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A tutorial on the use of PLS path modeling in longitudinal studies

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Abstract

Purpose – The purpose of this paper is to provide a systematic overview with guidelines how to use partial least squares (PLS) path modeling in longitudinal studies. Practical examples from a study of the acceptance of battery electric vehicles (BEVs) in corporate fleets are used for demonstration purposes.
Design/methodology/approach – In this study, data at three points in time were collected: before the initial use of a BEV, after three and after six months of extensive usage of BEVs.
Findings – Three different models are identified depending on the research objective and on the data basis. Multigroup analyses are suggested to test the difference between the path coefficients of latent variables at different points in time. Limitations for the use of repeated cross-sectional data have to be observed.
Originality/value – Academics and practitioners will benefit from this paper by receiving an overview of the different PLS path models in longitudinal studies. A decision-tree enables them to make a choice regarding the most appropriate model and suggests a sequence of complementary analyses. So far, there is a lack of a tutorial type paper delivering such guidance.
Keywords PLS, Panel data, Acceptance, Battery electric vehicles, Longitudinal study, Multigroup analyses
Paper type General review

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1. Introduction

In recent years, partial least squares (PLS) path modeling has become increasingly attractive in different disciplines (Hair *et al.*, 2012a, b; Hair *et al.*, 2012a, b; Henseler *et al.*, 2009; Lee *et al.*, 2011; Ringle *et al.*, 2012; Sosik *et al.*, 2009). Despite the increasing number of publications (Hair *et al.*, 2014), relatively few researchers have used PLS in longitudinal studies so far. Some notable exceptions are, for example, Jacobs *et al.* (2011), Johnson *et al.* (2006) or Jones *et al.* (2002).

The small number of papers using PLS in longitudinal studies is surprising, since changes in technologies nowadays enable us to collect a vast amount of longitudinal data. For example, online survey tools enable researchers to collect online panel data at low cost (e.g., Callegaro *et al.*, 2014). As another example, consumers' online transaction data are continuously collected in e-commerce (Turban *et al.*, 2015). The amount of data currently challenges many researchers and companies simultaneously creating a need for methods and tools to analyze longitudinal data (Columbus, 2015).

This need to analyze longitudinal data also holds true for phenomena in industrial management that are more complex in nature and require specific longitudinal research designs (Hassett and Paavilainen-Mäntymäki, 2013; Van de Ven, 1992). For example, industrial managers are interested in understanding and predicting the adoption of new integrated service solutions over time (Davies *et al.*, 2006; Ulaga and Loveland,

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2014). Or, as another example, industrial managers strive after understanding and predicting the creation of value in business relationships at different stages of the relationship lifecycle (Eggert *et al.*, 2006).

The analysis of unobservable, complex variables such as "adoption" or "relationship value" over time as well as related causal relationships requires adequate methods. In this case, researches turn toward structural equation modeling (SEM) techniques instead of regression analyses to incorporate unobservable variables (subsequently termed constructs, see Rigdon, 2012) that are indirectly measured by indicators (Hair *et al.*, 2014; Mooi and Sarstedt, 2011). Researchers have the option to choose between covariance-based SEM, represented by LISREL, and variance-based SEM, with PLS path modeling as the most prominent method (Henseler *et al.*, 2009; Mooi and Sarstedt, 2011). The choice of the appropriate SEM procedure should be based on its methodological characteristics (Hair *et al.*, 2014; Henseler *et al.*, 2009).

In this paper, we posit that PLS path modeling is highly appropriate to analyze development and change in constructs in longitudinal studies, since it offers three favorable methodological characteristics. First, constructs often need to be predicted in evolutionary models (e.g., Shea and Howell, 2000). Especially PLS path modeling gives researchers and practitioners the possibility to predict constructs (Hair *et al.*, 2011; Henseler *et al.*, 2009). Second, model complexity quickly increases when development and change shall be analyzed in longitudinal studies. This is due to the larger number of constructs that are measured at different points in time and the respective effects between those constructs (see also Johnson *et al.*, 2006). PLS path modeling is highly suitable to deal with such complex models (e.g., Fornell, 1982; Fornell and Cha, 1994; Wold, 1985). Third, sample sizes can become quite small in longitudinal studies (see also Jones *et al.*, 2002), for example, due to panel attrition (e.g., Frees, 2004; Laurie, 2008). This argument becomes even more severe, if longitudinal studies are conducted in areas of research in which the sample sizes are notoriously small, such as industrial market research (e.g., Slater and Narver, 2000). PLS path modeling is particularly appropriate in case of small sample sizes (Henseler *et al.*, 2014; Henseler *et al.*, 2009).

For these reasons, PLS has already been used in some papers in longitudinal research designs (e.g., Hennig-Thurau *et al.*, 2006; Jacobs *et al.*, 2011; Johnson *et al.*, 2006; Jones *et al.*, 2002; Shea and Howell, 2000). However, the way how data are treated, how PLS models are built and how additional analyses enrich PLS path analyses varies significantly between those papers. A systematic overview is still missing.

Therefore, this paper seeks to overcome this shortcoming by providing a systematic overview of how PLS path modeling can be used in longitudinal studies. In particular, the paper makes the following contributions:

(1) The paper identifies three different PLS path model types depending on the research objective and on the longitudinal data basis.

(2) It provides guidelines in the form of a decision-tree regarding the choice of a specific model and an appropriate sequence of complementary analyses, which are demonstrated by practical examples from a longitudinal study on the acceptance of battery electric vehicles (BEVs).

(3) It suggests the use of multigroup analyses to test the difference between the path coefficients of constructs at different points in time.

The remainder of this paper is structured as follows. The next section gives an overview of the three different PLS model types and the related hypotheses. In Section 3, the methods

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regarding the study of the acceptance of BEVs in corporate fleets are introduced. In Sections 4, 5 and 6, practical examples are provided to demonstrate how PLS and additional analyses can be used in the different model types. The paper closes with a summary as well as limitations and considerations for future research.

2. An overview of PLS model types in longitudinal studies

This paper proposes that PLS path models in longitudinal studies can be distinguished according to two criteria: the research objective and the data basis that is available. In a first step, PLS users should ask themselves, whether their main research objective is to investigate the evolution of effects (path coefficients) between the constructs over time or rather to investigate the change in the constructs from one point in time to another point in time and their causal effects. In a second step, the question is whether the data basis consists of panel data, for which the same group of individuals is surveyed repeatedly at different points in time, or of repeated cross-sectional data, for which different groups of individuals are surveyed at different points in time (Frees, 2004).

