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Valery OLEFIR

Structural equation modeling method in personal potential research

In the last decade, the method of structural equation modeling (SEM) is an increasingly popular approach to the analysis of data among foreign psychologists [3, 6, 8, 10]. The popularity of this method is due to several reasons:

1) The scientists use multidimensional approach to study the psychic phenomena and create sophisticated theoretical models for the researching, which is clearly insufficient bivariate correlations. Therefore, the method of SEM becomes the preferred method for the verification of theoretical models.
2) The increasing requirements for the validity and reliability of measurement instruments. If the traditional multivariate methods are not considered as residual terms of measurement, the SEM methods allow to do it.
3) The possibility of applying SEM to check extra advanced theoretical models, such as several groups models, multilevel models, estimation of main effects and interaction effects and others.
4) The development of the flexible user-friendly software packages for the analysis of covariance structures, such as AMOS [1], EQS

[2], LISREL [5], Mplus [9], which makes this SEM method available for a significant community of researchers.

However, it is still not widely used among the Ukrainian researchers. In addition, there is no methodological works written in Ukrainian.

The purpose of this article is to provide a non-mathematical introduction to the various aspects of the structural equation modeling method for the researchers in psychological field.

The SEM method concept.

The structural equation modeling method is a comprehensive statistical approach for testing hypotheses about the relationship between the observed and latent variables [7]. The observed variables are also called indicator variables or explicit variables. Latent variables represent unobserved variables or factors. The examples of latent variables in psychology are intelligence, depression and personal potential. The latent variables cannot be measured directly.

The SEM models types

The structural equations models are used in different researches. There are four types of models that are widespread today: path analysis; confirmatory factor analysis model; structural regression models, and the latent changes models.

Path analysis model (PA model) is a logical continuation of multiple regression models. In path analysis, the structural relationship between the observed variables is modeled. Structural relationship is the hypotheses about the influence directions or several variables relationship that is as independent variables affect the dependent variable. Therefore path analysis is sometimes called a causal modeling. In fact using this method rather verified theoretical understanding of causal relationships.

The confirmatory factor analysis model (CFA model) is commonly used to investigate the relationships among the various constructs. Each construct in the model is measured near the observed variables. The main feature of CFA models is that no specific relationships are directed between the constructs as they can only be correlated with each other.

Structural regression models (SR model) are based on the CFA models postulating certain explanatory relations (i.e., latent regression) among variables. SR models are often used to verify or refute the theory of proposals, including the explanatory relations among different latent variables.

The models of latent changes (LC model) are used to study the changes through the time. For example, LC models are used to analyze changes in a longitudinal study of data and allow the researchers to study the interpersonal.

Data example

As a rule, structural equation modeling includes five steps: model specification, identification, estimation, evaluation, and modifications (if it's necessary). These five steps will be illustrated in the following sections using the data obtained in the study. The purpose of research was to investigate the contribution of personal potential and regulatory resources rescuers in ensuring the reliability of their actions in stressful emergency situations. In this example we will present a step by step overview of structural equation modeling using the software package AMOS, when the hidden and observable variables are continual.

The sample size had 248 participants. Next procedures have been used to measure three constructs: personal potential, self-regulation and reliability professional actions. Personal potential indicators were autonomy oriented (AO), tolerance for ambiguity (TA), self-efficacy (SE), action orientation subsequent to failure (AOF), action orientation during (successful) performance (AOP), vitality and optimism attributive (OA). The self-regulation indicators were modeling (M), programming (P) and evaluation of results (ER).The reliability indices for action were the infallibility (of action (IA), resistance skills with technology and equipment (RS), the interaction in the team (IT).

Measurement and Structural Models

In general the structural equation modeling includes an assessment of the two models between the studied variables: the measurement model and the structural model. Measurement model or factor model, defines the relationship between the observed variables and latent variables. The structural model defines the relationship between the latent variables involving the theory.

The connection between the measurement and structural models can be defined the two-step approach to modeling the structural variables. Two-step approach emphasizes the measurement and analysis of structural models as two conceptually different models.

