THE INFLUENCE OF OBSERVED HETEROGENEITY ON PATH COEFFICIENT SIGNIFICANCE: TECHNOLOGY ACCEPTANCE WITHIN THE MARKETING DISCIPLINE

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The technology acceptance model (TAM) is arguably one of the most widely used models for studying user adoption in the information systems discipline and has started to be used increasingly within the marketing area. While two of its three main hypotheses have received consistent empirical support, the same is not true for the remaining relationship (i.e., the influence of perceived ease of use on the behavioral intention to adopt a system; PEOU–BI). Previously, this empirical contradiction has been explained by introducing the concept of task motivation borrowed from Davis, Bagozzi, and Warshaw (1992). Our paper provides a different explanation. We show that for the same task (and, hence, the same task motivation), the significance can also depend on observed population heterogeneity. We do this by applying partial least squares (PLS) structural equation modeling (SEM) to data stemming from a survey among approximately 2,000 individuals regarding their intention to adopt a customized newspaper. Our findings result in the following three contributions: first, our results provide an alternative explanation for the inconsistent empirical support of the PEOU–BI link within the TAM. Second, we provide a methodological contribution by proposing an approach to control for gamma change when analyzing moderating effects using PLS analysis. Third, our study highlights the importance of conducting a statistical power analysis in order to determine critical *t*-values in the context of a PLS path analysis.

Since Herman Wold's (1975) seminal research on path models with latent variables, which was later taken up by Jan-Bernd Lohmöller (1988), partial least squares (PLS) structural equation modeling (SEM) has gained increasing interest within the marketing discipline (e.g., Henseler, Ringle, and Sinkovics 2009). It is considered the method of choice when sample size is limited, statistical power is of particular relevance (Reinartz, Haenlein, and Henseler 2009), or constructs are measured with a very high number of indicators (Haenlein and Kaplan 2004). Yet compared to other disciplines, specifically the area of information systems (IS) research, PLS is still used relatively rarely within the marketing field. While, for example, 15 articles using PLS were published in leading marketing journals between 1995 and 2005 (Reinartz, Haenlein, and Henseler 2009), the corresponding number for the IS discipline is more than 50 percent higher (25), as can be seen in Table 1.

This paper focuses on another heritage of the IS discipline that has increasingly begun to diffuse into the marketing area over the past few years, that is, the technology acceptance model (TAM) (Davis 1989; Davis, Bagozzi, and Warshaw 1989). The TAM states that the behavioral intention (BI) to adopt an IS is influenced by two variables: perceived usefulness (PU) and perceived ease of use (PEOU). PU is hereby assumed to directly influence BI while PEOU is hypothesized to have both a direct and an indirect effect by influencing PU. The TAM is arguably one of the most widely used models for studying user adoption in the IS discipline, and Venkatesh et al. (2003) count it among the eight most prominent user acceptance models. Reflecting this importance, a search of the Social Science Citation Index turns up more than 700 citations of Davis (1989) and more than 600 of Davis, Bagozzi, and Warshaw (1989).

Within the marketing discipline, we are still far from these impressive citation figures. Nevertheless, during the past decade, the TAM has been applied increasingly to the different elements of the marketing mix, such as advertising (Rodgers and Chen 2002; Zhang and Mao 2008), online distribution (Childers et al. 2001; Kim and Forsythe 2008; Zhang, Prybutok, and Strutton 2007), and product adoption (Dellaert and Stremersch 2005; Kaplan, Schoder, and Haenlein 2007). It has also been used in the context of organizational technology adoption (Hernandez, Jimenez, and Martin 2010; Srinivasan, Lilien, and Rangaswamy 2002) and cross-cultural comparisons of organization behavior

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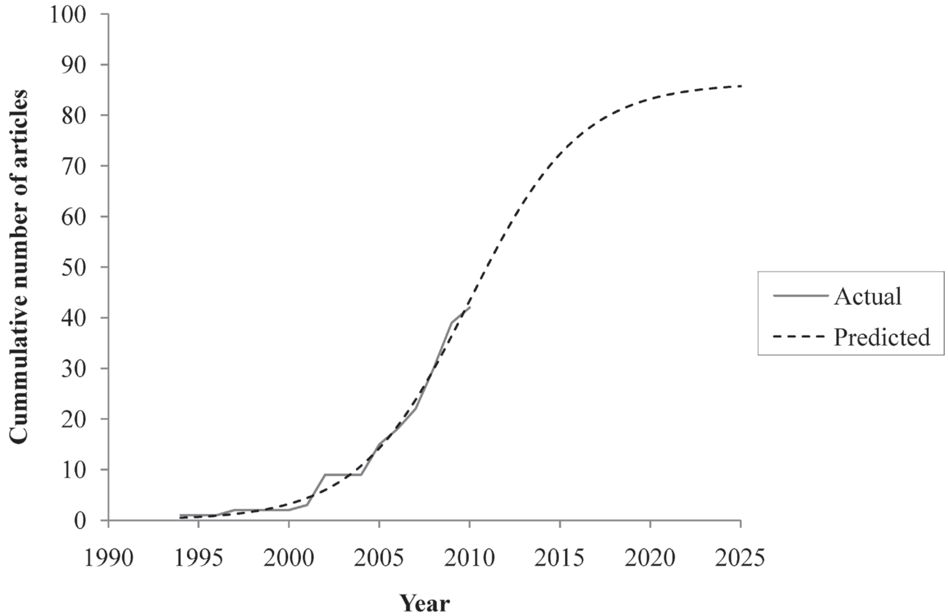
Table 1
Articles Published in Leading IS Journals Between 1995 and 2005 Using PLS

