



# New Challenges of Economic and Business Development – 2014

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## SMARTPLS FOR THE HUMAN RESOURCES FIELD TO EVALUATE A MODEL

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### Abstract

This paper describes the Partial Least Square model to test the robustness and value of the statistical evaluation. The test is to evaluate the fit of the model for a small sample. The statistical data is calculated with the SmartPLS software. SmartPLS is a tool created for statistical analysis, namely PLS – SEM (Structural Equation Model). The paper describes the advantages and disadvantages of SmartPLS and provides an argument for the use of SmartPLS in the scientific world. At the moment the use of SmartPLS in science concentrates mainly in the information technology field and the marketing area. The authors describe the use of SmartPLS for the human resources area which is a new field for SmartPLS software. The paper further describes the validity and reliability for PLS – SEM.

**Key words:** *SmartPLS, PLS, SEM, Model*

**JEL codes:** C52, M5

### Introduction

This paper describes the SmartPLS method to test models. SmartPLS is a second generation SEM tool. It calculates and tests models. SmartPLS has advantages and disadvantages for research. The paper uses a model to measure social capital under consideration of the employment seeking process to demonstrate the method and to test the model. SmartPLS is a new product and mainly used in the management and information systems environment. The paper further provides a guide to use SmartPLS to explain the validation and reliability values for this construct and to compare the results from different studies.

The data for the test has been collected at the university of Ludwigshafen in Germany. The participants used an online survey platform to submit their data. The collected answers have been coded and prepared for the evaluation with the PLS model. There are 56 participants in the study. The validation and reliability has been done with the SmartPLS tool from Ringle et al<sup>2</sup>. The questionnaire is concerned with the use of social capital to identify an employment opportunity by employment seeking individuals on social network sites. The research focus is to determine the use of social network sites by members to identify employment opportunities. The results can be used to improve the recruiting processes of organizations and to gain more knowledge about social network sites and the difference between social network sites e.g. business and private social network sites.

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<sup>2</sup> Source <http://www.smartpls.de>



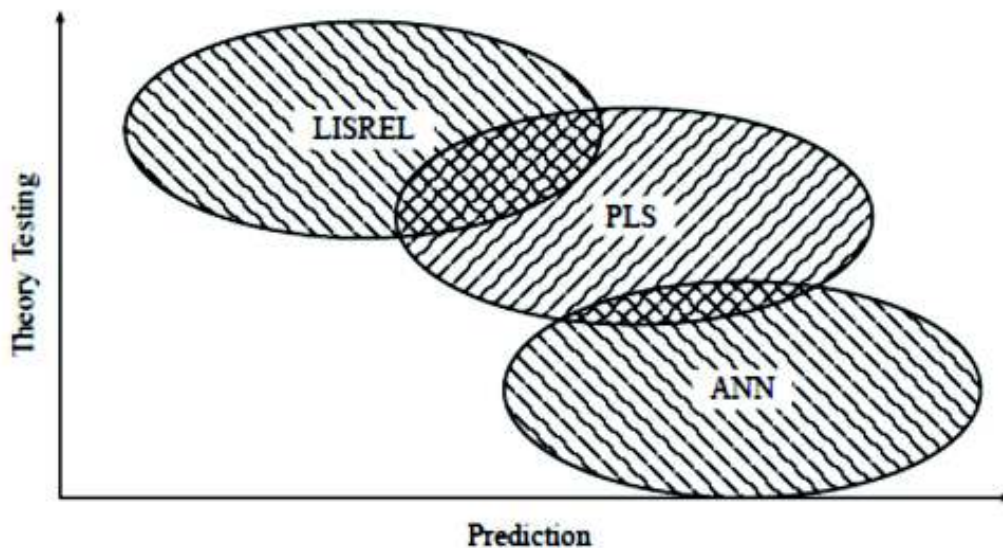
## Structural Equation Model (SEM)

The Structural Equation Model provides the opportunity to measure unobservable variables with indicators. This is an important point for the social capital theory as there exist variables which needs indicators to be described. This represents a large advantage for scientific work (Haenlein & Kaplan, 2004) (Fuchs, 2011). The indicators can describe reflective and formative constructs in the model (C. M. Ringle & Sinkovics, 2009).

There exist covariance and variance based methods. SmartPLS is a variance based model. The basis for a model is a theory and hypothesis. The variables with their indicators and the hypothesis create the paths in the model. These paths and hypotheses are fundamental for the theory and the theory explains the causal mechanism. The advantage of the model is to explore the construct visibly and to simplify the research so that scientists can measure the relationship between indicators and variables to test the hypothesis (Urban & Mayerl, 2013). The danger is that the model oversimplifies and the measured data and reality is too different. That decreases the value of the model.

