UX and MARS paper analysis output

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```
ggsave("C:/Users/ponpanich/Desktop/Sperounes_Ponpanich_Applolnik_Wenzel_Sagan_Ernstein_Apolnik_Sharon_UX_and_MARS_paper_analysis_output_variable_distributions.pdf",
plot = ggarrange(ggplot(data=ux_mars_df, aes(x=Age)) + geom_density(),
ggplot(data=ux_mars_df, aes(x=Gender)) + geom_bar(),
ggplot(data=ux_mars_df, aes(x=Ethnicity)) + geom_bar(),
ggplot(data=ux_mars_df, aes(x=Education)) + geom_bar(),
ncol=2, nrow=2))
```

variable distributions

```
fig.height=7 ggplot(data=ux_mars_df,aes(x=Age)) +
  geom_density(fill="#ff0000") + ggtitle("Age") +
  ggplot(data=ux_mars_df,aes(x=Gender)) + geom_bar() +
  ggtitle("Gender") +
  ggplot(data=ux_mars_df,aes(x=Ethnicity)) + geom_bar() + ggtitle("Ethnicity") +
  ggplot(data=ux_mars_df,aes(x=Education)) + geom_bar() + ggtitle("Education") +
  ncol=2, nrow=2)
```

```
## Warning: Removed 2 rows containing non-finite values (stat_density).
```

Distribution of variables (n=50-56)

Figure 1.

```
## Warning: Removed 2 rows containing non-finite values (stat_density).
```

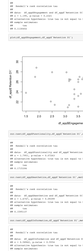
```
## ,Age,Gender,
## Female: 29.0000000 Female:0.5000000,
## Male: 29.0000000 Male:0.5000000,
## Caucasian: 29.0000000 Caucasian:0.5000000,
## Hispanic: 29.0000000 Hispanic:0.5000000,
## African American: 29.0000000 African American:0.5000000,
## Asian: 29.0000000 Asian:0.5000000,
## Other: 29.0000000 Other:0.5000000,
## Bachelor's degree: 29.0000000 Bachelor's degree:0.5000000,
## Master's degree: 29.0000000 Master's degree:0.5000000,
## Doctorate: 29.0000000 Doctorate:0.5000000,
## Some college: 29.0000000 Some college:0.5000000,
## High school: 29.0000000 High school:0.5000000,
## Vocational degree: 29.0000000 Vocational degree:0.5000000,
## Other: 29.0000000 Other:0.5000000,
## Density: 0.0000000 Density:0.0000000,
## count: 1.0000000 count:1.0000000,
## Ethnicity,Education,
## Caucasian: 29.0000000 Bachelor's degree: 29.0000000,
## Hispanic: 29.0000000 Master's degree: 29.0000000,
## African American: 29.0000000 Doctorate: 29.0000000,
## Asian: 29.0000000 Some college: 29.0000000,
## Other: 29.0000000 High school: 29.0000000,
## Density: 0.0000000 Vocational degree: 29.0000000,
## count: 1.0000000 Other: 29.0000000,
## Density: 0.0000000,
## count: 1.0000000,
```

Pre-registered analyses

```
fit.lm.age=lm(Age ~ Gender + Ethnicity + Education + Gender:Ethnicity + Gender:Education,
data=ux_mars_df)
ggplot(data=ux_mars_df,aes(x=fitted.fit.lm.age,y=Age)) + geom_jitter(height=0.1)
```

```
##
## Call:
## lm(formula = Age ~ Gender + Ethnicity + Education + Gender:Ethnicity +
## Gender:Education, data = ux_mars_df)
##
## Coefficients:
## (Intercept)       Gender  Ethnicity  Education  Gender:Ethnicity
##  -1.0000000  -0.0000000   0.0000000   0.0000000   0.0000000
## Gender:Education
##   0.0000000
##
## NA degrees of freedom
## NA residual
## NA residual sum of squares
## NA R-squared, NA adjusted R-squared
## NA F-statistic, NA DF, NA DF, NA p-value
```

