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Determining Key Factors in Consumer Evaluation of an Airport

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Abstract

In this paper we perform a factor analysis on eleven variables involving attributes and usage of services at the San Francisco Airport (SFO), in order to determine, from among these variables, the underlying structure of the factors that are primary in leading a customer of SFO to his/her overall rating of SFO. We then perform a stepwise logistic regression analysis using these factors as independent variables, and an overall evaluation of SFO as the dependent variable, to find out how these factors affect the overall evaluation of SFO.

Key words: Factor analysis, Stepwise logistic regression, San Francisco airport (SFO), Use of technology at SFO, Survey data

Introduction

We use data collected at the San Francisco International Airport (SFO). A questionnaire was designed by SFO staff and was filled out by flyers from a random sample of flights. All airport terminals at SFO, and all boarding areas within these terminals, were utilized. Data were collected in mid-2013. First, we conducted an exploratory factor analysis using several variables as described below. The objective was to discover the underlying structure among these several variables. Then, using the factors derived from the factor analysis as independent variables, we performed a stepwise logistic regression with a binary dependent variable of the overall evaluation of SFO as "good/ outstanding" vs. "average or below," where an ordinal satisfaction-scale, described in more detail later in the paper, is divided into these two categories.

Literature Review

There have been a variety of studies that have examined satisfaction, loyalty, and overall evaluations of airports by consumers of (flyers at) specific airports. Mattazo et al. (2012), studied customer satisfaction at the Augusto Severo airport in Brazil. They determined that key variables affecting consumer attitudes toward the airport were confidence in the safety of the premises, waiting time for a taxi, availability and quality of seats in the airport, as well as prices of the food at terminal restaurants.

Suki (2014) considered passenger satisfaction with airline service at the major airport in Malaysia. His key finding was that customer service is a major determinant of the content of word-of-mouth and recommendations. A study at the Jordan airport by Al Refaie et al. (2014) considered the impact of aspects of flight performance and ticket pricing. They found that satisfaction was related to the reservation process, ticketing process, and perceived value. They also found that loyalty was driven most by service recovery, price and perceived value.

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Chang (2013) examined factors affecting airport access mode-choice by elders at Taiwan Airport. His key finding was that the elderly strongly prefer to be driven to the airport by family members as opposed to taking a taxi, relative to the general population.

Baker (2013) examined not just one airport, but focused on several airports, while comparing *different airlines*. He found that the low-cost airlines received significantly better ratings on service quality than the legacy airlines. Harvey (1987) conducted the first study at the San Francisco Airport (SFO). He focused on choice of 3 airports in the San Francisco Bay area including SFO. He also distinguished between business travelers and non-business travelers. His main findings were that ground access time and frequency of direct flights to destinations were the key factors in airport choice. Hess and Polak (2005) also studied the different airports in the San Francisco area, including SFO, and found results similar to Harvey's. Ishii et al. (2009) did a subsequent study of 4 airports in the San Francisco Bay area, and found, for the most part, similar results to the previous two studies. A study by Wang et al. (2015) also considered the San Francisco Airport and studied the variables that drive satisfaction, both positively and negatively. The most influential variables were found to be three "negative" variables - driving down satisfaction: airport food rated unacceptable, airport shopping rated unacceptable, and level of information on monitors and screens rated as unacceptable. The most positive variable was directional signs in the airport being rated at outstanding.

The study in this paper considers only SFO, and was not concerned with choice modeling among airports. Indeed, our study considered very different variables than the all the other SFO studies cited. In addition, none of the other studies cited used exploratory factor analysis to home in on the underlying structure of important factors in determining consumer/flyer attitudes toward the specific SFO airport. There have also been examinations of other subjects at airports, such as employee satisfaction and aircraft scheduling. We do not consider these studies as relevant to our current study. There were some additional studies of various actions in airports outside of North America that either had very different goals as this paper, or did not indicate the importance of variables other than what was reported in the above cited papers.

Method

There were about 70 questions in the questionnaire and over 3500 people who filled out the questionnaire. Each question can be viewed as a different variable; in this type of situation, it is not uncommon to factor analyze the questions (first) to produce a smaller set of "factors" that well represent the set of initial variables, and, if chosen to be so, these "factors" will be orthogonal to each other (Hair et al., 2010). This orthogonality may be very useful in subsequent analyses, such as regression analysis, discriminant analysis, and others; the interpretations of the results are aided by the lack of multicolinearity among the factors, representing the independent variables. We use eleven questions from the questionnaire in our exploratory factor analysis. We describe them below. Subsequently, we define and discuss our dependent variable.