Regarding the research objective and the data basis, three different model types can be distinguished. Figure 1 provides an overview regarding the choice of the model type (decision phase) and it suggests a sequence of stages in the analysis (analysis phase) as well as key references.

2.1 The evolution model for panel data – model type A.1

Models of type A.1 are probably the most intuitive way how longitudinal data can be used in PLS path models. The indicators at different points in time are used to create the exogenous and endogenous constructs at the different points in time in the PLS path model (e.g., Johnson *et al.*, 2006; Shea and Howell, 2000). The main research objective in this case is to study the evolution of direct and indirect effects between constructs over time (see Step 1 in the decision phase in Figure 1, "yes" option).

With the availability of panel data (see Step 2 in the decision phase in Figure 1, "yes" option), the evolution model (model type A.1) is a suitable modeling type. With panel data, changes at the individual level of the research unit (e.g., employees, companies) can be analyzed over time (Frees, 2004). The name "evolution model" is appropriate since papers with a similar research aim are entitled "The evolution of loyalty intentions" by Johnson *et al.* (2006) or "Efficacy-performance-spirals: an empirical test" by Shea and Howell (2000). In these papers, two or more points in time have been analyzed to demonstrate the evolution effects more clearly. For example, Johnson *et al.* (2006) use two points in time, while Shea and Howell (2000) use four points in time. Researchers and practitioner investigating the evolution of constructs and to model temporal patterns in the data are advised to use several points in time (Frees, 2004).

In model type A.1, carry-over-effects are special effects that emerge (Johnson *et al.*, 2006). Carry-over-effects are effects from one construct at one point in time to the same construct at a subsequent point in time (Mittal *et al.*, 1999). In this way, an evaluation of a construct at a subsequent point in time represents an updated version of its prior evaluation (Bolton and Drew, 1991; Oliver, 1980). For the interpretation of the carry-over-effects, we draw on auto-regressive effects in latent growth curve modeling, a covariance-based approach to model longitudinal data. These auto-regressive effects relate to the stability of the constructs from one point in time to the next point in time (Duncan *et al.*, 2013). A sizeable effect means that the individuals' estimation of the construct remains stable over time (Duncan *et al.*, 2013). In contrast, a small effect means that "there has been a substantial reshuffling of the individuals' standings on the construct over time" (Selig and Little, 2012, p. 266).

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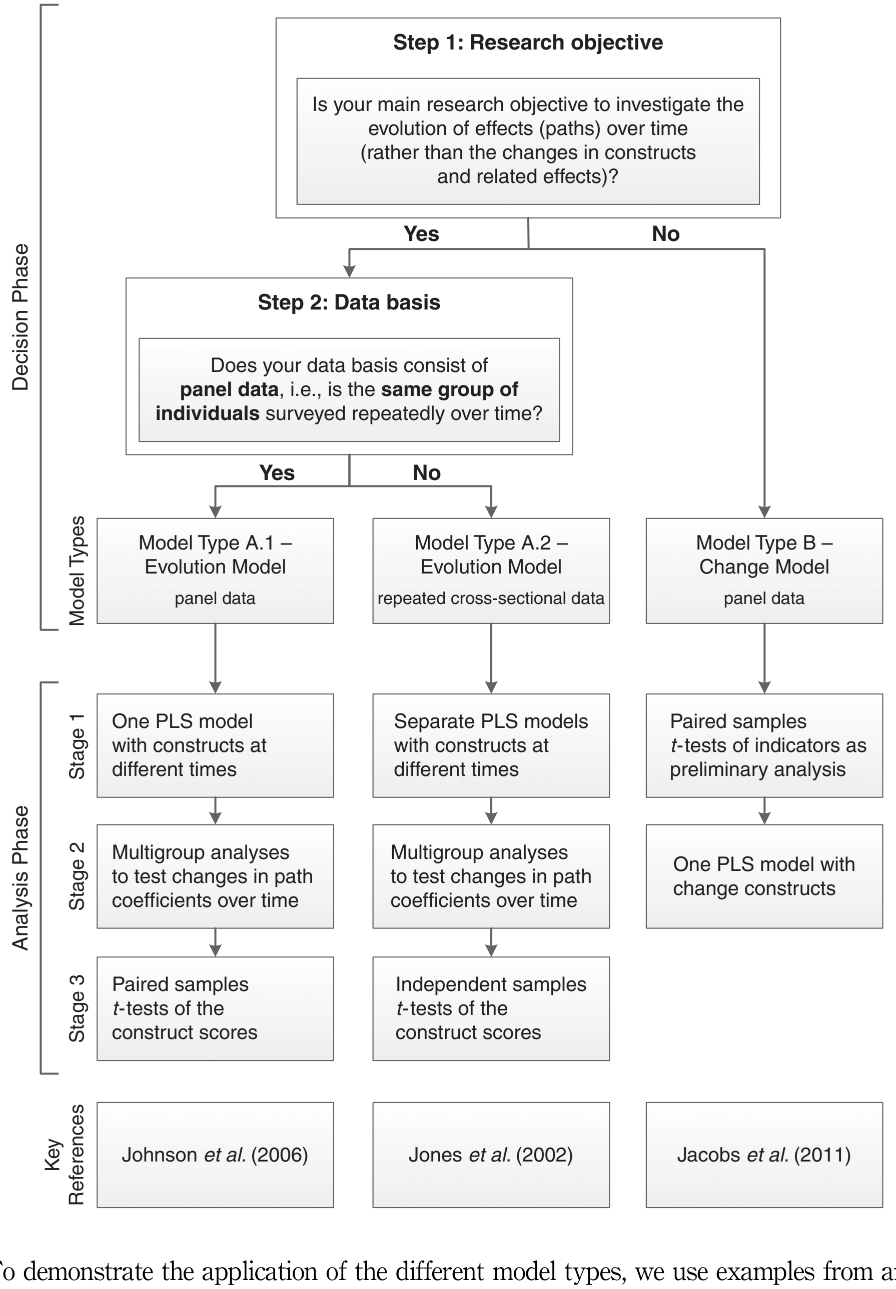

Figure 1.
Choice of PLS models and analyses in longitudinal studies

To demonstrate the application of the different model types, we use examples from an empirical study investigating the acceptance of BEVs in corporate fleets. It is important to note, that the analyses presented in this paper only represent a small fraction of the whole study that is conducted. The major purpose of this paper is to demonstrate the use of PLS in longitudinal studies and not to add to scientific research. Due to the tutorial nature of the paper, the hypotheses are introduced in abbreviated form.