```
ggplot(data=ux_mars_df,aes(x=fitted.fit.lm.age,y=Age)) + geom_jitter(height=0.1)
```




```
fit.lm.age.gender=lm(Age ~ Gender,data=ux_mars_df)
```

```
##
## Call:
## lm(formula = Age ~ Gender, data = ux_mars_df)
##
## Coefficients:
## (Intercept)       Gender
##  -1.0000000   0.0000000
##
## NA degrees of freedom
## NA residual
## NA residual sum of squares
## NA R-squared, NA adjusted R-squared
## NA F-statistic, NA DF, NA DF, NA p-value
```

```
ggplot(data=ux_mars_df,aes(x=fitted.fit.lm.age.gender,y=Age)) +
  geom_jitter(height=0.1) + ylab("Age") +
  ggtitle("NAMS Mean Predicting Age Revenue") +facet_wrap(~ Gender)
```

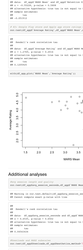
```
## Warning: Removed 2 rows containing non-finite values (stat_smooth).
```

```
fit.lm.age.ethnicity=lm(Age ~ Ethnicity,data=ux_mars_df)
```

```
##
## Call:
## lm(formula = Age ~ Ethnicity, data = ux_mars_df)
##
## Coefficients:
## (Intercept)  Ethnicity
##  -1.0000000   0.0000000
##
## NA degrees of freedom
## NA residual
## NA residual sum of squares
## NA R-squared, NA adjusted R-squared
## NA F-statistic, NA DF, NA DF, NA p-value
```

```
ggplot(data=ux_mars_df,aes(x=fitted.fit.lm.age.ethnicity,y=Age)) +
  geom_jitter(height=0.1) + ylab("Age") +
  ggtitle("NAMS Mean Predicting Age Revenue") +facet_wrap(~ Ethnicity)
```

```
## Warning: Removed 2 rows containing non-finite values (stat_smooth).
```




```
fit.lm.age.education=lm(Age ~ Education,data=ux_mars_df)
```

```
##
## Call:
## lm(formula = Age ~ Education, data = ux_mars_df)
##
## Coefficients:
## (Intercept)  Education
##  -1.0000000   0.0000000
##
## NA degrees of freedom
## NA residual
## NA residual sum of squares
## NA R-squared, NA adjusted R-squared
## NA F-statistic, NA DF, NA DF, NA p-value
```

```
ggplot(data=ux_mars_df,aes(x=fitted.fit.lm.age.education,y=Age)) +
  geom_jitter(height=0.1) + ylab("Age") +
  ggtitle("NAMS Mean Predicting Age Revenue") +facet_wrap(~ Education)
```

```
## Warning: Removed 2 rows containing non-finite values (stat_smooth).
```

```
fit.lm.age.gender.ethnicity=lm(Age ~ Gender + Ethnicity,data=ux_mars_df)
```

```
##
## Call:
## lm(formula = Age ~ Gender + Ethnicity, data = ux_mars_df)
##
## Coefficients:
## (Intercept)       Gender  Ethnicity
##  -1.0000000   0.0000000   0.0000000
##
## NA degrees of freedom
## NA residual
## NA residual sum of squares
## NA R-squared, NA adjusted R-squared
## NA F-statistic, NA DF, NA DF, NA p-value
```

```
ggplot(data=ux_mars_df,aes(x=fitted.fit.lm.age.gender.ethnicity,y=Age)) +
  geom_jitter(height=0.1) + ylab("Age") +
  ggtitle("NAMS Mean Predicting Age Revenue") +facet_wrap(~ Gender,Ethnicity)
```

```
## Warning: Removed 2 rows containing non-finite values (stat_smooth).
```

```
fit.lm.age.gender.education=lm(Age ~ Gender + Education,data=ux_mars_df)
```

```
##
## Call:
## lm(formula = Age ~ Gender + Education, data = ux_mars_df)
##
## Coefficients:
## (Intercept)       Gender  Education
##  -1.0000000   0.0000000   0.0000000
##
## NA degrees of freedom
## NA residual
## NA residual sum of squares
## NA R-squared, NA adjusted R-squared
## NA F-statistic, NA DF, NA DF, NA p-value
```