Article	No Assumptions Regarding Indicator Distribution/ Measurement Scale	Suitability for Small Sample Size	Focus on Prediction and Theory Development	Suitability for Unlimited Number of Formative Indicators	Lack of Improper Solutions/Factor Indeterminacy
Thong, Yap, and Raman (1996)		Yes	Yes		
Armstrong and Sambamurthy (1999)		Yes			
Compeau, Higgins, and Huff (1999)	Yes		Yes		
Karahanna, Straub, and Chervany (1999)	Yes	Yes			
Agarwal and Karahanna (2000)	Yes	Yes			
Agarwal, Sambamurthy, and Stair (2000)	Yes	Yes			
Keil et al. (2000)	Yes		Yes		
Ravichandran and Rai (2000)				Yes	
Chwelos, Benbasat, and Dexter (2001)			Yes	Yes	
Wixom and Watson (2001)		Yes	Yes	Yes	
Yoo and Alavi (2001)		Yes	Yes		
Chatterjee, Grewal, and Sambamurthy (2002)		Yes		Yes	
Enns, Huff, and Higgins (2003)		Yes			
Ho, Ang, and Straub (2003)	Yes	Yes			
Lewis, Agarwal, and Sambamurthy (2003)	Yes	Yes			
Miranda and Saunders (2003)		Yes			
Teo, Wei, and Benbasat (2003)	Yes		Yes	Yes	
Bassellier and Benbasat (2004)		Yes			
Bhattacherjee and Premkumar (2004)	Yes	Yes			
Subramani (2004)	Yes	Yes			
Ahuja and Thatcher (2005)	Yes	Yes			
Bock et al. (2005)		Yes		Yes	
Chidambaram and Tung (2005)	Yes		Yes		
Ko, Kirsch, and King (2005)		Yes			
Zhu and Kraemer (2005)	Yes	Yes	Yes	Yes	

Figure 1
Number of Articles in Leading Marketing Journals Covering the Technology Acceptance Model



Notes: The solid line ("predicted") represents the estimated diffusion curve based on a Bass model (M = 86.3485, p = 0.0013, q = 0.3251).

(Calantone, Griffith, and Yalcinkaya 2006), or been applied to the public and educational sphere (Kaufman-Scarborough and Childers 2009; Robinson 2006). Looking at the total number of articles that have used the TAM and have been published in leading marketing journals (Figure 1) shows that the TAM is in the middle of its growth phase with a predicted plateau in about 10 to 15 years. Our analysis covers all the articles applying the TAM in the 41 marketing journals ranked by Hult, Neese, and Bashaw (1997). Expected diffusion has been estimated using a Bass model (1969).

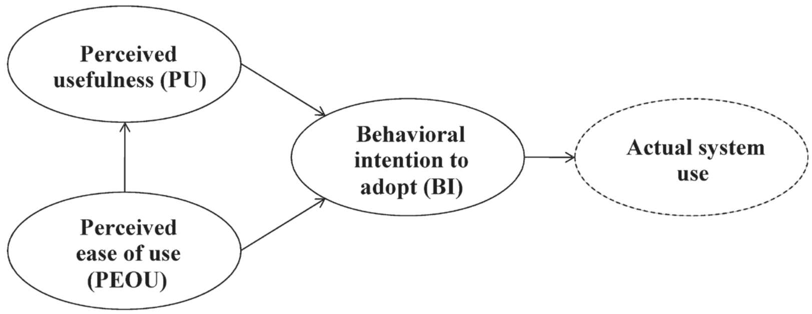
The objectives of our paper are threefold: first, we intend to introduce the TAM to a larger audience among marketing academics and practitioners alike. Because technology acceptance in general is frequently discussed in marketing (Brashear et al. 2009; Curran and Meuter 2007; Jelinek et al. 2006), a presentation of one of the most widely used TAMs in the IS discipline seems particularly fruitful. Second, we intend to provide insight into a specific relationship within the TAM (i.e., the influence of perceived ease of use on the behavioral intention to adopt a system) that has only received inconsistent empirical support so far. This is of high importance since the TAM is in a steady growing phase within the marketing discipline and therefore such explanations and insights about this unclear link might come just in time. Third, we introduce a new methodological approach that can combine traditional PLS analysis with ordinary least squares (OLS) regression (to control for gamma change) and statistical power analysis with PLS (to determine critical t-values), and that can be used to test for observed population heterogeneity within a PLS path model.

LITERATURE REVIEW

Technology Acceptance Model

The TAM was developed by Davis (1985) and can be considered an adaptation of the theory of reasoned action (TRA; Ajzen and Fishbein 1980) to the analysis of information systems/technology adoption. The TRA assumes that an individual's behavior is determined by the person's intention to perform that behavior, which is again influenced by the attitude toward the behavior and the individual's subjective norm. Both attitude and subjective norm are assumed to depend on a small number of salient beliefs that the individual holds about performing the behavior. Within the TAM, these salient beliefs are replaced by two variables: perceived usefulness (PU) and perceived ease of use (PEOU). PU is hereby defined as "the degree to which a person believes that using a particular system would enhance his or her job performance" (Davis 1985, p. 320), whereas PEOU refers to using the system being "free of effort" (Davis 1989). Both variables are assumed to directly influence the behavioral intention (BI) of an individual to

Figure 2
Technology Acceptance Model (TAM)



use a system. In addition, PEOU is also hypothesized to have an indirect effect on BI through PU.

As can be seen in Figure 2, unlike the TRA, the TAM does not include an attitude construct mediating the relationship between salient beliefs (i.e., PU and PEOU) and BI. Although the attitude toward using the system was included in the first version of the TAM (Davis 1985), Davis (1989) decided for its exclusion because attitude only partially mediated the effect of PU and PEOU on BI. As highlighted by Venkatesh et al. (2003), this exclusion of the attitude construct helped to provide a more parsimonious explanation of user acceptance, and this parsimony allowed the TAM to be immediately generalized to the investigation of a wide set of different computer systems and user populations. During the past two decades, it has evolved from a theory used to explain the adoption of specific technologies (e.g., Philipps, Calantone, and Lee 1994) to an approach used for analyzing the intention to adopt mass-customized products (Kaplan, Schoder, and Haenlein 2007) or the analysis of consumer behavior in the context of e-commerce (Hernandez, Jimenez, and Martin 2009).

