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Master thesis

Struktūrinis inovatyvaus elgesio darbe modeliavimas

Structural modelling of innovative work behaviour

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Santrauka

Inovacijos – vienas svarbiausių progresą ir plėtrą lemiančių veiksnių, tačiau, visų pirma, reikia žmonių galinčių ir norinčių jas kurti. Siekiant skatinti darbuotojų inovatyvų elgesį, svarbu atkreipti dėmesį į inovatyvaus elgesio sąsajas su asmens lygio faktoriais, kuriuos būtų galima stiprinti. Šiame darbe buvo tirtos inovatyvaus elgesio darbe (domėjimosi naujovėmis, idėjų tyrinėjimo ir kūrimo, idėjų išbandymo ir įvertinimo, paramos siekio ir idėjų įgyvendinimo) sąsajos su profesiniu saviveiksmingumu ir įsitraukimu į darbą. Darbe taikytas struktūrinis modeliavimas siekiant atrasti geriausiai duomenims tinkantį modelį ir įvertinti kintamųjų ryšius. Taip pat, atliktos Monte Karlo simuliacijos siekiant atrasti geriausiai modeliui tinkantį įvertinį ir įvertinti patį modelį. Tyrimo rezultatai atskleidė, kad tiek didesnis profesinis saviveiksmingumas, tiek įsitraukimas į darbą siejasi su stipriau išreikštu inovatyviu elgesiu darbe. Įsitraukimas į darbą yra statistiškai reikšmingas tarpinis veiksnys tarp profesinio saviveiksmingumo ir inovatyvaus elgesio darbe. Galiausiai, domėjimasis naujovėmis, idėjų tyrinėjimas ir kūrimas, idėjų išbandymas ir įvertinimas ir idėjų įgyvendinimas – reikšmingi latentinio inovatyvaus elgesio indikatoriai sukurtame modelyje.

Raktiniai žodžiai : struktūrinis modeliavimas, Monte Carlo simuliacijos, inovatyvus elgesys darbe

Structural modelling of innovative work behaviour

Abstract

Innovations is an important factor for any progress and development, however, first, people, that are able and willing to innovate, are necessary. Therefore, to have a more expressed innovative work behaviour, it is important to research the relationships with its antecedents, personal factors, which could be built up to strengthen the innovative work behaviour. The aim of this paper was to investigate the relationships among innovative work behaviour (interest in novelty, exploration and creation of ideas, idea testing and evaluation, search for support and idea implementation), occupational self-efficacy and work engagement. Structural equation modelling was applied to find the best data fitting model and evaluate the relationships. In addition, Monte Carlo simulations were performed to select the best estimator and evaluate the overall model. Results indicate that occupational self-efficacy and work engagement have a positive effect on innovative work behaviour. Work engagement is a statistically significant mediating factor between occupational self-efficacy and innovative work behaviour. Finally, interest in novelty, exploration and creation of ideas, idea testing and evaluation, and idea implementation are strong indicators of innovative work behaviour in the model.

Key words : structural equation modelling, Monte Carlo simulations, innovative work behaviour

1 Introduction

Innovations is an important factor contributing to the progress and development in any sector, be it social, education, science, medicine, economics, business or any other, see [40; 68; 69]. Especially now, when the resources are abundant as never before, the possibilities to innovate form the technological side are almost endless, and at the same time, the competition, especially for businesses, is really strong – only the ones that innovate, stand the chance of being exceptional within the market. In addition, innovations are beneficial at an individual level as well and are associated with greater self-confidence, communication and personal growth. Therefore, it is affecting both, the general well-being of the society and every one of us individually as well, see [70].

For the above reasons, naturally, people are looking on how to increase the amount of innovations. It is people, who by acting creatively, are developing, adjusting, and implementing new and innovative ideas. Therefore, to have more innovations, it is important to strengthen the employee innovative work behaviour. Here, the academia and researchers, play an important role, who are trying to indicate an underlying mechanism of innovative work behaviour and it's antecedents, that could be built up to increase the innovative work behaviour. Such research, dedicated to innovative behaviour, have been increasing in recent years, see [70]. However, the research on the relationships among personal factors and innovative work behaviour is still scarce, see [71].

In this paper, we will look into the relationships among individual level factors: professional self-efficacy and work engagement, and innovative work behaviour. The two personal factors are selected as both are motivational, their predictive relationships with work related behaviour have been proven in research and also they can be strengthened to obtain better outcomes at work, for example, see [47; 58, 60; 64; 72]. In addition, currently, it is not clear how the combination of both affects innovative behaviour at work, see [73]. Identifying the patterns, could provide a more complete picture of innovative work behaviour and the possibilities to strengthen it in the workplace.

Therefore, the aim of this study is to investigate the relationships among the three factors: occupational self-efficacy, work engagement and the latent factor – innovative work behaviour.

In the first part of the paper, we will look into the theoretical background of innovative work behaviour, occupational self-efficacy and work engagement and the research done relating to the relationships among them. Then we will cover the main theoretical concepts of the applied statistical technique in the paper – structural equation modelling. The second part of the paper will contain the practical application. We will start by the necessary assumption testing prior the structural equation modelling, follow up with the discussion of applied structural equation models to find the best data fitting model and evaluate the relationships, and finalise with the Monte Carlo study to evaluate and select the better suited estimator for our data and evaluate the selected final model. A short discussion of the results and their meaning will be found at the end of the paper.

2 Theoretical overview of innovative work behaviour, occupational self-efficacy and work engagement

In this section we will first define the main constructs modelled in this work and then discuss the literature on the inter-relations between innovative behaviour, occupational self-efficacy and work engagement to better understand how the research fits into the existing work on this topic.

2.1 Innovative work behaviour

In this section we will try to define innovative work behaviour and shortly discuss the research relating to it.

