Analyzing factorial data using PLS: Application in an online complaining context

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Summary

Structural equation modeling (SEM) can be employed to emulate more traditional analysis techniques, such as MANOVA, discriminant analysis, and canonical correlation analysis. Recently, it has been realized that this emulation is not restricted to covariance-based SEM, but can easily be extended to components-based SEM, or partials least squares (PLS) path analysis (Guinot et al. 2001; Tenenhaus et al. 2005; Wetzels et al. 2005). In this paper we will apply PLS path analysis to a fixed-effects, between-subjects factorial design in a online complaint handling context. The results of our empirical study reveal that satisfaction with online recovery is determined by both the level of procedural and distributive justice. Furthermore, customers' satisfaction with the way their complaints are handled has a positive influence on the customers' intentions to repurchase and to spread positive word of mouth. Taking into account the entire chain of effects, we find the influence of justice perceptions on behavioral intentions is almost fully mediated by satisfaction. From a managerial perspective, the results of our study provide insight in how to design effective complaint handling strategies in order to maintain a satisfied and loyal customer base.

Keywords: Multivariate Data Analysis, Factorial design, PLS, Complaint management, Online Services

1 Introduction

Structural equation modeling (SEM) has the potential to fundamentally improve experimental research in social sciences (MacKenzie 2001). Compared to traditional approaches (i.e. (M)AN(C)OVA) to analyze data from factorial experimental designs the use of SEM offers the following advantages: ability to control for measurement error and enhanced testing of nomological webs among multiple dependent variables (cf. MacKenzie 2001). Despite these fundamental strengths it appears that the proposed covariance-based SEM approaches to analyzing experimental data perform rather poorly in small sample conditions, under non-normality and does not have the ability to handle complex models (e.g. Bagozzi et al. 1991; McDonald et al. 2002). Given the fundamental properties of PLS estimation, PLS estimation has the potential to offer a method for analyzing data from factorial experimental designs that offers many of the abovementioned advantages of SEM-based analysis but overcomes the often-encountered drawbacks. Thus, a PLS-based approach to experimental designs offers a strong methodological tool that can be applied in many circumstances. In this paper we show how PLS can be used to analyze data from factorial experimental designs.

In this chapter we will apply the proposed PLS-approach to data obtained from a factorial experimental design in an online service recovery context. The significance of this application and the relevant literature will be discussed in section 2. In section 3 we will demonstrate how PLS can be used to analyze factorial data and how to interpret the accompanying output. We will end this chapter with a discussion and conclusion.

2 Online service recovery: significance and literature review

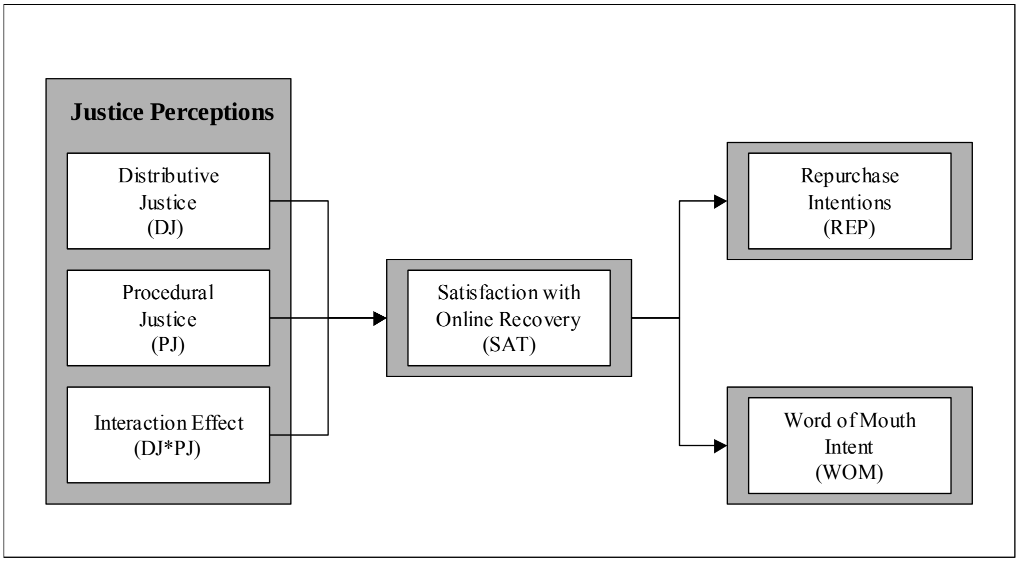
Several empirical studies indicate that organized service recovery policies are an important tool in order to maintain satisfied and loyal customers (Blodgett, Hill, and Tax 1997; Maxham and Netemeyer 2002; Tax, Brown, and Chandrashekaran 1998). In contrast to complaint handling in traditional (i.e. offline) services, only limited attention has been paid to the antecedents and consequences of satisfaction with complaint handling in online settings despite the great differences that exist between online and offline settings and therefore the way complaint management procedures are perceived by customers in both settings. First of all, effective complaint management is particularly important for e-services as customers can terminate their relationship with the service provider by just a simple mouse click (Holloway and Beatty 2003). Second, Holloway and Beatty (2003) state that satisfaction with complaint recovery is especially crucial for online service providers as poor service online may hurt online as well as offline sales. Third, in an online environment customers cannot directly see and touch the product, nor can they directly bring it home after buying it (Reichheld and Schefter 2000). Fourth, the formation of customer evaluative judgments are different in online settings (Shankar, Smith, and Rangaswamy 2003). Fifth, the types of service failures experienced may be different for the online and offline environment and customers tend to complain more online than in traditional marketplace (Holloway and Beatty 2003). Finally, given the lack of human interaction in e-services we cannot simply extrapolate the empirical findings concerning complaint handling that were established in offline / regular services (Reichheld and Schefter 2000).

The research objectives guiding our work are formulated as follows:

1. To examine how justice perceptions of complaint handling procedures influence key customer evaluative judgments in an online setting.
2. To show how PLS path modeling can be used to analyze factorial design (i.e. data from experimental studies).