Inconsistent Empirical Support for the PEOU–BI Relationship

In all these applications, two of the TAM's three main hypotheses received consistent empirical support—namely, the relationship between PEOU and PU and between PU and BI. This consistency is, however, not applicable to the direct influence of PEOU on BI. In one of the first analyses carried out by Davis, Bagozzi, and Warshaw (1989), PEOU showed a significant influence on BI in only one out of two settings. This mixed empirical support was also found in various other publications that appeared in the following years. In their summary of 45 TAM studies published between 1989 and 2000, Gefen and Straub (2000) highlight 9 studies that found support for a direct relationship between PEOU and BI and 25 that did not. From the remaining 11 studies, this specific path was not examined in 4 studies, not reported in 2 studies, not relevant in 2 studies, not measured in 2 studies, and deleted to improve model fit in 1 study. It is, therefore, still not completely clear whether the impact of PEOU on BI is fully mediated by PU.

To explain this apparent contradiction in results, Gefen and Straub (2000) relied on the concept of task motivation. As discussed, for example, by Davis, Bagozzi, and Warshaw (1992), there are two main types of motivation to perform an activity: extrinsic motivation and intrinsic motivation. Extrinsic motivation hereby refers to "the performance of an activity because it is perceived to be instrumental in achieving valued outcomes that are distinct from the activity itself" (Davis, Bagozzi, and Warshaw 1992, p. 1112). For example, a business graphics program is used to prepare a presentation to be given during the next board meeting—not because of the pleasure of preparing presentations. On the other hand, intrinsic motivations refer to "the performance of an activity for no apparent reinforcement other than the process of performing the activity per se" (Davis, Bagozzi, and Warshaw 1992, p. 1112). For example, computer games are usually only played for the fun of playing and not to achieve some tangible outcome as the result of this play.

With respect to user adoption, Davis, Bagozzi, and Warshaw (1992) stated that PU can be considered as an example of extrinsic motivations while enjoyment, which is closely related to and influenced by PEOU, can be seen as an example of intrinsic motivations. Gefen and Straub (2000) investigated this question in more detail and stated the hypothesis that PEOU should only directly influence BI when task motivation is primarily intrinsic, that is, when the main purpose of using the system under investigation is the use of this system per se. They subsequently found empirical support for this statement within an experiment where task motivation was controlled for in the analysis of user adoption of an online book retailer's Web page.

Observed Versus Unobserved Population Heterogeneity

Statistically speaking, controlling for task motivation when analyzing user acceptance of information technology (IT) within TAM, as done by Gefen and Straub (2000), is nothing other than controlling for population heterogeneity. Generally, the term *population heterogeneity* refers to situations where subpopulations exist within one larger population (Lubke and Muthén 2005). Those subpopulations consist of individuals that show similar behavior to other individuals within the same subpopulation, but different behavior compared to individuals in other subpopulations. When population heterogeneity exists but is not controlled for, estimation results can be severely biased (see Jedidi, Jagpal, and DeSarbro 1997 for a discussion in the context of covariance-based SEM).

If the overall population can be split into subpopulations by making use of observed variables (such as gender, age, or income), we speak of observed heterogeneity, and the subpopulations are then also often referred to as *groups*. Several approaches have been proposed to test for observed heterogeneity, the most common of which is probably multigroup comparison (see Henseler and Fassott 2010 or Qureshi and Compeau 2009 for a more detailed discussion). If such a split can only be done by relying on latent variables, the term *unobserved heterogeneity* is used. If those latent variables are completely unobserved, the subpopulations are sometimes called *latent classes* and the method of choice for dealing with heterogeneity is finite mixture models (Jedidi, Jagpal, and DeSarbro 1997; Ringle, Sarstedt, and Mooi 2010). If they are partially observed using a set of indicators, population heterogeneity can be controlled for using, for example, a product indicator approach (Chin, Marcolin, and Newsted 2003).

Each of those cases, not accounting for population heterogeneity when performing any statistical analysis, can introduce a bias into the parameter estimation process. As discussed, for example, by Shugan (2006), neglected population heterogeneity can lead to a systematic underestimation of path and regression coefficients. Applying this reasoning to the PEOU–BI relationship within the TAM implies that neglected population heterogeneity could lead to the fact that the impact of PEOU on BI is consistently underestimated. Because all statistical tests applied to judge the significance of a (structural) relationship always rely on some standardized form of such path or regression coefficients (e.g., the *t*-value used in PLS analysis is nothing other than the estimated path coefficient divided by its standard deviation), this underestimation can result in a relationship that appears to be insignificant when it is actually not.

These statistical problems resulting from not accounting for population heterogeneity are the main reason for the increasing interest in moderating relationships within the marketing discipline. A moderator is a qualitative or quantitative variable that affects the direction or strength of the relation between an independent and a dependent variable (Baron and Kenny 1986). Accounting for potential moderating effects within a statistical analysis is nothing other than accounting for population heterogeneity. Hence, it is not surprising that Baron and Kenny argue that

> moderator variables are typically introduced when there is an unexpectedly weak or inconsistent relation between a predictor and a criterion variable (e.g., a relation holds in one setting but not in another or for one subpopulation but not for another). (1986, p. 1178)

Our paper deals with the hypothesis that, besides unobserved population heterogeneity as discussed by Gefen and Straub (2000), observed population heterogeneity can also be seen as a reason for the inconsistent empirical support of the PEOU–BI relationship within the TAM. As mentioned above, the fact PEOU has a significant effect on BI in some settings but not in others lends itself perfectly to an investigation of potential moderating effects influencing this relationship. In our subsequent analysis, we show that for the same task, and hence the same type of task motivation (i.e., the same type of unobserved heterogeneity), the significance of the PEOU–BI relationship varies between different groups defined by a set of observed variables. We do this by analyzing 11 different moderating effects within the investigation of user adoption of a customized newspaper by using the TAM.

