Do emojis speak louder than words?

Decoding the power of emojis in Facebook Marketplace Messages

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1 Introduction

Emojis are a common way of expressing emotion in modern forms of virtual communication. They are used in a wide variety of contexts to convey different feelings and can significantly change the tone and meaning of the message. Previous research has already expressed the attention-grabbing nature of Non-Facial emojis (Orazi et al., 2023) and the ability for Facial Emojis to replace traditional likert scales (SwaneyStueve et al., 2018), which highlights their impact on modern English. In our experiment, we sent different messages, with and without emojis, to sellers who listed headphones on Facebook Markerplace. The response rate of each condition was then calculated, along with the percentage of sellers who were willing to reduce their initial listing price. In doing so, we set out to answer…

Do emojis influence seller willingness to reduce price in FB Marketplace?

Emojis in our messages are expected to drive engagement due to their visual appeal and personal nature. We examine whether the presence complementary Non-Facial Emojis (NFE) or Facial Emojis (FE) influences seller behavior compared to messages that do not contain any emojis. In this context, "complementary" refers to an emoji's ability to enhance meaning of a word or phrase and "facial" refers to face emojis evoking sentiment or feeling. All messages will contain the same phrasing, only differing in terms of NFE, FE, or no emoji inclusion. This allows us to draw causal inference whether observed changes in seller willingness to reduce price can be attributable to emoji-use. Such findings would be practical for small businesses, marketing, brands, e-commerce, and many more industries to understand consumer behaviors and motivators behind user engagement.

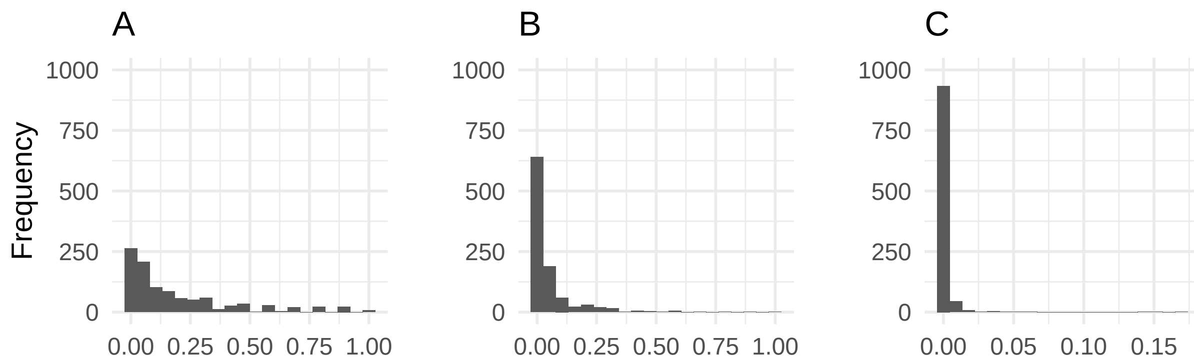
2 Literature Review

In published research about emoji usage, the majority gather observational data from large repositories like web scraping Tweets to create complex engagement models (Wang et al., 2022), rather than designing an experiment to understand true casual influence. Many other studies assessed how people rated messages containing emojis (Orazi et al., 2023) but did not explicitly test how the emoji alters behavior in either a positive or negative manner. They are interested in the perception of emoji, however, we desire to understand their usefulness and practicality. This experiment builds upon the study "Non-face emojis in digital marketing: Effects, contingencies, and strategic recommendations" by Orazi, et al., where the authors express that FE may elicit more emotional contagion effects compare to NFE. Using an Airbnb dataset, they find that NFE have the third-largest impact on electronic word of mouth (eWOM) volume next to seller quality and ease-of-booking. eWOM is where customers share their experiences, opinions, and recommendations on posts. They find that NFE can be more effective than FE in driving eWOM volume in the Airbnb digital marketplace. They also found that use of too many NFE and FE led to worse eWOM because it actually reduced processing fluency to the audience. Based on this past study, we will focus on replicating the effects of using emojis on messages to see if it will increase how many potential sellers would be willing to reduce their price.

3 Power Analysis

Considering no publications detailed the ATE of emoji inclusion for willingness to reduce price, we believed 10, 15, or 25% effect to be reasonable starting points; this was ultimately corroborated with our pilot data of 126 FB Marketplace messages which showcased an ATE between 10-13%. Due to platform limitations (one of our buyers, no longer had sellers to message) we capped our messages to approximately 120 per treatment group. Therefore, our power analysis utilizes sample sizes of n = 120 to determine the likelihood of detecting a statistically significant effect if one exists given our current experimental design. For a 10% ATE, a detection rate of 34% meant that we would often miss the true effect (low statistical power). At 15% ATE, detection rate nearly doubled to 72.1% which still leaves substantial room for type II errors, but detects the true effect most of the time. Lastly, for a 25% ATE, we found that we would be able to detect the true effect 99.1% of the time. The data generation process and results are showcased in code below and in Figure 1.

```r
# Sample code of generating 10% ATE
# picked arbitrary values

# Generate control values with 75% 0s (Willingness) and 25% 1s (No Willingness)
d1 <- data.table(treatment = rep(0, 500))
d1[, response := c(rep(0, 375), rep(1, 125))]

# 65% 0s and 35% 1s, 10% increase compare to control
d2 <- data.table(treatment = rep(1, 500))
d2[ , response := c(rep(0, 325), rep(1, 175))]

# Concatenate row-wise
data <- rbind(d1, d2)

# fill this in with the p-values from your power analysis
t_test_p_values <- rep(NA, 1000)

for(sim in 1:1000) {
    # Resample and randomly selects 120 treatment
    # Resample and randomly selects 120 control without replacement
    sample <- data[, .SD[sample(.N, 120)], by = treatment]

    # Run the t-test
   test_result <- t.test(response~treatment, data=sample)

    # Store Pvalue from the T.Test
    t_test_p_values[sim] <-  test_result$p.value
}

#The same process is repeated for 15 and 25% ATE
```