Figure 1 provides an overview of the conceptual model underlying our study. The relevant literature underlying our conceptual framework will be summarized below.

Figure 1 Conceptual model



Concerning traditional offline service delivery formats, equity or justice theory has been proven to be a powerful approach to understand and explain customer's perceptions regarding company's service recovery efforts (e.g. Smith, Bolton, and Wagner 1999; Blodgett, Hill, and Tax 1997; Maxham and Netemeyer 2002; Tax et al. 1998). In the literature two reasons can be distinguished that clarify the significant explanatory power of justice perceptions in understanding customer's perceptions of service recovery strategies. First of all, Maxham and Netemeyer (2002) state that implicit promises of fairness are salient because it is often difficult for customers to evaluate service before, and sometimes after, the transaction is made. This is especially true for (online) complaint management procedures as these are characterized by high degree of experience quality, meaning that a customer can only evaluate the service in retrospection (Brush and Artz 1999; Klein 1998). Second, as complaint handling can be considered as a process (Tax et al. 1998) justice theory provides researchers with a comprehensive framework to understand customer evaluations as each part of the complaint handling process is subject to fairness considerations and that each aspect of a complaint resolution creates a justice episode (Bies 1987; Tax et al. 1998). As these characteristics apply to online service delivery formats as well, justice theory in our opinion will also very likely be a strong approach to explain customer's post-recovery attitudes and behaviors in an online context.

Building on the principals of equity theory, we believe that the evaluation of an online recovery process is a function of the recovery process itself (referred to as procedural justice) and the outcomes of the recovery process (referred to as distributive justice). The suggested impact of procedural and distributive justice on online service evaluations is supported by the work of Zeithaml, Parasuraman, and Malhotra (2000) who state customer evaluative judgments in an online service context are based on what customers receive as outcome as well as on how the process of service delivery takes place.

Procedural justice can be defined as the perceived fairness of the way the complaint is handled (Netemeyer and Maxham 2002). According to Tax et al. (1998) procedural justice is meaningful because it aims to resolve conflicts in ways that encourage the continuation of a relationship even when outcomes are not satisfactory to one/both parties. Flexibility, speed of recovery, accessibility of complaint procedure, the freedom of the complainant in rejecting or accepting the refund offered and the extent to which a complainant is free to express his own view on the complaint handling procedure are important factors in the formation of procedural justice perceptions (Tax et al. 1998; Blodgett et al. 1997). Although the complaint handling in online settings may be different in form, the positive effect of procedural justice on recovery satisfaction may still hold (Janda, Trocchia, and Gwinner 2002; Montoya-Weiss, Voss, Grewal 2003). Consequently, we hypothesize:

H_1 *Procedural justice positively affects satisfaction with the online complaint recovery*

Distributive justice relates to the outcome of the complaint handling effort. The degree to which a customer perceives the outcome of complaint handling fair in terms of distributive justice depends on the benefits received and the costs associated with the experienced service failure (Netemeyer and Maxham 2002). It is reasonable to assume that the outcome of complaint handling efforts itself is independent of the channel through which the service is provided. Based on this assumption we believe that the positive relationship between perceived distributive justice and satisfaction with complaint handling as empirically supported in offline service settings can be extended to an online setting. Therefore, we hypothesize:

H_2 *Distributive justice positively affects satisfaction with the online complaint recovery*

It has been empirically demonstrated (e.g. Sparks and McColl-Kennedy 2001) that in a service recovery context outcomes and procedures work together to create a sense of justice. Following the principle of referent cognition theory, Tax et al. (1998) state that the value of a service recovery outcome may be enhanced or comprised by the procedures by which the outcome is established. We extend this finding to an online service context. The underlying premise is that human-computer interaction is fundamentally social and that individuals respond to computers in much the same way that they respond to human beings (cf. Reeves and Nash 1996). Hence, we posit:

H_3 *Perceptions of procedural justice affect the nature of the positive relationship between distributive justice and satisfaction with the online complaint recovery.*

This study examines the effects of procedural and distributive justice on three types of customer outcomes: satisfaction, loyalty intentions and word of mouth intentions. Ample empirical evidence is available concerning the relevance of these three outcome variables in a complaint management context (e.g. Maxham and Netemeyer 2002; Blodgett et al. 1997). In brief, these customer outcomes can be described as follows. Satisfaction is the customer's overall affective psychological response based on subjective evaluations of the overall service performance after organizational recovery efforts (Hess et al. 2003). Word of mouth intent can be defined as the likelihood that one would favorable recommend doing business with a certain firm after a failure and recovery effort, and purchase intent refers to the degree to which customers intend to purchase a firm's products/services in the future (Netemeyer and Maxham 2002).

Although both satisfaction and behavioral intentions are key constructs in studying the effectiveness of service recovery efforts, consideration of the nomological web that exists among them is crucial to obtain valid and unbiased estimates of the effects justice perceptions have on these outcome variables.

Our previously formulated hypotheses state that justice perceptions only have a direct impact on the formation of satisfaction. This is congruent with the existing literature (e.g. Maxham and Netemeyer 2002; Wirtz and Mattila 2004) on service recovery, which states that satisfaction mediates the positive impact of justice perceptions on repurchase intentions and the intention to engage in word of mouth. Finally, it should be noted that similar to traditional services, the relationship between satisfaction and behavioral intentions is also evidenced in e-services (Anderson and Srinivasan 2003, Holloway, Wang, and Parish 2005). Overall, the literature cited above leads to the formulation of the following hypotheses:

H_4 *Satisfaction with service recovery positively affects repurchase intentions*

H_5 *Satisfaction with service recovery positively affects the intention to engage in word of mouth*

H_6 *Satisfaction with service recovery mediates the relationship between justice perceptions and (a) repurchase intentions and (b) word of mouth intentions.*

3 Method

3.1 Study design

In order to test the hypotheses outlined above a 2*2 between groups, quasi experimental design using written scenarios was employed. Subjects were randomly assigned to the various treatments and were ask asked to read a scenario in which a customer was dissatisfied with a product (a pair of athletic shoes starting to fall apart after only limited use) s/he bought online and sought to redress from the online retailer via the website. Sport shoes are chosen as it is a product that most subjects are familiar with and have at least some experience in purchasing them (cf. Blodgett et al. 1997).