RESEARCH METHODOLOGY

Statistical Power Analysis

A problem frequently highlighted in the context of moderator analysis is that of statistical power and specifically the difficulty of detecting interaction effects due to low statistical power (see also McClelland and Judd 1993 for an extensive discussion). In any analysis based on inferential statistics, that is, an analysis dealing with the decision whether to accept or reject a certain null hypothesis H_0, there are two different types of errors that need to be considered—Type I and Type II. A Type I error (often represented by the significance criterion, α), describes the probability of incorrectly rejecting H_0, that is, finding a relationship when none exists. A Type II error (β), on the other hand, is the probability of incorrectly sustaining H_0, that is, failing to detect a relationship when one does exist. Statistical power, which is the probability of correctly rejecting a false H_0, can be calculated as $1 - \beta$.

Together with the effect size, which is an estimate of the magnitude of the investigated relationship in the population (see, e.g., Cohen 1992 for a detailed discussion) and sample size, Type I and Type II errors form a closed system in which the fourth parameter can always be calculated when the other three are known. Due to a long tradition that dates back to Ronald Fisher in 1925 (for a detailed review, see Cowles and Davis 1982), researchers usually assume an alpha level of 5 percent or less and pay only limited attention to a detailed investigation of Type II errors. Within the marketing discipline, this has resulted in the fact that statistical power in empirical studies often falls below an acceptable minimum threshold. Sawyer and Ball (1981) found an average power (assuming medium effect size) as low as 0.60, and similar findings have been reported in other disciplines (Baroudi and Orlikowski 1989). This implies that some studies had, on average, a 40 percent chance of not detecting the phenomenon under investigation, even though it may exist, which is only slightly better than a naive coin-flipping exercise.

To address the problem of statistical power within our analysis, we applied two different strategies: first, we used PLS analysis instead of the more traditional covariance-based approach to SEM, as PLS tends to achieve higher levels of statistical power than covariance-based SEM (Reinartz, Haenlein, and Henseler 2009) under equal conditions. Second, we followed an approach previously recommended in the literature to increase the statistical power of a study and adjusted the alpha level used in our analysis (e.g., Cascio and Zedeck 1983) based on the relative severity of Type I and Type II errors. Specifically, this implies that instead of choosing an absolute alpha level, we determined an α-β ratio (e.g., a ratio of 1, indicating that Type I and Type II errors are equally severe) and determined the resulting alpha level analytically using statistical power analysis, given a certain effect and sample size.

Note that in contrast to other articles (e.g., Areskoug 1982; Cassel, Hackl, and Westlund 1999; Reinartz, Haenlein, and Henseler 2009), our power analysis does not try to assess the overall ability of PLS to detect underlying relationships. Instead, we aim to analytically determine an alpha level (Type I error rate), taking into account effect size, sample size, and relative importance of Type I versus Type II errors. While the first question is of importance when choosing between PLS analysis and alternative statistical techniques (e.g., covariance-based SEM), the second point is of relevance for the practicing researcher at the point of significance testing, given that the choice for PLS analysis has already been taken.

Given that the sample sizes differ for each group and each moderator, this approach results in different critical *t*-values for each significance test conducted in the context of our empirical analysis. The last two columns in Table 2 show the critical *t*-values used when assuming an effect size of $f = 0.20$ or $f = 0.25$. As can be seen, the *t*-values differ significantly from one subpopulation to another and span a range from a low of 1.2151 to a high of 4.4683. Instead of using a more traditional approach, which would consist of assuming a *t*-value of 1.96 for all comparisons (corresponding to a constant Type I error rate of 5 percent), our approach enables us to maintain a constant α-β ratio across all comparisons and therefore takes account of Type I and Type II errors simultaneously.

Alpha, Beta, and Gamma Change

As discussed by Rigdon, Ringle, and Sarstedt (2010), one approach to account for observed heterogeneity in a latent variable model is to conduct a multiple group analysis. In any research relying on self-reported measures, to analyze change in a latent variable between two different conditions, it is important to differentiate between alpha, beta, and gamma change (e.g., Terborg, Howard, and Maxwell 1980). Alpha change hereby refers to a true change in the latent variable between the two conditions, beta change describes a change because respondents use different ideal (reference) points when giving their answers in the two conditions, and gamma change occurs when the meaning (domain) of the construct is different in each condition. In an analysis of moderating effects, the researcher is primarily interested in alpha change. For example, the primary interest may be whether PEOU influences BI differently for men than for women.

Beta and gamma change are undesired effects from the researcher's perspective and should be controlled for. Regarding beta change, respondents are usually split into different groups only *after* they have been surveyed in any analysis investigating moderating effects. Hence, although beta change can be an issue in some research settings, it is unlikely to have occurred in our case. This is, however, different for gamma change. As discussed extensively elsewhere (e.g., Lohmöller 1988; Rigdon 2005; Tenenhaus