The justification of a two-stage approach is given by K.G. Jöreskog and D. Sörbom [5] who states that the verification of theoretical assumptions (structural model) does not make sense if the model does not provide a measurement of the required level of convergent and discriminant validity. This is because the selected data does not measure constructs that are defined by the theory, the figures have to be changed before the structural relationships will be checked.

The measurement model is the step of the SEM model, which defines the relationship between the observed and latent variables. The confirmatory factor analysis is used to check the measurement models. The researcher must choose the measurement observable indicators in the model to determine the latent factors. The accuracy of determining the latent variable depends on how closely related the observed indicators are. Obviously if one indicator is weakly related to other indicators it will lead to an inaccurate definition of the variable latent. In the SEM's terms this means that there was an error in the specification alleged relationship between variables.

Figure 1 is an example of the measurement model of the construct, which is called a «Personal potential». The model contains three latent factors (ovals), each of them is rated by two or three observed variables (rectangles). Straight lines with arrows indicate the projected effects of some variables to the others. In the circle on the left of each rectangle indicates the values of measurement errors (e1 ÷ e7). For purposes of this example, the assessment of internal consistency, as an indicator of

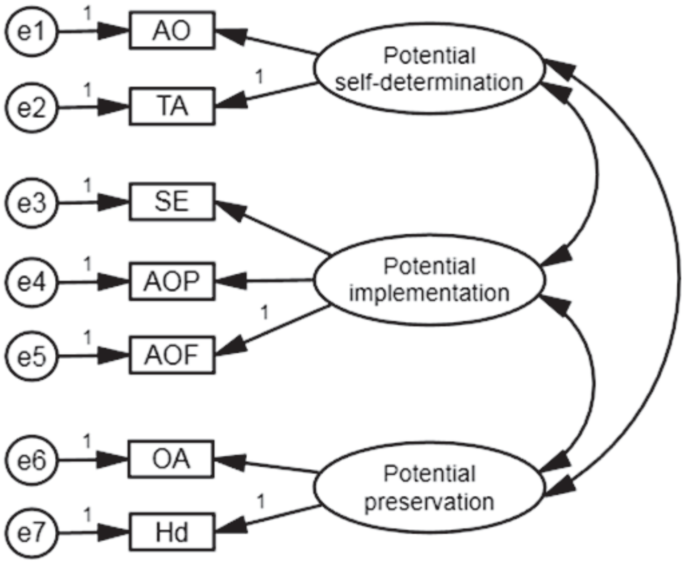

Figure 1. The measurement model of the construct «personal potential»

reliability ranged from 0.64 to 0.76.

Estimated effects in SEM

The SEM method allows to evaluate the effects of two types:

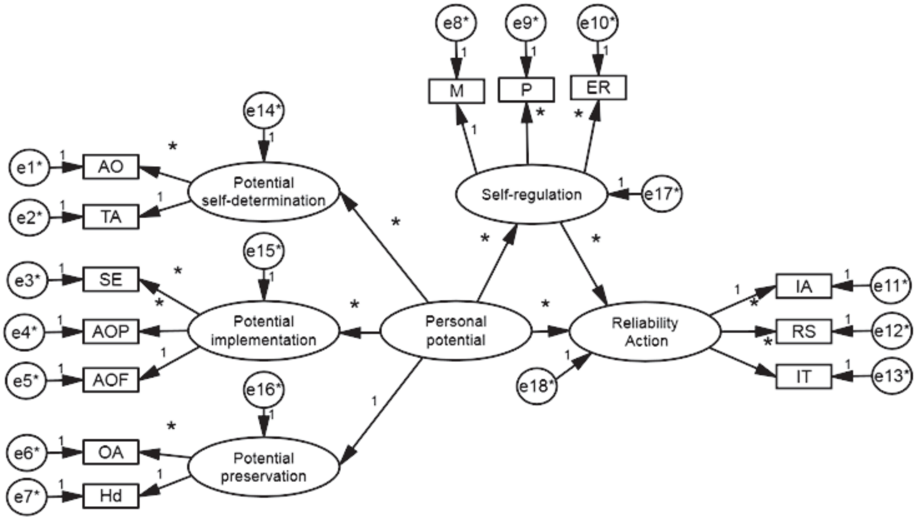

Figure 2. Example of a structural model

direct and indirect effects. The direct influence that are designated by arrowheads represents the relationship between the latent variables. For example, in Figure 2 is a direct impact between self-regulation and reliable operations. In this case, the directional arrows to indicate direction of influence and do not imply a causal relationship. Indirect impacts reflect the relations between the independent hidden (external, exogenous variable) variable, for example, Personal potential and latent dependent (internal, endogenous variable) variable, such as reliability of action. Indirect interactions are mediated by one or more of the latent variable, for example, self-regulation (see. Figure 2).

The structural equation modeling method's using steps

According to the current concepts, the process of structural equation modeling involves five steps: 1) specification, 2) identification, 3) estimation, 4) testing and as an opportunity 5) modifying step model.

The Model's specification

At this stage, the researcher defines the expected relations among observed and latent variables, which are contained (or not contained) in the model.

The relationships among the variables are presented by options or paths. This relationship may be designated as fixed, free or restricted. The fixed parameters are not estimated from the sampled data, and as a rule, either fixed to zero, that indicates no connection between the variables or unity. In the case the parameter is fixed at zero, there is no path denoted as arrow is not shown in the diagram. The free parameters are estimated from the observed data and as the researchers suggest they differ from the zero (these parameters are indicated by asterisks in the figure). The limited options are options, which are set to be equal to a certain value (e.g., 1.0).

The choice of parameters which are free and which are fixed in the model must be based on the results of the analysis of the literature, knowledge in a particular area, the researchers own assumptions. In other words, the model should be theoretically justified.

There are three types of indicators that should be determined at the stage of the specification: direction effects, variance and covariance.

The directional effects describe relations between the observed variables (factor loadings) and the hidden variables and the relationship between the latent variables (travel coefficients). Arrowheads from the Figure 2 from the latent variable to the *Potential implementation* of measured variables SE (self-efficacy) and AOP (action orientation during (successful) performance of activities) are the examples of the factor loadings to be estimated, while the load factor AOF (action orientation subsequent to failure) has been established 1.0. The arrow from variable *Self-regulation* to variable *Reliability action* is the example of path coefficients showing the relationship between the latent variable (exogenous variable) and the other (endogenous variable). The directed effects specified fig. 2 – eight factorial loadings between latent variables and observed variables, two factorial loadings between a latent factor of the second order (Personal potential) and three latent factors of the first order and three path coefficients between latent variables that in total give thirteen parameters (in Figure 2 are marked with asterisks).

Dispersions are estimated for the independent latent variables which path loadings were established in 1.0. Figure 2 and evaluated for the variance of measurement errors (e1-e13) associated with thirteen observable variables, error latent variables (e14-e16) and associated errors connecting with two endogenous variables (*Self-regulation* and *Reliability action*) and the only exogenous variable (*Personal potential*).

Covariance is the non-directional connections among the independent latent variables (curved double-headed arrows). They exist when the researcher hypothesizes that two factors are correlated. The model is shown in Figure 2, do not provide any covariance. In general the parameter 32 (3 path coefficient factor loads 10 and 19 dispersions) in Figure 2 were determined for the evaluation.

Model Identification

The researcher posed the question in this stage if the free parameters of the observed data for each unique value could be obtained. The identification of the model depends of the specification of the parameters as fixed, free or restricted. There are three types of identification patterns:

A model is *underidentified* (or not identified) if one or more parameters may not be uniquely determined because there is not enough information in the matrix *S.*

A model is *just-identified* if all of the parameters are uniquely determined because there is just enough information in the matrix *S.*

A model is *overidentified* when there is more than one way of parameter (or parameters) estimation because there is more than enough information in the matrix *S.*

The model should be *overidentified* to be assessed and to be available for testing the hypotheses about relationships among variables. The researcher must ensure that the number of off-diagonal elements of the correlation matrix, which are derived from the observed variables are more than the number of parameters should be estimated. If the difference between the number of elements in the correlation matrix and the number of parameters should be estimated is a positive number (called the degree of freedom) then the model is overidentified. It is used the following formula to calculate the number of elements in the correlation matrix: $[p(p + 1)] / 2$, where p is the number of observed (measured) variables.