Manipulations were conducted as follows. Under the high distributive justice condition the customer received a full refund, whereas under the low distributive justice condition the customer was offered a 15% discount on a new pair of shoes. Concerning procedural justice we manipulated the scenarios with regard to time that the complainant receives a response from the company and the level of effort the customer must exert in obtaining this response. Under the high procedural justice condition the customer received a response within 24h of his/her first email, whereas under the low procedural justice condition the customer received an answer from the company only after 5 working days after having send a second email.

After having read one of the four scenarios respondents were asked to fill out a questionnaire containing the following measures. To assess whether manipulations indeed achieved the desired effect we included the items of Blodgett et al.'s scale (1997) on procedural (3 items) and distributive justice (3 items). Furthermore, we included measures to assess customer satisfaction (Maxham and Netemeyer 2002; 3 items), repurchase intentions (Blodgett et al. 1997; 3 items) and word of mouth intent (Maxham and Netemeyer 2002; 3 items). For all constructs we used 7-point Likert scales, with higher scores reflecting a more favorable attitude. Table 1 provides an overview of the items used to measure customer satisfaction, repurchase intentions, and word of mouth intent. The items used for the manipulation checks are presented in the appendix A to this chapter.

3.2 Sampling procedure and sample characteristics

All respondents (n = 147) were students participating in a business research course at a European university. They were asked to take part in the study and filled out the questionnaire during the last 15-20 minutes of their classes. Participation in the study was rewarded with a candy bar.

The mean age of the respondents was 23.12 years with a standard deviation of 2.88 years. Furthermore, the proportion of males and females in the sample was equal (i.e. 49.7% male ; 50.3% female). As a results of the international orientation of the university at which we collected the data various nationalities are represented in the sample: Dutch (51.0%), German (35.4%), Belgian (4.1%), and 9.5% of the respondents were Non-European.

3.3 Analytical results

Unless mentioned otherwise, we used PLS-GRAPH version 3.0 to estimate the parameters in our model, with the number of bootstrap samples J equaling 1000 and all containing 147 cases. Below we describe the empirical results pertaining to our study. First, we assess the measurement properties of the scales used in our study. More specifically, we assess whether the multiple-items scales used possess favorable psychometric properties in terms of unidimensionality, reliability, convergent and discriminant validity. Second, we discuss how PLS can be used to analyze factorial data and its relative advantage of existing methods and apply the suggested approach to our data.

3.3.1 Measurement properties

In order to assess the psychometric properties of the multiple item scales used in our study, we follow the procedures suggested by Tenenhaus et al. (2005). The empirical results related to the analysis of the scale's measurement properties are summarized in table 1.

Table 1 Measurement properties

	Coefficient	t-value	p-value
Satisfaction			
$\lambda_1 = 2.570$ $\lambda_2 = 0.291$ $\lambda_3 = 0.139$ $\alpha = 0.95$ $ave = 0.86$			
1 Company provided a satisfactory resolution to problem	0.95	115.79	< 0.0001
2 Not satisfied with company's problem handling (-)	0.90	32.41	< 0.0001
3 Regarding the problem resolution satisfied with company	0.90	49.74	< 0.0001
Word of mouth			
$\lambda_1 = 2.746$ $\lambda_2 = 0.161$ $\lambda_3 = 0.093$ $\alpha = 0.97$ $ave = 0.92$			
1 Likelihood to spread positive word-of-mouth about company	0.96	153.04	< 0.0001
2 Recommend company to others	0.94	70.97	< 0.0001
3 If asked for advice, recommend company	0.97	115.83	< 0.0001
Repurchase intent			
$\lambda_1 = 2.552$ $\lambda_2 = 0.271$ $\lambda_3 = 0.177$ $\alpha = 0.95$ $ave = 0.85$			
1 Likelihood to shop at this online retail store in the future	0.92	62.86	< 0.0001
2 If this situation happened, would never shop there again (-)	0.91	37.10	< 0.0001
3 If this situation happened, would still shop there in the future	0.94	60.02	< 0.0001

Satisfaction 1 = totally disagree ; 7 = totally agree
Word of mouth and Repurchase intent 1= very unlikely; 7= very likely

Starting with assessment of unidimensionality, we conducted a principle component analysis (using SAS v8) for each of the three scales. For all three scales unidimensionality is evidenced as the first eigenvalue (λ_1) of the block of variables exceeds 1 and the second eigenvalue (λ_2) is smaller than 1 (see also table 1)

Internal consistency of the measurement scales under study is evidenced by the fact that the composite reliability values, indicated by α, all exceed the recommended cut-off values of 0.70 (Nunnally and Bernstein 1994).

Having substantiated the existence of unidimensionality and reliability of the scales used in this study, we proceed by examining whether the scales possess a substantial degree of within-method convergent validity and discriminant validity. Within-method convergent validity is evidenced by the large (> 0.50) and significant item loadings on their respective constructs (cf. Anderson and Gerbing 1984). Finally, discriminant validity is established as the square root value of average trait extracted is greater than the correlation coefficient between the two relevant constructs. Figures regarding the evidence of discriminant validity are provided in table 2. Furthermore, table 2 provides key descriptive statistics of the scales used in our study, as well as correlations and covariances among all pairs of variables.