The data for the model can be collected with a survey or scientists can use panel data for example. The results of the model are calculated with statistical methods and predictions. That is the reason that the data has to be valid for the statistic of tests and the quality of the data is important to get a result without biases. The data is used to test the model and to confirm or disprove the hypothesis.

The model has a measurement model and a structural model. The measurement model describes the variables with their indicators. The indicators measure and describe variables if the variables are not measurable. This is a typical case in sociological and human resources related research. The variables are embedded in a theoretical frame. The indicators are measurable and provide data for immeasurable variables. The structural model describes the relationship between independent and dependent variable. The structural model provides the opportunity to test the hypothesis and to explain the causal mechanism if the model does not fail (Urban & Mayerl, 2013).



Source: (C. M. Ringle & Sinkovics, 2009)

Fig. 1. Use of Models for the Research Purpose



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There are two kinds of measurement models. The first one is the reflective measurement model. This model measures the effect of variables on the indicator. The indicators can be switched and substituted without any compunction. There has to be a high correlation between the indicators and the indicators are founded on the same cause. The formative measurement model cannot change or substitute the indicators without compunction. These indicators influence the construct, they are cause indicators and there is only a small correlation between the indicators. The indicators have a similar effect (Fuchs, 2011) (Urban & Mayerl, 2013). Some Structural Equation Models methods do not provide the opportunity to use reflective and formative models in one model.

Models have different purposes. Some models are more useful for theory testing and other models are used for predictions. Ringle et al provide with the diagram the position of PLS methods compared with LISREL and ANN. This gives the information that PLS can be used for prediction and theory testing. There does not exist a strength in prediction and theory testing which means both kind of research is possible with PLS, for a theoretical testing research question LISREL would be a better indicator (C. M. Ringle & Sinkovics, 2009). This means different methods have different advantages and this has to be considered when choosing the of a model and software to evaluate the collected data and to test the model.

### The Advantages and Disadvantages of SmartPLS Software

SmartPLS is a beneficial tool which is used in management science to calculate, create and validate models. Many articles use SmartPLS and journals accept SmartPLS as a method (C. M. Ringle & Sinkovics, 2009) (Shackman, 2013). The model explains causal mechanism and validates empirically theoretical hypotheses and applies predictive oriented measures. SmartPLS is a technique of the second SEM generation (Fuchs, 2011) (Chin, 2010).

The main area of SmartPLS is the field of Information Systems and Marketing. This is the reason to use this instrument and to test this instrument for the human resources and social capital field to open a new scientific field for SmartPLS. A study about social network sites or human resources related environments is not yet known. There are literature reviews which do not identify any study under consideration of the combination of social network sites, social capital and human resources (Hair, Sarstedt, Pieper, & Ringle, 2012) (Shackman, 2013) (C. Ringle, Sarstedt, & Straub, 2012). Therefore, this study will be a very new approach in this area of study.

Besides, SmartPLS offers the path model that is able to describe the relationship between the variables and indicators. These come as a vital important point to provide an understandable picture and support to demonstrate the results. However, the disadvantage is the complexity of the reality which could be not demonstrated perfectly in a model. There are often biases and 100% validity does not exist. Models are imperfect and incomplete because the model has to handle the complexity of the real world (Haenlein & Kaplan, 2004) (Chin, 2010). The path models refer hypothesis and the task of the model is to explain the impact of the different hypotheses on each other. The scientist tests the hypotheses and urges for the confirmed or unconfirmed hypotheses with this approach to get a result (Nitzl, 2010).

SmartPLS is software created to test models. The software provides the opportunity to draw the path model between the variables and to define the indicators to the variables. The advantage of this path modelling technique is in the smaller sample size and a lack of distributional assumptions (Fuchs, 2011) (Chin, 2010) (Hair et al., 2012). The variable for SmartPLS can be nominal, ordinal or interval scaled e.g. likert scale (Nitzl, 2010) (Fuchs, 2011) (Chin, 2010). The main point to use SmartPLS is the sample size. Some SEM need samples of at least 200 samples or more. Shackman and other authors identified studies with sample size between 51 and 274 for the PLS method for example (C. Ringle et al., 2012) (Shackman, 2013) (Hair, Ringle, & Sarstedt, 2013) (C. M. Ringle & Sinkovics, 2009) (C. M. Ringle & Sinkovics, 2009) (C. Ringle, 2004a) (Fuchs, 2011). Under consideration has to be that the number of



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cases has to exceed the number of indicators or the matrix is not defined (Haenlein & Kaplan, 2004). Some author writes that PLS provides more accurate and valid results if the sample size is below 250 than other methods to test models or explain causal mechanism. The advantage is that the studies can use very specific populations. International business scientists need an instrument to build group analysis with relatively small sample sizes. The need to compare valid and accurate groups does not compute a fit statistically. Next, SmartPLS requires no distributional assumptions, other SEM assumes a normal distribution of data (C. Ringle et al., 2012) (Shackman, 2013) (C. M. Ringle & Sinkovics, 2009) (Nitzl, 2010). This gives more flexibility. The usefulness of PLS – SEM is given for explanatory research because covariance methods could not give valid or reliable results or it is not possible to use these methods for explanatory research (Hair et al., 2012).