Variables

The eleven variables used as input to the exploratory factor analysis are listed and defined in Table 1. The table uses the numbers in the questionnaire in order of appearance in the questionnaire; later, we shorten the notation. After presenting the table, we describe each variable's scale.

TABLE 1: Independent Variables

Q9F_OVERALL.CLEANLINESS (How do you rate the overall cleanliness at SFO?)
Q10_SAFE (How safe do you feel at SFO?)
Q11A_USE.WEB
Q11B_USE.SFO.MOBILE.APP
Q11C_USE.OTHER.AIRPORT-RELATED.APPS (Have you ever used XYZ?)
Q11D_USE.SFO.SOCIAL.MEDIA.CHANNELS
Q11E_USE.SFO.FREE.WIFI
Q13_RATE.GET.TO (Rate your experience getting to SFO today)
Q14A_FIND (Rate the ease of finding your way around SFO)
Q14B_ SECURITY (Rate your experience going through security and screening)
Q15_PROBLEMS (Did you encounter any problems today?)

The scale for Q9F_OVERALL.CLEANLINESS was:

1= Dirty
2= somewhat dirty
3=Average
4=Somewhat Clean
5=Clean
6=Have never visited/not applicable
0=Blank

The scale for Q10_SAFE was:

1=Not safe at all
2=below average
3=Neutral
4=Good
5=extremely safe
6=don't know
0=Blank

The scale for Q13_RATE.GET.TO was:

1=Difficult
2=below average
3=Average
4=Above average
5=Easy
6=Don't know/not applicable
0=Blank

The scale for Q14A_FIND, and Q14B_SECURITY was:

1=Unacceptable,
2=Below average,
3=Average,
4=Good,
5=Outstanding,
6=Never used/don't know,
0=Blank.

For all these variables, the value 6 does not express any degree of rating and is not consistent with the numeric meaning of other values. Thus, to prevent interference that might be caused by the value 6 in these five variables, we consider 6 invalid and treat it as a missing value. The blank answer 0 is also treated as a missing value. The other six variables describe if the customers used a "service," and have four values: 1=Yes, 2=No, 3=I don't know and 0=Blank. The answer Blank and "I don't know" were considered as missing values. In the first type of questions (the five with the 0-6 scale), larger numeric values from 1-5 are considered as positive, since they suggest higher degrees of liking. In the second type of questions (the five "Do you use..." questions, and the "Did you encounter any problems today" question), we switched the meanings of the "1" and "2" answers to achieve consistency of scale direction. As a result, "1" stands for "no" and "2" stands for "yes" in these six questions:

Q11A_USE.WEB
Q11B_USE.SFO.MOBILE.APP
Q11C_USE.OTHER.AIRPORT-RELATED.APPS
Q11D_USE.SFO.SOCIAL.MEDIA.CHANNELS
Q11E_USE.SFO.FREE.WIFI
Q15_PROBLEMS

As can be noted, the scales of answers in the 2 types of variables are not the same. The range of the first type is from 1 to 5 and the second is from 1 to 2. We standardize all the variables, using a "Z transformation" - thus, each variable has a mean of 0 and a standard deviation of 1. In this way, the importance of a variable won't be over- or under-evaluated due to its magnitude.