Innovative work behaviour. Innovative work behaviour can be defined as intentional extra-role behaviour with a goal to create and innovate, see [39; 28; 40]. By being an extra-role behaviour, innovative work is done without any external request, instead, it is driven by internal initiative and a wish to bring gains to the organisation, see [38].

The variety of the behaviours that are manifested during innovative behaviour process varies between different authors. For example, Kanter (1988) distinguished four types of behaviour (idea generation, coalition creation, idea realisation and diffusion of the results, and commercial use), Janssen (2000) – three (idea generation, sharing of the ideas with supporters and idea realisation), and de Jong (2007) – four (search for opportunities, idea generation, creation of coalitions and idea implementation). In this work, we will be using the most recent definition of the behaviours, created by Geležinytė and Bagdžiūnienė

(2016), that include the largest number of innovative work behaviours: interest in novelty, idea exploration and generation, idea testing and evaluation, search for support and idea implementation.

Many conducted studies, exploring innovative work behaviour, measure it as a one-dimensional observable construct, despite it being manifested by numerous behaviours. In order to capture a more precise picture, this study will measure innovative work behaviour as a latent construct consisting of five behaviours. As Patterson (2002) notes, due to the variety of behaviours that are manifested during innovation at work, it is likely that different components of it will be affected by different personality features. Therefore, it is important to include all of them to the conducted research.

In order to strengthen innovative behaviour at work it is important to first define and explore the antecedents. The studied predictive factors can be grouped into four groups: individual factors, group level factors, organisational factors and environmental factors. This study focuses on two individual level factors: occupational self-efficacy and work engagement, that are described shortly below.

2.2 Occupational self-efficacy and work engagement

In this section we will provide definitions of occupational self-efficacy and work engagement.

Occupational self-efficacy. Self-efficacy consists of beliefs an employee has about his or her ability to successfully complete a task, see [42]. It is one of the most important constructs of Bandura's (2009) social-cognitive theory. According to the author, self-efficacy is a key factor for successful performance and one of the most influential factors on human motivation. It not only affects whether the person will take upon a task, but also how much effort will be put into completing it, despite the obstacles. Person's self-efficacy can differ depending on the area, moreover, a person can have high self-efficacy in only one area, several or many areas and activities.

As self-efficacy can vary depending on activity, it is important to measure the beliefs about one's efficacy related to the subject of the research. Therefore, in this work, since we are investigating self-efficacy as the predictor of work related innovative behaviour and engagement, we will assess and model the occupational self-efficacy – beliefs an employee has about his or her ability to successfully complete a work related task, see [43].

Work engagement. Work engagement is contrary to burnout and can be described as a positive emotional-motivational fulfilling, work-related state of mind that is characterized by vigour, dedication, and absorption, see [44]. According to Kahn (1990) it reflects physical, emotional and cognitive expression of self in tasks and the more employees are sure of their physical, emotional and cognitive capabilities the more active the performance of the task is and the more engagement is demonstrated.

Further, we will discuss the research that has been done related to the relationships among the three variables.

2.3 Inter-relations between variables

In the following section, we will first discuss the research done regarding association between self-efficacy and innovative work behaviour, and between work engagement and innovative work behaviour. Second, we will look at the role of work engagement and, finally, we will shortly discuss the limitations of the existing research regarding the topic.

Studies have confirmed that the higher the self-efficacy, the more a person will be engaged in his work, for example, see [45, 46]. As for the relation between self-efficacy and innovative behaviour, it has been confirmed that higher general self-efficacy predicts stronger innovative behaviour, see [47] and what is more, Hsiao et al. (2011) have confirmed that the level of teachers' self-efficacy positively predicts idea generation, search for support and idea implementation. Other research also confirm that self-efficacy has close relationship with interest in novelty, see [48], creative thinking, see [49] and new idea creation, see [50]. Therefore, studies suggest that higher self-efficacy is not only related to higher general innovative work behaviour, but with the different behaviours that it is manifested by as well. Positive association between work engagement and innovative work behaviour were found as well, see [51, 52], meaning that work engagement is important when predicting innovative behaviour at work.

As we can see, several studies confirm predictive relationships between self-efficacy and innovative work behaviour and work engagement and innovative work behaviour, however, there are no studies investigating the interaction among those three variables. In the research studying self-efficacy and work engagement in the context of other extra-role behaviours, work engagement often has a mediating role, for example, see [53]. According to the job demands and resources theory (JD-R), work engagement is an important intermediate factor between personal resources, such as optimism, self-worth or self-efficacy, and positive outcomes at work, for example, work related performance, organisational citizenship behaviour, proactive behaviour, commitment to the organisation or innovative work behaviour, see [59;

58; 54; 55; 56; 57].

Based on similar research and JD-R theory, we might expect work engagement to be a mediating factor between self-efficacy and innovative work behaviour as well, however, no research has been done so far to confirm it.

In addition, studies investigating the relations between self-efficacy and work engagement with innovative work behaviour, mainly explore general self-efficacy as oppose to occupational, which might be more appropriate when predicting work related innovative behaviour. Moreover, innovative work behaviour often is taken as a one-dimensional construct and the effect to different aspects of it remains unexplored, especially, with work engagement. In addition, no research has been done on the association between idea testing and evaluation and self-efficacy.

In the following section a theoretical overview of structural equation modelling will be presented to get a better understanding of the statistical technique.

3 Theoretical overview of structural equation modelling

Structural equation modelling (SEM) is a statistical modelling technique. It uses a conceptual model, derived from the theory, a path diagram and system of linked regression-style equations to capture complex and dynamic relationships among observed and unobserved variables. It can be defined as a multivariate analysis method consisting of studying the direct and indirect relationships between variables. SEM has the aim to test if the model constructed by researcher fits the data, see [11].

In the following subsections we will discuss the terminology and structure of structural equation models, model-fit indices, assumptions to be checked prior performing the structural modelling, estimation methods, and mediation mechanism in the structural equation models.