Table 2 Correlations, covariance, and descriptive statistics

	SAT	*WOM*	*REP*
SAT	*0.93*[a]	2.67[c]	2.56
WOM	0.82[b]	*0.96*	2.73
REP	0.88	0.84	*0.92*
Complete sample (n = 147)			
Mean	3.93	3.98	4.12
SD	1.63	1.81	1.79
Skewness (SE = 0.200)	-0.13	0.07	-0.19
Kurtosis (SE = 0.397)	-1.20	-1.14	-1.11
LP-LD (n = 37)			
Mean	2.32	5.60	2.37
SD	0.94	1.21	1.23
Skewness (SE = 0.388)	0.61	-0.79	0.84
Kurtosis (SE = 0.759)	-0.41	-0.21	-0.08
LP-HD (n = 36)			
Mean	4.34	3.61	4.74
SD	1.21	1.30	1.43
Skewness (SE = 0.393)	-0.40	-0.08	-0.51
Kurtosis (SE = 0.768)	-0.85	-0.98	-0.45
HP-LD (n = 38)			
Mean	3.53	4.46	3.53
SD	1.48	1.70	1.36
Skewness (SE = 0.383)	0.05	-0.11	-0.06
Kurtosis (SE = 0.750)	-1.25	-0.98	-0.31
HP-HD (n = 36)			
Mean	5.60	2.18	5.91
SD	0.71	0.98	0.75
Skewness (SE = 0.393)	0.38	0.55	-0.10
Kurtosis (SE = 0.768)	-0.57	-0.99	-0.91

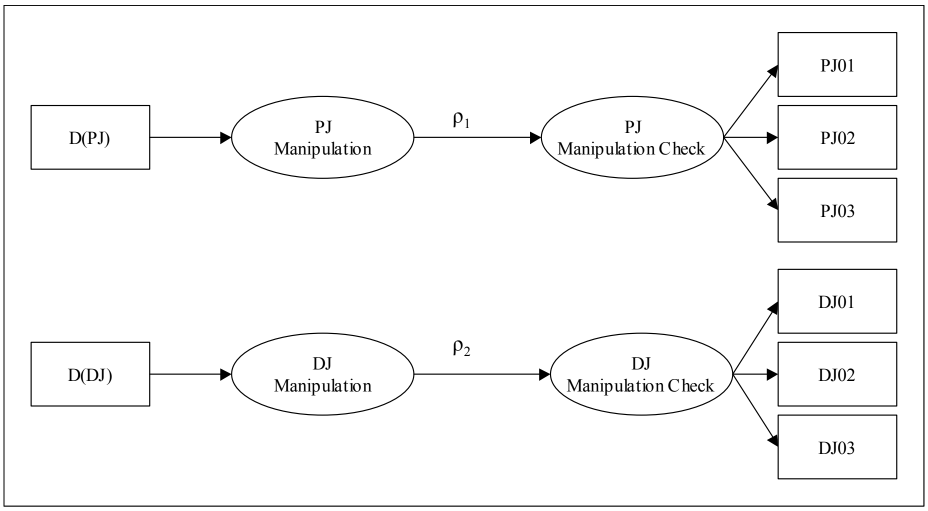
[a] Square root of average variance extracted values are on the diagonal of the matrix; [b] Correlation coefficients are placed in the lower triangle of the matrix; [c] Covariances are placed in the upper triangle of the matrix. A correlation / covariance matrix as well descriptive statistics at the item level of the constructs can be obtained from the first author.

Structural model

The effects of our factorial design are captured by dichotomous variables. As the number of respondents per cell are not equal we opted for dummy coding rather than effects coding the justice manipulations used in our study (cf. Pedhazur 1997).

Prior to the actual analysis of our conceptual model we first need to examine whether the intended justice manipulations achieved the desired effect. Although manipulation checks are typically conducted by means of a series of one-way ANOVAs, they can also be directly performed in PLS by estimating a model that connects the dichotomous manipulations to the variables intended to measure the effect of the manipulation as well. For the situation at hand, the model to conduct manipulation checks in PLS is graphically displayed in figure 2.

Figure 2 Conducting manipulation checks in PLS

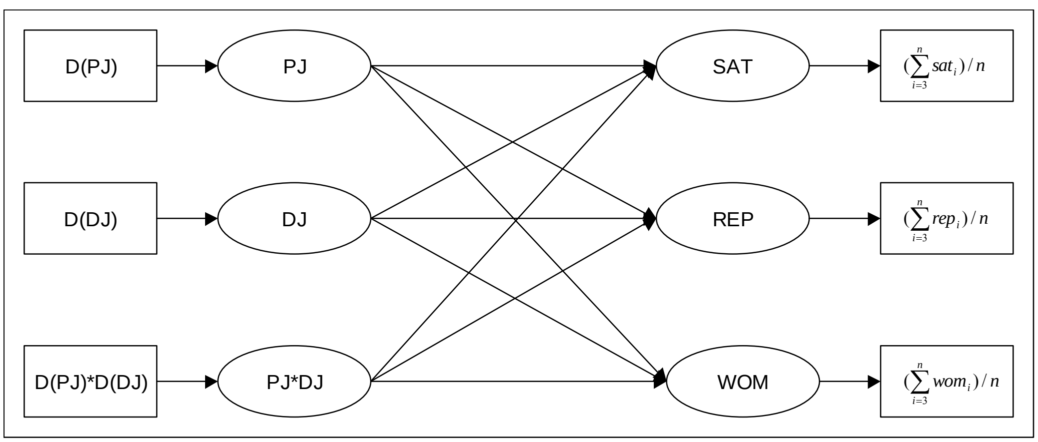


In figure 2, the variables $D(PJ)$ and $D(DJ)$ represent the dummy coded manipulations for procedural and distributive justice respectively and are formative indicators of a latent construct representing the *actual* manipulation used in the study. The constructs 'PJ Manipulation Check′ and 'DJ Manipulation Check' assess the respondents' perceptions regarding the manipulations of procedural and distributive justice. These latter constructs are both assessed by multi-item scales (see appendix A for details of the scales). Significant values of ρ_1 (t = 25.071; p < 0.0001) and ρ_2 (t = 20.359; p < 0.0001) indicate that the procedural justice and distributive justice manipulations achieved the desired effects.

Below, different types of models are outlined in order to clearly and convincingly demonstrate the added value of PLS over other methods (i.e. (M)ANOVA and covariance-based SEM) in analyzing data from factorial designs.

The first model is a PLS model that exactly replicates a (M)ANOVA estimation approach (see also figure 3)[1]. To achieve this, we propose a path model containing only latent variables with a single indicator. To capture the design effects formative indicators are used, whereas each outcome variable is represented by a latent variable for which the (reflective) indicator is formed by the sum of its items.

