How to increase satisfaction with online learning: Technical suggestions to enhance the usefulness of importance-performance analysis

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Abstract. The difference and the relationship between the measurement of importance and the measurement of performance are of central interest in analyzing customer satisfaction. Importanceperformance analysis (IPA) is known as a useful and convenient method for this purpose. Importance and performance are generally measured using five- or seven-points scales, so that they are intrinsically nominal or ordinal data. However, there is a tendency for IPA to be conducted as if observations were continuous data. In this paper, we propose to use categorical data model, such as the log-linear model and the multinomial logistic regression model, to analyze importance-performance data. We focus on two aspects for IPA to be more precise and useful in dealing with satisfaction/dissatisfaction: (1) IPA should be considered from the aspect of categorical data analysis and (2) how IPA contributes to satisfaction/dissatisfaction. We test the independence between the importance and the performance of attributes and test the dependency between (overall) satisfaction and performance using the log-linear model. Additionally, we investigate how the performance of attributes can raise overall satisfaction by utilizing the multinomial logistic regression model. This study uses data from a customer satisfaction survey for an on-line lecture program that prepares students for the Korean Scholastic Aptitude Test.

Keywords: categorical data analysis, IPA, multinomial logistic regression model, log linear models

1. Introduction

The IPA was first proposed by Martilla and James [14] as a consumer opinion survey technique for the automotive industry. It has since been used in various fields [4][5][7][11][20]. The IPA, as a multidimensional decision-making technique, provides comparative information with four types of decisions: (1) keep up the good work, (2) concentrate here, (3) low priority, and (4) possible overkill. Survey respondents were asked in the questionnaire about degrees of importance and performance for a number of quality attributes. The ordered pairs of the averages (or medians) of the responses on importance and performance for the attributes are located on a two dimensional grid, where the importance is indicated by the y-axis, the performance is indicated by the x-axis and the pair of overall averages (or medians) of importance and performance is the origin. IPA locates the attributes of a product or a service on a two-dimensional grid defined by the four quadrants: quadrant I-Keep up the good work, quadrant II-Concentrate here, quadrant III-Low priority, and quadrant IV-Possible overkill. Two implicit assumptions underlie the IPA [13]: (1) Performance and customer satisfaction is a linear relationship and (2) the variables, performance and importance, are independent and have no causal relationship. However, not all the researches executing IPA checked these assumptions. Importance and performance are usually measured using five- or seven-points scales, they should be considered as ordinal or nominal data. Log linear models [5][7][8][9][18] and multinomial logistic models [1][2][10][19] are useful in checking those assumption and analyzing importance-performance data. We demonstrate that the results from such categorical data analyses could

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provide useful information to analyze customer satisfaction. We focus on two aspects for IPA to be more precise and useful in dealing with satisfaction/dissatisfaction. First, IPA should be considered from the aspect of categorical data analysis; then determine how IPA contributes to satisfaction/dissatisfaction.

An empirical study on customer satisfaction with online education in Korea was undertaken. Online education or learning has experienced an early adaption across all sectors of education in Korea. The popularity of online courses or programs is rapidly rising, but at the same time, the students dissatisfied with them. Now is the right time to study what causes the students the learning satisfaction/dissatisfaction when participating in online courses or programs. IPA and categorical data analysis provide useful ways to enhance customer satisfaction.

2. Methods

After examining several previous studies [3][16] the five key quality attributes of online education for students preparing for the Korean Scholastic Aptitude Test were determined to be; 1. accessibility, 2. cost, 3. text, 4. Lecturer, and 5. interaction. The importance and performance of each attribute were investigated by asking questions as follows; for example, "How important is it to access online classes without regard for time and place?", and "How well are you able to access online classes without regard for time and place?" Respondents were asked to choose the appropriate response from one of five categories such as 1: extremely negative, 2: negative, 3: neutral', 4: positive, and 5: extremely positive. The overall satisfaction with the service quality of online education was also asked in addition to the questions concerning the five attributes. 245 college students responded to the survey. Statistical analysis is done using *SPSS 17.0*.