SmartPLS has been used for exploratory research and theory development. This means SmartPLS can be used for scientific work with different objectives (see Figure 1). The main contribution of SmartPLS is the prediction and opportunity to use non-normal data (C. Ringle et al., 2012).

Furthermore, SmartPLS has the ability to use reflective and formative scales. Both can be tested with SmartPLS software and give the opportunity to use a model with reflective and formative elements easily (Shackman, 2013). Hair identified in his study that 50% of the explored models are both reflective and formative (Hair et al., 2012). This is one important difference between SmartPLS and LISREL or other SEM software, that there does not exist any restriction to use formative and reflective model in one construct (C. Ringle, 2004b) (Fuchs, 2011).

The explanatory research has the advantage that PLS has greater statistical power for detecting statistically significant relationships within other kinds of models (Shackman, 2013).

The model has formative indicators which influence the construct and has an impact on the model. These indicators should not have a large correlation with each other. The reflective indicators depend on the model and explore the result of the model. This means the outcome of the model is measured by the reflective indicators. The model to measure an social network sites for example the use by members to identify an employment opportunity has reflective and formative indicators (Haenlein & Kaplan, 2004).

A disadvantage is the evaluation of the model as the evaluation has to be done on r-squares of the different dependent and mediating variables. This makes it more difficult to compare the model with other models (Shackman, 2013). SmartPLS has to identify the reliability and validity with less statistical methods compared to covariance constructs. That is the reason to use resampling procedures e.g. bootstrapping to get information about the validity and reliability of the model. This is a disadvantage but with an increased sample size this disadvantage is not apparent (Fuchs, 2011).

The PLS path model includes two models, one model is the measurement model and the other model is the structural model. The measurement model is the outer model and the indicators are measurable to describe the variables. There has to exist a correlation between manifest variables and latent variables (Tenenhaus, Vinzi, Chatelin, & Lauro, 2005).

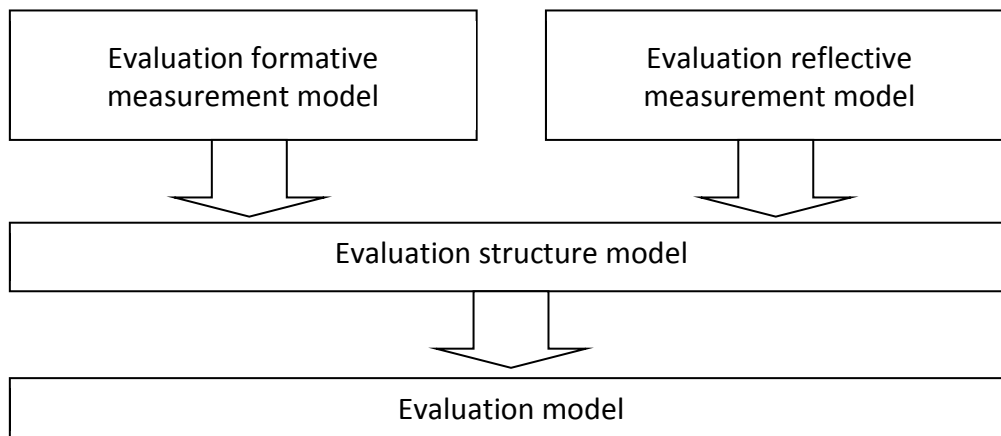
SmartPLS can use a wide range of variables to identify results. SmartPLS can use metric, quasi-metric, ordinal or categorical scales. This makes it very interesting to use this method to validate the model because there is a large flexibility (Hair et al., 2013). This means SmartPLS can be used for very complex models with many latent and manifest variables with different scales (C. M. Ringle & Sinkovics, 2009).

## Validation and Reliability

The validation and test of reliability of path models has three stages. The first level is the quality of the measurement model, the second stage is the quality of the structural model and the last stage is a structural regression equation (Tenenhaus et al., 2005). Small parts of models can be separately fitted. This helps to evaluate SmartPLS and to fulfil the quality criteria (Urban & Mayerl, 2013).