Figure 3 (M)ANOVA using PLS



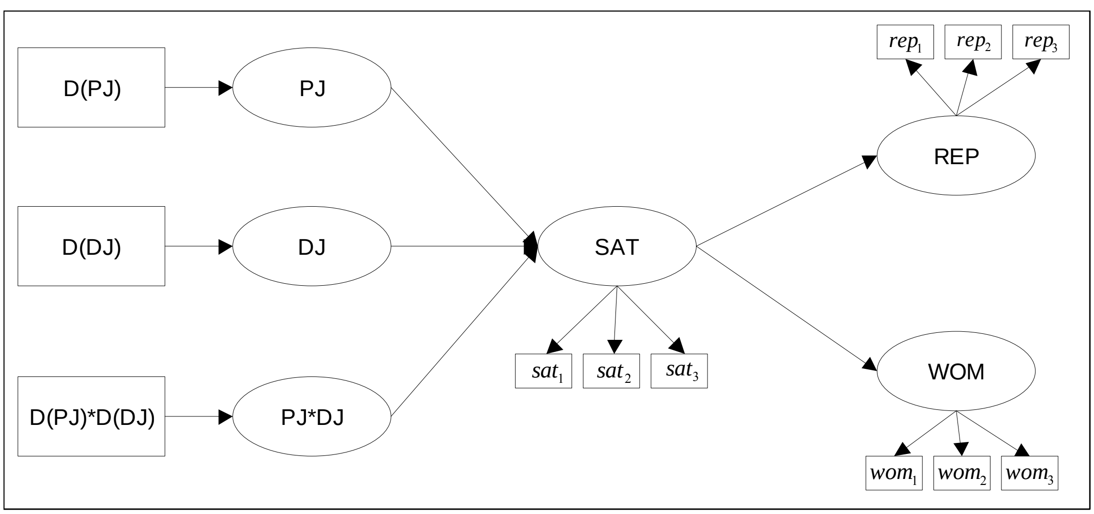
The added value of PLS analysis over traditional MANOVA is that one can allow for structural paths among the various outcome variables, thereby substantially diminishing the effects of omitted variable bias. The introduction of covariance-based SEM approaches to modeling factorial data (Bagozzi and Yi 1989) implied a giant leap forward in analyzing

[1] The model in figure 3 represents a MANOVA approach as typically used in the marketing literature (e.g. Blodgett et al. 1997): the experimental effects are hypothesized to influence all outcome variables and there are no effects hypothesized among the outcome variables. To exactly assess the hypotheses outlined in this paper following a (M)ANOVA approach one would actually need separate models. One ANOVA model with satisfaction as outcome variable and two regression models to estimate the estimate the effect of satisfaction on repurchase intentions and word of mouth intentions respectively.

factorial data, as structural paths among dependent variables can be taken into account whilst controlling for measurement error. However, the methodology is not always feasible to use in empirical research as it requires multivariate normal data, large sample sizes and cannot be used for complex models (Bagozzi, Yi, and Singh 1991). Compared to covariance-based SEM models the PLS approach offers the following advantages to analyzing factorial data. First of all, PLS poses less stringent assumptions regarding the distributional characteristics of the data. Second, its ability to model both reflective and formative indicators, whereas covariance-based SEM approaches typically can handle only reflective indicators. Third, PLS can well be used in case of small and medium sized samples. Fourth, PLS can handle more complex designs.

In figure 4 we outline a PLS model to model factorial data and that allows for structural relationships among the outcome variables as outlined in our conceptual model (see also figure 1).

Figure 4: A PLS approach to modeling factorial data



Regarding the model presented in figure 4, the experimental manipulations are modeled as latent variables with dummy variables as their formative indicators and the outcome variables are modeled as latent variables having multiple items as their reflective[2] indicators. As the model presented in figure 4 provides us with the most valid representation of the situation at hand, we will only discuss the empirical results pertaining to this model. Although in the majority of cases that build on the principles of Theory of Reasoned Action (TRA) develop by Fishbein and Ajzen (1975), the effects of beliefs (i.e. justice) on behavioral intentions (i.e. repurchase intent and word of mouth) are fully mediated by attitude (i.e. satisfaction with complaint recovery), Bagozzi (1982) provides empirical support for a model in which attitude only partially mediates the relationship between beliefs on behavioral intentions. Thus, in order to be able to increase the validity of our findings regarding the mediating role of satisfaction with complaint recovery in our conceptual model, we estimate a model that contains both indirect and direct effects between the justice manipulations and behavioral intentions.

To assess H_6, which states that satisfaction with online recovery mediates the effect of justice perceptions on behavioral intentions, we use the procedure outlined by Hoyle and Kenny (1999). In summary, the Hoyle and Kenny[3] approach requires the estimation of the two types of models presented in figure 5.

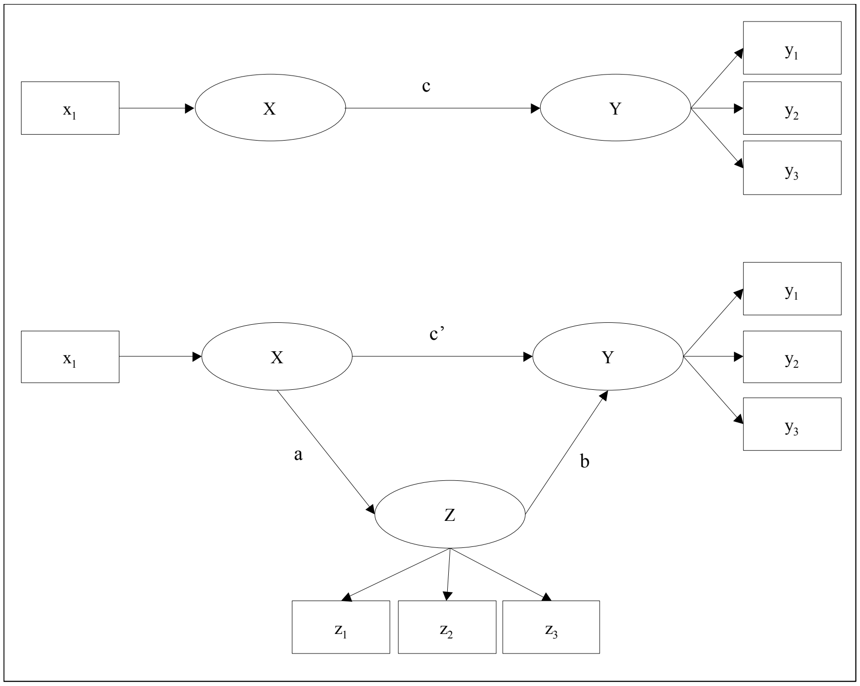
In terms of the labels used in figure 5 'X' denotes one of the justice perception, 'Y' the respondent's behavioral intentions (either repurchase intent or word of mouth intent), and 'Z' reflects the possible mediator, in this case satisfaction with the online recovery[4].