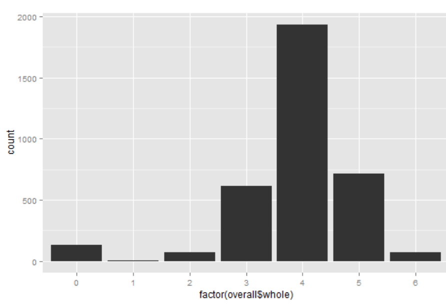
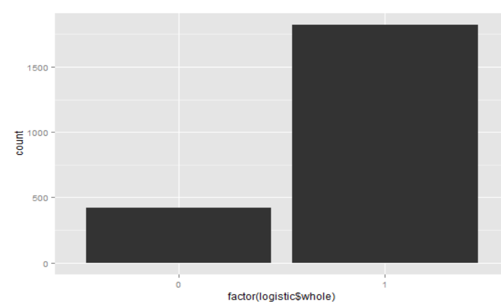
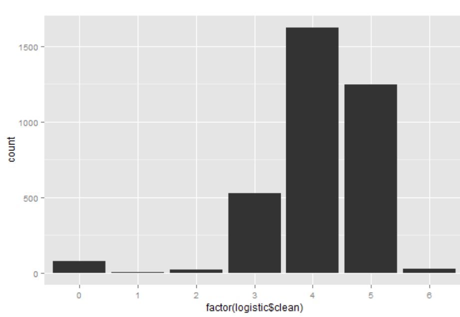
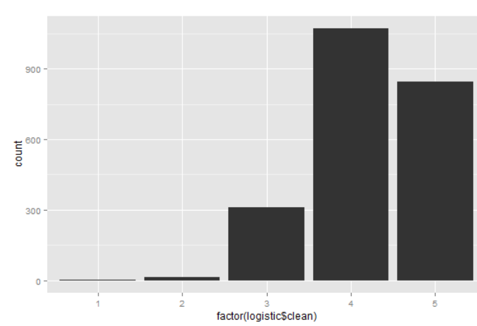
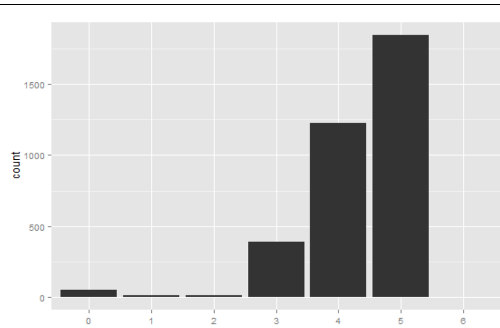
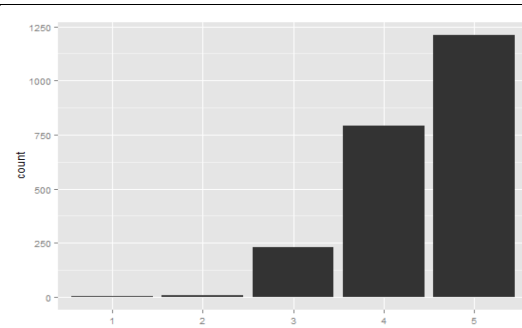
The target variable, "Y," is the response to the question: *How does the SFO Airport rate as a whole?* The scale for this variable was:

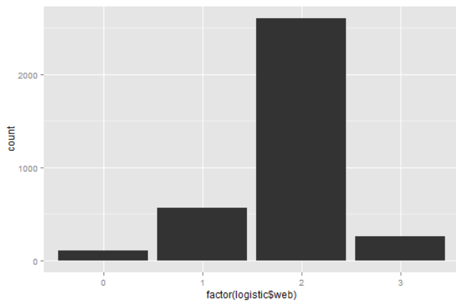
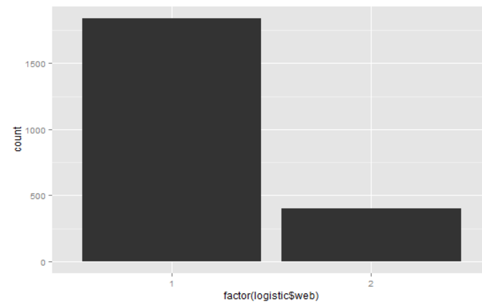
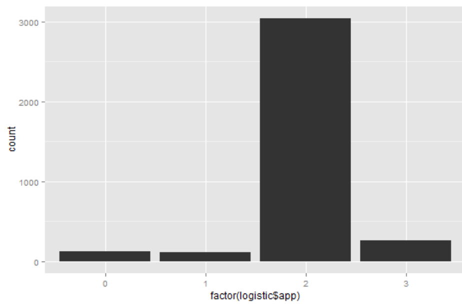
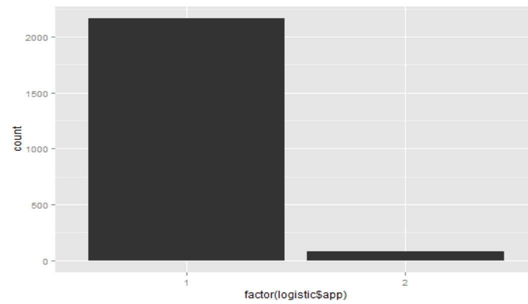
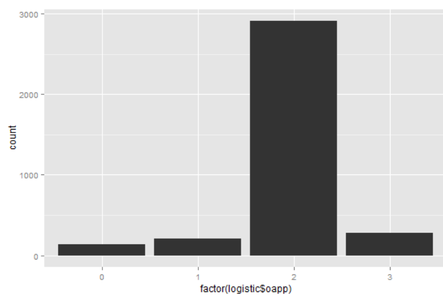
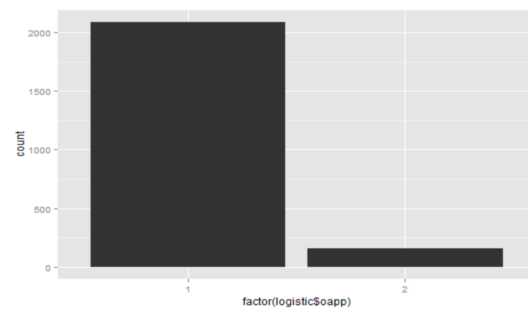
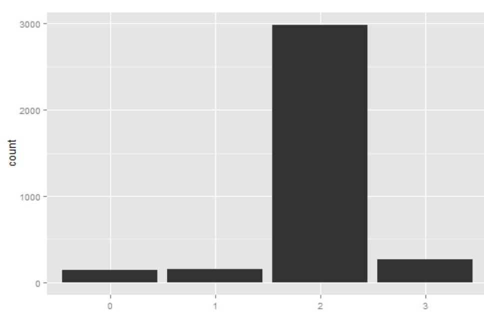
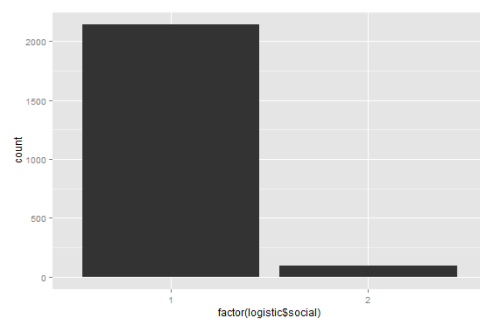
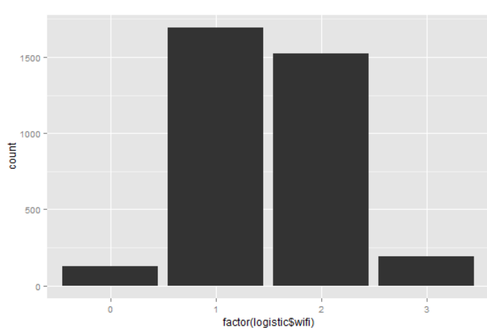
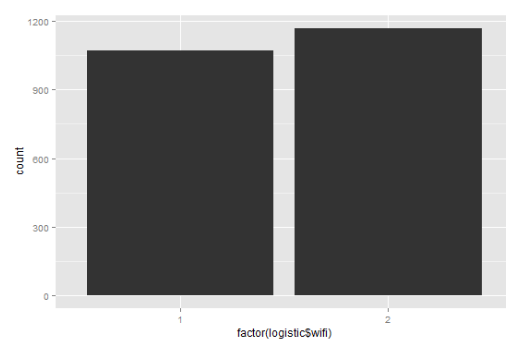
1=Unacceptable
2=Below Average
3=Average
4=Good
5=Outstanding
6=Have never used or visited
0=Blank

After viewing 0 and 6 as missing values, we considered the five-point scale 1-5, and regrouped the variable into two categories. Those customers who rate SFO as Good or Outstanding (i.e., a rating of 4 or 5) are in the group, 1. Those who rate SFO as Average, Below Average or Unacceptable (i.e., a rating of 1-3) in the group, 0.

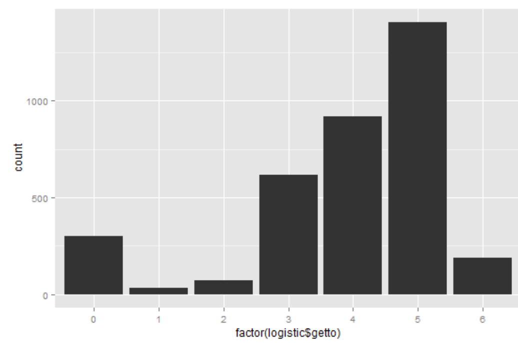
In Table 1, we see the distribution of each variable involved in the stepwise logistic regression model. The left side displays the original data and the right side displays the recoded data.