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Based on 16 expert interviews and theory of reasoned actions (TRA), as proposed by Fishbein and Ajzen (1975), the technology acceptance model (TAM) (Davis, 1989) and innovation diffusion theory introduced by Rogers (1995) we developed the hypotheses.

In the expert interviews, perceived ease of use (EOU) emerged as a driver of the acceptance of BEVs in corporate fleets. Moreover, several experts indicated in the interviews, that enjoyment is an important driver in the acceptance of BEVs in corporate fleets. For example, BEVs can accelerate much faster than vehicles with combustion engines thus providing an added value to the drivers. Based on the literature, we expected that the perceived ease of use of BEVs will positively influence the enjoyment (ENJ) of the vehicle (see similar Davis *et al.*, 1992). Moreover, we expected that this effect will become stronger in the course of time when the vehicles have actually been used. The following hypotheses will be tested for model A.1:

H1. Perceived ease of use will have a positive effect on enjoyment at times t_0, t_1 and t_2.

H2. The effect of perceived ease of use on enjoyment will become stronger over time.

H3. The carry-over-effects will become stronger over time.

H4. The levels of perceived ease of use and for enjoyment will improve over time.

2.2 The evolution model for repeated cross-sectional data – model type A.2

In many cases, however, researchers do not have panel data available for their analyses. Instead, researchers may have measured the same indicators at different points in time with different samples (Step 2 in the decision phase in Figure 1, "no" option). This case represents repeated cross-sectional data (Frees, 2004; Moffitt, 1993; Verbeek, 2008). In fact, many important studies are repeated cross-sectional studies such as the consumer price survey. In this case, the sample changes over time. Then, the focus is on changes on the aggregate level of the variables (Frees, 2004).

For example, researchers may have surveyed employees of a company at two points in time. However, responses at the different points in time cannot be traced back to the individual employee, so that it is unclear whether one employee has taken part in both surveys and what his/her responses have been. Another example is that, even if responses can be traced back to the individual employee, the sample size in the second wave of the survey may become smaller, e.g., due to staff fluctuation (attrition). If all responses are included in the analysis at each point in time, the samples differ from each other and analyses should be carried out on an aggregate level (Frees, 2004).

PLS may also be used to analyze evolution with repeated cross-sectional data (model type A.2) (see e.g., Jones *et al.*, 2002). For model type A.2, the main research aim is the same as for model A.1, i.e., to investigate the evolution of paths coefficients over time. Therefore, three hypotheses are similar to model A.1, i.e., *H1*, *H2* and *H4* (see Section 2.1). However, the carry-over-effects (*H3*) cannot be tested in this model type, since different PLS models have to be created based on different samples for different points of time.

With repeated cross-sectional data, changes of constructs on the level of the individual cannot be assessed, since the data cannot be traced back to the one and the same research unit (Frees, 2004; Moffitt, 1993). Heterogeneity biases may occur due to the different samples. Since the subjects in the sample differ from each other, additional checks need to be made to control for heterogeneity (for further readings, see Frees, 2004). In the case, in which the samples differ due to attrition, researcher should check for non-response biases (e.g., Jones *et al.*, 2002). When attrition is a problem, sample sizes should still be large enough to provide sufficient statistical power to conduct PLS (Hair *et al.*, 2014).

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2.3 The change model for panel data – model type B

The research aim of the change model (model type B) is to investigate the changes in exogenous and/or endogenous constructs and their effects in a PLS model (Step 1 in the decision phase in Figure 1, "no" option). Since the focus is on the change in a construct, the data basis has to consist of panel data. Otherwise, changes in the indicators cannot be computed and assigned to the constructs. Therefore, there is no alternative regarding the data basis and thus no choice in Step 2 in Figure 1.

As an example for model type B, Hennig-Thurau *et al.* (2006) studied change in customer positive affect in an experimental design, i.e., in a service encounter in a video rental shop, as an exogenous construct to study future loyalty intentions. In a similar manner, Lee (1997) used performance change as an exogenous change construct to assess the effect on risk-taking attitudes of six brewery companies. Finally, Jacobs *et al.* (2011) used exogenous and endogenous change constructs in their PLS model to analyze changes in physical activities.

By using the change model, researchers can investigate the changes in constructs and their effect on other constructs. To do so, change constructs are created in PLS. When two points in time shall be compared, as for example in experimental research designs (before and after a certain treatment), the difference of the indicators can be used to create the change constructs (e.g., Hennig-Thurau *et al.*, 2006). When more than two points in time are measured, growth rates of the indicators may be another option to create the change constructs (e.g., Lee, 1997).

Model B is particularly suitable for longitudinal PLS modeling with two points in time since the change from one point in time to another point in time is in the center of the analysis. Therefore, model B is highly suitable for experimental designs (e.g., Hennig-Thurau *et al.*, 2006) or clinical studies comparing situations before and after a treatment (e.g., Jacobs *et al.*, 2011).

To demonstrate the use of PLS in model type B in this paper, only two points in time regarding the acceptance of BEVs were analyzed, i.e., before the first use of a BEV and after three months of BEV usage. As indicated by some experts, participants' perceived ease of use was expected to increase after using BEVs. Equally, enjoyment was expected to increase and thus change. Therefore, the following hypothesis was put forward:

H5. A change in perceived ease of use will positively affect the change in enjoyment.

3. Methods

3.1 Questionnaire Development

Based on the insights from 16 expert interviews and based on an extensive literature review, a standardized questionnaire was developed to investigate factors fostering and impeding users' acceptance of BEVs in corporate fleets. Measurement scales from existing theories were adapted such as the TRA, as proposed by Fishbein and Ajzen (1975), the TAM (Davis, 1989) and innovation diffusion theory introduced by Rogers (1995). The items were adjusted or complemented with the results from the expert interviews (see Table AI).