[2] Concerning the outcome variables the choice of using reflective indicators guided by the work of Jarvis et al. (2003). If the guidelines presented by Jarvis et al. (2003) on the specification of indicators suggest the use of formative indicators, this can be readily applied in our suggested PLS approach to analyze factorial data.

[3] For situations in which the independent variable(s), mediator variable, and / or dependent variable(s) are embedded in a larger nomological network (i.e. have their own additional antecedents or consequences the approach of Iacobucci, Saldanha, and Deng (2006) is preferred over the Hoyle and Kenny (1999) approach.

[4] The form and number of indicators used in the models presented in figure 5 are chosen to reflect the situation of our study. The Hoyle and Kenny (1999) approach also applies to other forms and numbers of indicators.

Figure 5 **Hoyle and Kenny's (1999) mediation test**



Statistical evidence of mediation in a structural equation modeling context requires the following (cf. Hoyle and Kenny 1999). First, evidence of a causal influence of X on Y ($c \neq 0$). Second, a significant indirect effect of X on Y ($ab \neq 0$), indicative of a decline in the direct effect of X on Y when the mediator is accounted for (please note that $ab = c - c'$). If $ab \neq 0$ and $c' \neq 0$, M only partially mediates the relationship between X and Y. If $ab \neq 0$ and $c' = 0$, M fully mediates the effect of X on Y.

To assess the significance of the various effects we employed a bootstrap procedure (J=1000 with n=147). Based on the outcomes of the bootstrap procedure we constructed several 95% confidence intervals. The bootstrap percentile confidence interval is preferred over the standard normal confidence interval for small sample sizes (n<400), which are often characterized by a skewed and leptokurtic sample distribution of the indirect effect *ab* (Preacher and Hayes 2006, Shrout and Bolger 2002, Bollen and Stine 1990). A further improvement came from Efron and Tibshirani (1998) who proposed a bias-corrected bootstrap percentile confidence interval, which corrects for the bias in the central tendency of the estimate. A simulation study by MacKinnon, Lockwood, and Williams (2004) shows that the bias-corrected version of the bootstrap percentile method outperforms the regular bootstrap percentile method in terms of statistical power and accuracy of the confidence intervals. Computational details on how to construct (bias corrected) bootstrap percentile confidence interval are presented in appendix B. The accompanying estimation results of the structural model are presented in table 3.

Inspection of the estimation results of the structural model reveals the following. First of all, we can conclude that our conceptual model is well supported by the data as indicated by the R-squared values ($R^2_{SAT} = 0.54$ ($p < 0.0001$); $R^2_{REP} = 0.77$ ($p < 0.0001$); $R^2_{WOM} = 0.67$ ($p < 0.0001$)). Turning to the individual effects we see that both distributive and procedural justice have a significant[5] influence on the formation of satisfaction with service recovery in an online setting. Hence, H_1 and H_2 are supported. However, we fail to find a significant interaction effect of procedural and distributive justice in the development of satisfaction. Consequently, H_3 is not supported. The crucial role of satisfaction with recovery in shaping both customers' repurchase intentions and customers' intentions to spread word of mouth is also reflected in the data, thereby providing support for H_4 and H_5. In addition to the hypothesized direct effects, our analysis also reveals a direct influence of distributive justice on repurchase intent.

[5] Although the three types of confidence intervals very consistent for the effects found is this study. We base our hypothesis testing on the bias corrected bootstrap percentile confidence interval given its superior performance as demonstrated by MacKinnon et al. (2004).

Table 3 Estimation results structural model

Effects	Estimate	SE	95 % CI: Standard normal	95 % CI: Bootstrap percentile	95 % CI: Bias-corrected bootstrap perc.	Mean	Bootstrap SD
Direct effects							
$proc \rightarrow sat$	0.37	0.08	(0.21 ; 0.53)	(0.21 ; 0.54)	(0.21 ; 0.55)	0.37	0.09
$proc \rightarrow rep$	0.06	0.07	(-0.09 ; 0.20)	(-0.08 ; 0.18)	(-0.06 ; 0.22)	0.05	0.07
$proc \rightarrow wom$	0.07	0.09	(-0.11 ; 0.25)	(-0.07 ; 0.29)	(-0.12 ; 0.23)	0.11	0.09
$dist \rightarrow sat$	0.63	0.07	(0.48 ; 0.77)	(0.48 ; 0.77)	(0.46 ; 076)	0.63	0.07
$dist \rightarrow rep$	0.21	0.07	(0.07 ; 0.35)	(0.06 ; 0.36)	(0.09 ; 0.39)	0.20	0.07
$dist \rightarrow wom$	0.14	0.07	(-0.01 ; 0.28)	(0.00 ; 0.29)	(0.00 ; 0.28)	0.14	0.07
$proc * dist \rightarrow sat$	0.01	0.09	(-0.17 ; 0.19)	(-0.18 ; 0.19)	(-0.06 ; 0.33)	0.01	0.09
$proc * dist \rightarrow rep$	0.01	0.07	(-0.14 ; 0.15)	(-0.12 ; 0.14)	(-0.12 ; 0.14)	0.01	0.06
$proc * dist \rightarrow wom$	0.06	0.08	(-0.10 ; 0.22)	(-0.19 ; 0.14)	(-0.02 ; 0.22)	0.03	0.08
$sat \rightarrow rep$	0.73	0.06	(0.61 ; 0.85)	(0.62 ; 0.85)	(0.60 ; 0.83)	0.73	0.06
$sat \rightarrow wom$	0.67	0.08	(0.51 ; 0.83)	(0.50 ; 0.79)	(0.52 ; 0.81)	0.65	0.07
Indirect effects							
$proc \rightarrow sat \rightarrow rep$	0.27	0.06	(0.14 ; 0.39)	(0.15 ; 0.41)	(0.15 ; 0.41)	0.27	0.07
$proc \rightarrow sat \rightarrow wom$	0.25	0.06	(0.13 ; 0.37)	(0.14 ; 0.37)	(0.15 ; 0.39)	0.24	0.06
$dist \rightarrow sat \rightarrow rep$	0.45	0.06	(0.33 ; 0.58)	(0.34 ; 0.59)	(0.33 ; 0.56)	0.46	0.06
$dist \rightarrow sat \rightarrow wom$	0.42	0.07	(0.28 ; 0.56)	(0.28 ; 0.55)	(0.30 ; 0.58)	0.41	0.07
Total effects							
$(dist \rightarrow rep) + (dist \rightarrow sat \rightarrow rep)$	0.66	0.08	(0.50 ; 0.82)	41 % mediation			