2.1. Test of independence and dependence

In this section, we test independence or dependence among importance, performance, and satisfaction. Suppose X_l = importance of accessibility, X_2 , = performance of accessibility, X_3 = overall satisfaction and consider a log linear model:

$$\log m_{ijk} = u + u_{1(i)} + u_{2(j)} + u_{3(k)} + u_{12(ij)} + u_{13(ik)} + u_{23(ik)} + u_{123(ijk)} \text{ for } i, j, k = 1, \dots, 5;$$

where m_{ijk} is the expected frequency when the importance of accessibility, the performance of accessibility and the overall satisfaction are at levels of i, j, and k, respectively. Then we estimate the effects of interactions $u_{12(ij)}$, $u_{13(ik)}$ and $u_{23(jk)}$. We repeat such estimation for all other attributes. Table 1 lists the estimates and the corresponding significant probabilities of the interaction terms for the five attributes. We note that all the interactions between the importance and performance of the five attributes are significant, except for the 'text' attribute. That is, there is insufficient evidence to assume that the importance and performance of any attribute except 'text' are independent. In order to secure independence, we transform the five-point scale responses into three-point scale responses, by encoding categories '1 and $2 \rightarrow 1$ ' and '4 and $5 \rightarrow 5'$ and $3 \rightarrow 3'$ to assure independence. After transformation, the independence between importance and performance for all attributes is assured at the 0.01 level of significance (Table 1). The dependence between overall satisfaction and performance of the attributes is guaranteed in both three- and five-point scales (Table 1). The averages of the importance and performance for the five attributes in both three- and five-point scales are calculated and they are located on an IPA matrix in Figure 1. The IPA based on either five- or three-point scale places 'lecturer' in quadrant I, 'text' in quadrant II, both 'cost' and 'interaction' in quadrant III, and 'accessibility' in quadrant IV. The above transformation does not make big differences on the results of IPA, but the IPA based on three-point scale is justified and recommended for this example.

2.2. Logistic modeling to enhance satisfaction

We perform the five multinomial logistic regressions for the overall satisfaction (a dependent variable) with each one of the five attributes as an independent variable. For each attribute, consider the multinomial logistic model,

$$\log\left[\frac{P(Y=j \mid x_1, x_2)}{P(Y=1 \mid x_1, x_2)}\right] = \beta_0 + \beta_1 x_1 + \beta_2 x_2, \ j = 3,5$$

by taking the satisfaction's reference level (or category) as level 1 and by letting x_1 , x_2 be dummy variables, such that the attribute's level is 5 if $x_1=0$, $x_2=0$; 3 if $x_1=0$, $x_2=1$; and 1 if $x_1=1$, $x_2=0$, respectively. For example, if an attribute has been performed at the level of 1 ($x_1=1$, $x_2=0$), the odds of the satisfaction's level *j* to the level 1 is

$$\frac{P(Y=j \mid x_1 = 1, x_2 = 0)}{P(Y=1 \mid x_1 = 1, x_2 = 0)} = \exp[\beta_0 + \beta_1].$$

Then, the odds ratio of the satisfaction's level *j* to the level 1 if an attribute is performed at the level of 1 is

$$\frac{P(Y=j \mid x_1 = 1, x_2 = 0)}{P(Y=1 \mid x_1 = 1, x_2 = 0)} / \frac{P(Y=j \mid x_1 = 0, x_2 = 1, 0)}{P(Y=1 \mid x_1 = 0, x_2 = 1, 0)}$$
$$= \frac{\exp[\beta_0 + \beta_1]}{\exp[\beta_0 + \beta_2] + \exp[\beta_0]} = \frac{\exp[\beta_1]}{\exp[\beta_2] + 1}.$$