3.2 Measures

Enjoyment was operationalized by using the three-item scale from Davis *et al.* (1992). However, Davis *et al.* (1992) developed the original items to measure enjoyment of software programs. Inspired from the expert interviews, one further item was included to fully grasp the construct of enjoyment of driving a BEV instead of "just" using a software program (Item No. 3 in Table AI).

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Perceived ease of use was operationalized by adapting the items developed by Davis (1989). Again, Davis (1989) developed the original items to measure the ease of use of software programs and not of BEVs. Therefore, a number of items were not transferrable to the study of BEVs and had to be dropped. Instead, differences in the perceived ease of use of driving and/or handling BEVs (e.g., charging and starting the vehicle) were indicated by the experts and included as separate items in the questionnaire.

For the measurement of enjoyment and perceived ease of use before the first usage at time t_0, items were adapted regarding the use of future tense. All items were measured on seven-point Likert-type scales ranging from "strongly agree" (1) to "strongly disagree" (7).

3.3 Samples

Paper-based coded questionnaires were issued to employees of four companies across nine regions in Germany taking part in the project. Questionnaires were in German. All items were translated by using parallel-translation. The drivers had to complete a questionnaire before the first test drive (t_0), after three month (t_1) and after six months (t_2) of extensive BEV usage.

Overall, 164 respondents completed the questionnaire at t_0, 104 respondents completed their questionnaire at t_1 and 70 completed the questionnaire at t_2. Since the project is still running, more questionnaires are expected to be returned in future. To reduce the danger of panel attrition, participants were regularly reminded by telephone or mail to submit their questionnaires. Drop outs related to maternity leave or fluctuation.

In total, 65 respondents fully completed questionnaires at all three points in time t_0, t_1 and t_2 (for model A.1). One further case had to be deleted due to too many missing values in the items of interest in this paper. Using single-linkage hierarchical clustering, one outlier was detected and removed from the sample so that panel data for 63 respondents at times t_0, t_1 and t_2 could be used for the analysis. With 63 respondents and 24 items the data set would comprise 1,512 data points. The data set included eight missing values (0.5 percent). Missing data in all data sets was replaced by using the expectation maximization method (Schafer and Graham, 2002).

The sample size of 63 respondents was relatively small. To determine the minimum sample size for PLS modeling, Hair *et al.* (2014) recommend using power analyses. Cohen (1992) developed rules of thumb for power analyses for multiple regression models. For a statistical power of 80 percent, a significance level of 5 percent, a maximum of two arrows pointing at a construct and a minimum R^2 of 0.25 in the endogenous construct, at least 52 cases are needed. Our sample size of 63 cases lies above this minimum sample size requirement so that PLS can be used.

For the sample of model A.2, we included as many respondents as possible and created different data sets for each PLS path model at times t_0, time t_1 and time t_2. Out of the 164 respondents for time t_0, nine cases had to be eliminated due to too many missing values in the respective items and two more cases were identified as outliers. In total, 19 missing values were replaced, i.e., 1.6 percent out of 1,224 data points (for eight items and 153 respondents). For time t_1, out of the 104 valid responses, three outliers were detected, yielding 101 cases for the subsequent analysis. There were no missing values in the data set for time t_1. For time t_2, we detected one outlier resulting in 69 cases. Two missing values were replaced, i.e., 0.5 percent of 552 values (for eight items and 69 respondents).

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For model type B, a panel for times t_0 and t_1 was constructed. The panel was larger compared to model A.1, since the data set included valid responses from time t_0 and time t_1 only. Out of the 104 cases four more cases had to be eliminated due to too many missing values in the respective indicators at both times t_0 and t_1 and two cases were identified as outliers using single-linkage clustering. Finally, 98 cases were left in the panel for the analysis in model B. At time t_0, 12 missing values had to be replaced (1.5 percent out of 784 data points for t_0); there were no missing values for time t_1.

4. The analysis of the evolution model with panel data – model type A.1

4.1 Model type A.1: Stage 1 – create one PLS model with constructs at different times

For model A.1, the constructs for perceived ease of use at times t_0, t_1 and t_2 (EOUt_0, EOUt_1 and EOUt_2) as well as for enjoyment (ENJt_0, ENJt_1 and ENJt_2) were created based on the indicators at the three points in time. The model was estimated using the SmartPLS 3 software package (Ringle *et al.*, 2015). The constructs were modeled as composites (Henseler *et al.*, 2016; Rigdon, 2012).

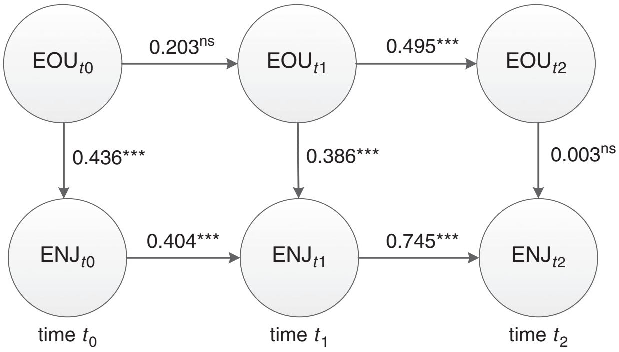
PLS estimates are only "consistent at large" (Wold, 1982), i.e., consistent with a large number of indicators and observations. With smaller samples, estimates are biased in a way that the paths in the structural model are underestimated and parameters in the measurement model are overestimated (Gefen *et al.*, 2011). Therefore, when consistent estimates are needed, researchers should turn to consistent PLS to include a correction for attenuation (Dijkstra and Henseler, 2015a, b). However, we have used PLS instead of consistent PLS (PLSc) in this paper for three major reasons. First, by using PLS we did not incur Heywood cases which would have been the case with PLSc (Henseler *et al.*, 2016). Second, the purpose of this paper is prediction and in prediction-oriented research PLSc shows no advantages over PLS (Henseler *et al.*, 2016). Third, we needed construct scores for our analysis in Stage 3 (see below). PLSc does not provide these scores.

When running the PLS algorithm, the following specifications were used. As the structural model weighting scheme, the path weighting scheme was chosen (Hair *et al.*, 2014). The model was estimated with a maximum of 1,000 iterations (Hair *et al.*, 2014). As the stop criterion, 10^{-7} was chosen (Henseler *et al.*, 2009) (Figure 2).