Table 2
Estimation Results from Moderator-Specific PLS Analyses

	t-Value			Critical *t*-Value	
	PEOU–PU	**PEOU–BI**	**PU–BI**	***f*** **= 0.20**	***f*** **= 0.25**
Age (in years)					
16–24	6.9253	**3.5224**	8.7967	1.7298	2.0932
25–44	5.9857	3.0604*	9.8052	2.8240	3.4768
45–64	7.0526	3.2032*	10.5945	2.7791	3.4246
65 and older	9.8742	2.4123*	11.5523	2.2269	2.7253
Base Category Consumption Frequency					
Daily	7.3859	3.2223**	9.2613	3.3465	4.1407
Almost daily	5.6812	**3.7847**	10.3960	2.0955	2.5585
Sometimes	6.7408	**3.7396**	9.0587	2.0214	2.4644
Rarely/never	4.7363	**2.9154**	9.2674	1.9286	2.3463
Education					
Low	8.5705	3.0320*	9.2953	2.7150	3.3435
Medium	5.6747	3.0071**	10.2247	3.2134	3.9729
High	7.1125	2.0711**	10.9351	2.3160	2.8384
Gender					
Male	6.6006	3.9098*	10.1929	3.2568	4.0277
Female	8.1319	2.8208**	11.6238	3.4425	4.2617
Household Income (in euros per month)					
≤ 999	10.5872	**4.7538**	8.2748	1.8053	2.1894
1,000–1,999	6.1252	3.5211*	9.3834	3.0050	3.7100
2,000–2,999	6.2686	1.7992**	13.6374	2.3742	2.9121
3,000 and over	6.0157	**3.2081**	13.1934	1.9286	2.3463
Household Size					
1 person	5.8578	**3.4328**	10.7071	2.4721	3.0362
2 people	6.3791	2.7934**	10.7551	2.9220	3.6051
3 people	5.6984	**3.0954**	11.9875	2.1386	2.6133
4 people	6.7124	**2.3161**	9.4943	1.8557	2.2536
5 or more people	5.3168	**4.4601**	12.0808	1.2151	1.4332
Labor Market Position					
Employed	6.1586	2.9896**	9.8814	3.3480	4.1426
Unemployed	6.4630	**4.9325**	10.0332	1.6158	1.9476
Homemaker	7.3205	**4.8693**	7.1954	1.2709	1.5055
Retired	7.9327	2.4954**	9.6006	2.5405	3.1228
Number of Residents					
≤ 5,000	5.5824	**2.3531**	10.5844	2.3006	2.8189
5,001–20,000	6.9994	4.0584*	10.8283	2.4965	3.0670
20,001–100,000	8.5232	**3.1417**	10.5568	2.4578	3.0180
100,001 and over	6.7718	**3.3429**	10.7999	2.4680	3.0310
Private Internet Access					
Yes	5.8008	2.2148**	11.7904	3.4337	4.2507
No	7.1751	3.5623*	7.8904	3.2429	4.0101
Social Level					
Low	9.7000	**2.8113**	9.3662	1.8446	2.2395
Medium	6.2679	4.2392*	11.3124	3.6858	4.4683
Medium/high	7.6297	1.4383**	12.5567	2.3635	2.8986
Urbanization Type					
City	6.4780	**3.0728**	11.3457	2.2585	2.7654
Small town	6.5570	3.5582*	10.3625	2.9630	3.6569
Village	6.2407	2.8433**	10.0968	3.0101	3.7163

Notes: Boldface figures are significant at $f = 0.20$ and $f = 0.25$; * not significant at $f = 0.25$; ** not significant at $f = 0.20$.

et al. 2005), PLS analysis differs from covariance-based SEM in that it does not work with latent variables, but with block variables, which are the weighted composites of the associated observed variables (Rigdon 2005). The PLS parameter estimation process continuously oscillates between estimating case values for the block variables and model parameters that depend on these case values. In case of a multigroup PLS analysis, it is therefore possible that weights differ between different groups. This results in the problem that block variables (which are simply a weighted average of their indicators) may be defined differently for different groups. This difference is equivalent to a change in the construct domain, hence, a gamma change, that should be controlled for (Carte and Russell 2003).

To control for such a gamma change in our analysis, we followed a two-step approach: first, we tested the null hypothesis of equal interitem variance–covariance matrices between different treatment groups for every moderator using Box's M-test (1950), which can be considered as a multivariate extension of Bartlett's criterion. In case the Box M-test did not indicate a significant difference in interitem variance–covariance matrices, we subsequently performed separate PLS analyses in each treatment group. However, in case the null hypotheses of equal variance–covariance matrices had to be rejected, separate PLS analyses could have resulted in different weights and case values, which would have led to biased path coefficient estimates due to gamma change.

To control for this effect and to assess the likely order of magnitude of this bias, we performed a traditional OLS regression analysis. We used the indicator weights from the baseline model, standardized all indicators to a mean of zero and a standard deviation of one, and calculated a weighted average of all the standardized indicators belonging to the same construct (PEOU, PU, and BI). We then divided these weighted averages by their standard deviation to obtain standardized latent variable scores, based on which we estimated regression coefficients mirroring the PLS path coefficients for each subpopulation. Regression coefficients obtained in this way are comparable to PLS path coefficients since PLS path coefficients are essentially regression coefficients between standardized latent variable scores. This procedure hence enabled us to take account of the latent nature of the variables included in our model while at the same time avoiding the problem of different weights resulting from subgroup-specific PLS analyses. These regression coefficients were subsequently compared with their associated path coefficients resulting from a PLS analysis within each treatment group using the mean absolute relative bias (MARB) to assess the likely order of magnitude of a gamma change. Only treatment groups where gamma change was not likely to be a severe issue (i.e., MARB < 5 percent) were retained in our subsequent analysis.

To the best of our knowledge, this is the first time that PLS-SEM has been used to analyze moderating effects while controlling for gamma change in a systematic way that can easily be replicated in other situations. Prior research has discussed the problem of gamma change (e.g., Qureshi and Compeau 2009), but solutions for how the issue can be addressed have frequently not been provided. Most related to our approach is the work of Hsieh, Rai, and Keil (2008). Yet the solution proposed by those authors is limited to a comparison of two groups and likely to suffer from a problem of accumulated alpha errors when being extended to settings where three, four, or five groups should be compared. The advantage of our method, which combines a Box M-test with traditional OLS regression and statistical power analysis, is that it follows the theoretical reasoning provided by Carte and Russell (2003) and that it can easily be applied in any other situation.