3.1 Latent and observed variables

SEM model can have two types of variables: observable that are measured and reflected by data and latent variables, theoretical constructs that are not being observed.

For each latent factor each measured variable (or item) receives a weight that varies between – 1 and + 1, called the "factor loading coefficient" – λ. It defines the importance of the latent factor for this variable. This means that the correlation between each pair of observed variables can be explained by their mutual association with the factor. Thus, the partial correlation between any pair of variables is assumed to be zero, see [11].

A simple example of the one-factor structure is shown in figure 1.

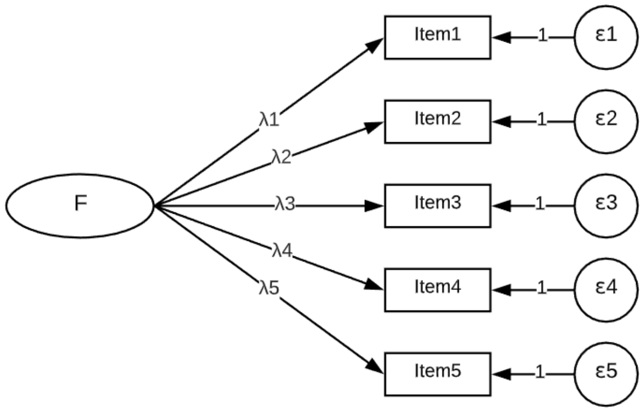

Figure 1: One-factor model.

Model in figure 1 can be written as a system of regression-type equations:

$$\begin{cases} Item1 = \lambda_1 F + \varepsilon_1 \\ Item2 = \lambda_2 F + \varepsilon_2 \\ Item3 = \lambda_3 F + \varepsilon_3 \\ Item4 = \lambda_4 F + \varepsilon_4 \\ Item5 = \lambda_5 F + \varepsilon_5 \end{cases} . \tag{1}$$

It can be assumed that the variance of each item is explained by two latent factors: one common to all items – factor F, and the other specific to each of the item – factor ε. Specific factor is a combination of item-specific variance and measurement error.

In the structural equation model the factor loading coefficient (λ) of each item is estimated. Rule of thumb is that $\lambda >= 0.4$ is sufficient to attribute the item as an indicator of the factor. A square factor loading represents the portion of the item's variance that is attributable to the latent factor – this is called the communality of the variable.

3.2 Components of SEM

Typical SEM model consists of two components. A measurement model, which describes the relationships between observed variables and latent construct, they are hypothesized to measure and a structural model – describing the inter-relationships among constructs. Therefore, structural equation model can be written by two equations (2), (3), see [20].

$$\vec{y} = \Lambda\vec{\eta} + \vec{\varepsilon}, \tag{2}$$

Equation (2) represents measurement model. Here, $\vec{y}$ is a vector of latent variable indicators. Λ is a matrix of factor loadings, with dimensions $p \times k$, p being the number of indicators' factor loadings (λ), k – the number of latent variables. Λ matrix containing factor loadings describes the relationships between the latent variable and its indicators. $\vec{\eta}$ is a vector of latent variables, and $\vec{\varepsilon}$ a vector of measurement errors, their p x p covariance matrix is noted as Θ_ε.

$$\vec{\eta} = \Gamma X + \vec{\zeta}. \tag{3}$$

Equation (3) represents structural model. Here $\vec{\eta}$ is a vector of latent variables, Γ – a matrix of regression coefficients describing the relationships between latent variables and their predictors, $\mathbf{X}$ – a matrix of the predictors of the latent variables, and $\vec{\zeta}$ is a vector of disturbances associated with latent variables, explaining it's variance that is unexplained by the predictors, the matrix of disturbances is marked as Ψ_ζ.

3.3 Model fit

A matrix of factor loading products can be called a model-implied matrix ($\mathbf{\Sigma}$), which represents the reproduced model implied covariances. The difference between observed covariances (observed matrix $\mathbf{S}$) and model implied covariance matrix ($\mathbf{\Sigma}$), measures the overall fitting of the model.

The fit of the model is assessed during an iterative process. It starts from an initial value specified automatically by the software and is refined in the process of successive iterations by the selected estimation method (for more, see section 3.6). The refinement stops when no new value for each parameter is able to reduce the difference between observed and model implied matrix, see [11].

The chi-square test indicates the statistical significance of the model and indicates whether the null hypothesis stating that observed and reproduced matrices are equal is admissible. The chi-square value tends to increase with the discrepancy.

Chi-square is calculated as in equation (4)

$$\chi^2 = (N)F_{min}, \tag{4}$$

where N is the sample size and F_{min} denotes minimum discrepancy obtained by the estimation method used, see [11].

It is worth noting that the chi-square test requires multivariate normal data assumption to be satisfied, its violation might result in a perfectly good model being rejected.

Therefore, in addition to chi-square test, it is recommended to include other model fit indices in the analysis. See the discussion on those in the following section.

3.4 Model-fit indices

SEM analysis requires indices to judge, how well the model fits the data. There are numerous indices in all packages to choose from.

Hu, Li-tze, and Peter M. Bentler (1998) suggested that one should report both, relative and absolute indices of model fit. Absolute indices of model fit compare the fit of constructed model to a perfect fitting model – RMSEA and SRMR are the most popular among those. Relative indexes of model fit compare the fit of constructed model to the fit of the (worst fitting) null model, where all covariances equal zero, for these, the recommendation is to choose TLI or CFI indices. Indices mentioned above are the most commonly used in SEM research.

The Root-Mean-Squared Error of Approximation (RMSEA; Browne & Cudeck, 1992) scales F_0 – the population minimum of the Maximum-Likelihood fitting function by the model degrees of freedom. F_0 defined as:

$$F_0 = log|S| - log|\hat{\Sigma}| + tr(\hat{\Sigma}S) - p. \tag{5}$$

Here, $\mathbf{S}$ is the $p \times p$ population covariance matrix, $\hat{\mathbf{\Sigma}}$ – $p \times p$ model-implied covariance matrix and p – the number of observed variables (more on the maximum likelihood function in section 3.6.1.)