Alpha levels of 0.05 were used; bins are at 0.05 increments; (A) 10% ATE, (B) 15% ATE, (C) 25% ATE

Figure 1: P-value Distribution per ATE

4 Hypothesis

We want understand the causal effect of using emojis on the willingness to reduce price. A two-sided hypothesis test was employed to assess for effect in either direction for statistical significance. The null and alternative hypotheses used for this experiment will be as follows:

Null Hypothesis (H_0): Neither emoji treatment has impact on willingness to reduce price[1]

$$H_0 : \beta_{FE} \; = \; 0 \;\; or \;\; \beta_{NFE} = 0$$

Alternative Hypothesis (H_1): Either emoji treatment has an effect on the willingness to reduce price:

$$H_1 : \beta_{FE} \; \neq \; 0 \;\; or \;\; \beta_{NFE} \neq 0$$

5 Methodology

During our experiment 352 sellers were contacted in FB Marketplace, with an intended target of 90 different sellers per each `buyer`. Sellers were randomly selected and assigned a treatment and contacted only once to ensure no seller received more than one type of message. We assessed both the seller's willingness to reduce the item's price in their response and the response rate. Both variables were coded as binary outcomes. The key treatment variable was message type sent to the sellers, which meant the message contained one of three possible conditions.

5.1 Experimental Design

A between-subject randomized controlled experiment was designed (seller-level randomization), to assess the casual effect of emoji inclusion on seller engagement in FB Marketplace. Sellers listing

[1] As mentioned previously and for simplicity, *FE* signifies Facial Emoji and *NFE* signifies Non-Facial Emoji for β subscripts.

premium headphones[2] were targeted to minimize heterogeneity in our sample due to different products and because initial FB Marketplace assessments indicated a robust market for headphones that would make the experiment feasible. Two different treatments were employed: Non-Facial Emoji (NFE), Facial Emoji (FE) and compared against our control No Emoji (NE). These three condition messages were crafted with identical wording, tone, and inquiry interest where the only thing altered text is NE, NFE, or FE at the very beginning of the message to ensure seller sees the message type in a notification or on the FB Messenger. The template message is provided below, alongside a screenshot of the three different treatment conditions in Figure 2.

"Hey, I am interested in this item. Would you be open to a price negotiation?"