The different stages are described below. A best fit criteria like the standardized fit index or goodness of fit for LISREL does not exist for SmartPLS at the moment. This means the good fit has to be reached by testing the path coefficient and to be defined by parts of the model. The models, part of the model and paths are tested for reliability and validity. The tests use the statistical known values of a factor analysis which are described below (Nitzl, 2010) (C. Ringle, Boysen, Wende, & Will, 2006) (Hooper, Coughlan, & Mullen, 2008) (C. Ringle & Spreen, 2007).



Source: cf (Nitzl, 2010) (C. Ringle, 2004a)

Fig. 2. Evaluation of a SmartPLS Model

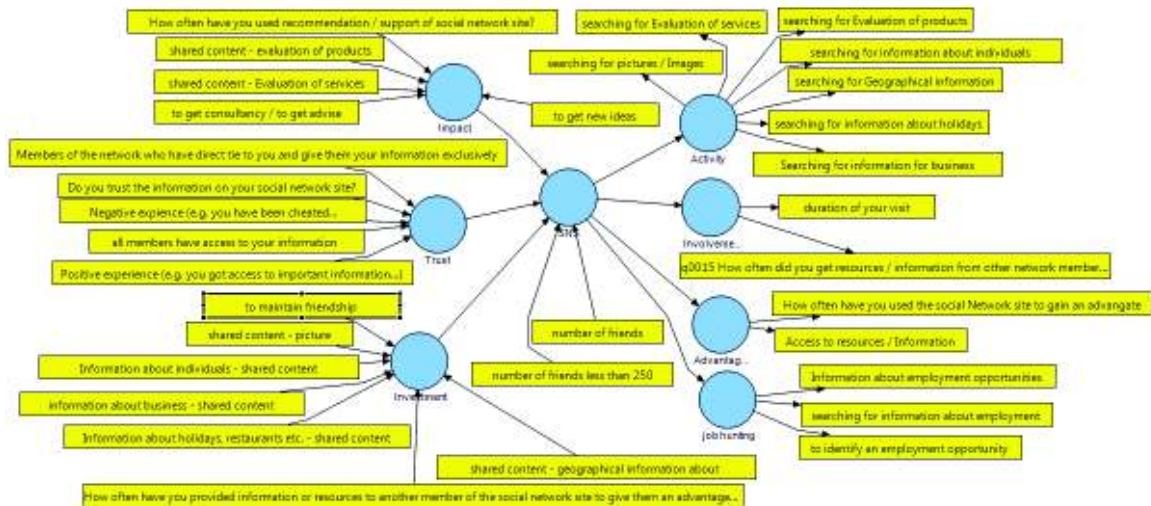
The robustness of the model can be tested with the bootstrapping method and gives information regarding the indicators and variables. A parametrical signification test to evaluate the model is not suitable. That difficulty is solved with a t-test. The t-Test is calculated with the bootstrapping process. The minimum value of the t-test should be larger than 1.65 to have an excellent significant value (Haenlein & Kaplan, 2004) (C. Ringle & Spreen, 2007).

With bootstrap it is possible to test the model properly. The bootstrap process provides the mean value and standard error for each path model coefficient. SmartPLS with the bootstrapping procedure further provides a t-test result for all paths. The t-test provides the confidence interval which is more valuable than the significant for a parameter (C. M. Ringle & Sinkovics, 2009).

Another opportunity to test the model is the blindfolding process. This test provides further opportunities to evaluate the model.

## The Model

The model is created with hypotheses and have a formative and reflective part. This paper tests the statistical robustness, validity and reliability to evaluate the statistical value of the construct. The construct is tested with data from an online survey. The data is collected at the University of Ludwigshafen. The test procedure has been done several times and some indicators has been deleted to improve the results and to fulfil the highest standards for the scientific and statistical requirements.



Source: Author

Fig. 3. The model to Measure the Causal Mechanism

## Testing of the Reflective Measurement Model

The reflective model is tested on convergence validity, indicator reliability and constructs reliability. The test has to provide results and values which are statistically acceptable. If the results are not in the range then the model and indicator has to be under consideration.

The indicator reliability is given if the variance should have a minimum of 0.7 and this result confirms as a first step the significance. The outer loadings are larger than 0.7 and t-values give the indication that the indicator reliability is given. In addition is the t-value an evident for the significant too. Outer loadings with a value above 0.6 are acceptable if the convergence criteria are fulfilled. Below is the convergence criteria is described and reached. This means the indicator reliability is confirmed (Nitzl, 2010) (Fuchs, 2011) (Chin, 2010) (C. Ringle & Spreen, 2007).