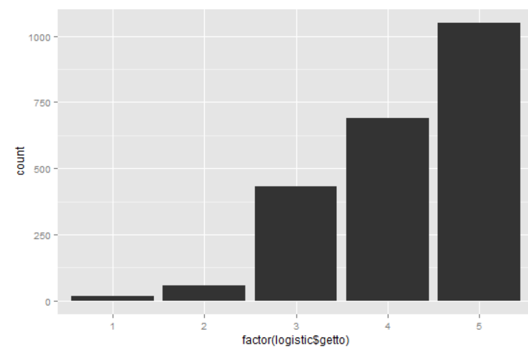
Table 1: Distribution of the dependent and independent variables

Y		
Q9F_ OVERALL. CLEANLINESS missing=(0,6)		
Q10_SAFE missing=(0,6)		

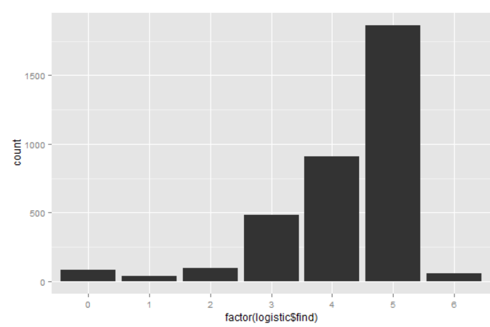
Q11A_USE.WEB missing=(0,3)		
Q11B_USE. SFO. MOBILE. APP missing=(0,3)		
Q11C_USE.OTHER AIRPORT-RELATED. APP missing=(0,3)		
Q11D_USE. SFO. SOCIAL. MEDIA. CHANNELS missing=(0,3)		
Q11E_USE. SFO.FREE WIFI missing=(0,3)		

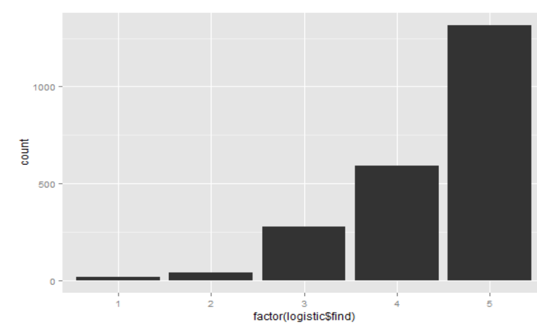
Q13_RATE. GET.TO missing=(0,6)



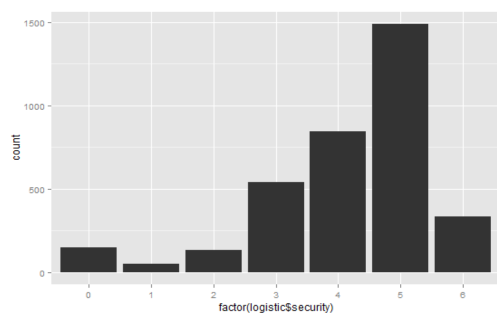


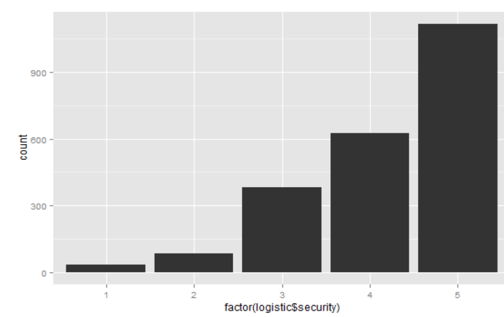
Q14A_FIND missing=(0,6)



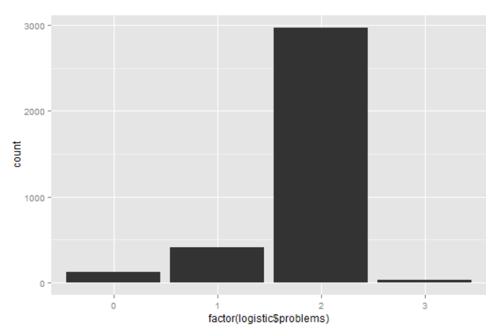


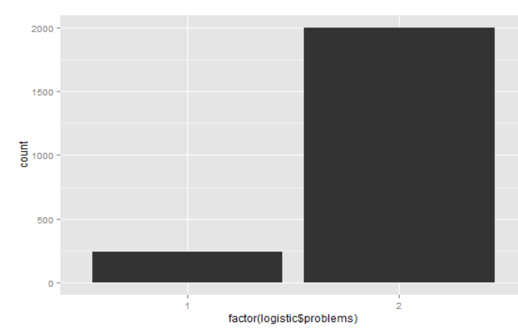
Q14B_ SECURITY missing=(0,6)





Q15_ PROBLEMS missing=(0,3)





Extracting the Factors

We can see from Table 2 that the overall MSA is about 0.72, which suggests that the inter-correlations among the variables satisfy the requirements for conducting factor analysis. In addition, seen in Table 2, the measure of sampling adequacy for each variable is higher than 0.6, which also satisfies the requirement to keep the variable. The variables have now been given shorter labels/names.