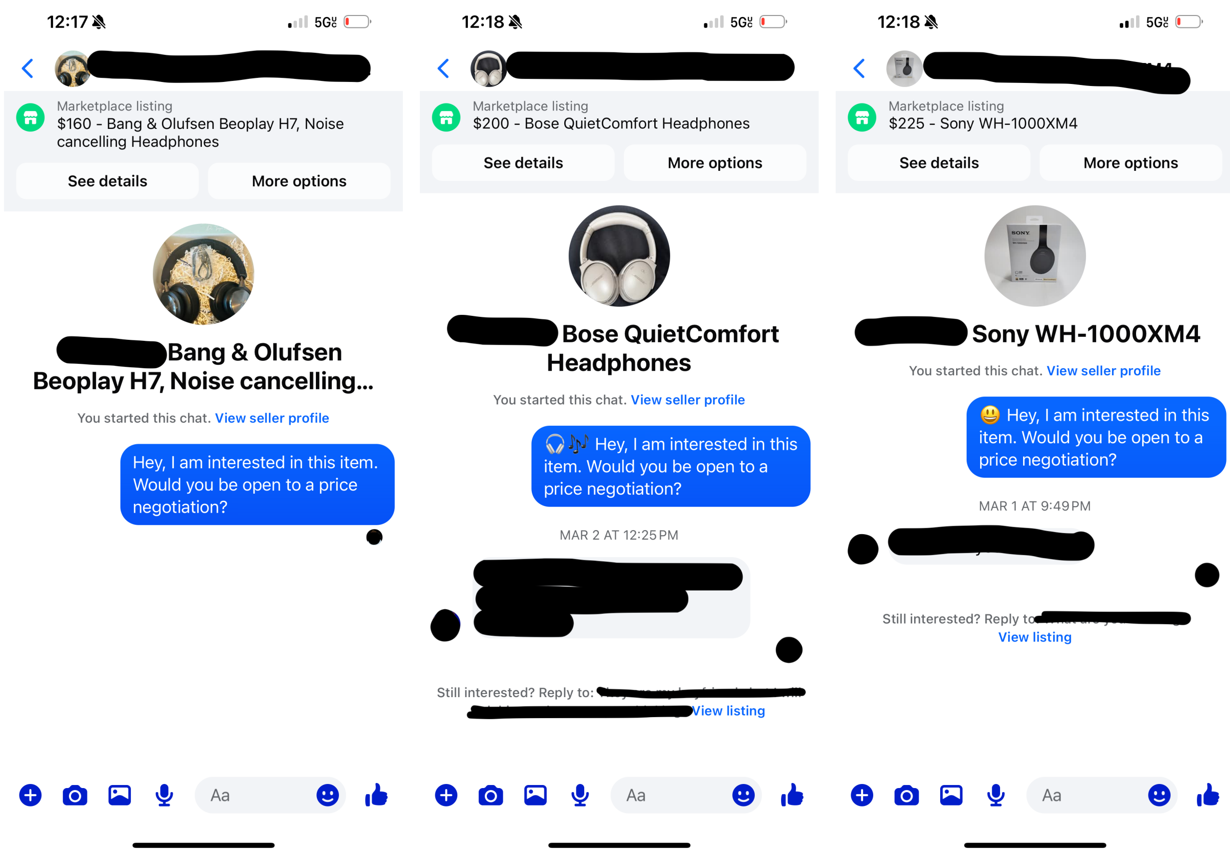


Figure 2: Message Treatment Conditions

5.2 Data Collection

Data was gathered through manual data entry from FB Messenger. For practicality, considering that we live in the age of smartphones, we considered all messages as successfully reaching our randomized sellers. The train of thought behind this is that notifications are common and actively choosing to ignore our message becomes even easier; we believe this scenario to be more likely than the idea that they never noticed the message. We strictly only considered responses within 48

[2]We established a price point of $USD 100+ to be considered as *premium headphones*

hours, to limit second choice or desperation messages in the event they chose to first willingly ignore our message and later contact us due to other buyers they were in contact with falling through. Names were collected to ensure multiple treatments were not administered to the same person and avoid some community-based spillover effect. Additionally, to avoid further spillover, each of us sent messages to sellers in non-overlapping regions of Los Angeles, Orange County, Bay Area, and Hawaii. Although, the seller demographics may vary from region to region, we believe controlling for only premium headphones, helps mitigate this variability.

5.3 Variables

Outcome Variables: `willingToReducePrice`, `response`
Independent Variables: `buyer`, `msgTime`, `day`, `dayType`, `priceDrop`, `justListed`, `sellerGender`
Treatment Condition Variable: `emoji`

5.4 Data Cleansing & Exploration

Data cleansing process involved manipulation and standardizing of multiple columns through `data.table()`. Treatment categories for emoji message types (one-hot encoded for tracking convenience) were consolidated into a single column, irrelevant variables were removed, and Weekday/Weekend categorization was created from `day` variable. Categorical variables were turned into factors with defined levels and time data was formatted for improved interpretability. Column names were altered to lower camel case for consistency and ease of use with rmarkdown latex output configurations.

Data was checked and confirmed to not possess any missing values or inconsistencies. All modification were necessary for clarity and usability of the data, ensuring it was well-suited for subsequent analysis. As part of our data exploration, we plotted figures such as bar plots and histograms and produced summary tables describing distributions of variables to visually examine any potential underlying issues. However, despite this, we could not find any readily apparent issues or anomalies in our collected data, giving us confidence in the integrity of our data. Process for data cleansing is captured in code below, a snippet of our data is shown in Table 1 for understanding of how our variables are encoded, and data exploration is highlighted in Figure 3 and Table 4 in the Appendix.

```r
# single col for one hot encoded
d[, emoji := fcase(
  non_facial_emoji == 1, "Non-Facial",
  facial_emoji == 1, "Facial",
  no_emoji == 1, "Control"
)]

# Drop unused column
d[, c("non_facial_emoji", "facial_emoji", "no_emoji", "seller_name", "counter",
      "response time", "condition",
      "price", "V18", "Rough Numbers", "V20" , "V21") := NULL]

# Normalize all day values.
d[day == "Fri", day := "Friday"]
```

```r
d[day == "Mon", day := "Monday"]
d[day == "Sat", day := "Saturday"]
d[day == "Thu", day := "Thursday"]
d[day == "Tue", day := "Tuesday"]

# refactoring for easier interpretability
d[, day := factor(day, levels = c("Sunday", "Monday", "Tuesday", "Wednesday",
                                  "Thursday", "Friday", "Saturday"))]
d[, seller_gender := factor(seller_gender, levels = c("M", "F"), #male red
                            labels = c("M", "F"))]
d[, emoji := factor(emoji, levels = c("Control", "Non-Facial", "Facial"))]


# Convert to ITime using data.table's built-in function:
d[, msg_time := as.ITime(msg_time, format = "%H:%M:%S")]


# create weekend/weekday
d[, dayType := ifelse(day %in% c("Saturday", "Sunday"), "Weekend", "Weekday")]

# create number col
d[, number := .I]


# reorder so relevant cols are closer together
d <- d[, c(12, 1:3, 11, 4:10)]

# convert lower cc
setnames(d, to_lower_camel_case(names(d)))

#data snippet
showcase_data <- kable(head(d, 3)[,c(4:11)], caption = "Snippet of Data",
                       booktabs = TRUE)

# assess missing
colSums(is.na(d))
```

Table 1: Snippet of Data

day	dayType	priceDrop	justListed	location	sellerGender	response	willingToReducePrice
Saturday	Weekend	0	0	Hawaii	M	1	1
Saturday	Weekend	0	0	Hawaii	F	0	0
Saturday	Weekend	0	0	Hawaii	F	1	1

5.5 Tests

Three regression models were developed to evaluate the relationship between message type and a seller's willingness to reduce price. We tested these models using R v4.3.2 `lm()`, `coeftest()`, and `sandwich` package to test the statistical significance of the coefficients in the linear regression models with robust standard errors (`HC1`) to mitigate potential heteroskedasticity biases in the error estimates.