Furthermore, the odds ratio of the satisfaction's level *j* to the level *i* if an attribute is performed at the performance level of 1 (x_1 =1, x_2 =0) is

$$\begin{split} &\frac{P(Y=j \mid x_1 = 1, x_2 = 0)}{P(Y=i \mid x_1 = 1, x_2 = 0)} \bigg/ \frac{P(Y=j \mid x_1 = 0, x_2 = 0, 1)}{P(Y=i \mid x_1 = 0, x_2 = 0, 1)} \\ &= \bigg[\frac{P(Y=j \mid x_1 = 1, x_2 = 0)}{P(Y=1 \mid x_1 = 1, x_2 = 0)} \bigg/ \frac{P(Y=j \mid x_1 = 0, x_2 = 0, 1)}{P(Y=1 \mid x_1 = 0, x_2 = 0, 1)} \bigg] / \bigg[\frac{P(Y=i \mid x_1 = 1, x_2 = 0)}{P(Y=1 \mid x_1 = 1, x_2 = 0)} \bigg/ \frac{P(Y=i \mid x_1 = 0, x_2 = 0, 1)}{P(Y=1 \mid x_1 = 0, x_2 = 0, 1)} \bigg]. \end{split}$$



Fig. 1: IPA diagram: three- & five-point scales

Table 2 displays the multinomial regression estimation results. Table 3 records the odds ratios for the levels of satisfaction with the five attributes. Here are some examples about how to interpret those numbers in Tables 2 and 3. On the top row in Table 2, the significant probability of satisfaction at level 3 when 'accessibility' is performed at level 1 is .151 (>.05), that is, the chance that a student is moderately satisfied rather than less satisfied is not significant when 'accessibility' is performed at level 0 for when 'accessibility' is performed at level 1 to level 3 is 0.533 if 'accessibility' is performed at level 1, while the ratio of satisfaction of the level 1 to level 5 is 0.267. This means that if the performance of 'accessibility' is low, the odds that the level of satisfaction goes from 'low' to 'moderate' will be about 1.99

times the odds that the level of satisfaction goes from 'low' to 'high'. In a plain language it is unlikely that the student, who is less satisfied now, is going to be moderately or highly satisfied, as long as 'accessibility' is performed at a low level. On the third row in Table 3, if the performance of 'accessibility' is low the odds ratio of satisfaction of level 5 to level 1 is 3.745, which is the largest number for 'accessibility'. We may say that even if a student is highly satisfied now, there is a high chance that one will become less satisfied as long as 'accessibility' is performed at a low level. We can interpret all other numbers in Tables 2 and 3 in similar ways.

3. Results

The results are summarized below.

- Accessibility: According to IPA, 'accessibility' has already achieved a high level of performance, but it has been over-invested. Even if a high level of performance of 'accessibility' would be achieved, a relatively small improvement in satisfaction is expected compared to other attributes.
- Cost: Since 'cost' turns out to be a low priority attribute, it should be running at a moderate level of performance. Then, there is a relatively equal chance for satisfaction to rise or fall. Only a high-level performance for this attribute is expected to guarantee an increase in satisfaction.
- Interaction: 'Interaction' is also classified as a low priority attribute, but a moderate level of performance should result in an increase in satisfaction. If it is performed at a high level, it is expected to cause the most dramatic increase in satisfaction
- Lecturer: This attribute belongs to 'keep up the good work', so it is necessary for 'lecturer' to be maintained in the current status. However, if this attribute is performed at a moderate level there would be a chance for satisfaction to increase or decrease. Unfortunately, if it is performed at a low level, there is a high chance that satisfaction will decrease. Hence, 'lecture' should be performed at least at the moderate level for satisfaction not to decrease.
- Text: IPA recommends that this attribute is the subject for improvement; otherwise, satisfaction is expected to decline if it is performed at a low level. The good news is that a sharp increase in satisfaction seems possible if it is performed at a high level.
- A dramatic rise in satisfaction is expected at high performance levels of 'interaction', 'instructor, and 'cost', in that order. Although IPA places 'interaction' and 'cost' in quadrant III (low priority), maintaining the highest level of performance in these attributes within revenue may optimize satisfaction.
- In contrast, if 'accessibility', 'cost', and 'lecturer' reach a low level of performance, satisfaction could fall sharply. These three attributes are categorized as low in importance according to IPA, but less investment in them could lower satisfaction rapidly.
- According to Kano, et al. [12], (1) 'accessibility' can be seen as a basic (or must-be) attribute, because satisfaction will remain unchanged at high level of performance while performance in low levels will result in downing satisfaction, (2) 'cost' and 'lecturer' can be classified as a one-dimensional attribute, because the level of satisfaction tend to move in the same direction as the level of performance, and (3) 'text' and 'interaction' are thought of as exciting (or attractive) attributes, because dramatic increases in satisfaction can be expected at high levels of performance for these two attributes, while satisfaction can be lowered or unchanged at the low level of performance.