The construct reliability is measured with the composite reliability. The result of this test should be between 0 and 1. Acceptable results are 0.6 or higher. A further indicator for the construct reliability can be cronbachs alpha. Cronbachs alpha should be 0.7 or more (Nitzl, 2010) (Fuchs, 2011). The results are presented in Table 2. The composite reliability is completely fulfilled, only the cronbachs alpha is twice misses 0.7 but the value is more than 0.6. This result is a weakness and has to be under consideration with a larger sample and further evaluations.



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Table 1

## Indicator Reliability – Outer Loadings, Mean, STDEV and t-values for the Reflective Model

Outer Loadings (Mean, STDEV, T-Values)	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	Standard Error (STERR)	T Statistics (O/STERR)
Access to resources / Information <- Advantage / Benefit	0.7777	0.7751	0.0418	0.0418	18.5853
How often have you used the social Network site to gain an advantage <- Advantage / Benefit	0.9256	0.9253	0.0197	0.0197	46.9357
Information about employment opportunities <- job hunting	0.9506	0.9503	0.0075	0.0075	126.948
Searching for information for business <- Activity	0.6289	0.6282	0.0369	0.0369	17.0314
duration of your visit <- Involvement / Engagement	0.8748	0.8742	0.0147	0.0147	59.4341
How often did you get resources / information from other network members or did you get something back from other network member who received information / resources in the last 12 month <- Involvement / Engagement	0.8128	0.8138	0.0325	0.0325	25.0139
searching for Evaluation of products <- Activity	0.8742	0.8738	0.0149	0.0149	58.6327
searching for Evaluation of services <- Activity	0.882	0.8816	0.0179	0.0179	49.3873
searching for Geographical information <- Activity	0.796	0.7948	0.022	0.022	36.217
searching for information about employment <- Job Hunting	0.9424	0.9422	0.0094	0.0094	100.1893
searching for information about holidays <- Activity	0.79	0.7901	0.0206	0.0206	38.2622
searching for information about individuals <- Activity	0.8434	0.8421	0.0191	0.0191	44.1357
searching for pictures / Images <- Activity	0.8521	0.8514	0.0174	0.0174	49.0312
to identify an employment opportunity <- Job Hunting	0.6282	0.6208	0.0584	0.0584	10.7524



Table 2

### Construct Reliability Measurement

Variable / Value	AVE	Composite Reliability	R Square	Cronbachs Alpha	Communality	Redundancy
Activity	0.6618	0.9313	0.4187	0.9131	0.6618	0.2731
Advantage / Benefit	0.7307	0.8434	0.1619	0.6503	0.7307	0.1125
Involvement / Engagement	0.7129	0.8322	0.3333	0.6002	0.7129	0.2362
Job Hunting	0.7288	0.8865	0.3274	0.8149	0.7288	0.2268

Convergence validity describes the average variance extracted (AVE) of the selected values between 0 and 1. The acceptable result is 0.5 or higher. The figure 0.5 describes that a minimum 50% of the indicators explain the construct (Nitzl, 2010) (C. Ringle & Spreen, 2007). Table 2 shows the AVE values for the variables and all variables fulfil the requirements. This gives more flexibility for the outer loadings as mentioned above.

The discriminate validity is given. The rule for discriminate validity for the reflective model is latent variables correlation<sup>2</sup> < AVE. The AVE value is in Table 2.

Table 3

### Latent Variables Discriminate Validity for Formative and Reflective Model

Latent variables correlation	Activity	Advantage / Benefit	Impact	Investment	Involvement / Engagement	SNS	Trust	Job hunting
Activity	1	0	0	0	0	0	0	0
Advantage / Benefit	0.5912	1	0	0	0	0	0	0
Impact	0.7275	0.5706	1	0	0	0	0	0
Investment	0.7238	0.5902	0.7404	1	0	0	0	0
Involvement / Engagement	0.6564	0.6529	0.5729	0.72	1	0	0	0
SNS	0.6471	0.4024	0.6978	0.8077	0.5774	1	0	0
Trust	0.7241	0.6677	0.7343	0.7833	0.6399	0.7253	1	0
Job Hunting	0.5596	0.3485	0.5457	0.4381	0.3756	0.5722	0.557	1

The result of the reflective measurement model is positive and gives a good overview of the value of the construct and it's robustness.

### Testing the Formative Measurement Model

The validity of the formative measurement model is the indicators relevance. The value is between -1 and 1. The accepted value is 0.1 or higher (Fuchs, 2011). If the variable is not suitable and has to be deleted then the value of the measurement model is reduced and the explanation of the model decreased (C. Ringle, 2004b).