The overall model fit was assessed by the standardized root mean square residual (SRMR) (Henseler *et al.*, 2014). With a value of 0.078 the model showed a sufficient fit of less than 0.080 (Hu and Bentler, 1999).

The measurement model was assessed by testing indicator reliability, composite reliability and convergent validity (Hair *et al.*, 2014; Henseler *et al.*, 2009). All factor loadings were higher than 0.5. Discriminant validity was assessed by using the Fornell-Larcker Criterion, cross-loadings as well as the HTMT-criteria (Henseler *et al.*, 2015). The measurement model fulfills the quality criteria recommended for PLS modeling; the structural model was assessed by using R^2 and Q^2 (see Tables AII and AIII).

To test the significance of the path coefficients, the bootstrapping procedure was run with 5,000 subsamples (Hair *et al.*, 2011). For the bootstrapping procedure, we chose the "no sign changes" option as the most conservative option (Hair *et al.*, 2014). Only two effects were not significant (ns), i.e., the direct effect of EOU_{t2} on ENJ_{t2} and the carry-over-effect of EOU_{t0} on EOU_{t1}. All the other effects were highly significant at a $p < 0.001$ level (see Table I).



Note: ***$p \leqslant 0.001$

Figure 2.
Evolution of the effects with panel data (model type A.1)

Table I.
Model type A.1 – Stage 1: results of the test of significance of the direct effects and carry-over-effects

Type	Time	Effect	Path coefficient	*t*-values	*p*-values	Significance
Direct effects	t_0	EOUt_0 → ENJt_0	0.436	4.132	0.000	Yes
	t_1	EOUt_1 → ENJt_1	0.386	4.200	0.000	Yes
	t_2	EOUt_2 → ENJt_2	0.003	0.026	0.980	No
Carry-over-effects	t_0/t_1	EOUt_0 → EOUt_1	0.203	1.228	0.219	No
	t_1/t_2	EOUt_1 → EOUt_2	0.495	5.517	0.000	Yes
	t_0/t_1	ENJt_0 → ENJt_1	0.404	3.851	0.000	Yes
	t_1/t_2	ENJt_1 → ENJt_2	0.745	11.484	0.000	Yes

Table I shows that the effects of ease of use on enjoyment are significant and positive at the first two times t_0 and t_1. However, this effect turns insignificant at time t_2. Therefore, *H1* is only partly supported.

4.2 Model type A.1: Stage 2 – multigroup analyses to test the changes in the path coefficients over time

As can be seen in Table I, the direct effects of perceived ease of use on enjoyment do not become stronger over time (*H2*). Instead, they become weaker over time. Regarding , the carry-over-effects become stronger for both ease of use and enjoyment showing a stabilization of the constructs over time. To test *H2* and *H3*, whether the changes in the path coefficients from one point in time to the next point in time are significant, additional analyses are needed. There are different ways to test the significance of changes in the effects (path coefficients) between constructs over time. In the PLS literature, these are subsumed under the term "multigroup analysis" (Henseler *et al.*, 2009; Sarstedt *et al.*, 2011). For model A.1, the different "groups" are interpreted as the different points in time[1].

The probably easiest and most appropriate way to test the differences between path coefficients is the non-parametric confidence set approach (Sarstedt *et al.*, 2011). For this approach, the distribution of the parameters is irrelevant which fits well with PLS' distribution-free nature.

The procedure to compare the path coefficients is as follows (Sarstedt *et al.*, 2011):

(1) Run the PLS path modeling bootstrapping algorithm with 5,000 subsamples with a significance level of 5 percent for two-tailed tests. Choose the "bias-corrected and accelerated" method for the estimation of the confidence intervals (CI).

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(2) Investigate the paths coefficients and the CI for the direct effects and the carry-over-effects from one point in time to another: if the path coefficient at time *t*-1 falls within the CI of the path coefficient at time *t*, there is no significant difference between the path coefficients. Conversely, if the path coefficient at time *t*-1 is outside the CI of path coefficient at time *t*, there is a significant difference between the path coefficients.

Table II shows the path coefficients, the bias corrected CI, the comparison of the path coefficients with the bias corrected CI as well as a judgment concerning whether the coefficient lies inside or outside the CI and whether the change is significant.

Table II shows that the direct effect of perceived usefulness on enjoyment did not significantly change from t_0 to t_1. However, from t_1 to t_2 the (negative) change was significant. The positive changes in carry-over-effects were significant for enjoyment [2]. Consequently, for *H2* no empirical support was found. On the contrary, the direct effects declined significantly over time, especially from t_1 to t_2. *H3* can only be supported for the carry-over-effects of enjoyment.

4.3 Model A.1: Stage 3 – paired samples t-test of the changes in the levels of the constructs over time

In addition to the change in the path coefficients over time, researchers may be interested in the change in the levels of the constructs over time (see e.g., Shea and Howell, 2000). To test whether there is a significant change in the levels of perceived ease of use and enjoyment from one point in time to another, the following procedure should be followed:

(1) Run the PLS importance performance map analysis to receive the unstandardized construct scores for the constructs.

(2) Use the unstandardized construct scores with a statistical software program (e.g., SPSS, SAS) to compute the descriptive statistics, such as means and standard deviations[3].

(3) Conduct a paired samples *t*-test to test for the difference in the levels of the constructs[4].

Table III shows the means (*M*), standard deviations (SD) as well as the mean differences of the constructs from one point in time to another point in time. The mean differences and the paired samples *t*-test show that the improvement for both perceived ease of use and enjoyment from t_0 to t_1 is significant. However, from t_1 onwards there is no further improvement of the means. Therefore, *H4* can only be partially supported. These results are consistent with our expectations based on the literature and the expert interviews that after the first test drive and "trying out" the new technology, ease of use and enjoyment increase drastically. However, after the first three months, ease of use and enjoyment rest at the higher levels of t_1.