RESULTS

The data used for our empirical analysis stems from a survey about the adoption of a mass-customized newspaper (Kaplan 2006; Kaplan, Schoder, and Haenlein 2007; Schoder et al. 2005; also see Kaplan and Haenlein 2006 for a more detailed discussion and definition of the "mass-customization" concept). In total, approximately 2,000 respondents were surveyed in face-to-face interviews by a professional market research agency. All interviewees were presented with the same information regarding a telephone-based configuration system that would give customers the possibility of selecting desired topics from a list provided by the newspaper publisher. A certain number of articles for each topic (also to be specified by the subscriber) would then be included in a customized newspaper, delivered personally to the customer each morning. In case of a change in preferences, the customer would be able to modify the topic list and number of articles using the same system. In addition to items covering PU, PEOU, and BI to adopt such a customized newspaper (we used four items for the operationalization of PEOU and PU and two items for BI, all of which were adapted from Davis 1989 and can be found in the Appendix), respondents were also asked to provide a set of 11 sociodemographic characteristics that we used as a basis for our analysis.

Table 3
Box's M-Test of Equal Interitem Variance–Covariance Matrices

	Number of Groups	Box's M	*F*-Value	*p*-Value
Age (in years)	4	222.348	1.330	0.003
Base Category Consumption Frequency	4	290.359	1.736	< 0.0005
Education	3	176.607	1.591	< 0.0005
Gender	2	71.833	1.298	0.068
Household Income (in euros per month)	4	231.238	1.382	0.001
Household Size	5	355.087	1.581	< 0.0005
Labor Market Position	6	391.966	1.372	< 0.0005
Number of Residents	4	194.020	1.164	0.074
Private Internet Access	2	98.701	1.783	< 0.0005
Social Level	4	237.923	1.369	0.001
Urbanization Type	3	113.977	1.027	0.404

As discussed above, we first conducted a Box M-test for every moderator (i.e., sociodemographic characteristic) to test the null hypothesis of equal interitem variance–covariance matrices between different treatment groups. The results of this test, which we conducted using SPSS, can be found in Table 3. Only for 3 of the 11 moderators (i.e., urbanization type, number of residents, gender) did the Box M-test not indicate a significant difference; for the remaining 8, the null hypothesis was rejected. This implies that for 8 out of 11 moderators, path coefficient estimates from treatment group–specific PLS analyses could suffer from a bias due to gamma change. Gamma change is therefore likely to affect the majority of all moderating effects included in our model.

To assess the likely order of magnitude of this bias, we compared the regression coefficients determined as detailed above with the treatment group–specific PLS path coefficient estimates using the MARB, defined as follows:

$$\text{ARB}_i = \left| \frac{p_{\text{Regression}} - p_{\text{PLS}}}{p_{\text{Regression}}} \right| \text{ and } \text{MARB} = \frac{1}{3}\sum_{i=1}^{3} \text{ARB}_i .$$

Note that MARB is based on three ARB values representing the three structural relationships of the TAM. Table 4 shows the result of this comparison. As can be seen, in three cases, MARB exceeds the 5 percent threshold, namely, one group for the moderator "social level" and two for "labor market position." In these cases, PLS path coefficient estimates are likely to be significantly biased due to gamma change. These two moderators (representing 20 percent from the initial pool of eight moderating variables) were therefore discarded from the subsequent analysis.

Tables 4 and 5 show the results of the group-specific PLS analyses conducted for each moderator. We refer to Kaplan (2006) for the theoretical rationale of focusing on these specific moderating effects and a discussion of the substantive findings. As can be seen in Table 5, the moderators we investigated show an average absolute ΔR^2 value of 2.13 percent for BI and 2.68 percent for PU. Table 2 provides details about PLS path coefficient *t*-values determined using bootstrapping. As discussed previously, our analysis does not rely on the traditional alpha level of 5 percent to test the significance of path coefficients, but on a critical *t*-value determined using statistical power analysis. Using the G*Power software[1] (Erdfelder, Faul, and Buchner 1996; Faul et al. 2007), we determined critical *t*-values for two effect sizes ($f = 0.20$ and $f = 0.25$). These effect sizes are located between a small ($f = 0.10$) and medium ($f = 0.25$) effect, following the findings of O'Grady (1982). Critical *t*-values have been determined using compromise statistical power analysis (accuracy mode) for a two-tailed *t*-test, an α-β ratio of 1, and $n - 2$ degrees of freedom, with n being the sample size used for the treatment group–specific PLS analyses.

As can be seen in Table 2, the total number of PLS analyses conducted is 38. In each of them, the path coefficients from PEOU to PU and from PU to BI are significant for both effect sizes. This is, however, not the case for the PEOU–BI link, which is significant for both effect sizes ($f = 0.20$ and $f = 0.25$) in 17 cases (45 percent), significant for the smaller but insignificant for the larger effect size in 10 cases (26 percent), and insignificant for both effect sizes in 11 cases (29 percent). Hence, our findings provide support for our hypothesis that the significance of the PEOU–BI relationship depends not only on unobserved heterogeneity, as discussed by Gefen and Straub (2000), but also on observed heterogeneity or moderating effects.