$Model_1$ included a basic specification where the dependent variable, `willingToReducePrice`, was regressed on the primary treatment and control variable `emoji` (NE, NFE, and FE messages).

$Model_2$ extended $Model_1$ by including the seller's gender as an additional covariate to control for potential gender-related differences in negotiation behavior.

$Model_3$ further expanded the model by incorporating a broader set of covariates: the buyer identifier, message time, message day, whether the item had experienced a price drop, whether the item was recently listed, and the seller's gender.

We also explored whether the effect of message type on a seller's willingness to reduce price varied by the seller's gender. To assess potential interaction effects between seller gender and message type, we ran the saturated Model 3 separately for male and female sellers. This approach allowed us to examine whether treatment effects differed by gender by filtering the dataset to include only male sellers in one model and only female sellers in another.

6 Results

We ran three models for a seller's willingness to reduce price. $Model_1$ included only `emoji` (Control, Non-Facial, and Facial) as the predictor. $Model_2$ added completely by including `sellerGender`. $Model_3$, our saturated model, included all additional covariates: `buyer`, `msgTime`, `day`, `priceDrop`, `justListed`, and `sellerGender`. All models are combined into a single table for easier referencing in Table 2.

In all three models, both Non-Facial and Facial emojis were associated with a statistically significant decrease in willingness to reduce price compared to the Control group (no emoji). So instead of driving more flexibility, the presence of emojis made sellers less likely to offer discounts. In the saturated model, the average treatment effects (ATE) were -0.18 for Non-Facial (p = 0.004) and -0.17 for Facial (p = 0.004), meaning that emoji use decreased the probability of a seller offering a price cut by roughly 17–18% relative to Control. Baseline averages confirm this pattern. In the control NE group, willingness to reduce was 71.1%. In the NF group, that dropped to 56.4%, and for FE it was even lower at 55.3%. Similarly, as reported in Table 5 response rates followed comparable patterns, with both NF and FE being less likely to respond than the Control group. This reinforces the idea that emoji-use, rather than enhancing engagement, may have a counterproductive effect on both response rates and willingness to negotiate price.

Table 2: All Willingness to Reduce Price Models

	$Model_1$: **Base**			$Model_2$: **Middle**			$Model_3$: **Saturated**		
Characteristic	**Beta**	**95% CI**	**p-value**	**Beta**	**95% CI**	**p-value**	**Beta**	**95% CI**	**p-value**
Emoji Treatment									
Control	—	—		—	—		—	—	
Non-Facial	-0.15	-0.27, -0.02	**0.018**	-0.15	-0.27, -0.03	**0.018**	-0.18	-0.30, -0.06	**0.004**
Facial	-0.16	-0.28, -0.04	**0.012**	-0.16	-0.28, -0.03	**0.012**	-0.17	-0.29, -0.06	**0.004**
Gender of Seller									
M				—	—		—	—	
F				-0.09	-0.20, 0.02	0.11	-0.11	-0.21, 0.00	0.056
Prospective Buyer									
Kevin							—	—	
Maged							-0.31	-0.50, -0.12	**0.001**
Missael							0.04	-0.16, 0.24	0.67
Patrick							-0.06	-0.37, 0.25	0.71
Hour of Message							0.00	0.00, 0.00	0.70
Day of Message									
Sunday							—	—	
Monday							0.08	-0.32, 0.49	0.68
Tuesday							-0.02	-0.39, 0.35	0.92
Wednesday							0.02	-0.42, 0.46	0.94
Thursday							0.01	-0.31, 0.34	0.94
Friday							-0.05	-0.40, 0.29	0.76
Saturday							-0.10	-0.46, 0.25	0.57
Price Drop							0.20	0.09, 0.32	**<0.001**
Just Listed							0.03	-0.16, 0.23	0.73

Abbreviation: CI = Confidence Interval

```r
# Sample code for Model 3 of Willingness to Reduce
# saturated model
model3 <- d[ , lm(willingToReducePrice~emoji +
                    buyer + msgTime + day + priceDrop +
                    justListed + sellerGender)]


# if you want to compare to check robust std
# model3_robust <- coeftest(model3, vcov = vcovHC(model3, "HC1"))
# model3_robust

#output table with robust se
tbl_model3 <-
  tbl_regression(
    model3,
    pvalue_fun = label_style_pvalue(digits = 2),
    tidy_fun = \(x, ...) tidy_robust(x, vcov = vcovHC(model3, "HC1"), ...),
    label = list(emoji = "Emoji Treatment",
                 sellerGender = "Gender of Seller",
                 buyer = "Prospective Buyer",
                 msgTime = "Hour of Message",
                 day = "Day of Message",
                 priceDrop = "Price Drop",
                 justListed = "Just Listed")
    ) %>%
  bold_p() %>%
  modify_caption("(Saturated) Model 3 for Willingness to Reduce with Robust SE")
```