5. The analysis of the evolution model with repeated cross-sectional data – model type A.2

5.1 Model type A.2: Stage 1 – create separate PLS models with constructs at different times

The data basis for model type A.2 may consist of repeated cross-sectional data from different samples or from one sample that has suffered from attrition. For model type A.2, PLS path models need to be created separately, i.e., one model is created for the

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Table II. Model type A.1 – Stage 2: results of the test of significance of the changes in path coefficients (multigroup analysis)

Type	Time	Effect	Path coefficient	Size of the change	Bias corrected CI	Comparison of path coefficient t+1 with CI t and path coefficient t with CI t+1	Path coefficient t+1 inside CI t? Path coefficient t inside CI t+1?	Significant change?
Direct effects	t_0	EOUt_0 → ENJt_0	0.436	−0.050	(0.264; 0.654)	0.264 < 0.386 < 0.654	Yes	No
	t_1	EOUt_1 → ENJt_1	0.386		(0.220; 0.578)	0.220 < 0.436 < 0.578	Yes	
	t_1	EOUt_1 → ENJt_1	0.386	−0.383	(0.220; 0.578)	0.003 < 0.220	No	Yes
	t_2	EOUt_2 → ENJt_2	0.003		(−0.172; 0.230)	0.230 < 0.386	No	
Carry-over-effects	t_0/t_1	EOUt_0 → EOUt_1	0.203	0.292	(−0.045; 0.580)	−0.045 < 0.495 < 0.580	Yes	No
	t_1/t_2	EOUt_1 → EOUt_2	0.495		(0.347; 0.689)	0.203 < 0.347	No	
	t_0/t_1	ENJt_0 → ENJt_1	0.404	0.341	(0.194; 0.602)	0.602 < 0.745	No	Yes
	t_1/t_2	ENJt_1 → ENJt_2	0.745		(0.602; 0.851)	0.404 < 0.602	No	

sample at time t_0, one model is created for the sample at time t_1 and one model is created for the sample at time t_2. In these PLS models at the three points in time, the effect of perceived EOU on enjoyment is modeled. There are no carry-over-effects in this model type since only separate PLS models for each point of time (for each sample) can be created.

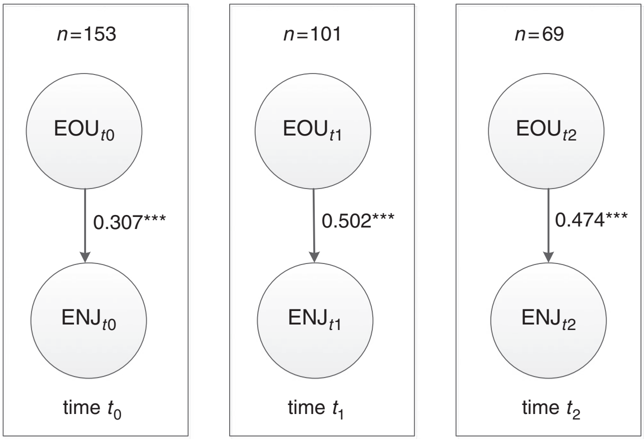
The same estimation settings were used as outlined for model type A.1. The overall model fits were sufficient. SRMR was 0.060 for the model at time t_0, 0.063 for the model at time t_1, and 0.071 for the model at time t_2. In addition, all measurement models fulfill the quality criteria (see Tables AIV and AV). Figure 3 shows a graphical representation of the three models for the three samples at times t_0, t_1 and t_2.

Table IV summarizes the results of the analysis of the direct effects.

In Figure 3 and Table IV, all path coefficients for the times for t_0, t_1 and t_2 are positive and significant. Based on these analyses, we found support for *H1*.

Table III.
Model type A.1 – Stage 3: results of the test of significance of the changes in level of the constructs

Construct	Time	No. of pairs	M	SD	Mean Difference	*t*-value	*p*-value	Significance
EOU	t_0 to	63	2.868	0.999				Yes
	… t_1	63	2.312	0.942	−0.556	4.519	0.000	
	t_1 to	63	2.312	0.942				No
	… t_2	63	2.328	0.912	0.016	−0.190	0.850	
ENJ	t_0 to	63	2.151	0.866				Yes
	… t_1	63	1.598	0.615	−0.554	4.601	0.000	
	t_1 to	63	1.598	0.615				No
	… t_2	63	1.666	0.555	0.068	−0.914	0.364	



Note: ***$p \leqslant 0.001$

Figure 3.
Evolution of the effects with repeated cross-sectional data (model type A.2)

Table IV.
Model type A.2 – Stage 1: results of the test of significance of the direct effects

Time	Effect	*n*	Path Coefficient	*t*-values	*p*-values	Significance
t_0	EOU → ENJ	153	0.307	4.688	0.000	Yes
t_1	EOU → ENJ	101	0.502	8.854	0.000	Yes
t_2	EOU → ENJ	69	0.474	5.746	0.000	Yes

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5.2 Model type A.2: Stage 2 – multigroup analyses to test the changes in the path coefficients over time

In contrast to the results of model A.1, path coefficients did not decline over time; instead they slightly increased at time t_1 and then decreased at time t_2. A test of the changes in the path coefficients between the different points in time by comparing the CI reveals the following results (Table V)[5].

When comparing the path coefficients for the models from one point in time to the next, it can be noted that only the path coefficient at t_0 is significantly different from t_1 (and also from t_2) in the repeated cross-sectional data set. For the following reasons, differences in the results for the path coefficients between models A.1 and A.2 may have occurred:

- The direct effects are separately modeled in A.2, so that there is no inclusion of the earlier/later direct effects as in model A.1.
- The direct effects are separately modeled in A.2, so that there are no carry-over-effects having an impact from one point in time to another point in time as in model A.1.

Therefore, *H2* and *H3* should not be tested with model A.2.

Additional analyses to test for differences between the samples should be conducted. For example, at time t_0, differences between the respondents that are not included in the panel (these are non-respondents at the later points in time) and the respondents that are included in the panel (respondents) should be detected by using independent samples *t*-tests and tests comparing correlations of independent samples. Finally, sample sizes should be sufficiently large in repeated cross-sectional studies to reduce biases.

5.3 Model type A.2: Stage 3 – independent samples t-tests of the construct scores

In Stage 3 for model type A.2, the change in the levels of the constructs from one point in time to the next point in time should be analyzed with repeated cross-sectional data sets. The procedure is similar to model A.1 – Stage 3 (see Section 4.3). In contrast, the procedure needs to be repeated with each data set. One data sheet should be prepared containing the unstandardized construct scores for each construct in the columns and a new group variable distinguishing the responses at the different points in time. Instead of using paired samples *t*-tests as for model A.1, independent samples *t*-test should be used, since the samples differ from each other (Table VI)[6].