RMSEA is defined as:

$$RMSEA = \sqrt{(F_0/df)}. \tag{6}$$

Here df denotes degrees of freedom. The lower values of RMSEA – indicate better fit. However, it has been noted that RMSEA tends to penalize small samples, especially having small number of df. SRMR and CFI are relatively sample size independent, which gives them more flexibility. For these reasons, further in this study, we will be using RMSEA in addition with SRMR and CFI goodness of fit measures.

The Standardized-Root-Mean-Square Residual (SRMR) is a measure of the average difference between the standardized model-implied and population covariance matrix, it takes values from 0 to 1. With SRMR, the lesser the deviation between model-implied and population covariance, the lesser the value of SRMR. The fit is better when the value is close to 0, but the value equal or less than 0.8 indicate a good model fit, see [11].

Let s_{ij} be the sample covariances, $\hat{\sigma}_{ij}$ – model implied covariances, s_{ii} and s_{jj} – observed standard deviations, and p – the number of observed variables. Then SRMR can be defined as, see [74]:

$$SRMR = \sqrt{\frac{2\sum_{i=1}^{p}\sum_{j=1}^{i}[\frac{(s_{ij}-\hat{\sigma}_{ij})}{s_{ii}s_{jj}}]^2}{p(p+1)}}. \tag{7}$$

The Comparative Fit Index (CFI) is an incremental index expressing the proportionate reduction of misfit associated with hypothesized model in relation to the null-model (that constrains all covariances to zero). CFI is calculated as in equation (8).

$$CFI = \frac{1 - max[(\chi^2{}_t - df_t), 0]}{max[(\chi^2{}_t - df_t), (\chi^2{}_n - df_n), 0]}, \tag{8}$$

- $\chi^2{}_t$ - the chi-square value of the specified and estimated theoretical model;
- df_t - the degrees of freedom of the specified and estimated theoretical model;
- $\chi^2{}_n$ - the chi-square value of the baseline model ("null" model);
- df_n - the degrees of freedom of the baseline model ("null" model);
- max - indicates the use of the highest value, or even zero if this is the highest value.

According to Hu and Bentler (1998) a value CFI $\geqslant$ 0.95 indicates a significant increase in the goodness-of-fit with respect to a null model, however the value CFI $\geqslant$ 0.9 is still used to judge, whether model is acceptable or not.

3.5 Assumptions

SEM is based on assumptions that ought to be met for researchers to trust the results. Violating assumptions can produce biased results in terms of data-model fit, parameter estimates and their associated significance tests. These, in turn, might result in incorrect decisions about the theory being tested. Therefore, it is important to check for assumptions before proceeding with modelling in order to choose the most appropriate, producing least biased estimates, estimation method.

If all of the assumptions are met, the parameter estimates have three desirable properties: asymptotic unbiasedness (neither over nor under-estimate true parameters), consistency (parameter estimate converges to population parameter as sample size increases), and asymptotic efficiency (smallest asymptotic variance of all consistent estimators), see [1].

Assumptions of the required sample size, distribution of the data, data type, missing data and multicollinearity will be discussed in the following subsections.

3.5.1 Sample size

The importance of sample size, although widely discussed in the literature on structural equation modelling (SEM), has not been widely recognized among applied SEM researchers. It is important to pay attention to the necessary number of participants to be collected in order to obtain an acceptable level of accuracy and statistical power of the estimates and reliable goodness-of-fit indices. SEM requires sufficiently large sample size as application to samples that are too small may bias the estimates. However, there are still no clear rules on how to decide, how many participants are sufficient, see [11].

There are, however, several guidelines to refer to. Firstly, different authors indicate general number of minimum sample size as a reference, it ranges from 100 to 200 observations, see [13, 14]. Second, there is a link between sample size and free parameters, it can vary from 5 times more participants than free parameters in the model to 10 or, ideally, up to 20 times more. ML estimator can handle the smaller ratio, see [15, 16]. Other authors state that the study should have at least 50 participants per variable, see [21], meanwhile, some – that the ratio between sample size and item number sould be at least 20, see [14].

However, all of the above are only guidelines that are not flexible in terms of model complexity, varying number of *df*, variables, free parameters, strength of the relationships among the indicators, etc. Muthén and Muthén (2002) argue for the use of Monte Carlo analysis, where sample size is estimated under various conditions. It allows taking into account the statistical precision, power of individual parameter estimates and various data conditions: non-normality, type of indicators (i.e., binary, categorical, and continuous), the amount and patterns of missing data. Numerous sample datasets of parameters are generated based on those known population parameters. Then this procedure is iterated a sufficient number of times. The results are averaged for each parameter across the samples and are compared to examine divergences (i.e., bias) between the population value and the sample averaged value, see [17]. According to Barrett (2007), Brown (2006), and McIntosh (2007), the Monte Carlo approach is currently the best way to evaluate sample size in SEM.

Several criteria are used to determine a sufficient sample size. The first criterion is that parameter and standard error biases do not exceed 10 percent for any parameter in the model. The corresponding percent is calculated by subtracting the population parameter value from the averaged parameter estimate value across replications and then divided by population parameter estimate value.

The second criterion is that the standard error bias for the parameter for which power is being assessed does not exceed 5 percent. Standard error bias is calculated in the same way as parameter estimate bias, described above.

The third criterion is that coverage remains between 0.91 and 0.98. It gives the proportion of replications for which the 95% confidence interval contains the true parameter value.

Once these three conditions are satisfied, the model power for the given sample size can be determined. The value of 0.80 is a commonly accepted value for sufficient power, see [21].