The saturated model also revealed that both `buyer` (*Maged*, ATE: *-0.31*, p= *0.001*) and `priceDrop` (*Yes*, ATE: *0.2*, p< *0.001*) were statistically significant predictors of seller's willingness to reduce price. The `priceDrop` variable, an indication whether a seller's item was re-listed at a lower price since the original post, was positively associated with our outcome. This variable likely embodies a psychological shift on the seller's part…once they understand their product isn't attracting buyers, they may become more receptive to entertaining further price reduction. Meanwhile, the `buyer` variable, which serves almost as a fixed-effect to control for unobserved buyer characteristic, also showed a strong influence on our outcome. Additionally, since `buyer` was inherently tied to locations, due to study design convenience, disentanglement between location effects from buyer effects was not feasible. Therefore, we acknowledge that the observed `buyer` effects may include regional variation effects that could play a huge part in our outcome; in the context of our experiment, this means the headphone market in Los Angeles could strongly influence our observed outcome.

Due to the interesting underlying balance of sellers in the premium headphone market, 65.1% male and 34.9% female, we believed there to be potential for gender based effects. Therefore, we estimated $Model_3$ separately for male and female sellers by partioning the data with `data.table()` between the two genders. Among male sellers, both treatments (NFE and FE) had strong negative effects that were statistically significant. Among female sellers, the effects were in the same direction but didn't reach significance. This suggests that the presence of emojis is more detrimental when messaging male sellers. Code and table output for those results are summarized below.

```r
#gender specific subanalysis
#data.table can do rowwise filtering without creating new tables
model_male <- d[sellerGender == "M"
                       , lm(willingToReducePrice ~ emoji + buyer + msgTime +
                              day + priceDrop + justListed )]

model_female <- d[sellerGender == "F",
                  lm(willingToReducePrice ~ emoji + buyer + msgTime +
                       day + priceDrop + justListed )]

#robust SE for genders
male_robust <- coeftest(model_male, vcov = vcovHC(model_male, type = "HC1"))
female_robust <- coeftest(model_female,  vcov = vcovHC(model_female, type = "HC1"))

#male table
tbl_male <-
  tbl_regression(
    model_male,
    pvalue_fun = label_style_pvalue(digits = 2),
    tidy_fun = \(x, ...) tidy_robust(x, vcov = vcovHC(model_male, "HC1"), ...),
    label = list(emoji = "Emoji Treatment",
                 sellerGender = "Gender of Seller",
                 buyer = "Prospective Buyer",
                 msgTime = "Hour of Message",
                 day = "Day of Message",
                 priceDrop = "Price Drop",
                 justListed = "Just Listed"),
    caption = NULL
    ) %>%
  bold_p() %>%
  modify_caption("Male Specific Model")

#female table
tbl_female <-
  tbl_regression(
    model_female,
    pvalue_fun = label_style_pvalue(digits = 2),
    tidy_fun = \(x, ...) tidy_robust(x, vcov = vcovHC(model_female, "HC1"), ...),
    label = list(emoji = "Emoji Treatment",
                 sellerGender = "Gender of Seller",
                 buyer = "Prospective Buyer",
                 msgTime = "Hour of Message",
                 day = "Day of Message",
                 priceDrop = "Price Drop",
                 justListed = "Just Listed"),
    caption = NULL
    ) %>%
```

```
  bold_p() %>%
  modify_caption("Female Specific Model")

#combined gender table
combined_gender<- tbl_merge(list(tbl_female, tbl_male),
                            tab_spanner = c("$Model_1$ : **Female**",
                                            "$Model_2$ : **Male**")) %>%
  modify_caption("Combined Gender Model Table") %>%
  as_gt() %>%
  tab_options(latex.tbl.pos = "H") %>%
  as_latex()
```

Table 3: Combined Gender Model Table

	$Model_1$: **Female**			$Model_2$: **Male**		
Characteristic	**Beta**	**95% CI**	**p-value**	**Beta**	**95% CI**	**p-value**
Emoji Treatment						
Control	—	—		—	—	
Non-Facial	-0.20	-0.42, 0.03	0.088	-0.20	-0.34, -0.06	**0.006**
Facial	-0.16	-0.38, 0.05	0.13	-0.20	-0.34, -0.07	**0.003**
Prospective Buyer						
Kevin	—	—		—	—	
Maged	-0.18	-0.56, 0.19	0.34	-0.32	-0.54, -0.09	**0.006**
Missael	-0.07	-0.44, 0.30	0.71	0.16	-0.09, 0.40	0.21
Patrick	-0.29	-0.84, 0.27	0.31	0.11	-0.25, 0.48	0.54
Hour of Message	0.00	0.00, 0.00	0.91	0.00	0.00, 0.00	0.44
Day of Message						
Sunday	—	—		—	—	
Monday	0.34	-0.38, 1.1	0.35	0.00	-0.52, 0.51	0.99
Tuesday	0.04	-0.63, 0.71	0.91	0.01	-0.45, 0.47	0.96
Wednesday	-0.31	-1.1, 0.44	0.42	0.18	-0.39, 0.75	0.54
Thursday	-0.04	-0.63, 0.55	0.89	0.10	-0.32, 0.51	0.64
Friday	-0.08	-0.70, 0.54	0.80	0.02	-0.42, 0.46	0.93
Saturday	-0.08	-0.77, 0.61	0.82	-0.08	-0.52, 0.36	0.73
Price Drop	-0.07	-0.32, 0.17	0.55	0.32	0.20, 0.44	**<0.001**
Just Listed	0.01	-0.34, 0.37	0.94	-0.05	-0.30, 0.21	0.72