Table 2: Overall MSA and Kaiser's measure of sampling adequacy

Kaiser's Measure of Sampling Adequacy: Overall MSA = 0.72296845										
clean	safe	web	app	other.app	social	wifi	get.to	find	security	problems
0.769	0.772	0.670	0.640	0.701	0.681	0.626	0.802	0.711	0.736	0.730

When the number of variables is between 20 and 50, factors that have eigenvalue greater than 1 (the "Kaiser Criterion") are generally considered "legitimate factors." Since we have only 11 variables, we will not adopt directly the Kaiser Criterion, but, rather, use significance testing to see how many factors should be sufficient for these variables. We set the significance level at 5%. From Table 3, we can see that 4 factors are not sufficient. (We started at 4 factors arbitrarily. Had 4 factors been sufficient, we would have then tested whether 3 factors were significant, and continued the process until we found the dividing line between how many were and were not sufficient?) The p-value =.0112 < .05, indicating that we reject H0 and conclude that more factors are needed.

Table 3: Significance testing for 4 factors

Significance Tests Based on 2241 Observations			
Test	DF	Chi-Square	Pr > Chi.Sq (p-value)
H0: No common factors	55	2845.4036	<.0001
H1: At least one common factor			
H0: 4 Factors are sufficient	17	33.0127	0.0112
H1: More factors are needed			

From Table 4, we can see that 5 factors <u>are</u> sufficient. We accept H0 with a p-value = .7745 > > .05, and as a result, we select having 5 factors as our mandate.

Table 4: Significance testing for 5 factors

Significance Tests Based on 2241 Observations			
Test	DF	Chi-Square	Pr > Chi.Sq (p-value)
H0: No common factors	55	2845.4036	<.0001
HA: At least one common factor			
H0: 5 Factors are sufficient	10	6.4681	0.7745
HA: More factors are needed			

In Table 5, we see the rotated factor pattern.

Table 5: Rotated Factor Pattern with 5 factors

Rotated Factor Pattern					
	Factor1	Factor2	Factor3	Factor4	Factor5
clean	0.34549	0.06058	0.36925	-0.04519	0.35143
safe	0.21281	0.06121	0.70192	0.02397	0.00080
web	0.02224	0.40039	0.03006	0.26206	-0.03214
app	0.03536	0.75820	-0.00780	-0.03871	0.02090
oapp	0.02268	0.38118	0.07312	0.08743	-0.06931
social	0.03630	0.37983	-0.00205	0.06750	0.19713
wifi	-0.02266	0.17881	-0.00482	0.67879	0.01401
getto	0.44138	0.04327	0.24377	-0.04064	0.08656
find	0.79592	0.02535	0.11675	0.06245	0.00430
security	0.62614	0.04511	0.12972	-0.01598	0.08644
problems	0.29146	0.01486	-0.00677	-0.01632	-0.19548

In Table 5, within factor 3, the variable safe has a comparatively high loading of 0.7 and other variables all have loadings lower than 0.4; it is the only factor satisfying these two conditions. The proportion of factor 3 explained by other variables are, thus, relatively small, and factor 3 is mostly explained by variable *safe*. To compare the variables purely from their meanings, *safe* also seems independent from the other variables (and, indeed, the factors are orthogonal and *safe* does not load highly on any other factor.) So, for simplicity and clarity, we exclude the variable *safe* from the factor exploration and consider it as a factor *by itself*. Then, we ran a factor analysis with the remaining variables and four factors. The output is presented in Table 6.

Table 6: Rotated Factor Pattern with 4 factors

Rotated Factor Pattern				
	Factor1	Factor2	Factor3	Factor4
clean	0.14860	0.07157	0.62797	-0.02516
web	0.03131	0.39126	-0.00994	0.27884
app	0.03906	0.78241	0.00200	-0.04660
oapp	0.03817	0.36791	0.00028	0.09724
social	-0.02054	0.37490	0.12804	0.07874
wifi	-0.01998	0.17828	-0.02924	0.64298
getto	0.36347	0.04469	0.34318	-0.02962
find	0.73379	0.02282	0.33401	0.07465
security	0.54079	0.04539	0.34619	-0.00496
problems	0.33204	0.00678	-0.03667	-0.01906

In Table 6, we can see that in factor 3, the variable *clean* has a comparatively high loading of 0.63 and other variables all have loadings lower than 0.4. (Factor 4 also satisfies the basic conditions; however, since the factors enter in general order of importance, we chose factor 3 over factor 4 for this next step.) For similar reasons as those stated above, we now exclude the variable *clean* from the factor exploration and consider it as a factor by itself. Then, we ran a factor analysis with the remaining variables and 3 factors. The output is presented in Table 7.