As we already have data collected, a post-hoc Monte Carlo simulations will be produced and a post-hoc model power for the given sample will be evaluated.

3.5.2 Normal distribution

Three indices of univariate and multivariate non-normality are typically used to evaluate the distribution: univariate skew and kurtosis and multivariate kurtosis, see [1].

Skewness describes the symmetry of the distribution:

$$Skewness(Y_i) = \frac{\sum_{i=1}^{N}(Y_i - \overline{Y})^3/N}{s^3}, \tag{9}$$

where $\overline{Y}$ is the mean, s is the standard deviation, and N is the number of data points.

If the skewness is between -0.5 and 0.5, the data is fairly symmetrical, between the absolute values of 1 and 0.5, the data is moderately skewed and if the skewness is less than the absolute value of 1, the data is highly skewed.

Kurtosis is the fourth standardized moment:

$$Kurtosis(Y_i) = \frac{\sum_{i=1}^{N}(Y_i - \overline{Y})^4/N}{s^4}, \tag{10}$$

where $\overline{Y}$ is the mean of the variable, s is the standard deviation, and N is the number of data points.

Ideally kurtosis value should be around 3.

Studies examining the impact of univariate normality on maximum likelihood estimator based results, suggest that problems arise, the type I error rate increases, when absolute values of *skewness* $>= 2$ and *kurtosis* $>= 7$, are reached, see [1].

In SEM, the multivariate normality is of greater importance. Even when the marginal distribution of each variable is univariate normal, it is possible that the variables are not multivariate normally distributed. To evaluate multivariate normality, Mardia (1970) developed a measure of multivariate kurtosis and a test statistic for this measure.

$$b_p = \frac{1}{n} \sum_{n=1}^{\infty} [(x_i - \overline{x})' S^{-1} (x_i - \overline{x})]^2, \tag{11}$$

where x is a $p \times 1$ vector of random variables and $\mathbf{S}$ is the biased sample covariance matrix of x defined as:

$$S = \frac{1}{n} \sum_{n=1}^{\infty} [(x_i - \overline{x})(x_i - \overline{x})']. \tag{12}$$

The expected Mardia's kurtosis is $p(p+2)$ for a multivariate normal distribution of p variables. It has been suggested that values greater than 5 could produce inaccurate results, when used with ML estimator and would lead to chi-square and standard error biases, see [11].

If variables are non-normal, and data transformations do not prove to be useful, then estimators for non-normal continuous variables should be used.

There are three popular strategies used to accommodate non-normal data in SEM: Satorra-Bentler (S-B) scaled chi-square and robust standard errors – for non-normal variables and bigger samples; Yuan-Bentler chi-square (YB chi-square) for non-normal variables and smaller samples, and diagonally weighted least squares (DWLS) estimation, for non-normal categorical variables, see [1]. More on estimation methods is written in section 3.6.

3.5.3 Continuous data

One of the SEM assumptions is that data would be continuous, which is implied by multivariate normal distribution.

Studies have been conducted to look at the extent of bias when applying normal theory estimator, such as maximum likelihood, to ordered categorical data, by comparing robust diagonally weighted least squares (DWLS) estimation, suitable for ordinal data, to unadjusted maximum likelihood estimator, see [1].

Beauducel and Herzberg (2006) when comparing the two estimators for two to six response category data, found slightly higher robust DWLS-based TLI and CFI values and lower RMSEA values when two- and three-category data were present (i.e., robust DWLS performed better). This difference in estimators diminished for the CFI for five or six categories and actually reversed order for the TLI and RMSEA (i.e., ML performed better). Studies conducted afterwards suggest to use unadjusted ML for five or more category data and treat it as continuous, see [1], which is the case in this study.

3.5.4 Missing Data and Multicolinearity

Data used for structural equation modelling should not contain many missing values and should have no multicollinearity, as both can have negative effect on the outcome.

The two main problems caused by missing data are bias and error. Bias refers to the systematic over- or underestimation of a parameter (e.g., underestimated mean, correlation, or regression coefficient). Parameter estimation bias can be thought of as an external validity problem, because the biased estimates reflect a different population from the target population the researcher intends to understand. Error refers to hypothesis testing errors of inference, such as Type I error and Type II error, see [36].

In addition, if correlations within data reach close to the value of one, it might distort the dependencies between variables and increase the Type II error rate, see [37].

3.5.5 Outliers and influential observations

For SEM, both univariate and multivariate outliers should be assessed. Univariate outliers can be considered standardized cases that are outside the absolute value of 3.29. Univariate outliers are easy to find by inspecting frequency distributions of z-score (e.g., $|z| > 3.00$ indicates an outlier). Multivariate outliers are of even more importance as they can easily jeopardize fit indices, see [14].

Multivariate outliers can be identified by using of Mahalanobis distance, see [26], which is the distance of a data point from the calculated centroid of the other cases, where the centroid is calculated as the intersection of the mean of the variables being assessed. Each point is recognized as an X, Y combination and multivariate outliers lie a given distance from the other cases. The distances are interpreted using a $p < 0.001$ and the corresponding χ^2 value with the degrees of freedom equal to the number of variables.

Although the outliers should be investigated carefully, unless outlying data point is a measurement or data error, it should not be removed without careful investigation of removal impact on parameter estimates, overall model fit and residual matrix.

3.6 Estimation method

Model estimation involves finding a value for each unknown (free) parameter in the specified model during an iterative procedure. Central to SEM is the choice of an estimation method used to obtain such parameter estimates, standard errors, and fit indices. The objective of the estimator is to iteratively render the discrepancy function between two matrices. The major difference between the estimators is the manner in which the mathematical discrepancy function is used to minimize deviations from the observed correlation matrix.

