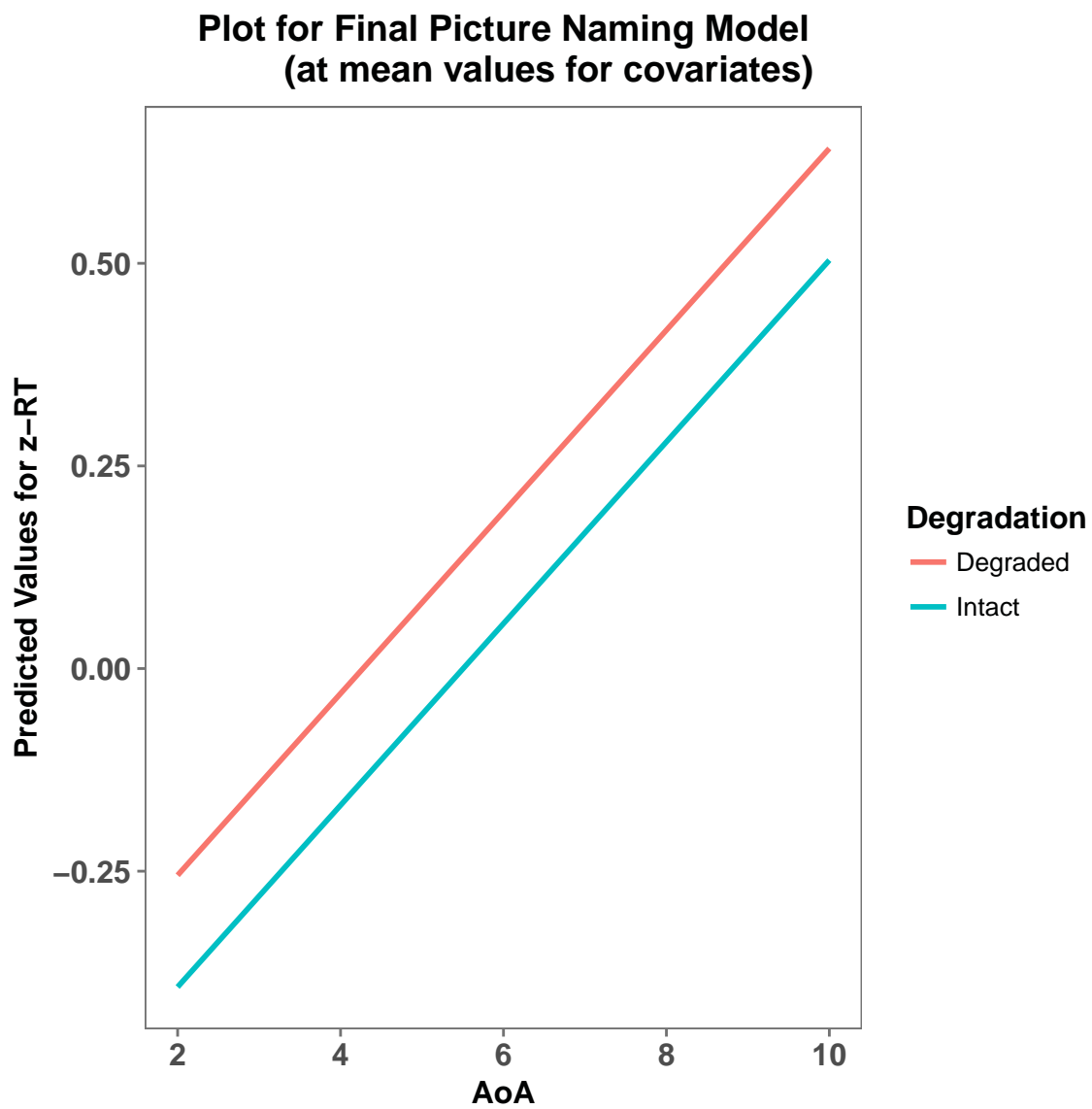
Correlation of Fixed Effects:

	(Intr)	H.stts	VISUAL	Length	PctTFP	AA_Kp_.	L_F_HA	PctTFP:AA_K_.
H.statistic	-0.050							
VISUAL_COMP	-0.129	0.072						
Length	-0.073	0.082	-0.002					
PctrTypFl1P	-0.747	-0.018	-0.026	-0.058				
AoA_Kp_lm.x	-0.930	-0.028	-0.024	-0.126	0.737			
Log_Frq_HAL	-0.973	0.024	0.006	0.008	0.750	0.957		
PctTFP:AA_K_.	0.731	0.013	0.020	0.057	-0.957	-0.777	-0.749	
PTFP:L_F_HA	0.729	0.024	0.024	0.056	-0.981	-0.735	-0.757	0.963