```
ggplot(data=ux_mars_df,aes(x=fitted.fit.lm.age.gender.education,y=Age)) +
  geom_jitter(height=0.1) + ylab("Age") +
  ggtitle("NAMS Mean Predicting Age Revenue") +facet_wrap(~ Gender,Education)
```

```
## Warning: Removed 2 rows containing non-finite values (stat_smooth).
```



```
fit.lm.age.gender.ethnicity.education=lm(Age ~ Gender + Ethnicity + Education,
data=ux_mars_df)
```

```
##
## Call:
## lm(formula = Age ~ Gender + Ethnicity + Education, data = ux_mars_df)
##
## Coefficients:
## (Intercept)       Gender  Ethnicity  Education
##  -1.0000000   0.0000000   0.0000000   0.0000000
##
## NA degrees of freedom
## NA residual
## NA residual sum of squares
## NA R-squared, NA adjusted R-squared
## NA F-statistic, NA DF, NA DF, NA p-value
```

```
ggplot(data=ux_mars_df,aes(x=fitted.fit.lm.age.gender.ethnicity.education,y=Age)) +
  geom_jitter(height=0.1) + ylab("Age") +
  ggtitle("NAMS Mean Predicting Age Revenue") +facet_wrap(~ Gender,Ethnicity,Education)
```

```
## Warning: Removed 2 rows containing non-finite values (stat_smooth).
```

Pearson Chi-Squared and GAM p-values corrected 0.05, all ns randomness ns
Pearson Chi-Squared and GAM p-values corrected 0.05, all ns randomness ns

```
ANOVA GAM p.adjusted(p.fit,method="fdr",n=length(p.fit)) p.adjusted(p.fit,method="fdr",n=length(p.fit))
fit.lm.age.gender.ethnicity.education.pvalues=c(p.fit.lm.age,p.fit.lm.age.gender,p.fit.lm.age.ethnicity,p.fit.lm.age.education,p.fit.lm.age.gender.ethnicity,p.fit.lm.age.gender.education,p.fit.lm.age.ethnicity.education,p.fit.lm.age.gender.ethnicity.education)
```

```
##
## Call:
## lm(formula = fit.lm.age.gender.ethnicity.education.pvalues ~
## 1)
##
## Coefficients:
## (Intercept)
##  -1.000000
##
## NA degrees of freedom
## NA residual
## NA residual sum of squares
## NA R-squared, NA adjusted R-squared
## NA F-statistic, NA DF, NA DF, NA p-value
```

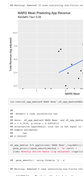
```
plot(fit.lm.age.gender.ethnicity.education.pvalues)
```

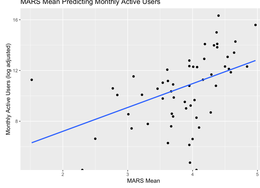


```
fit.lm.age.gender.ethnicity.education.pvalues.fdr=p.adjust(fit.lm.age.gender.ethnicity.education.pvalues,method="fdr",n=length(fit.lm.age.gender.ethnicity.education.pvalues))
```

```
##
## Call:
## lm(formula = fit.lm.age.gender.ethnicity.education.pvalues.fdr ~
## 1)
##
## Coefficients:
## (Intercept)
##  -1.000000
##
## NA degrees of freedom
## NA residual
## NA residual sum of squares
## NA R-squared, NA adjusted R-squared
## NA F-statistic, NA DF, NA DF, NA p-value
```

```
plot(fit.lm.age.gender.ethnicity.education.pvalues.fdr)
```


fit.lm.age.gender.ethnicity.education.pvalues.fdr



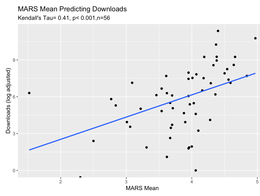