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Ringle has done a study and found 93.85% of PLS studies has done bootstrapping method. This method is used to identify relationships between construct and indicator. The value should be between 1 and -1 and not 0. This will be the outer weight of the indicators and gives an indication for the significant (Nitzl, 2010) (C. Ringle et al., 2012).

Table 4

## Outer Weights, Reflective Model

Outer Weights (Mean, STDEV, T-Values)	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	Standard Error (STERR)	T Statistics (O/STERR)
Do you trust the information on your social network site? -> Trust	0.1532	0.1712	0.1116	0.1116	1.373
How often have you provided information or resources to another member of the social network site to give them an advantage in the last 12 months -> Investment	0.0212	0.0404	0.0312	0.0312	<b>0.679</b>
How often have you used recommendation / support of social network site? -> Impact	0.5362	0.5335	0.0955	0.0955	5.6146
Information about holidays, restaurants etc. - shared content -> Investment	0.4178	0.4138	0.0575	0.0575	7.2703
Information about individuals - shared content -> Investment	-0.1986	-0.203	0.0928	0.0928	2.1385
Members of the network who have a direct tie to you and give them your information exclusively -> Trust	0.6022	0.5932	0.0884	0.0884	6.8151
Negative experience (e.g. you have been cheated... -> Trust	0.3406	0.3259	0.1016	0.1016	3.3532
Positive experience (e.g. you got access to important information...) -> Trust	0.1579	0.163	0.0967	0.0967	1.6334
All members have access to your information -> Trust	0.1816	0.1786	0.0747	0.0747	2.4297
Information about business - shared content -> Investment	0.0132	0.0555	0.0435	0.0435	<b>0.3032</b>
Number of friends -> SNS	1.0046	1.0047	0.0365	0.0365	27.4884
number of friends less than 250 -> SNS	0.9682	0.9686	0.0402	0.0402	24.0981
Shared content - Evaluation of services -> Impact	-0.1148	-0.1291	0.0861	0.0861	1.3338
Shared content - evaluation of products -> Impact	0.6454	0.6301	0.092	0.092	7.0123
Shared content - geographical information about -> Investment	-0.2539	-0.2462	0.0839	0.0839	3.0252
Shared content - picture -> Investment	0.7176	0.7117	0.1118	0.1118	6.4192
To get consultancy / to get advise -> Impact	-0.5301	-0.5211	0.0707	0.0707	7.4952
To get new ideas -> Impact	0.2486	0.2405	0.0932	0.0932	2.6667
To maintain friendship -> Investment	0.3724	0.372	0.0645	0.0645	5.7739



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Two indicators have a weak t-value but both indicators are important for the research and bold. Two more indicators are italic because their t-value gives a lower significant than the other results. The expectation for these indicators is a higher value for another population. The indicators have to be under consideration.

Multicollinearity tests the relevance of the indicators and the dependence between the indicators. If multicollinearity exists between two indicators then the indicator should be under consideration. A multicollinearity effect is not desirable because then the indicator is not independent. This could be a reason to delete an indicator. The results of the Multicollinearity fulfil the requirements as demonstrated in Table 5 (Nitzl, 2010) (Fuchs, 2011).

Table 5

## Adjusted R<sup>2</sup> and Multicollinearity for outer weights, formative model

Variable Name Outer weights	Adjusted R <sup>2</sup>	Multicoll.
Do you trust the information on your social network site? -> Trust 18	0.734	3.7593985
Members of the network who have direct tie to you and give them your information exclusively -> Trust 22	0.615	2.5974026
Negative experience (e.g. you have been cheated... -> Trust 16	0.286	1.40056022
Positive experience (e.g. you got access to important information...) -> Trust 17	0.705	3.38983051
All members have access to your information -> Trust 23	0.399	1.66389351
How often have you provided information or resources to another member of the social network site to give them an advantage in the last 12 months -> Investment 14	0.374	1.59744409
Information about holidays, restaurants etc. - shared content -> Investment 20_7	0.503	2.01207243
Information about individuals - shared content -> Investment 20_8	0.507	2.02839757
Information about business - shared content -> Investment 20_4	0.296	1.42045455
Shared content - geographical information about -> Investment 20_6	0.565	2.29885057
Shared content - picture -> Investment 20_1	0.669	3.02114804
To maintain friendship -> Investment 11_1	0.498	1.99203187
Shared content - Evaluation of services -> Impact 20_3	0.672	3.04878049
Shared content - evaluation of products -> Impact 20_2	0.64	2.77777778
How often have you used recommendation / support of social network site? -> Impact 19	0.388	1.63398693
To get consultancy / to get advise -> Impact 11_06	0.181	1.22100122
To get new ideas -> Impact 11_07	0.323	1.47710487

The t-test should be done to test the model. The expected results are a minimum of 1.65 with 10% probability of error or larger than 1.96 with 5% probability of error. The t-test has the advantage that the significant is included in the t-test.