Abbreviation: CI = Confidence Interval

Additionally, to confirm the model's validity, we verified that the covariates were randomly distributed with respect to treatment assignment and did not predict the treatment effect. An F-test comparing a simple model to a saturated model indicated that the covariates did not significantly predict outcomes. Variance Inflation Factor (VIF) scores also showed no multicollinearity issues.

```r
# F-test  to compare full model to null mode with no predictive features
# Create a new table with the transformed 'emoji' column
new_table <- copy(d)

# Update the 'emoji' column in the new table
new_table[, emoji := fcase(
  emoji == "Non-Facial", 1,
  emoji == "Facial", 2,
  emoji == "Control", 0
)]
# Fit full model
full_model <- lm(emoji ~ 1+ buyer + msgTime + day +
                   priceDrop + justListed + sellerGender, data = new_table)

# Fit null model (intercept only)
null_model <- lm(emoji ~ 1, data = new_table)

# Compare models
anova_mod_response <- anova(null_model, full_model, test = "F")
anova_mod_response
```

```
## Analysis of Variance Table
##
## Model 1: emoji ~ 1
## Model 2: emoji ~ 1 + buyer + msgTime + day + priceDrop + justListed +
##     sellerGender
##   Res.Df    RSS Df Sum of Sq      F Pr(>F)
## 1    351 234.86
## 2    338 231.54 13    3.3173 0.3725 0.9776
```

```r
# Check for multicollinearty
vif_values_response <- vif(full_model)
vif_values_response
```

```
##                   GVIF Df GVIF^(1/(2*Df))
## buyer        24.925081  3        1.709121
## msgTime       2.862030  1        1.691754
## day          28.868739  6        1.323434
## priceDrop     1.062635  1        1.030842
## justListed    1.520969  1        1.233276
## sellerGender  1.052891  1        1.026105
```

7 Discussion

The findings of this study provide preliminary experimental evidence that the use of emojis in buyer messages on Facebook Marketplace can negatively influence seller behavior. Contrary to expectations, sellers were significantly less likely to reduce their price when messages included emojis, both facial and non-facial, compared to messages with no emojis. This result challenges the common belief that emojis universally enhance communication by adding emotional tone or visual appeal.

While prior literature has suggested that complementary emojis may aid engagement without reducing processing fluency, our results indicate that in transactional contexts, even well-intentioned emoji use can backfire. Facial emojis, in particular, performed the worst in both response rate and willingness to negotiate. These effects were especially pronounced among male sellers, suggesting possible gender-based differences in how such messages are interpreted. Likewise, changing of listing price reflects deeper psychological elements at play and isolating location may reveal community-based social dynamics. Together, these findings highlight the importance of understanding audience expectations and platform context in peer-to-peer marketplace communications and suggests that simplicity may be more effective than expressiveness.

We also explored whether more meaningful day variables impacted seller behavior by recoding message days into weekday versus weekend categories. While this temporal variable did not yield any statistically significant effects on seller willingness to reduce price (Table 6), we did observe a notable difference in response rates. Sellers were statistically significantly less responsive to messages sent during the weekend as shown in Table 7 in the Appendix, suggesting that timing may play a subtle but relevant role in initiating engagement. Though these effects were not the primary focus of the study, they raise interesting questions about the rhythm of online activity and how platform engagement patterns may alter communication outcomes.

8 Limitations

Limitations that affect the generalizability of our findings are as follows:

1. Our experiment was conducted in largely metropolitan areas that may not be generalizable to rural communities or others with different demographics.

2. The participants of this study that sent out the Facebook messages were all male, so we may have widely different treatment effects if the messenger is a female.

3. Participants who sent out messages had different profile images, history/ratings on Facebook marketplace, and of different ethnicities, which may have impacted the treatment effects.

4. Treatment was delivered to users selling pricey headphones over $100. Facebook users who sell and own expensive headphones may react differently to the treatment compared to Facebook users that sell other items. It would be difficult to generalize to all types of items sold on the marketplace.

9 Conclusions

Including emojis, whether facial or non-facial—does not increase seller accommodation on Facebook Marketplace. In fact, it decreases it. Sellers were significantly less likely to reduce their price when messages included emojis, and this effect was strongest among male sellers. These results run counter to the belief that emojis boost engagement or friendliness.

For anyone using outreach messages, whether personal or automated, this finding matters. Emojis might make messages feel more informal or approachable to the sender, but to the receiver, especially in transactional settings, they might seem flippant or off-tone. That mismatch seems to reduce effectiveness. There's still room for future work here. It would be worth testing, for example, where the emoji goes (beginning vs. end), how different emoji types perform, or whether certain product categories respond differently. It could also help to gather qualitative data, asking sellers directly what they thought about the tone of the messages, to back up the behavioral findings.