Based on the empirical results we can conclude that the effect of procedural justice on behavioral intentions is fully mediated by satisfaction, whereas the effect of distributive justice on behavioral intentions is only partially mediated (41%) by satisfaction with online recovery. Overall, H_6 is supported fully for procedural justice and only partly for distributive justice. Please note that the mediation analysis does not apply for the interaction effect as there is no effect of $PJ * DJ$ on SAT (i.e. $a = 0$).

4 Discussion and Conclusion

The use of factorial experimental design is ubiquitous in social sciences. Although traditional analysis techniques, such as (M)AN(C)OVA, for this type of study can be considered as powerful under certain conditions, they fail to meet some often-encountered modeling circumstances such as structural dependency among outcome variables, non-normal data, and small samples. Although considerable research has been devoted to developing covariance-based models to overcome the limitations of these traditional estimation approaches, only limited effort has been directed at showing how component-based techniques such as PLS can be used to estimate these more realistic but more complex models of factorial experimental data.

In this paper we showed how PLS can be used to analyze data of factorial designs. First, we indicated how PLS is related to traditional MANOVA. Compared to traditional estimation approaches (i.e. MANOVA) the PLS model provides a more accurate and insightful picture of the phenomenon under study as it allows researchers to take into account the nomological web that may exist among the dependent variables. Compared to covariance-based SEM approaches to analyzing factorial data, the PLS approach offers a much greater practical applicability as it requires no distributional assumptions regarding the data, can well be used in small and medium sample sizes, can incorporate both reflective and formative indicators, and does not run into trouble when estimating complex models.

As choosing the best technique for the research design at hand is a critical step in conducting sound research, it is also important to acknowledge that there are circumstances in which covariance-based SEM approaches to modeling factorial data are preferred over PLS path modeling. Based on a Monte Carlo simulation conducted by Hoyle and Kenny (1999) it can be concluded that the bias in parameter estimates is inversely related with the reliability of the constructs. As covariance-based SEM techniques allow to correct parameter estimates for measurement error, it is favored in situations in which the reliability of the measures is less optimal.

Balancing the relative (dis)advantages of covariance-based SEM and PLS, we can nevertheless state that PLS has the potential to fundamentally improve the analysis of experimental designs in social sciences.

From a marketing perspective our work offers the following insights. In contrast to studies conducted in offline service settings, it appears that distributive and procedural justice have independent positive effects on satisfaction with online recovery. A possible explanation for this finding could be due to the inherent differences of electronic services compared to traditional services. Due to the lack of human interaction both with employees and other customers, e-service customers may produce less strong and clear perceptions regarding the procedures in complaint recovery situations. As such, the prediction based on referent cognitions theory (cf. Folger 1984, Tax et al. 1998) that perceived procedural injustice will exacerbate feelings of distributive injustice when believe a better outcome could have been achieved with a fairer procedure may not hold.

Taking a look at the individual effects of procedural and distributive justice we see that distributive justice has a larger positive impact on the formation of satisfaction with online recovery than procedural justice. This finding contrasts the empirical results obtained by various researchers (e.g. Maxham and Netemeyer 2002; Tax et al. 1998) in offline service settings. Again, the difference in nature of the interaction of offline and online service contexts may play a key role in explaining this finding. In an offline context, the costs involved in the actual complaint recovery procedure may be substantially higher compared to online service delivery formats (e.g. traveling to the store, waiting in line). Consequently, customers may be more likely to form more negative perceptions of procedural justice in an offline service delivery format. Drawing on prospect theory (cf. Mittal, Ross, and Baldasare 1998), more negative evaluations are weighted more heavily, thereby explaining the larger effect of procedural justice in traditional service delivery formats. From a different angle, distributive justice in online service complaint handling may be easier for customers to evaluate than procedural justice. As a result, customers may place more weight on the evaluation of distributive justice in developing their post-recovery attitudes and behaviors. From a practical perspective, the finding that customers place more value on distributive justice compared to procedural justice, provides insight to managers in setting priorities in developing effective online recovery strategies.

In line with research conducted in offline complaint handling situations we also find support for positive associations between satisfaction with recovery efforts and the intent of the customer to do business again with the company. This relationship is relevant as loyalty intentions are a significant antecedent of actual behavior, which is crucial to a firm's long-term survival. In a similar vein, the significant positive relationship between satisfaction with the online recovery and customer's intent to engage in word of mouth entails good news for the company as satisfied customers may persuade others to do business with the company.

Finally, several limitations of the current study need to be recognized, which hopefully provide fruitful directions for further research efforts. First of all, our results relate to a single setting. Although on one hand this allows us to control for cross-industry difference, it would be interesting to examine the generalizability of our findings. Second, in terms of measurement a cross-sectional approach was pursued. Related work in offline service settings demonstrates interesting longitudinal effects (e.g. Maxham and Netemeyer 2002), which have remained unexplored in online service contexts. Third, our chain of effects ends with behavioral intentions. Extending this chain with actual behavior or financial measures would allow managers to make an economically justified analysis on the value and design of effective recovery strategies.