Table 4
Comparison of PLS Path Coefficients and Corresponding Regression Coefficients

	Path Coefficient			Regression Coefficient			MARB (Percent)	Sample Size
	PEOU–PU	PEOU–BI	PU–BI	PEOU–PU	PEOU–BI	PU–BI		
Age								
16–24	0.403	0.222	0.565	0.400	0.209	0.570	2.62	241
25–44	0.377	0.198	0.598	0.382	0.199	0.596	0.72	731
45–64	0.397	0.201	0.571	0.393	0.201	0.570	0.40	708
65 and older	0.491	0.163	0.601	0.485	0.166	0.595	1.35	434
Base Category Consumption Frequency								
Daily	0.467	0.209	0.559	0.465	0.198	0.579	3.15	1,054
Almost daily	0.421	0.249	0.577	0.421	0.254	0.576	0.71	378
Sometimes	0.400	0.246	0.529	0.402	0.235	0.560	3.57	348
Rarely/never	0.366	0.185	0.532	0.361	0.190	0.559	2.95	312
Education								
Low	0.491	0.211	0.569	0.492	0.210	0.570	0.28	673
Medium	0.371	0.192	0.579	0.371	0.192	0.579	0.00	967
High	0.455	0.125	0.628	0.457	0.127	0.627	0.72	474
Household Income (in euros per month)								
≤ 999	0.541	0.301	0.496	0.538	0.303	0.494	0.54	267
1,000–1,999	0.420	0.215	0.569	0.418	0.214	0.570	0.37	838
2,000–2,999	0.412	0.116	0.641	0.411	0.117	0.639	0.47	501
3,000 and over	0.389	0.184	0.655	0.389	0.187	0.653	0.64	312
Household Size								
1 person	0.435	0.205	0.565	0.435	0.208	0.562	0.66	548
2 people	0.427	0.184	0.598	0.424	0.185	0.597	0.47	789
3 people	0.373	0.200	0.580	0.373	0.198	0.579	0.39	396
4 people	0.459	0.163	0.584	0.463	0.167	0.580	1.32	285
5 or more people	0.407	0.226	0.598	0.412	0.220	0.597	1.37	96
Labor Market Position								
Employed	0.378	0.203	0.585	0.378	0.203	0.584	0.06	1,055
Unemployed	0.404	0.289	0.558	0.397	0.291	0.559	0.88	204
Homemaker	0.453	0.291	0.492	0.450	0.298	0.487	1.35	109
Retired	0.482	0.162	0.584	0.480	0.160	0.584	0.56	582
Students	0.465	0.071	0.713	0.465	0.061	0.713	**5.46**	96
Trainees	0.526	0.145	0.613	0.502	0.102	0.623	**16.18**	68
Private Internet Access								
Yes	0.401	0.155	0.629	0.403	0.155	0.629	0.17	1,113
No	0.449	0.229	0.528	0.447	0.228	0.529	0.36	986
Social Level								
Low	0.466	0.184	0.552	0.462	0.189	0.546	1.54	281
Medium	0.421	0.235	0.571	0.422	0.236	0.570	0.28	1,292
Medium/high	0.452	0.093	0.632	0.447	0.094	0.631	0.78	496
High	0.421	0.064	0.684	0.397	0.044	0.694	**17.65**	45

Note: Boldface figures are MARB values exceeding 5 percent.

DISCUSSION

To summarize, our analysis results in the following three contributions: first, we provide a methodological contribution by proposing an approach to control for gamma change when analyzing moderating effects using PLS analysis. The nature of PLS may lead to biased parameter estimates due to gamma changes because subgroup-specific PLS analyses may result in different parameter estimates due to observed heterogeneity or to a different weighting scheme and, hence, a different definition of the block variable construct domain. We propose an approach based on traditional OLS regression that can help to assess the order of magnitude of this bias and, hence, support the researcher in his or her decision on whether or not PLS parameter estimates can be trusted. Especially in the light of an increasing use of PLS analysis in the marketing discipline (Reinartz, Haenlein, and Henseler

Table 5
Impact of Moderating Variables on Explained Variance

	Sample Size	BI		PU	
		R^2	ΔR^2	R^2	ΔR^2
Overall (baseline) Model	**2,114**	47.8	NA	18.6	NA
Age (in years)	**2,114**				
16–24	241	47.0	–0.8	16.2	–2.4
25–44	731	48.6	+0.8	14.2	–4.4
45–64	708	45.8	–2.0	15.8	–2.8
65 and older	434	48.4	+0.6	24.1	+5.5
Base Category Consumption Frequency	**2,092**				
Daily	1,054	46.5	–1.3	21.8	+3.2
Almost daily	378	51.6	+3.8	17.8	–0.8
Sometimes	348	44.5	–3.3	16.0	–2.6
Rarely/never	312	39.0	–8.8	13.4	–5.2
Education	**2,114**				
Low	673	48.6	+0.8	24.1	+5.5
Medium	967	45.5	–2.3	13.8	–4.8
High	474	48.2	+0.4	20.7	+2.1
Gender	**2,114**				
Male	995	49.0	+1.2	17.4	–1.2
Female	1,119	46.2	–1.6	19.1	+0.5
Household Income (in euros per month)	**1,918**				
≤ 999	267	49.8	+2.0	29.2	+10.6
1,000–1,999	838	47.3	–0.5	17.6	–1.0
2,000–2,999	501	48.5	+0.7	17.0	–1.6
> 3,000	312	55.7	+7.9	15.2	–3.4
Household Size	**2,114**				
1 person	548	46.3	–1.5	18.9	+0.3
2 people	789	48.5	+0.7	18.3	–0.3
3 people	396	46.3	–1.5	13.9	–4.7
4 people	285	45.5	–2.3	21.1	+2.5
5 or more people	96	51.9	+4.1	16.6	–2.0
Labor Market Position	**2,114**				
Employed	1,055	47.3	–0.5	14.3	–4.3
Unemployed	204	52.6	+4.8	16.3	–2.3
Homemaker	109	45.7	–2.1	20.5	+1.9
Retired	582	45.8	–2.0	23.2	+4.6
Number of Residents	**2,114**				
≤ 5,000	467	46.3	–1.5	15.6	–3.0
5,001–20,000	560	48.3	+0.5	18.0	–0.6
20,001–100,000	541	46.8	–1.0	21.8	+3.2
100,001 and over	546	50.8	+3.0	19.0	+0.4
Private Internet Access	**2,099**				
Yes	1,113	49.8	+2.0	16.1	–2.5
No	986	44.0	–3.8	20.1	+1.5
Social Level	**2,114**				
Low	281	43.4	–4.4	21.7	+3.1
Medium	1,292	49.4	+1.6	17.7	–0.9
Medium/high	496	46.1	–1.7	20.4	+1.8
Urbanization Type	**2,102**				
City	448	49.9	+2.1	19.6	+1.0
Small town	813	47.3	–0.5	20.2	+1.6
Village	841	47.1	–0.7	16.8	–1.8

Notes: ΔR^2 refers to a comparison with the overall (baseline) model. NA = not applicable. Figures in boldface represent total value.