Table 7: Rotated Factor Pattern with 3 factors

Rotated Factor Pattern			
	Factor1	Factor2	Factor3
web	0.02148	0.39521	0.26251
app	0.02932	0.77171	-0.04279
oapp	0.02979	0.37195	0.09038
social	0.03894	0.37704	0.06789
wifi	-0.03204	0.18003	0.67962
getto	0.47378	0.05006	-0.03439
find	0.81394	0.02912	0.07189
security	0.63141	0.05160	-0.00862
problems	0.27295	0.00760	-0.01154

From Table 7, we can see that in factor 3, the variable *wifi* has a comparatively high loading of 0.68 and other variables all have loadings lower than 0.3. So, again, for the similar reasons stated in the previous sections, we exclude the variable *wifi* from the factor exploration and consider it as a factor by itself. Then, we ran a factor analysis with remaining variables and two factors. The output is presented in Table 8.

Table 8: Rotated Factor Pattern with 2 factors

Rotated Factor Pattern

	Factor1	Factor2
web	−0.00371	0.18652
app	−0.02583	0.56671
oapp	−0.00300	0.17417
social	−0.00044	0.17471
getto	0.15250	0.01021
find	0.60088	−0.01710
security	0.26551	0.00865
problems	0.07451	−0.00469

In Table 8, we name factor 1 as *convenience* since *find* and *security* have the highest loadings and no other variable has a loading above .2. (We decided that the ability to easily find your way around the airport, and to have a good/better experience navigating the security screening, can reasonably be called "*convenience*." We, of course, recognize that the naming of factors is somewhat arbitrary, and understand that another group of analysts might choose a different name for factor 1.) We name factor 2 *social media* since *app* has by far the highest loading, and next group of higher loadings include *web*, *oapp* (other apps), and *social*, and the remaining variables have loadings that are virtually zero (lower than .02;) the same caveat about naming a factor holds for factor 2 also.

The above applied exploratory factor analysis aimed at determining the underlying structure among the original 11 variables. We used principal component factor analysis with orthogonal factors and varimax rotation. From the Table 9, we can see that the model is statistically significant and the MSA of every variable meets the requirement (> .5).

Table 9: Overall MSA and Kaiser's measure of sampling adequacy

Kaiser's Measure of Sampling Adequacy: Overall MSA = 0.65905549							
web	app	oapp	social	getto	find	security	problems
0.68316532	0.61793296	0.67848928	0.66282721	0.73076894	0.62222201	0.65296716	0.76484014

In Table 10, we present the standardized scoring coefficients corresponding to the loadings in Table 8

Table 10: Standardized scoring coefficients

Standardized Scoring Coefficients		
	Factor1	Factor2
web	−0.02573	0.37381
app	−0.02089	0.45346
oapp	−0.01907	0.35576
social	−0.00994	0.34868
getto	0.34515	−0.00158
find	0.43345	−0.01235
security	0.40576	−0.00496
problems	0.23460	−0.03735

From Table 10, we have:

Convenience (Factor1) =

-.026*web - .021*app -.019*oapp - .010*social + .345*getto+.433*find+.406*security + .235*problems

Social Media (Factor2) =

.374*web + .453*app + .356*oapp + 0.349*social -0.002*getto - .012*find - .005*security - .037*problems

Logistic Regression

In order to have an even distribution of the two values (0 and 1), and to achieve a large sample, we randomly sampled, *with replacement*, 3,000 observations from each group, to form a new dataset of 6000 data points. The original data, after dropping the missing values (6's and 0's) have about 2650 1's and about 700 0's. In Table 11, initial output from the logistic regression, indicates that we have 3,000 observations for each value in the target variable.

Table 11: Initial classification table from logistic regression

Classification Tablea,b					
	Observed		Predicted		
			whole		Percentage Correct
			.0	1.0	
Step 0	whole	.0	0	3000	.0
		1.0	0	3000	100.0
	Overall Percentage				50.0
a. Constant is included in the model.					
b. The cut value is .500					

We ran a stepwise logistic regression with the five factors extracted from the previous section as independent variables. The stepwise algorithm went through 3 steps and stopped after the third step, thus including three factors. Table 12 begins the output for the aforementioned 3rd step.

Table 12: Step 3 model summary for stepwise logistic regression

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
3	6138.268a	.305	.406

a. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001.