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Appendix A

Overview of the items used in the manipulation checks. All items are based on the work of Blodgett et al. (1997). Conform the work of Blodgett et al. (1997) and other researchers who employed the scale, the items were modeled as reflective indicators.

Table A1 Scales and psychometric properties

	Coefficient	t-value	p-value
Distributive justice			
$\lambda_1 = 3.564$ $\lambda_2 = 0.213$ $\lambda_3 = 0.094$ $\alpha = 0.97$ $ave = 0.92$			
1. Taking everything into consideration the company's refund offer was quite fair	0.97	139.54	< 0.0001
2. Regarding the refund the customer did not get what s/he deserved (-)	0.95	47.88	< 0.0001
3. Given the circumstances, I feel that the company offered adequate compensation	0.96	107.76	< 0.0001
Procedural justice			
$\lambda_1 = 2.669$ $\lambda_2 = 0.212$ $\lambda_3 = 0.119$ $\alpha = 0.96$ $ave = 0.92$			
1. The customer's complaint was handled in a very timely manner	0.93	38.16	< 0.0001
2. The customer's complaint was not resolved as quickly as it should have been (-)	0.96	86.86	< 0.0001
3. The customer had to write too many e-mails in order to resolve the problem	0.95	104.29	< 0.0001

Scale anchors: 1 = totally disagree ; 7 = totally agree

Table A2 Descriptive statistics

	LD-LP*	HD-LP	LD-HP	HD-HP	Overall
n	37	36	38	36	147
Mean DJ	2.34	5.81	3.00	6.52	4.38
SD DJ	0.89	0.93	1.34	0.61	2.03
Skewness DJ	0.36	-0.40	0.63	-1.49	-0.13
Skewness DJ SE	0.39	0.39	0.38	0.39	0.20
Kurtosis DJ	-0.37	-0.86	-0.27	1.84	-1.47
Kurtosis DJ SE	0.76	0.77	0.70	0.77	0.40
Mean PJ	2.14	2.71	6.04	6.79	4.43
SD PJ	0.79	1.13	1.13	0.34	2.22
Skewness PJ	0.56	0.88	-1.37	-1.49	-0.09
Skewness PJ SE	0.39	0.39	0.38	0.39	0.20
Kurtosis PJ	-0.62	1.05	0.97	0.98	-1.68
Kurtosis PJ SE	0.76	0.77	0.70	0.77	0.40

* LD = Low distributive justice ; HD = High distributive justice ; LP = Low procedural justice ; HP = High procedural justice. Data on item level as well as correlation /covariance matrices can be obtained from the first author.

Appendix B

Constructing a bootstrap percentile confidence interval

The bootstrap percentile interval for parameter β (regardless whether it is a direct of indirect effect) is constructed by the following steps (Shrout and Bolger 2002; Bollen and Stine 1990):

1. Using the original data set as a population reservoir, create J bootstrap samples of N subjects by randomly sampling observations with replacement from the data set. Parameters J and N can be set in PLSGRAPH via *options* > *resampling*.

2. For each bootstrap sample, estimate parameter $\hat{\beta}$ and save the result. The possibility to save bootstrap estimates can also be found under *options* > *resampling* in PLSGRAPH. To proceed with the following step we pasted the bootstrap results produced by PLSGRAPH into Excel ® (SPSS® is also a good option).

3. Examine the distribution of the bootstrap estimates and determine the $(\alpha/2)*100\%$ and $(1-\alpha/2)*100\%$ percentiles of the distribution. These percentile represent , respectively, the lower and upper bound of the confidence interval.

Constructing a bias corrected bootstrap confidence interval

1. Define Z_{lower} and Z_{upper} as the corresponding z-scores in a standard normal distribution.

2. Define Z'_{lower} and Z'_{upper} as the z-scores that define the percentile for the bias-corrected bootstrap confidence interval. Equations B1-2 summarizes how to determine Z'_{lower} and Z'_{upper}.

$$Z'_{lower} = Z_0 + \frac{Z_0 + Z_{lower}}{1 - \hat{a}(Z_0 + Z_{lower})} \quad \text{(B1)}$$

$$Z'_{upper} = Z_0 + \frac{Z_0 + Z_{upper}}{1 - \hat{a}(Z_0 + Z_{upper})} \qquad \text{(B2)}$$

where Z_0 is the z-score corresponding to the percentage of the q bootstrap estimates that are less than the original sample estimate. To determine Z_0 the following website offer very helpful calculator: http://davidmlane.com/hyperstat/z_table.html.

Furthermore, coefficient $\hat{a}$ is the acceleration constant as is defined as:

$$\hat{a} = \frac{\sum_{i=1}^{n}(\bar{\theta} - \theta_i)^3}{6\left[\sum_{i=1}^{n}(\bar{\theta} - \theta_i)^2\right]^{3/2}} \qquad \text{(B3)}$$

where θ_i is the i^{th} jackknife estimate of the parameter computed after deleting case i, and $\bar{\theta}$ is the average value of the n jackknife estimates.

3. After having computed Z'_{lower} and Z'_{upper}, determine the proportion of the normal distribution to the left of Z'_{lower} and Z'_{upper} respectively. Again, a handy calculator can be found on http://davidmlane.com/hyperstat/z_table.html.

Assume that the proportion of the normal distribution to the left of Z'_{lower} and Z'_{upper} is respectively π_{lower} and π_{upper}, then the limits of the confidence interval are determined as follows (with J denoting the number of bootstrap samples).

The lower bound is the $(\pi_a * J)^{th}$ estimate in the sorted distribution of bootstrap estimates and the upper bound is the $(\pi_b * J)^{th}$ estimate in the sorted distribution of bootstrap estimates.

We conducted the calculations needed to construct the bias corrected bootstrap interval in Excel®. For more details on the construction of bias corrected bootstrap confidence intervals see Preacher and Hayes (2006) and Efron and Tibshirani (1998).