The choice of an estimator becomes even more important when dealing with non-normal or categorical data. Different estimators have been defined and recommended to be used depending on the nature of data, although, the debate upon the performance is still open. Two estimators: maximum likelihood and Yuan-Bentler chi-square will be discussed in the following sections, being considered the most relevant to this study, keeping in mind the nature of the data, discussed in more detail in section 4.5.

3.6.1 Normally distributed data: Maximum likelihood (ML) estimator

The two most common estimators used in SEM, given that all assumptions are met, are ML and GLS. GLS has been found to produce overly optimistic fit indices and more biased parameter estimates if model is misspecified, therefore, ML has been recommended over GLS, if all assumptions are met, see [1].

Commonly used version of the likelihood ratio statistic is defined in the following way:

$$T_{ML} = nF_{ML}(\hat{\theta}). \tag{13}$$

Here $nF_{ML}(\hat{\theta})$ is the value of the discrepancy function evaluated at its minimizer $\hat{\theta}$.

$$F_{ML}(\hat{\theta}) = ln|\Sigma(\hat{\theta})| - ln|S| + tr(S\Sigma(\hat{\theta})^{-1}) - p, \tag{14}$$

- tr is the trace matrix algebra function which sums diagonal elements;
- p – number of variables in the model;
- **Σ** is the model-implied population covariance matrix;
- **S** - sample covariance matrix.

Parameters are estimated during an iterative process. The final set of parameters minimises the discrepancy between observed sample covariance matrix – $\mathbf{S}$, and the model-implied covariance matrix, calculated from the estimated model parameters – $\mathbf{\Sigma}(\hat{\theta})$. When applying SEM, we minimise the differences by adjusting model parameters θ.

The fit function in (14), that is minimised, will equal zero, if the model perfectly reproduces the elements in the sample covariance matrix. If the assumptions are met, the overall fit between the data and the model can be expressed as a statistic $T_{ML} = F_{ML}(N-1)$, where N is the sample size. Statistic follows a central chi-square distribution with $df = p(p+1)/2 - q$, where q is the number of free parameters.

If the value is statistically significant, T follows a non-central chi-square distribution, and the hypothesis that the population covariance matrix equals the reproduced covariance matrix calculated from the estimated model parameters, can be rejected and model can be treated as misspecified.

Studies have noted, that when all assumptions are satisfied maximum likelihood estimation is the most efficient, providing the most accurate estimates. The bias increases as the degree of non-normality increases and/or sample size decreases, see [24].

The problem is that often the modelled data collected from surveys do not follow a multivariate normal distribution. The effect of violating the assumption of non-normality can be seen on chi-square, fit-indices and standard errors, while the parameter estimates are found to be relatively accurate even under the non-normal distribution. Positive kurtosis inflate the chi-square statistic and attenuate standard errors, which might lead to an increased Type I error rate (greater rate of rejecting a correctly specified model than expected by chance). Negative kurtosis attenuate the chi-square statistic and inflate standard errors, which might lead to an increased Type II error rate. In addition, as many fit indices are a function of the obtained chi-square, these too can be affected by the same factors. It has been shown that if non-normal data are paired with a small sample (<250), model fit indices (CFI, TLI or RMSEA) might over-reject correctly specified models, see [1, 2]. For example, in Hu et al. (1992), ML estimator rejects a correct model with non-normally distributed data 97%, which is substantially higher than the nominal rate 5%, see [11].

3.6.2 Non-normal distribution of data and small sample size: Yuan-Bentler estimator with robust standard errors (MLR)

When all assumptions are satisfied maximum likelihood estimator is considered to be the most efficient and no other estimator can outperform it. However, when the data is non-normal, the efficiency of the ML estimator changes, it becomes less efficient and the standard errors are more biased. Therefore, with non-normal data, corrections are needed. Jöreskog and Sörbom (1989) encouraged using Yuan-Bentler estimator when the sample is small and data violates normality.

Yuan and Bentler (1998) created a robust maximum likelihood estimator that uses robust standard errors computed from robust covariance matrix to describe the changed variability of the ML estimator with non-normal data.

When a covariance matrix for maximum likelihood estimator can be written as:

$$nCov(\hat{\theta}) = A^{-1} = [-Hessian]^{-1} = [-\partial F(\hat{\theta})/(\partial\hat{\theta}\partial\hat{\theta}')]^{-1}. \tag{15}$$

When using MLR standard errors are computed using a different "sandwich" approach:

$$nCov(\hat{\theta}) = A^{-1}BA^{-1} = A_0^{-1}B_0A_0^{-1} = C_0, \tag{16}$$

where

$$A_0 = -\sum_{i=1}^{n} \frac{\partial logL_i}{\partial\hat{\theta}\partial\hat{\theta}'}, \tag{17}$$

is sample covariance matrix and B_0 equal to the correction factor:

$$B_0 = -\sum_{i=1}^{n} \left(\frac{\partial logL_i}{\partial\hat{\theta}}\right) \times \left(\frac{\partial logL_i}{\partial\hat{\theta}}\right)'. \tag{18}$$

This way the computation of the robust covariance matrix of parameter estimates essentially forms a "sandwich" or a triple product, where the sample covariance matrix of parameter estimates is the "bread" that forms the outside of the computation, and the correction is the "meat".

In addition, when having non-normally distributed data, the computation of the model test statistic (T_{MLR}) also requires a correction, as test statistic requires an accurate estimate of the variability of parameter estimates. In case of non-normally distributed data, this estimate is off and the distribution of the statistic is no longer asymptotically χ^2, and the nominal Type I error is not maintained. Therefore, the test statistic – χ^2 is also made to be robust to non-normality by scaling it by the correction factor:

$$T_{MLR} = T_{ML}/c. \tag{19}$$

The scaling factor c is usually computed by $c = tr[M]$, M here is:

$$M = C_1(A_1 - A_1\Delta(\Delta' A_1 \Delta)^{-1}\Delta' A_1), \tag{20}$$

where A_1 and C_1 are computed under the unrestricted (H_1) model, and $\Delta = \frac{\partial\hat{\Sigma}}{\partial\hat{\theta}'}$

3.7 Mediation in SEM

In mediation, we consider an intermediate variable, called the mediator, that helps explain how or why an independent variable influences an outcome.