Applying this formula to the model in Figure 2, thirteen observable variables, giving [13 (13 + 1)] / 2 = 91. 32 parameters defined for the evaluation of the freedom degree 91-32 = 59, which makes the model shown in Figure 2 overidentified. When the degree of freedom is zero, the model is easy to identify. In the other hand, if the degree of freedom is a negative number, then the model has not been identified, and the parameter estimation is not possible.

An important task of the SEM method is to find the simplest model to represent the relations between variables, which accurately reflects the relationship of empirical data. Thus a large number of degrees of freedom implies simpler model. Typically the identification pattern specification precedes data collection. Before proceeding to the evaluation of the model the researcher has to deal with issues related to the sample size and data validation.

Sample size. Determining the size of the sample, some researchers consider the following requirements: error model specifications, the complexity of models used and the method of assessment model features of the distribution of observed variables [4, 8]. The error specification of the model can be called in case of exclusion or inclusion of certain variables or parameters. The sample size affects the probability of a correct evaluation of the model and the definition of the error specification. Typically when a complexity of the model is increased the volume of the sample is increased too.

The useful rule for determining the sample size depending of the complexity of the model is suggested by R.B. Kline [8, p.12]. This N / q rule, where N – number of participants, and q – the number of model parameters that require statistical estimates. The ideal ratio of sample size to parameters is 20:1. Less ideal ratio is 10:1.

Multicollinearity. This applies to situations where the measured variables (indicators) are too closely related. This is a problem for the application of the method of SEM, because researchers use related indicators as indicators of constructs and if these figures are too strongly connected they can influence certain statistical tests results. The common practice to check the data for multicollinearity is to calculate the bivariate correlations for all measured variables. Any pair of variables with correlations greater than r = 0,85 causes potential problems. In such cases one of these two variables should be excluded from further analysis.

Multivariate normal. Commonly used methods of LSG suggest that multivariate distribution usually has a normal distribution. R.B. Kline (2005) showed that if all the one-dimensional distributions are normal, and the joint distribution of any pair of variables is bivariate normal. Violation of these assumptions can affect the accuracy of the statistical tests in structural equation modeling. Multivariate normality is investigated using the normalized multivariate kurtosis values which is called Mardia. This is done by comparing the coefficient data Mardia for studies with values calculated according to the formula $p \times (p + 2)$, where p is equal to the number of observed variables in the model. If the coefficient of Mardia lower than the value obtained from the above formula the data are considered as multivariate normal.

Missing data. The presence of missing data often occurs due to factors outside the control of the researcher. Depending on the extent and nature the missing data should be restored if they do not occur randomly and make up more than ten percent of the total data. To cope with the problem of missing data using such techniques as the complete removal, pairwise deletion, and the multiple recovery method.

Model Estimation

Objective evaluation of the model is to reproduce the matrix Σ (θ) (model implied the estimated covariance matrix), which resembles the matrix S (the estimated sample covariance matrices) of the observed variables with the residual matrix (S - Σ (θ)) as small as possible. When S - Σ (θ), = 0, then the χ^2 becomes zero, and gets a great model for the data. The rating model includes the definition of the values of the unknown parameters and the errors associated with the estimated values.

The evaluation process involves the use of special functions of conformity to minimize the difference between the covariance / correlation matrix Σ (θ), and S. There are some functions of selection or assessment procedures – or unweighted ordinary least squares (ULS or OLS), generalized least squares (GLS) and evaluation maximum likelihood (ML).