Table 13 displays the classification table for this 3rd (and final) step. The model classifies 72.7% of the 0 group and 74.0% of the 1 group correctly. The overall classification rate is 73.4%. If we were to use hypothesis testing to test whether 73.4% is higher than 50% (the percent we can guarantee to get correct without a model at all - just by "guessing" - sometimes referred to as the C_{max} criterion), we would find a p-value close to zero, a clear indication that the regression model is, with virtually no doubt, able to predict better than without the model.

Table 13: Classification table for 3rd and last step of stepwise logistic regression

Classification Tablea

	Observed		Predicted		
			whole		Percentage Correct
			.0	1.0	
Step 3	whole	.0	2182	818	72.7
		1.0	779	2221	74.0
	Overall Percentage				73.4

a. The cut value is .500

The three factors selected from the algorithm are *convenience*, *safety* and *clean*. The excluded variables, *social media* and *wifi* have p-values of 0.799 and 0.203, respectively, were they to enter the model at a step 4; of course, they did not enter, since neither p-value is below .05.

Remembering that Y = 1 represents an overall rating of SFO of either good or outstanding, the step 3 regression equation is:

{The Ln of the odds that Y = 1} = .489 + 0.950**clean* + 0.406**safety* + 0.455**convenience*

As in any logistic regression, the coefficients stand for the change in the Ln of the odds ratio per unit change of each factor, which is structured from standardized variables. As noted earlier, the Ln of the odds ratio pertains to a customer giving SFO a "superior" rating.

The Ln of the odds ratio of a customer having a superior rating of SFO increases by 0.950 when the standardized variable, *clean*, increases by 1 with the other factors/"variables" held constant. The Ln of the odds ratio of a customer having a superior rating of SFO increases by .406 when the standardized variable, *safety*, increases by 1 with the other factors/"variables" held constant. The Ln of the odds ratio of a customer having a superior rating of SFO increases by 0.455 when the standardized variable, *convenience*, increases by 1 with the other factors/"variables" held constant.

Clean appears to have the greatest impact per unit on overall rating of the SFO airport. While all coefficients are positive, the coefficient of *clean* is more than double each of the other two coefficients. Table 14 displays the Step 3 results, including the statistics of the "Variables not in the Equation."

Table 14: Statistics of step 3 of the stepwise logistic regression

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 3	cconvenience	.455	.032	203.659	1	.000	1.577
	safe	.406	.031	166.860	1	.000	1.501
	clean	.950	.036	680.547	1	.000	2.585
	Constant	.489	.034	211.443	1	.000	1.631

Variables not in the Equation

			Score	df	Sig.
Step 3	Variables	social	.065	1	.799
		wifi	1.619	1	.203
	Overall Statistics		1.887	2	.389

Conclusions

The overall feelings about the SFO can be divided into five criteria (or "factors," or "dimensions") : the perceived cleanliness of SFO, the perceived feeling of safety at SFO, the perceived "convenience" of SFO (viewed from Table 10 as ease of finding one's way around the airport, ease of going through the security process, ease of getting to SFO, and, overall, not having problems during the entire airport process), the use of the wifi at SFO, and the "social media." at SFO (defined as use of the web, use of the SFO mobile app, use of other airport-related apps, and use of social media channels.) The first three criteria are apparently more important than the latter two, and per unit increase, cleanliness is indicated to have the largest impact on customers' overall evaluation of the airport.

If SFO needs to prioritize its expenditures, it should, in theory, first concentrate on the cleanliness of the airport, then the "convenience" for the customers; the latter, as noted above, includes getting to the airport, finding one's way around in the airport, more easily navigating the security process, and not having problems at the airport.

A feeling of safety is "statistically" the next most important factor. ***However*****,** we can tell from common sense that safety is an issue with zero tolerance, and likely is the true most important variable/factor of all; fortunately, the data indicate that the vast majority of responders rated the safety as outstanding, or at least, good. In reality, *safety* is likely an attribute that is taken for granted as important and, thus, potentially not as highlighted by customers as other variables. This can be considered as analogous to the way *accurate bank statements* are viewed by customers when giving an overall rating to banks. It is clearly one of the most important attributes in rating banks, but is rarely cited by customers in studies of banks, since virtually all banks understand this and already have an abundance of this attribute (Clancy et al., 2013).

It should be no surprise that the issue of *technology* should be increasingly prominent - essentially, the variable, *social media*, stands for use of technology. *These days, technology is increasingly important in most endeavors in life.*

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