2009), this approach should be very useful for the practicing researcher.

Second, our study highlights the importance of conducting a statistical power analysis in order to determine critical *t*-values in the context of a PLS analysis. The marketing discipline has long been criticized for a lack of statistical power (Sawyer and Ball 1981). In many cases, PLS is applied in situations where the sample size is too limited for covariance-based SEM. However, given that studies in behavioral sciences can usually be expected to produce small or medium effect sizes (O'Grady 1982), an alpha level of 5 percent combined with a relatively low sample size will automatically result in a deterioration of statistical power. Nevertheless, until now, statistical power analysis has rarely been combined with PLS, potentially because of a lack of procedural clarity. Our study shows how critical *t*-values can easily be determined using the G*Power software tool. We encourage every researcher applying PLS to conduct a statistical power analysis instead of simply using a traditional alpha level of 5 percent. Such a procedure, which represents only a light increase in computational complexity, can be expected to significantly improve the quality of results obtained using PLS.

Finally, our results provide an alternative explanation for the inconsistent empirical support of the PEOU–BI link within the TAM. Besides the importance of task motivation as discussed by Gefen and Straub (2000), we show that observed sample heterogeneity may also be one reason influencing the significance of the PEOU–BI relationship. We highlight that for the same type of task (and, hence, the same task motivation), PEOU significantly influences BI in some situations but not in others, depending on observed heterogeneity. This underlines the general importance of accounting for (observed and unobserved) heterogeneity when analyzing user adoption using the TAM.

In the context of our study, it is necessary to differentiate between situations where the focus lies on estimating parameters in a well-established relationship versus testing a theory in the light of new data. As discussed extensively by Shugan (2006), an explicit modeling of observed or unobserved heterogeneity (as well as several other statistical approaches) may not be consistent with classical theory testing. Potentially, the fact that many studies have not found support for a direct influence of PEOU on BI simply implies that the relationships postulated within the TAM may be wrong and should be corrected. By trying to find other explanations for this apparent inconsistency (e.g., measurement error, omitted variables, heterogeneity), researchers may run the risk of saving a theory that should be amended in the light of contradictory empirical evidence.

In terms of areas of future research, we see two areas that are particularly promising: first, it would be particularly interesting to combine our approach with the permutation procedure for multigroup comparisons proposed by Chin (2003; see also Dibbern and Chin 2005). As discussed by Chin (2003), assessing the significance of treatment group–specific path coefficient differences is usually done using a *t*-test. Yet this procedure can lead to problems when certain statistical assumptions, such as normal distribution or similarities in sample size, are not met. Given that parametric tests are generally only valid if they yield results similar to those obtained by randomization tests, a permutation procedure may be preferable for multigroup comparisons. In our study, we were mainly interested in differences in path coefficient significance among different treatment groups, which made a comparison of actual path coefficient estimates less relevant. Yet in most empirical applications, the researcher will actually be interested in an investigation and subsequent interpretation of such differences. In these cases, combining our approach to test for gamma change with the randomization-based multigroup comparison test proposed by Chin (2003) seems to be a promising option.

Second, we encourage studies that combine our findings with those obtained by Gefen and Straub (2000) and simultaneously account for observed and unobserved heterogeneity when investigating user adoption within the TAM. Such an analysis could be conducted by combining our approach with the PLS product indicator approach proposed by Chin, Marcolin, and Newsted (2003). Those authors present an approach for the analysis of latent moderating variables (such as task motivation) that is based on PLS analysis. In their analysis, Chin, Marcolin, and Newsted show that their approach outperforms alternative methods (such as regression analyses using summated scales) in terms of parameter estimation efficiency. Alternatively, one could also substitute the classical SEM approach by a factor finite mixture model that explicitly takes account of covariates. Factor finite mixture models (Lubke and Muthén 2005) are a combination of latent class and common factor models that can easily be analyzed using the Mplus software tool (Muthén and Muthén 2007). By giving the researcher the possibility of using covariates, factor finite mixture models help to account for heterogeneity that is partly observed and partly unobserved. This is exactly the situation given for the TAM, where at the same time differences in task motivation (Gefen and Straub 2000) and observable moderating variables need to be controlled to obtain unbiased estimates of key model parameters.

NOTE

1. G*Power can be downloaded free of charge from www.psycho.uni-duesseldorf.de/abteilungen/aap/gpower3/.

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APPENDIX
Construct Operationalization

Perceived Ease of Use (PEOU) (measured on a 5-point Likert scale)

- I think the process of customizing is clear and understandable.
- After several uses, I will probably become more skillful in the process of customization.
- The process of customizing seems to me easy to learn.
- I think that I could operate such a customization process well.

Perceived Usefulness (PU) (measured on a 5-point Likert scale)

- I would find an individualized newspaper very useful to me.
- Using an individualized newspaper would enable me to attain important information faster.
- Using an individualized newspaper would increase my degree of being informed.
- I would enjoy reading a newspaper customized according to my interests.

Behavioral Intention to Adopt (BI) (measured on an 11-point Likert scale)

- How probable would it be that you test such an individualized newspaper?
- How probable would it be that you order such an individualized newspaper?