The results confirm the results from the earlier analysis of model A.1 – Stage 3 (see Table III). *H4* is again partially supported.

Time	Effect	*n*	Path coefficient	Size of the change	Bias corrected CI	Comparison of path coefficient *t*+1 with CI *t* and path coefficient t with CI *t*+1	Path coefficient *t*+1 inside CI *t*? Path coefficient t inside CI *t*+1?	Significant change?
t_0	EOU → ENJ	153	0.307	0.195	(0.209; 0.462)	0.462 < 0.502	No	Yes
t_1	EOU → ENJ	101	0.502		(0.408; 0.628)	0.307 < 0.408	No	
t_1	EOU → ENJ	101	0.502	−0.028	(0.408; 0.628)	0.408 < 0.474 < 0.628	Yes	No
t_2	EOU → ENJ	69	0.474		(0.332; 0.652)	0.332 < 0.502 < 0.652	Yes	

Table V. Model type A.2 – Stage 2: results of the test of significance of the changes in path coefficients (multigroup analysis)

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6. The analysis of the change model – model type B

6.1 Model type B: Stage 1 – paired samples t-test of the indicators as preliminary analysis

As a preliminary analysis for the change model (model type B), a paired samples *t*-test of the indicators of the change constructs should be conducted to make sure that the differences in the indicators are sufficiently large. The paired samples *t*-test shows that the indicators for perceived ease of use and enjoyment differed significantly from t_0 to t_1 (see Table VII). Therefore, the indicators are appropriate for the creation of the change constructs.

6.2 Model type B: Stage 2 – create one PLS model with change constructs

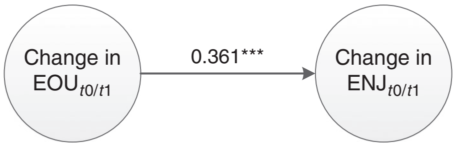
After having tested the differences in the indicators for ease of use and enjoyment at t_0 and t_1, new indicators are computed for each case in the data set, i.e., indicator value at t_1 minus the respective indicator value at t_0. Then, the PLS model was run with the same settings as models A.1 and A.2. The overall model fit, as assessed by SRMR, was sufficient with 0.077. The measurement model fulfills the quality criteria recommended for PLS modeling (see Table AVI). R^2 and Q^2 were at weak levels ($R^2 = 0.131$; $Q^2 = 0.085$) mainly due to the small number of predictors. The PLS path model testing *H5* reveals the following results (Figure 4).

Table VI. Model Type A.2 – Stage 3: results of the test of significance of the changes in levels of the constructs

Construct	Time	*n*	M	SD	Mean difference	*t*-value	*p*-value	Significance
EOU	t_0 to	153	2.243	0.913	−0.654	6.953	0.000	Yes
	… t_1	101	1.589	0.586				
	t_1 to	101	1.589	0.586	0.097	−1.066	0.288	No
	… t_2	69	1.686	0.575				
ENJ	t_0 to	153	2.889	0.945	−0.627	5.238	0.000	Yes
	… t_1	101	2.263	0.916				
	t_1 to	101	2.263	0.916	0.106	−0.750	0.454	No
	… t_2	69	2.369	0.898				

Table VII. Model type B – Stage 1: results of the test of significance of differences in the indicators

		Paired differences				
Construct	Indicators	M	SD	*t*-value	*p*-value	Significance
EOU	EOUt_{0_1} and EOUt_{1_1}	0.722	1.038	6.846	0.000	Yes
	EOUt_{0_2} and EOUt_{1_2}	0.423	1.009	4.127	0.000	Yes
	EOUt_{0_3} and EOUt_{1_3}	0.684	1.154	5.864	0.000	Yes
	EOUt_{0_4} and EOUt_{1_4}	0.592	1.014	5.780	0.000	Yes
ENJ	ENJt_{0_1} and ENJt_{1_1}	0.615	1.251	4.812	0.000	Yes
	ENJt_{0_2} and ENJt_{1_2}	0.656	1.034	6.216	0.000	Yes
	ENJt_{0_3} and ENJt_{1_3}	0.537	1.192	4.389	0.000	Yes
	ENJt_{0_4} and ENJt_{1_4}	0.316	1.151	2.674	0.009	Yes



Note: ***$p \leqslant 0.001$

Figure 4. Effect between change constructs (*t*0/*t*1) (model type B)

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Figure 4 shows that the change in perceived ease of use after three months of BEV usage has an impact on the change of enjoyment of the drivers driving the vehicles (path coefficient of 0.361, *t*-value of 4.399 and *p*-value of 0.000). This effect is significant at $p < 0.001$. *H5* is therefore supported.

7. Conclusions, limitations and future research

The aim of this paper was to provide an overview of how data from longitudinal studies can be used in PLS path modeling. Depending on the research question and the structure of the data, three different types of models were identified such as "evolution models" (model type A.1 for panel data and model type A.2 for repeated cross-sectional data), in which an evolution of path coefficients is investigated for sequential points in time, as well as "change models" (model type B), in which change constructs are used in a PLS model. Additional analyses have been recommended to complement PLS path modeling. Practical examples from a study on users' acceptance of BEVs have demonstrated the application of the three different model types. Methods for multigroup analyses, in particular the non-parametric confidence set approach, have been suggested and to test for the difference in the evolution of path coefficients.

Nevertheless, some limitations should be noted opening up avenues for future research. First, the data sets that have been used for illustrative examples are still very small, in particular for the panel (63 cases) at the three points in time (model type A.1). One reason is that the data collection is still running in the project. However, there may be several causes for non-responses (Frees, 2004). Therefore, tests for non-respondent biases should be addressed in more details as well as the treatment of missing data.

Second, model type B is particularly useful, when there is a certain "event" taking place to compare situations before and after the event. In this paper, this event is the actual use of a BEVs. However, other effects that researchers should control for may have an impact on the results of the study. In the present study, problems with the charging infrastructure should be controlled for since they may have an impact on the ease of use and consequently on enjoyment. This may, however, pave ways for further insights into the analysis of evolution type models A. Conversely, PLS path modeling as presented in models A may also be used in event studies, in which the effect of an event on the value of a firm is assessed.