The discriminant validity needs a value of the latent variables correlation below 0.9 for the formative variables. This result is fulfilled and demonstrated in Table 3 (Fuchs, 2011).

## Testing the Structural Model

The coefficient of determination is  $r^2$  and the values between 0 and 1. The results should be above 0.19 then the coefficient is weak. Results above 0.33 are good and higher than 0.67 are excellent. The objective should be to have excellent results above 0.67. The higher the  $r^2$  the better is the result (Nitzl, 2010) (C. Ringle, 2004a) (Fuchs, 2011) (Chin, 2010). The results for  $r^2$  are presented in Table 2.

Path coefficients should be between 1 and -1. Coefficients should be next to 1 or -1. Results between 0.2 and -0.2 are weak. The t-value gives an indication for the significant of the path coefficients (Nitzl, 2010) (Fuchs, 2011) (Chin, 2010).

Table 6

### Path Coefficient

Path coefficients	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	Standard Error (STERR)	T Statistics (O/STERR)
Impact -> SNS	0.161	0.1571	0.0721	0.0721	2.2334
Investment -> SNS	0.551	0.5602	0.072	0.072	7.6526
SNS -> Activity	0.6471	0.65	0.0379	0.0379	17.0956
SNS -> Advantage / Benefit	0.4024	0.4039	0.0486	0.0486	8.2849
SNS -> Involvement / Engagement	0.5774	0.5808	0.0571	0.0571	10.1135
SNS -> Job Hunting	0.5722	0.5735	0.0489	0.0489	11.7088
Trust -> SNS	0.1755	0.1788	0.0577	0.0577	3.0438

Blindfolding Procedures describe the prediction of the model. The Prediction is defined as  $Q^2$  and any result above 0 has a good prediction, results below 0 are not useful for a prediction. The results 0,02 or lower have a very low prediction, 0.15 or lower are on a middle level and higher than 0.35 have a high prediction for the variable (Nitzl, 2010) (C. Ringle, 2004a) (Fuchs, 2011) (C. Ringle & Spreen, 2007). The structural model has a good prediction. The results for  $Q^2$  are all above 0.16 and 7 of 8 variables are above 0.35.

Table 7

### $Q^2$ Values for the Model – Prediction Power

Total	$Q^2$
Activity	0.6377
Advantage / Benefit	0.5335
Impact	0.4125
Investment	0.4361
Involvement / Engagement	0.7345
SNS	0.1693
Trust	0.5028
Job hunting	0.7193



## Conclusion and Future Works

This paper successfully evaluated the model. The result is compared to get an overview. The different values have to be under consideration and the result for the model should be independent of one result. The whole picture of this paper has provided an important overview of the model and confirmed the theory. It has shown a positive effect on the model.

The next step of the authors study is to test the model with a larger sample of data to increase the reliability and validity. On the other hand, the hypothesis has to be tested to identify a causal mechanism and to explore the use of social network sites to identify employment opportunities by network members. Some results are forwarded for future evaluations of their value or to eliminate weak indicators and variables apart from analysis

SmartPLS is a valid tool to test a model and to describe complex structures. The program helps to create a model and to evaluate the model. This model has not been used in the research field of human resources under consideration of the employment seeking process before so this is a novel research undertaking creating new opportunities in this field. The flexibility of the SmartPLS software and less restricted rules enables scientists to explore causal mechanism with small samples and undistributed data.