The direct effect is the pathway from the exogenous variable to the outcome while controlling for the mediator. The indirect effect describes the pathway from the exogenous variable to the outcome through the mediator. Finally, the total effect is the sum of the direct and indirect effects of the exogenous variable on the outcome.

In order to test the significance of the mediation effect in SEM a separate approach is required. Preacher and Hayes (2008) approach, bootstrapping mediation, considered to be a powerful method to detect mediation, is used the most. The method involves obtaining confidence intervals for indirect effects that are more able to adequately capture the skewed, asymmetric nature of sampling distributions.

It involves taking multiple repeated samples with replacement from the data set in question. For each bootstrapped sample, the structural equation model is refit and estimates for all the parameters are retained (including mediation). After collecting all the results, lower and upper percentile values on each sorted set of values are determined. For a standard 95% CI, these values would represent the 2.5th and 97.5th percentile values. Bias-corrected CIs, involve a slight adjustment of these percentile values depending on the proportion of bootstrapped values that are less than or equal to the original sample value. According to this approach, note that determining whether the resulting (1 - α)% CI for an indirect effect does not contain 0 is equivalent to a two-sided, α – level hypothesis test for whether the original sample value for that indirect effect significantly differs from 0, see [29].

The next section will include the practical part of the thesis. We will start by setting the aim and hypothesis for the study based on literature review, describing the data and the necessary assumption testing conducted prior the structural equation modelling. Then, we will follow up with the discussion of applied structural equation models to find the best data fitting model and evaluate the relationships and finalise with the Monte Carlo study to evaluate and select the better suited estimator for our model and data and finally evaluate the selected final model. A short discussion of the results and their meaning will be found at the end of the paper.

4 Application

4.1 Aim and hypotheses of the study

Aim of this study was to investigate the relationships among innovative work behaviour, occupational self-efficacy and work engagement.

Hypotheses based on the literature review:

- Occupational self-efficacy and work engagement have a positive effect on innovative work behaviour.
- Work engagement acts as a mediating factor between occupational self-efficacy and innovative work behaviour.
- Interest in novelty, exploration and creation of ideas, idea testing and evaluation, search for support and idea implementation are strong indicators of innovative work behaviour in the mediation model.

4.2 Data

Data used in this paper was collected with a questionnaire constructed from demographic questions such as gender, age, education, job position (managerial or non-managerial), work experience in years. In addition to demographic questions, questions to measure the types of innovative work behaviour (LIEDK, by Geležinytė & Bagdžiūnienė, 2016), occupational self-efficacy (Occupational Self-Efficacy Scale, by Schyns & Collani, 2002) and work engagement (Utrecht Work Engagement Questionnaire, by Shaufeli et al., 2006) were included. All questions were answered in a Likert type scale. LIEDK and occupational self-efficacy from 1 to 5, work engagement from 0 to 6 (in calculations transformed to 1 to 7) – 1 being the lowest, 5/7 being the highest evaluation. As questionnaires contain multiple questions for each variable, the average score was calculated to represent overall score of each variable for each participant. Examples of the questions can be found in appendix A.

Only people, employed at the time of the survey, were asked to fill in the questionnaire. In total, 181 employees participated, out of which 76% were women, age varied from 20 to 59 with the average of 31 years, 89% of participants had university degree, 26% of respondents were managers as oppose to having a non-managerial position.

Note that data was collected as a part of doctoral dissertation of Rasa Geležinytė in collaboration with assoc. prof. dr. Dalia Bagdžiūnienė.

4.3 Software

Data analysis provided in this paper was produced with *lavaan* and *simsem* packages in R for SEM analysis and structural equation simulation.

The choice was made considering the additional benefits of the package compared to other softwares such as *AMOS*, *Lisrel* or *Mplus*, which are intuitive and quite easy to use for the beginners, having drag and click interface and possibility to draw model instead of write equations, but have computational disadvantages compared to *R*. *R* is an open source program, it provides the possibility to extract standardized residuals that are essential to diagnose misfitting models and most importantly, accommodates the possibility to compute robust standard errors that are not available in AMOS.

Therefore, all of the below computations were made using *R* software. The code can be provided upon request.

4.4 Conceptual SEM model for innovative work behaviour, occupational self-efficacy and work engagement

Based on the literature reviewed in section 2, a theoretical model that will be used in the analysis is displayed in figure 2.

The one in figure 2 and all the following charts and tables will include abbreviations for the variables in order to make the reading less heavy:
NOVE stands for interest in novelty,
EXPL – exploration and creation of ideas,
TEST – idea testing and evaluation,
SUPP – search for support,
IMPL – implementation of ideas,