Finally, it should be mentioned that instead of PLS path modeling there are also other methods, such as latent growth curve modeling, which may be helpful in the analysis of longitudinal data (e.g., Duncan *et al.*, 2013).

Notes

1. When applying multigroup analyses, researchers should make sure that the measurement of the constructs under investigation is equivalent between the groups (see similar Steenkamp and Baumgartner, 1998). This may not be the case, if constructs are measured in very different groups as, e.g., in different cultures. Then, researchers are advised to check for measurement invariance before comparing structural estimates between different groups (Rigdon *et al.*, 2010; Ringle *et al.*, 2011). Measurement invariance may occur in longitudinal studies if the time between the measurements becomes very large and/or if very different samples are used in repeated cross-sectional samples (especially model type A.2). Even though this was not the case for our example, we computed modified Welsh tests for models A.1 and A.2 to compare estimates for composite reliabilities and average variance extracted (for further information on the procedure, see Ringle *et al.*, 2011). For the different constructs

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at times t_0, t_1 and t_2, measurement invariance was established, i.e., there was no significant difference between the measurements of the constructs at times t_0, t_1 and t_2.

2. Additional comparisons of path coefficients could be carried out, e.g., regarding the difference in direct effects from t_0 to t_2 or regarding the different path coefficients of the carry-over-effects, e.g., from t_1 to t_2. Since it is intended to show an evolution from one point in time to another, these comparisons are not shown in this paper.
3. PLS is traditionally based on standardized data for the indicators (Hair *et al.*, 2014). However, for the comparison of the means, standardized construct scores cannot yield any mean differences, since their mean is 0 with a standard deviation of 1. Therefore, we used unstandardized construct scores to test the difference in the levels of the constructs.
4. Alternatively, the Wilcoxon Signed Ranks test can be conducted as a non-parametric test.
5. For model A.2, Henseler's PLS-MGA approach (Henseler *et al.*, 2009; Sarstedt *et al.*, 2011) could be used to test the significance of differences in path coefficients as an alternative to the comparison of the CI, since different bootstrapping samples can be generated and compared at times t_0, t_1 and $t_{2.}$
6. Omnibus tests can be conducted to test whether there is a difference at all, when different samples for more than two points in time should be compared (Sarstedt *et al.*, 2011).

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Appendix 1

Perceived Ease of Use (EOU) adapted from Davis (1989)		
EOU	t_0	$t_{1/2}$
1	I will find that driving a battery electric vehicle is easy	I find that driving a battery electric vehicle is easy
2	Learning to drive a battery electric vehicle will be easy	Learning to drive a battery electric vehicle is easy
3	I will find that handling a battery electric vehicle is easy	I find that handling a battery electric vehicle is easy
4	Learning to handle a battery electric vehicle will be easy	Learning to handle a battery electric vehicle is easy
Enjoyment (ENJ) adapted from Davis et al. (1992)		
ENJ	t_0	$t_{1/2}$
1	I will have fun driving a battery electric vehicle	I have fun driving a battery electric vehicle
2	I will find driving a battery electric vehicle pleasant	I find driving a battery electric vehicle pleasant
3	Driving a battery electric vehicle will thrill me	Driving a battery electric vehicle thrills me
4	I will enjoy driving a battery electric vehicle	I enjoy driving a battery electric vehicle

Table AI. Constructs and their measurement items

Appendix 2. Model type A.1 – quality of the measurement model and the structural model

Constructs	No. of items	Composite reliability	Average variance extracted	1	2	3	4	5	6
1 EOUt_0	4	0.944	0.807	*0.898*					
2 EOUt_1	4	0.953	0.835	0.203	*0.914*				
3 EOUt_2	4	0.949	0.822	0.114	0.495	*0.907*			
4 ENJt_0	4	0.943	0.805	0.436	0.238	0.106	*0.897*		
5 ENJt_1	4	0.954	0.838	0.135	0.482	0.418	0.496	*0.916*	
6 ENJt_2	4	0.952	0.832	0.211	0.435	0.314	0.495	0.746	*0.912*

Notes: Numbers shown in the diagonal denote the square root of the AVE; the other numbers represent correlations between the constructs

Table AII. Model type A.1 – composite reliability, convergent validity and discriminant validity

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Table AIII. Model type A.1 – results for R^2, R^2 adjusted and Q^2

Endogenous constructs	R^2	R^2 adjusted	Q^2
1 EOU_{t1}	0.041	0.026	0.021
2 EOU_{t2}	0.245	0.233	0.183
3 ENJ_{t0}	0.190	0.177	0.150
4 ENJ_{t1}	0.386	0.366	0.312
5 ENJ_{t2}	0.557	0.542	0.454

Appendix 3. Model type A.2 – quality of the measurement model and the structural model

Table AIV. Model type A.2 – composite reliability, convergent validity and discriminant validity

Time	Constructs	No. of items	Composite reliability	Average variance extracted	1	2	3	4	5	6
t_0	EOUt_0	4	0.955	0.841	*0.885*					
	ENJt_0	4	0.935	0.784	0.307	*0.917*				
t_1	EOUt_1	4	0.961	0.861			*0.904*			
	ENJt_1	4	0.947	0.817			0.502	*0.928*		
t_2	EUOt_2	4	0.965	0.873					*0.907*	
	ENJt_2	4	0.949	0.822					0.474	*0.934*

Notes: Numbers shown in the diagonal denote the square root of the AVE; the other numbers represent correlations between the constructs

Table AV. Model type A.2 – results for R^2, R^2 adjusted and Q^2

Endogenous Constructs	R^2	R^2 adjusted	Q^2
ENJt_0	0.094	0.088	0.068
ENJt_1	0.252	0.245	0.194
ENJt_2	0.225	0.213	0.161

Appendix 4. Model type B – quality of the measurement model and the structural model

Table AVI. Model type B – composite reliability, convergent validity and discriminant validity

Change constructs	No. of items	Composite reliability	Average variance extracted	1	2
1 Change in EOU t_0/t_1	4	0.911	0.721	*0.849*	
2 Change in ENJ t_0/t_1	4	0.922	0.746	0.361	*0.864*

Notes: Numbers shown in the diagonal denote the square root of the AVE; the other number represents the correlation between the change constructs

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