## Bibliography

- Chin, W. W., 2010. How to Write up and Report PLS Analyses. In V. Esposito Vinzi, W. W. Chin, J. Henseler, & H. Wang (Eds.), *Handbook of Partial Least Squares* (pp. 655-685). Berlin, Heidelberg: Springer Berlin Heidelberg. doi:10.1007/978-3-540-32827-8.
- Fuchs, A., 2011. Methodische Aspekte linearer Strukturgleichungsmodelle Methodische Aspekte linearer Strukturgleichungsmodelle Ein Vergleich von kovarianz- und varianzbasierten Kausalanalyseverfahren. Würzburg.
- Haenlein, M., & Kaplan, A. M., 2004. A Beginner's Guide to Partial Least Squares Analysis. *Understanding Statistics*, 3(4), pp. 283-297. doi:10.1207/s15328031us0304\_4.
- Hair, J. F., Ringle, C. M., & Sarstedt, M., 2013. Partial Least Squares Structural Equation Modeling: Rigorous Applications, Better Results and Higher Acceptance. *Long Range Planning*, 46(1-2), pp. 1-12. doi:10.1016/j.lrp.2013.01.001.
- Hair, J. F., Sarstedt, M., Pieper, T. M., & Ringle, C. M., 2012. The Use of Partial Least Squares Structural Equation Modeling in Strategic Management Research: A Review of Past Practices and Recommendations for Future Applications. *Long Range Planning*, 45(5-6), pp. 320-340. doi:10.1016/j.lrp.2012.09.008.
- Hooper, D., Coughlan, J., & Mullen, M., 2008. Structural equation modelling: guidelines for determining model fit. *Electronic Journal of Business Research Methods*, 6(1), pp. 53-60. [Online] Available at: <http://arrow.dit.ie/cgi/viewcontent.cgi?article=1001&context=buschmanart>.
- Nitzl, C., 2010. Eine anwenderorientierte Einführung in Partial Least Square (PLS)-Methode. Available at SSRN 2097324. [Online] Available at: <http://papers.ssrn.com/sol3/Delivery.cfm?abstractid=2097324>.
- Ringle, C., 2004a. *Gütemaße für den Partial-least-squares-Ansatz zur Bestimmung von Kausalmodellen*. Hamburg. [Online] Available at: [https://www.wiwi.uni-muenster.de/mcm/studium/veranstaltungen/downloads/2011\\_WS/AdvancedMarketResearch/Ringle\\_WP\\_2004\\_Guetemasse.pdf](https://www.wiwi.uni-muenster.de/mcm/studium/veranstaltungen/downloads/2011_WS/AdvancedMarketResearch/Ringle_WP_2004_Guetemasse.pdf).
- Ringle, C., 2004b. Messung von Kausalmodellen. *Ein Methodenvergleich, Arbeitspapier*, (14). [Online] Available at: [https://www.wiwi.uni-muenster.de/mcm/studium/veranstaltungen/downloads/2011\\_WS/AdvancedMarketResearch/Ringle\\_WP\\_2004\\_Messung\\_von\\_Kausalmodellen.pdf](https://www.wiwi.uni-muenster.de/mcm/studium/veranstaltungen/downloads/2011_WS/AdvancedMarketResearch/Ringle_WP_2004_Messung_von_Kausalmodellen.pdf).
- Ringle, C., Boysen, N., Wende, S., & Will, A., 2006. Messung von Kausalmodellen mit dem Partial-Least-Squares-Verfahren. *Das Wirtschaftsstudium*, 01. [Online] Available at: <http://scholar.google.com/scholar?hl=en&btnG=Search&q=intitle:Messung+von+Kausalmodellen+mit+dem+Partial-Least-Squares-Verfahren#0>.



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- Ringle, C. M., & Sinkovics, R. R., 2009. The use of partial least squares path modeling in international marketing. (J. Henseler, C. M. Ringle, & R. R. Sinkovics, Eds.) *New Challenges to international marketing*, 20(2009), pp. 277-319. doi:10.1108/S1474-7979(2009)0000020014.
- Ringle, C., Sarstedt, M., & Straub, D. (2012). A Critical Look at the Use of PLS-SEM. *MIS Quarterly*, 36(1). [Online] Available at: <http://scholar.google.com/scholar?hl=en&btnG=Search&q=intitle:A+critical+look+at+the+use+of+pls-sem#4>.
- Ringle, C., & Spreen, F., 2007. Beurteilung der Ergebnisse von PLS-Pfadanalysen. *Das Wirtschaftsstudium*, 02. [Online] Available at: <http://scholar.google.com/scholar?hl=en&btnG=Search&q=intitle:Beurteilung+der+Ergebnisse+von+PLS-Pfadanalysen#0>.
- Shackman, J., 2013. The Use of Partial Least Squares Path Modeling and Generalized Structured Component Analysis in International Business Research: A Literature Review. *International Journal of Management*, 30(3), pp. 78-86. [Online] Available at: <http://search.ebscohost.com/login.aspx?direct=true&profile=ehost&scope=site&authtype=crawler&jrnl=08130183&AN=89139082&h=8iVyzLYwTjwS73WDkz4AfDDsZS6BorAhVUBggt%2Bqa8CKA1pS9IsUdYZlxZy48URMt%2FR5g5u%2BWX1KPCqAvPwSHA%3D%3D&crl=c>.
- Tenenhaus, M., Vinzi, V. E., Chatelin, Y.-M., & Lauro, C., 2005. PLS path modeling. *Computational Statistics & Data Analysis*, 48(1), pp. 159-205. doi:10.1016/j.csda.2004.03.005.
- Urban, D., & Mayerl, J., 2013. *Strukturgleichungsmodellierung*. Wiesbaden: Springer Berlin Heidelberg.