10 Appendix

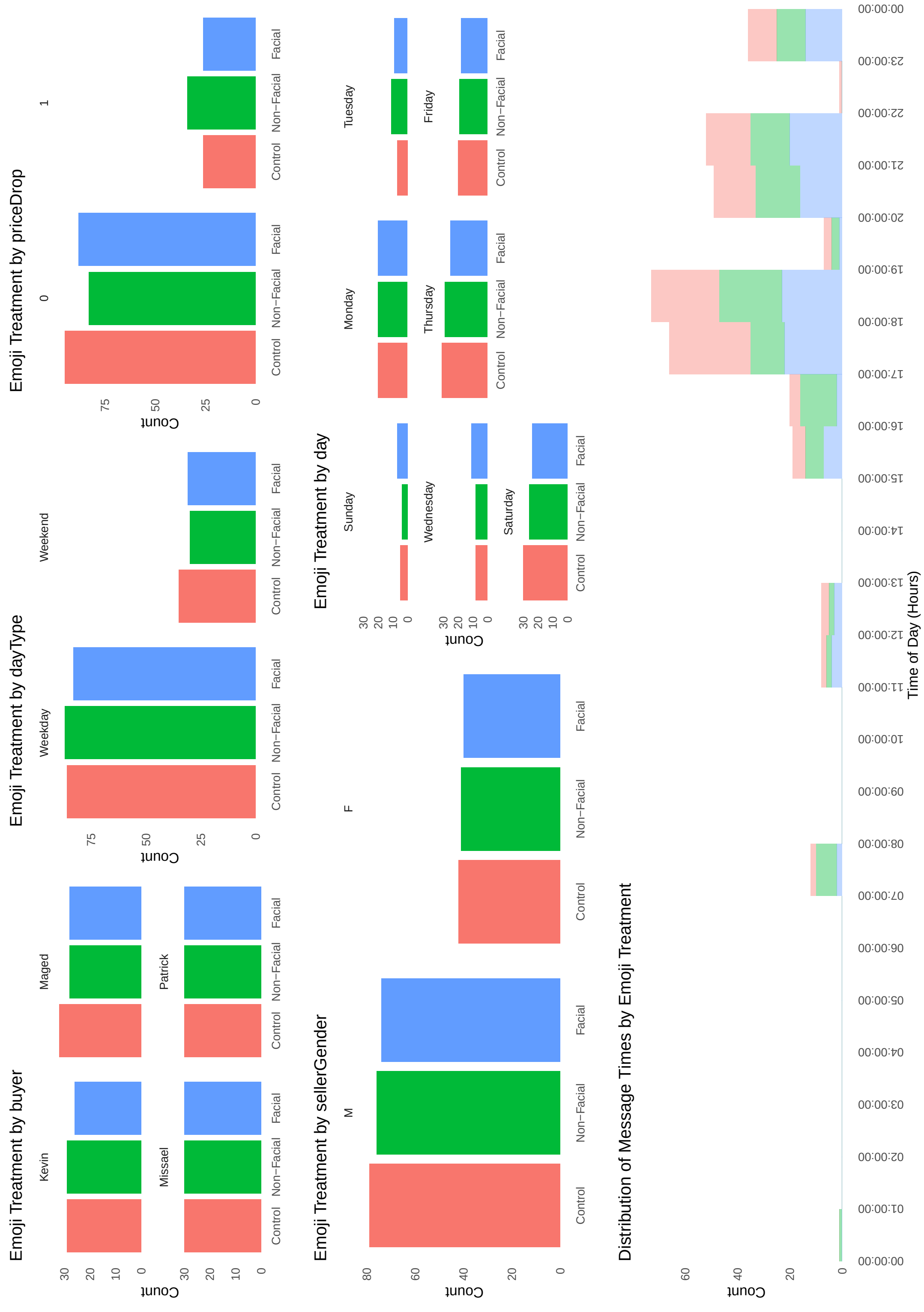


Figure 3: Combined Treatment Distribution

Table 4: Combined Table

Characteristic	Responses to Messages: **0** N = 103[1]	Responses to Messages: **1** N = 249[1]	Price Reduction Willingness: **0** N = 137[1]	Price Reduction Willingness: **1** N = 215[1]
Prospective Buyer				
Kevin	23 (22%)	61 (24%)	28 (20%)	56 (26%)
Maged	44 (43%)	44 (18%)	54 (39%)	34 (16%)
Missael	18 (17%)	72 (29%)	27 (20%)	63 (29%)
Patrick	18 (17%)	72 (29%)	28 (20%)	62 (29%)
Hour of Message	18:00:00 (17:00:00, 20:00:00)	18:00:00 (17:00:00, 21:00:00)	18:00:00 (17:00:00, 21:00:00)	18:00:00 (17:00:00, 20:00:00)
Day of Message				
Sunday	4 (3.9%)	12 (4.8%)	4 (2.9%)	12 (5.6%)
Monday	9 (8.7%)	51 (20%)	15 (11%)	45 (21%)
Tuesday	6 (5.8%)	21 (8.4%)	9 (6.6%)	18 (8.4%)
Wednesday	12 (12%)	15 (6.0%)	16 (12%)	11 (5.1%)
Thursday	21 (20%)	64 (26%)	31 (23%)	54 (25%)
Friday	13 (13%)	44 (18%)	21 (15%)	36 (17%)
Saturday	38 (37%)	42 (17%)	41 (30%)	39 (18%)
Day Type				
Weekday	61 (59%)	195 (78%)	92 (67%)	164 (76%)
Weekend	42 (41%)	54 (22%)	45 (33%)	51 (24%)
Price Drop	13 (13%)	73 (29%)	22 (16%)	64 (30%)
Just Listed	10 (9.7%)	19 (7.6%)	11 (8.0%)	18 (8.4%)
Gender of Seller				
M	60 (58%)	169 (68%)	82 (60%)	147 (68%)
F	43 (42%)	80 (32%)	55 (40%)	68 (32%)
Emoji Treatment				
Control	25 (24%)	96 (39%)	35 (26%)	86 (40%)
Non-Facial	37 (36%)	80 (32%)	51 (37%)	66 (31%)
Facial	41 (40%)	73 (29%)	51 (37%)	63 (29%)