```
cor.test(df_app_median$`MARS Mean`,df_app_median$Downloads,method='kendall')
```

```
##
##  Kendall's rank correlation tau
##
## data:  df_app_median$`MARS Mean` and df_app_median$Downloads
## z = 4.4331, p-value = 0.00009929
## alternative hypothesis: true tau is not equal to 0
## sample estimates:
##       tau
## 0.4068712
```

```
df_app_median %>% ggplot(aes(`MARS Mean`,log(Downloads)))+
  geom_point()+geom_smooth(method = 'lm',se=F)+
  ylab('Downloads (log adjusted)')+
  ggtitle('MARS Mean Predicting Downloads',"Kendall's Tau= 0.41, p< 0.001,n=56")
```

```
## `geom_smooth()` using formula `y ~ x`
```

```
## Warning: Removed 1 rows containing non-finite values (stat_smooth).
```

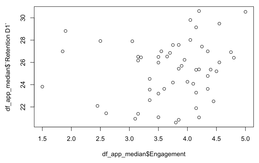



```
#note that Downloads and MAD are correlated 0.99, so its redundant to
#include both in the same paper. Revenue is correlated with them ~.45


#RQ:The MARS's Engagement, Functionality, and Aesthetics subscales will predict
#user retention more strongly than the Information subscale
cor.test(df_app_median$Engagement,df_app_median$`Retention D1`,method='kendall')
```

```
##
##  Kendall's rank correlation tau
##
## data:  df_app_median$Engagement and df_app_median$`Retention D1`
## z = 1.195, p-value = 0.2321
## alternative hypothesis: true tau is not equal to 0
## sample estimates:
##       tau
## 0.1130402
```

```
plot(df_app_median$Engagement,df_app_median$`Retention D1`)
```




```
cor.test(df_app_median$Functionality,df_app_median$`Retention D1`,method='kendall')
```

```
##
##  Kendall's rank correlation tau
##
## data:  df_app_median$Functionality and df_app_median$`Retention D1`
## z = 1.7951, p-value = 0.07263
## alternative hypothesis: true tau is not equal to 0
## sample estimates:
##       tau
## 0.1715306
```

```
cor.test(df_app_median$Aesthetics,df_app_median$`Retention D1`,method='kendall')
```

```
##
##  Kendall's rank correlation tau
##
## data:  df_app_median$Aesthetics and df_app_median$`Retention D1`
## z = 1.6747, p-value = 0.09399
## alternative hypothesis: true tau is not equal to 0
## sample estimates:
##       tau
## 0.1595137
```

```
cor.test(df_app_median$Information,df_app_median$`Retention D1`,method='kendall')
```

```
##
##  Kendall's rank correlation tau
##
## data:  df_app_median$Information and df_app_median$`Retention D1`
## z = 0.58962, p-value = 0.5556
## alternative hypothesis: true tau is not equal to 0
## sample estimates:
##       tau
## 0.05567802
```

```
cor.test(df_app_median$`MARS Mean`,df_app_median$`Retention D1`,method='kendall')
```

```
##
##  Kendall's rank correlation tau
##
## data:  df_app_median$`MARS Mean` and df_app_median$`Retention D1`
## z = 1.6942, p-value = 0.09023
## alternative hypothesis: true tau is not equal to 0
## sample estimates:
##       tau
## 0.1592992
```

```
cor.test(df_app_median$Engagement,df_app_median$`Retention D7`,method='kendall')
```

```
##
##  Kendall's rank correlation tau
##
## data:  df_app_median$Engagement and df_app_median$`Retention D7`
## z = -0.26887, p-value = 0.788
## alternative hypothesis: true tau is not equal to 0
## sample estimates:
##       tau
## -0.02543604
```

```
cor.test(df_app_median$Functionality,df_app_median$`Retention D7`,method='kendall')
```

```
##
##  Kendall's rank correlation tau
##
## data:  df_app_median$Functionality and df_app_median$`Retention D7`
## z = 0.27675, p-value = 0.782
## alternative hypothesis: true tau is not equal to 0
## sample estimates:
##       tau
## 0.02644429
```