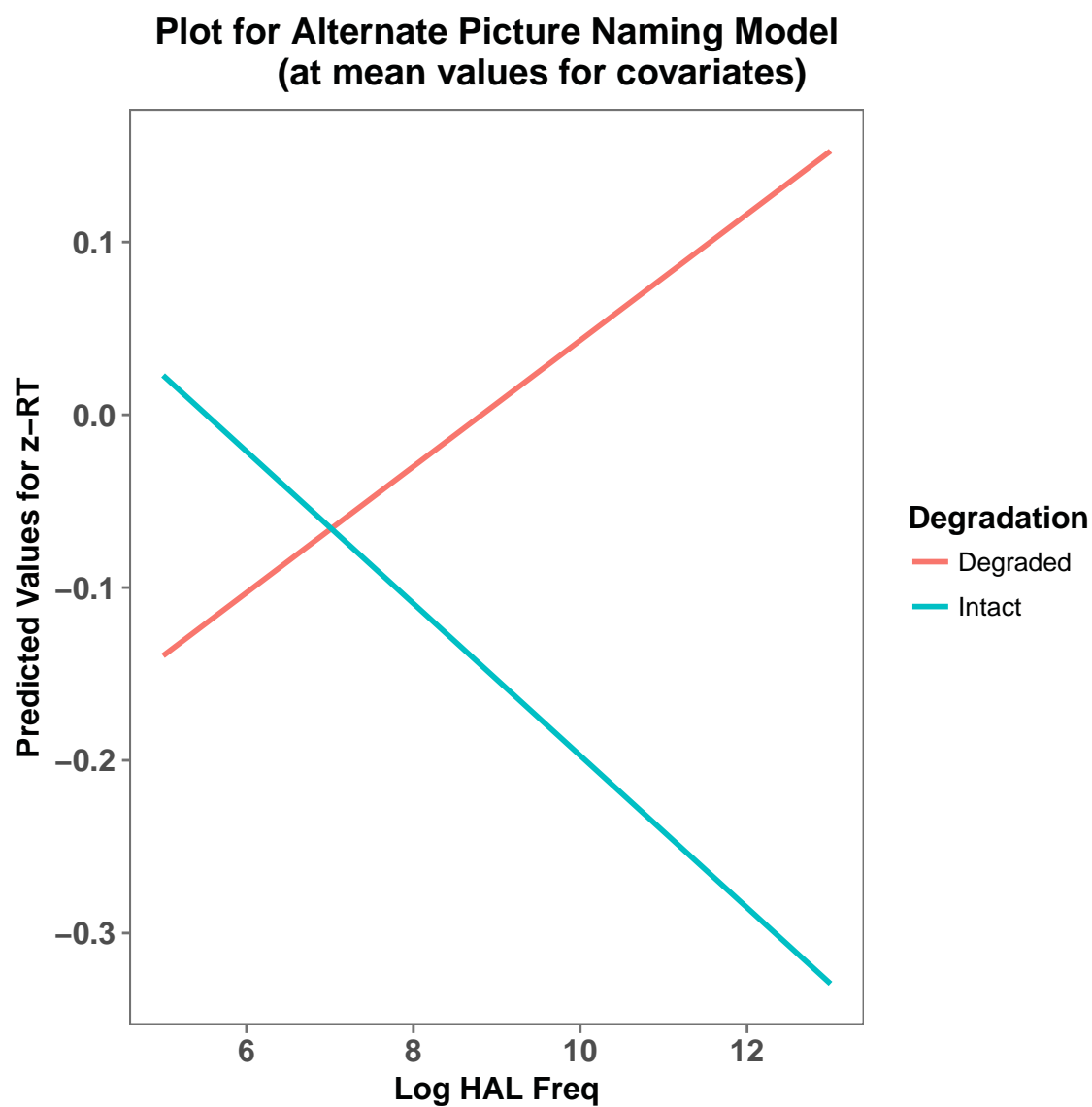


AA_K_.:L_F_	0.902	0.001	0.003	0.084	-0.707	-0.981	-0.957	0.764
PTFP:AA_K_.	-0.692	-0.019	-0.018	-0.052	0.912	0.754	0.736	-0.980
PTFP:L AA_K_.								
H.statistic								
VISUAL_COMP								
Length								
PctrTypFllP								
AoA_Kp_lm.x								
Log_Frq_HAL								
PcTFP:AA_K_.								
PTFP:L_F_HA								
AA_K_.:L_F_	0.731							
PTFP:AA_K_.	-0.956	-0.769						

## 19 Plotting Final Model: p5



## 20 Plotting Final Model: p6



## 21 Plotting Final Model: p7

### 3-way Picture Naming Model (at mean values for covariates)