[1] n (%); Median (Q1, Q3)

Table 5: All Response Models

	$Model_1$: **Base**			$Model_2$: **Middle**			$Model_3$: **Saturated**		
Characteristic	**Beta**	**95% CI**	**p-value**	**Beta**	**95% CI**	**p-value**	**Beta**	**95% CI**	**p-value**
Emoji Treatment									
Control	—	—		—	—		—	—	
Non-Facial	-0.11	-0.22, 0.00	0.055	-0.11	-0.22, 0.00	0.054	-0.13	-0.24, -0.02	**0.018**
Facial	-0.15	-0.27, -0.04	**0.009**	-0.15	-0.27, -0.04	**0.009**	-0.17	-0.27, -0.06	**0.002**
Gender of Seller									
M				—	—		—	—	
F				-0.09	-0.19, 0.01	0.094	-0.10	-0.21, 0.00	0.050
Prospective Buyer									
Kevin							—	—	
Maged							-0.20	-0.38, -0.02	**0.033**
Missael							0.05	-0.15, 0.25	0.63
Patrick							-0.05	-0.32, 0.22	0.72
Hour of Message							0.00	0.00, 0.00	0.57
Day of Message									
Sunday							—	—	
Monday							0.07	-0.34, 0.48	0.74
Tuesday							0.03	-0.34, 0.40	0.88
Wednesday							-0.06	-0.55, 0.43	0.81
Thursday							0.01	-0.35, 0.36	0.97
Friday							-0.03	-0.38, 0.33	0.89
Saturday							-0.22	-0.60, 0.16	0.26
Price Drop							0.21	0.11, 0.31	**<0.001**
Just Listed							-0.02	-0.21, 0.17	0.82

Abbreviation: CI = Confidence Interval

Table 6: All Willingness Models with Recoded Weekday/Weekend

	$Model_1$: **Base**			$Model_2$: **Middle**			$Model_3$: **Saturated Recoded**		
Characteristic	**Beta**	**95% CI**	**p-value**	**Beta**	**95% CI**	**p-value**	**Beta**	**95% CI**	**p-value**
Emoji Treatment									
Control	—	—		—	—		—	—	
Non-Facial	-0.15	-0.27, -0.02	**0.018**	-0.15	-0.27, -0.03	**0.018**	-0.18	-0.30, -0.06	**0.003**
Facial	-0.16	-0.28, -0.04	**0.012**	-0.16	-0.28, -0.03	**0.012**	-0.17	-0.28, -0.05	**0.004**
Gender of Seller									
M				—	—		—	—	
F				-0.09	-0.20, 0.02	0.11	-0.11	-0.22, 0.00	**0.041**
Prospective Buyer									
Kevin							—	—	
Maged							-0.31	-0.45, -0.17	**<0.001**
Missael							0.06	-0.10, 0.21	0.45
Patrick							-0.01	-0.15, 0.14	0.90
Hour of Message							0.00	0.00, 0.00	0.41
Day of Message									
Weekday							—	—	
Weekend							-0.09	-0.21, 0.04	0.17
Price Drop							0.20	0.09, 0.32	**<0.001**
Just Listed							0.03	-0.16, 0.22	0.77

Abbreviation: CI = Confidence Interval

Table 7: All Response Models with Recoded Weekday/Weekend

	$Model_1$: **Base**			$Model_2$: **Middle**			$Model_3$: **Saturated Recoded**		
Characteristic	**Beta**	**95% CI**	**p-value**	**Beta**	**95% CI**	**p-value**	**Beta**	**95% CI**	**p-value**
Emoji Treatment									
Control	—	—		—	—		—	—	
Non-Facial	-0.11	-0.22, 0.00	0.055	-0.11	-0.22, 0.00	0.054	-0.14	-0.24, -0.03	**0.013**
Facial	-0.15	-0.27, -0.04	**0.009**	-0.15	-0.27, -0.04	**0.009**	-0.16	-0.27, -0.06	**0.002**
Gender of Seller									
M				—	—		—	—	
F				-0.09	-0.19, 0.01	0.094	-0.11	-0.21, -0.01	**0.036**
Prospective Buyer									
Kevin							—	—	
Maged							-0.24	-0.37, -0.10	**<0.001**
Missael							0.09	-0.05, 0.24	0.22
Patrick							0.00	-0.13, 0.13	>0.99
Hour of Message							0.00	0.00, 0.00	0.87
Day of Message									
Weekday							—	—	
Weekend							-0.18	-0.30, -0.06	**0.003**
Price Drop							0.21	0.11, 0.31	**<0.001**
Just Listed							-0.04	-0.21, 0.14	0.68

Abbreviation: CI = Confidence Interval