```
cor.test(df_app_median$Aesthetics,df_app_median$`Retention D7`,method='kendall')
```

```
##
##  Kendall's rank correlation tau
##
## data:  df_app_median$Aesthetics and df_app_median$`Retention D7`
## z = 0.089717, p-value = 0.9285
## alternative hypothesis: true tau is not equal to 0
## sample estimates:
##       tau
## 0.008545574
```

```
cor.test(df_app_median$Information,df_app_median$`Retention D7`,method='kendall')
```

```
##
##  Kendall's rank correlation tau
##
## data:  df_app_median$Information and df_app_median$`Retention D7`
## z = -0.6344, p-value = 0.5258
## alternative hypothesis: true tau is not equal to 0
## sample estimates:
##       tau
## -0.05969154
```

```
cor.test(df_app_median$`MARS Mean`,df_app_median$`Retention D7`,method='kendall')
```

```
##
##  Kendall's rank correlation tau
##
## data:  df_app_median$`MARS Mean` and df_app_median$`Retention D7`
## z = -0.097025, p-value = 0.9227
## alternative hypothesis: true tau is not equal to 0
## sample estimates:
##       tau
## -0.009122863
```

```
cor.test(df_app_median$Engagement,df_app_median$`Retention D30`,method='kendall')
```

```
##
##  Kendall's rank correlation tau
##
## data:  df_app_median$Engagement and df_app_median$`Retention D30`
## z = -0.60494, p-value = 0.5453
## alternative hypothesis: true tau is not equal to 0
## sample estimates:
##       tau
## -0.0572066
```

```
cor.test(df_app_median$Functionality,df_app_median$`Retention D30`,method='kendall')
```

```
##
##  Kendall's rank correlation tau
##
## data:  df_app_median$Functionality and df_app_median$`Retention D30`
## z = -0.32142, p-value = 0.7477
## alternative hypothesis: true tau is not equal to 0
## sample estimates:
##       tau
## -0.03072182
```

```
cor.test(df_app_median$Aesthetics,df_app_median$`Retention D30`,method='kendall')
```

```
##
##  Kendall's rank correlation tau
##
## data:  df_app_median$Aesthetics and df_app_median$`Retention D30`
## z = -0.35138, p-value = 0.7253
## alternative hypothesis: true tau is not equal to 0
## sample estimates:
##       tau
## -0.03345769
```

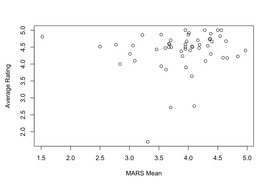
```
cor.test(df_app_median$Information,df_app_median$`Retention D30`,method='kendall')
```

```
##
##  Kendall's rank correlation tau
##
## data:  df_app_median$Information and df_app_median$`Retention D30`
## z = -1.1041, p-value = 0.2693
## alternative hypothesis: true tau is not equal to 0
## sample estimates:
##       tau
## -0.1038972
```

```
cor.test(df_app_median$`MARS Mean`,df_app_median$`Retention D30`,method='kendall')
```

```
##
##  Kendall's rank correlation tau
##
## data:  df_app_median$`MARS Mean` and df_app_median$`Retention D30`
## z = -0.55228, p-value = 0.5808
## alternative hypothesis: true tau is not equal to 0
## sample estimates:
##       tau
## -0.051912
```

```
# H1: Google Play store and Apple app store ratings will be correlated with the MARS mean.
cor.test(df_app_median$`Average Rating`,df_app_median$`MARS Mean`,method='kendall')
```

```
##
##  Kendall's rank correlation tau
##
## data:  df_app_median$`Average Rating` and df_app_median$`MARS Mean`
## z = 1.2769, p-value = 0.2016
## alternative hypothesis: true tau is not equal to 0
## sample estimates:
##       tau
## 0.1205925
```

```
with(df_app_median,plot(`MARS Mean`,`Average Rating`))
```