4. Conclusions

IPA is known as a simple yet useful method to understand the effects of various factors for satisfaction. In this article, we propose two additional techniques to enhance the usefulness of IPA. We use a satisfaction survey of online education as an example. The log linear method enables us to check the basic assumptions on IPA, so we could fix the violations on such assumptions. Once IPA has been done, with the help of the multinomial logistic regression, we could determine how to enhance the satisfaction in conjunction with the results of IPA. With the help of the categorical data analysis, we could discover the some interesting facts that should be overlooked if only IPA is considered.

Effect		five-point scales		three-point scales	
Elicer	df	Chi-Square	Sig.	Chi-Square	Sig.
accessibility_i accessibility_p	16	57.347	.000	31.681	.011
cost_i cost_p	16	47.890	.000	22.182	.137
interaction_i interaction_p	16	51.170	.000	18.689	.285
lecturer_i lecturer_p	16	4.032	.001	12.255	.726
text_i text_p	16	23.751	.095	6.711	.978
satisfaction accessibility_p	16	48.431	.000	22.121	.000
satisfaction cost_p	16	41.955	.000	33.196	.000
satisfaction interaction_p	16	84.839	.000	44.909	.000
satisfaction lecturer_p	16	11.960	.000	66.412	.000
satisfaction text_p	16	84.369	.000	58.654	.000

Table 1.Effect of interaction between importance and performance

(_p and _i abbreviate performance and importance, respectively)

Table 2.Results of multinomial logistic regression (reference category is satisfaction level 1)

attribute	satisfaction	performace	В	Sig.	Exp(B)
	3	1	629	.151	.533
		3	.788	.001	2.200
aaaaaibility		5	.480	.055	1.615
accessionity	5	1	-1.322	.019	.267
		3	041	.886	.960
		5	.592	.015	1.808
	3	1	.092	.710	1.097
		3	.847	.001	2.333
cost		5	.310	.435	1.364
COSI	5	1	601	.047	.548
		3	043	.884	.958
		5	1.157	.001	3.182
	3	1	405	.097	.667
		3	1.218	.000	3.381
interaction		5	.693	.327	2.000
Interaction	5	1	.388	.001	.357
		3	2.183	.038	1.762
		5	19.335	.001	7.667
	3	1	-2.398	.001	.091
		3	.794	.000	2.212
lecturer ·		5	1.003	.004	2.727
	5	1	-1.299	.005	.273
		3	361	.184	.697
		5	1.431	.000	4.182
text —	3	1	375	.176	.687
		3	1.114	.000	3.045
		5	.288	.451	1.333
	5	1	-1.163	.001	.313
		3	.343	.219	1.409
		5	1.041	.002	2.833

		a dala wa ti a	antiafantia	. i	
	odds ratio		sausiacuon j		
attribute	periornace	satisfaction i	1	3	5
	1	1	1.000	.533	.267
		3	1.876	1.000	.501
		5	3.745	1.996	1.000
	3	1	1.000	2.200	.960
accessibility		3	.455	1.000	.436
		5	1.042	2.292	1.000
	5	1	1.000	1.615	1.808
		3	.619	1.000	1.120
		5	.553	.893	1.000
	1	1	1.000	1.097	.548
		3	.912	1.000	.500
cost		5	1.825	2.002	1.000
	3	1	1.000	2.333	.958
		3	.429	1.000	.411
		5	1.044	2.435	1.000
	5	1	1.000	1.364	3.182
		3	.733	1.000	2.333
		5	.314	.429	1.000
	1	1	1.000	.667	.357
interaction		3	1.499	1.000	.535
		5	2.801	1.868	1.000
	3	1	1.000	3.381	1.762
		3	.296	1.000	.521
		5	.568	1.919	1.000
	5	1	1.000	2.000	7.667
		3	.500	1.000	3.834
		5	.130	.261	1.000
lecturer	1	1	1.000	.091	.273
		3	1.989	1.000	3.000