Evaluation example. The represented model in Figure 2 is estimated using maximum likelihood in AMOS18,0. Figure 3 shows the standardized results for the structural part of the full model. Structural parts are also called structural regression model. The AMOS provides standardized and non-standardized results that are similar to the standardized β and non-standardized B weights in regression analysis. As a rule standardized

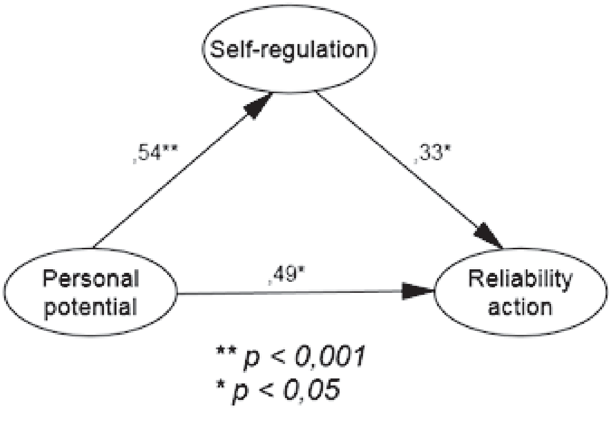

Figure 3. Structural model with path coefficients

assessments are shown in the travel diagrams and non-standardized part of the results are checked for statistical significance. For example, in Fig. 3 shows the significant associations ($p < 0.05$ level) between the three latent variables. The value of the coefficient of limit on personal capacity for self-regulation was determined by viewing the non-standardized results which equaled 0.213 and had a standard error of 0.057.

Although the critical attitude (i.e., Z-score) is automatically calculated and is given in the output in AMOS and other programs to easily determine whether the coefficient is significant (i.e., $Z \geq 1{,}96$ for $p \leq 0{,}05$) at this level alpha by dividing the standardized rate to the standard error. In this case, 0,213 divided by 0,057 equals 3.745, which is greater than the critical Z-value of 1.96 ($p = 0.05$), which indicates the significance of the parameter.

Model Fit

Once we obtain estimates of parameters for a given model SEM, the researcher must determine the extent of the theoretical model is supported by the given obtained samples.

In order to judge the adequacy of the theoretical model there are two ways: firstly, to explore some universal test compliance of all model data, and secondly, to consider the adequacy of the individual parameters of the model.

Global tests in the method are known as SEM model selection criteria. In structural equation modeling, there is a large number of indexes fitness model. Many of these measures are based on a comparison of the model implied covariance matrix Σ with the sample covariance matrix S. If Σ and S are similar in some way, it can be argued that the data are consistent with the theoretical model. If Σ and S are very different we can say that the data does not correspond to the theoretical model.

Also the researcher must consider the individual parameters of the model. One should consider three main characteristics of the individual parameters. The first feature is if the free parameter significantly different from zero. If the critical value is greater than the expectation of a predetermined level (e.g., 1.96 for two-tailed test at 0.05), the parameter significantly different from zero. The second feature is if the sign of the parameter does the same expectation from the theoretical model. For example, if the expectation consists of the high quality education and it definitely leads to the higher income, the assessment with a positive sign confirms this expectation. The third feature is that parameter estimates should be meaningful so they must be within the expected range of values. For example, the dispersions should not be negative values and the correlation should not exceed 1. So all the free parameters have to be in the expected direction and statistically it should be different from zero and have a practical sense.

In general the model selection indices are divided into three categories: absolute conformity, compliance and conformity comparative simple model.

Absolute index of fitness provides an assessment of how well the theory corresponds to the researcher sample data. The main index of absolute fitness – χ^2 (chi-square), which verifies the degree of model misspecification. Also statistically significant χ^2 suggests that the model does not match the selected data. In contrast the non-significant χ^2 is typical for a model that fits the data well. However, χ^2, as stated is too sensitive to the increased sample volume so that the level of probability tends to be meaningful. χ^2 also tends to be greater when the number of observed variables increases. Therefore, χ^2 can not be used as the sole indicator of model selection in the SEM.

The index of the fit (*GFI*) assesses the relative amount of the observed differences and the covariance explaining the model. It's like the R^2 in the regression analysis. For a good fit of the recommended value should be $GFI > 0{,}95$ (with $GFI = 1$ achieved a perfect fit). Adjusted goodness of fit index (*AGFI*) takes into account models of varying complexity and adjusts *GFI* ratio of degrees of freedom used in the model to the total amount of degrees of freedom. The standardized root means square residuals (*SRMR*) is a sign of the value of the error as the result from the evaluation of the given model. The root means square error of approximation (*RMSEA*) corrects the tendency to reject the model χ^2 large or many variables. As *SRMR*, the lower value *RMSEA* ($<0{,}05$) indicates a good fit and it is often reported with 95% confidence level to account for sampling error associated with the estimated *RMSEA*.

In the comparative fit hypothetical model is judged by the extent to which it is better than competing models. As a final it often performs basic model (the so-called null model) which assumes that all of the observed variables are not correlated. A widely used example of the index is the index of the comparative selection (*CFI*) which indicates a relative lack of selection of this model against the base model. It is normalized and ranges from 0 to 1 with higher values representing the best fit of the model. The *CFI* is widely used because of its advantages, including its relative insensitivity to the complexity of the model. The value of *CFI* $> 0{,}95$ indicates a good model. Another benchmark index of fitness is

Tucker-Lewis index (*TLI*), also called non-standard capability indices (*NNFI*) it is used to compare the proposed model with zero model. Since *TLI* is not normalized, its value may be less than 0 or greater than 1. As a rule the models with a good fit for its value approach to 1.0.

Test example model selection. Most of these indices were used to test the suitability of the model in Figure 2 and the results were: $\chi^2 = 93{,}657$, $p < 0{,}05$; *GFI* = 0,955; *AGFI* = 0,931; *RMSEA* = 0,046; *CFI* = 0,952; *TLI* = 0,936. It is seen that the suitability indices are not contradictory and generally satisfy the recommended level. This indicates that the hypothetical model generally corresponds well to the empirical data.

Estimates of the parameters. After discussing the structural model it is important to consider the significance of the estimated parameters. As in the regression model which fits the data well but has little statistically significant parameters that are not desirable.

From standard ratings shown in Fig. 3, it is seen that there is a reasonable relationship between the *Personal potential* and *Self-regulation* of $\beta = 0{,}54$), *Personal potential* and reliable action potential ($\beta = 0{,}49$). Nevertheless, the relationship between *Personal potential* and *Reliability of action* is also mediated by self-regulation. So, the two paths of *Personal potential* for *Reliability of action* can be traced to the model (*Personal potential* ◎ *Self-regulation* ◎ *Reliability of action*). In general, *Reliability of action* and *Self-regulation* explain 51.1% of the variance in the reliability of action. This is known as the square of the multiple correlation.

Model modification

If the intended theoretical model is not as we would like, the next step is to change the model and subsequently evaluate the modified model. This stage is often called re-specification. In a modification of the model, the researcher either adds or removes the options for improving the selection of models. In addition, the parameters can be changed or fixed on the availability to the unconnected fixed.

To modify the model, the researcher should perform the following steps:

To study estimates of regression coefficients and the corresponding covariance. Ratio of the standard error is equivalent to the Z test for significance of relations with $p < 0{,}05$ and boundary value equal to 1.96. When considering the regression weights and covariances in the originally specified model, it is likely that there is some regression weights and covariances that are not statistically significant.

To correct the covariance or travel rates to make the selection of the model better. This is usually the first step in improving the adequacy of the model.

To run the model again to see whether the fit. After making the adjustment it should be noted that the new model is a subset of the previous one. In the terminology of the new model SEM is the nested model. In this case the difference in the χ^2 test indicates whether some important information was lost with the degrees of freedom of χ^2, equal to the number of corrected paths.