Table 3. odds ratios between satisfaction levels

$\begin{array}{c ccccccccccccccccccccccccccccccccccc$						
3 1 1.000 2.212 .697 3 .452 1.000 3.15 5 1.435 3.174 1.000 5 1 1.000 2.727 4.182 3 .367 1.000 1.534 5 .239 .652 1.000 1 1 1.000 .487 3.133 3 1.456 1.000 .456 5 3.195 2.195 1.000 3 1 1.000 .456 5 3.195 2.195 1.000 4 3 .328 1.000 .456 5 .710 2.161 1.000 5 1 1.000 .483 3 .750 1.000 2.125 5 .353 .471 1.000			5	3.663	.333	1.000
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$		3	1	1.000	2.212	.697
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$			3	.452	1.000	.315
5 1 1.000 2.727 4.182 3 .367 1.000 1.534 5 .239 .652 1.000 1 1 1.000 .687 .313 3 1.456 1.000 .456 5 3.195 2.195 1.000 3 1 1.000 .3.045 1.409 4 3 .328 1.000 .463 5 .710 2.161 1.000 5 1 1.000 .463 5 .710 2.161 1.000 5 1 1.000 .463 5 .710 2.161 1.000 5 1 1.000 1.333 2.833 3 .750 1.000 2.125 5 5 .353 .471 1.000			5	1.435	3.174	1.000
3 .367 1.000 1.534 5 .239 .652 1.000 1 1 1.000 .657 .313 3 1.456 1.000 .456 5 3.195 2.195 1.000 4 3 1.456 1.000 .456 5 3.195 2.195 1.000 4 3 .328 1.000 .463 5 .710 2.161 1.000 5 1 1.000 .433 3 .750 1.000 .463 5 .710 2.161 1.000 5 1 1.000 .463 3 .750 1.000 2.125 5 .353 .471 1.000	-	5	1	1.000	2.727	4.182
5 .239 .652 1.000 1 1 1.000 .687 .313 3 1.456 1.000 .456 5 3.195 2.195 1.000 3 1 1.000 3.045 1.409 3 1 1.000 3.045 1.409 5 .710 2.161 1.000 5 1 1.000 1.333 2.833 3 .750 1.000 2.125 5 5 .353 .471 1.000 2.125			3	.367	1.000	1.534
1 1 1.000 .687 .313 3 1.456 1.000 .456 5 3.195 2.195 1.000 3 1 1.000 3.045 1.409 3 .328 1.000 .463 5 .710 2.161 1.000 5 1 1.000 .463 5 .710 2.161 1.000 5 1 1.000 1.333 2.833 3 .750 1.000 2.125 5 .353 .471 1.000			5	.239	.652	1.000
3 1.456 1.000 .456 5 3.195 2.195 1.000 3 1 1.000 3.045 1.409 4 3 .328 1.000 .463 5 .710 2.161 1.000 5 1 1.000 1.333 2.833 3 .750 1.000 2.125 5 .353 .471 1.000		1	1	1.000	.687	.313
5 3.195 2.195 1.000 3 1 1.000 3.045 1.409 403 3.288 1.000 4.63 5 .710 2.161 1.000 5 1 1.000 1.333 2.833 3 .750 1.000 2.125 5 .353 .471 1.000			3	1.456	1.000	.456
3 1 1.000 3.045 1.409 text 3 .328 1.000 .463 5 .710 2.161 1.000 5 1 1.000 1.333 2.833 3 .750 1.000 2.125 5 .353 .471 1.000			5	3.195	2.195	1.000
text 3 .328 1.000 .463 5 .710 2.161 1.000 5 1 1.000 1.333 2.833 3 .750 1.000 2.125 5 .353 .471 1.000		3	1	1.000	3.045	1.409
5 7.10 2.161 1.000 5 1 1.000 1.333 2.833 3 .750 1.000 2.125 5 .353 .471 1.000	text		3	.328	1.000	.463
5 1 1.000 1.333 2.833 3 .750 1.000 2.125 5 .353 .471 1.000			5	.710	2.161	1.000
3 .750 1.000 2.125 5 .353 .471 1.000	-	5	1	1.000	1.333	2.833
5 .353 .471 1.000			3	.750	1.000	2.125
			5	.353	.471	1.000

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