To consult the modification indices (MI), provided by the most programs SEM, if the selection model still does not fit the following steps 1-3. The value of the index modification is the amount that is expected to reduce the value of χ^2, if the corresponding parameter will be free. Every step the parameter is released, which makes the greatest improvement of selection, and the process continues until the correct selection is reached.

Because the software SEM offers all the changes that will improve the fit of the model, some of these changes may be meaningless. The researcher must always be guided by the theory and to avoid making changes, regardless of how well they can improve the fit of the model.

Conclusion

In this article we have tried to give a general description of the structural equation modeling method and illustrate the various stages of the application of this method in applied psychological research. The Analysis of the results of a particular psychological research shows the possibilities of the local government to identify the complex relations between the studied variables.

Despite of the emergence of many new and easy to use software (e.g., AMOS, LISREL, Mplus), which increased the availability of the SEM method, this method involves a complex family of statistical procedures and requires that the researcher has adopted a number of decisions to avoid misuse and misinterpretation of the method results. Some of these solutions include the answers to the questions: how many subjects we need to use the method correctly; how to normalize data; what methods of assessment and fitness models use indexes; how to assess the value of these indices fitness.

We have tried consistently to present approaches to answer for these questions in this article. However the use of the SEM method is more than a simple attempt to address the application of the rules. The application of this method in psychology involves a combination of the correct application of the complex statistical procedures and theoretical understanding of the investigated problem.

This article is intended in some way to fill the existing gap in the literature of a methodological nature, representing non-mathematical and step by step introduction to the application of the structural equation modeling method which is oriented for the psychologists who have minimal mathematical knowledge and skills. So the article examines the experience of applying the method to the example of a specific SEM psychological research. In addition it will be added the sources for the independent studying in the reference list which will contribute the understanding of the features and capabilities of the structural equation modeling method in applied psychological researches.

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The Author

Valery Olefir,
PhD, Associate Professor,
Department of Applied Psychology,
Ukrainian Engineering and Pedagogical Academy,
Kharkiv, Ukraine
E-mail: vaolefir@gmail.com

Abstracts

WALERIJ OLEFIR. **Badania potencjału osobowości metodą modelowania równiań strukturalnych.** *W artykule przedstawiono ogólnącharakterystykę metody modelowania równań strukturalnych. Opisano etapy w zastosowaniu metody modelowania równań strukturalnych na przykładzie danych, uzyskanych w wyniku badań konstruktu «potencjał osobowości». Przedstawiono zalecenia w stosowaniu metody oraz interpretacji wyników.*
Słowa kluczowe: *Modelowanie równań strukturalnych, potencjał osobowości, rzetelność badań.*

ВАЛЕРІЙ ОЛЕФІР. **Метод моделювання структурними рівняннями у дослідженні особистісного потенциалу.** *У статті дана загальна характеристика методу моделювання структурними рівняннями. Описано етапи, які необхідні для проведення методу моделювання структурними рівняннями, які проілюстровані даними, отриманими в рамках дослідження конструкту «особистісний потенціал». Наводяться рекомендації коректного вживання методу і тлумачення результатів.*
Ключові слова: *моделювання структурними рівняннями, особистісний потенціал, надійність дій.*

ВАЛЕРИЙ ОЛЕФИР. **Метод моделирования структурными уравнениями в исследовании личностного потенциала.** *В статье дана общая характеристика метода моделирования структурными уравнениями. Описаны этапы, которые необходимы для проведения метода моделирования структурными уравнениями, которые проиллюстрированы данными, полученными в рамках исследования конструкта «личностный потенциал». Приводятся рекомендации корректного употребления метода и истолкования результатов.*

Ключевые слова: *моделирование структурными уравнениями, личностный потенциал, надежность действий.*

VALERY OLEFIR. **Structural equation modeling method in personal potential research.** *The article gives a general description of the method of structural equation modeling. We describe the steps that are necessary for carrying out the method of structural equation modeling, which are illustrated in the data obtained in the study of the construct "personal capacity". Recommendations are given the correct use of the method and interpretation of results.*
Key words: *structural equation modeling, personal potential, the reliability of action.*