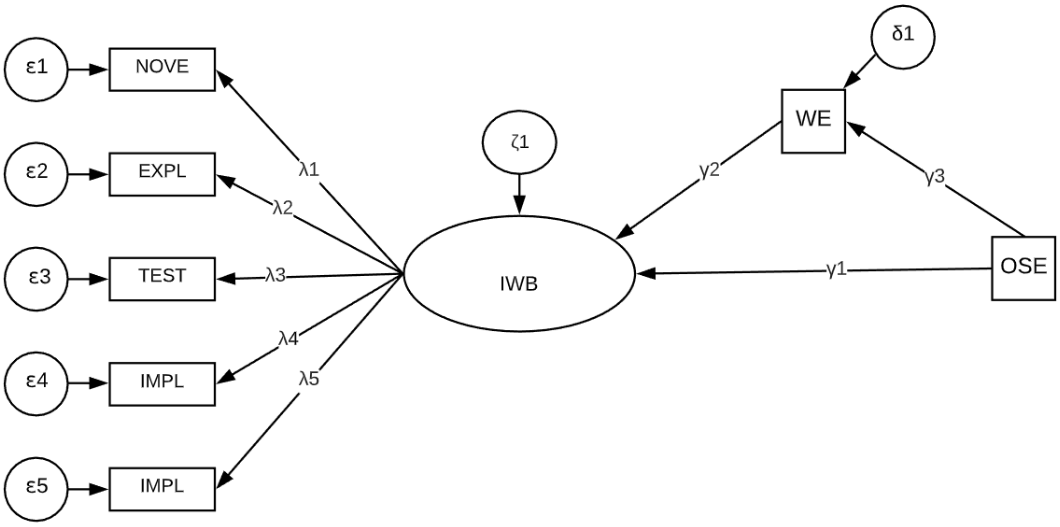

Figure 2: Theoretical SEM model for innovative work behaviour.

IWB – innovative work behaviour,

WE – work engagement, and

OSE – occupational self-efficacy

SEM models are best represented by path diagrams. A path diagram consists of nodes representing the variables and arrows showing relations among these variables. By convention, in a path diagram, latent variables (e.g., IWB here) are represented by a circle or ellipse and observed variables (e.g., OSE or NOVE) are represented by a rectangle or square. Rectangles on the left of the chart are indicators of the latent variable. The rectangles on the right are the predictors of the latent variable - innovative work behaviour.

Arrows are generally used to represent relationships among the variables. A single straight arrow indicates a causal relation from the base of the arrow to the head of the arrow. For the sake of convenience we drop unit weights for error terms in the path diagram.

The model constructed for this study is a partial mediation model in which observed variable OSE is a regressor for the latent variable IWB. WE here acts as a mediator between OSE and IWB. NOVE, EXPL, TEST, SUPP, and IMPL are the indicators of the latent factor IWB.

The model can also be written in equations representing structural model, measurement model and mediation. See equations (20), (21), (22), respectively.

$$\begin{cases} IWB = \gamma_1 OSE + \zeta_1 \\ IWB = \gamma_2 WE + \zeta_1 \end{cases}, \tag{21}$$

$$\begin{cases} NOVE = \lambda_1 IWB + \varepsilon_1 \\ EXPL = \lambda_2 IWB + \varepsilon_2 \\ TEST = \lambda_3 IWB + \varepsilon_3 \\ SUPP = \lambda_4 IWB + \varepsilon_4 \\ IMPL = \lambda_5 IWB + \varepsilon_5 \end{cases}, \tag{22}$$

$$\begin{cases} x_{WE} = \gamma_3 \times x_{OSE} + \delta_1. \end{cases} . \tag{23}$$

4.5 Descriptive statistics and diagnostics in SEM

Critical part, before proceeding with structural equation modelling, is data exploration and identification of any assumption violations in order to take respective actions during the analysis and avoid biased estimates and incorrect inferences. Data used in this study contains no missing values, no multicollinearity was detected and all variables were correlated (see Appendix B and C). Other assumption testing, checking normality of variables and outlier detection is described in more detail in the following sections.

4.5.1 Normal distribution

As discussed in section 3.5.2 normal data distribution is one of the SEM assumptions, which may alter the choice of estimation method used later on in the analysis. Therefore, one of the first steps in the analysis was the data normality investigation.

A univariate skewness and kurtosis and multivariate kurtosis were calculated (see tables 1 and 2). In addition, variable histograms were investigated (see figure 3).

We have applied Shapiro-Wilk test to check for univariate normality. As all p-values are less than 0.05, we can conclude that all variables do not have a normal distribution.

Looking at skewness values, it is clear that all variables have negative skew, where the curve is shifted to the right. Almost all variables are fairly symmetrical, with the exception of WE, NOVE and SUPP variables that are moderately skewed.

As for the kurtosis, we have both types of variables, with high and low kurtosis.

Figure 3 presents the distributions of all variables. It can be seen that none of the variables follow the normal distribution, although they seem to be only slightly skewed.

For multivariate normality, Mardias test of normality was applied. The p-value of multivariate kurtosis statistic should be greater than 0.05. As can be seen in table 2, our data

Table 1: Univariate normality

Variable	Univariate skewness	Univariate kurtosis	Shapiro-Wilk	Shapiro-Wilk p-value	Univariate normality
OSE	-0.21	2.94	0.9411	<0.001	No
WE	-0.73	2.80	0.9760	0.0033	No
NOVE	-0.62	3.13	0.9706	7,00E-04	No
EXPL	-0.39	3.47	0.9553	<0.001	No
TEST	-0.36	3.25	0.9726	0.0012	No
SUPP	-0.53	2.98	0.9481	<0.001	No
IMPL	-0.39	2.85	0.9730	0.0014	No

Table 2: Multivariate normality

Multivariate normality statistic	p-value	Result
4.87	1.1307362144386e-06	NO

does not follow multivariate normal distribution.

With all of the above in mind, several transformations have been applied to the data in order to achieve normal distribution and better model fit with ML estimator, such as log or box-cox transformations. As neither provided improved results with ML estimator, the decision was made to instead use different estimator, which should be more efficient with non-normally distributed data.

As we can see univariate skewness and kurtosis and multivariate kurtosis indicate slight non-normality of the data, and although is close to, it does not exceed the margins indicated in the literature that might be affecting the efficiency of the maximum likelihood estimator. Univariate skewness and kurtosis are significantly smaller than the indicated absolute values of 2 and 7, respectively, and multivariate kurtosis is slightly below 5.

For this reason, when having non-traditional, marginal case, we will apply both, the ML estimator, which is the most efficient when all assumptions are satisfied, and Yuan-Bentler estimator with robust standard errors, which is more efficient for non-normally distributed data. We will then compare the standard error biases to choose the most efficient estimator for our data.

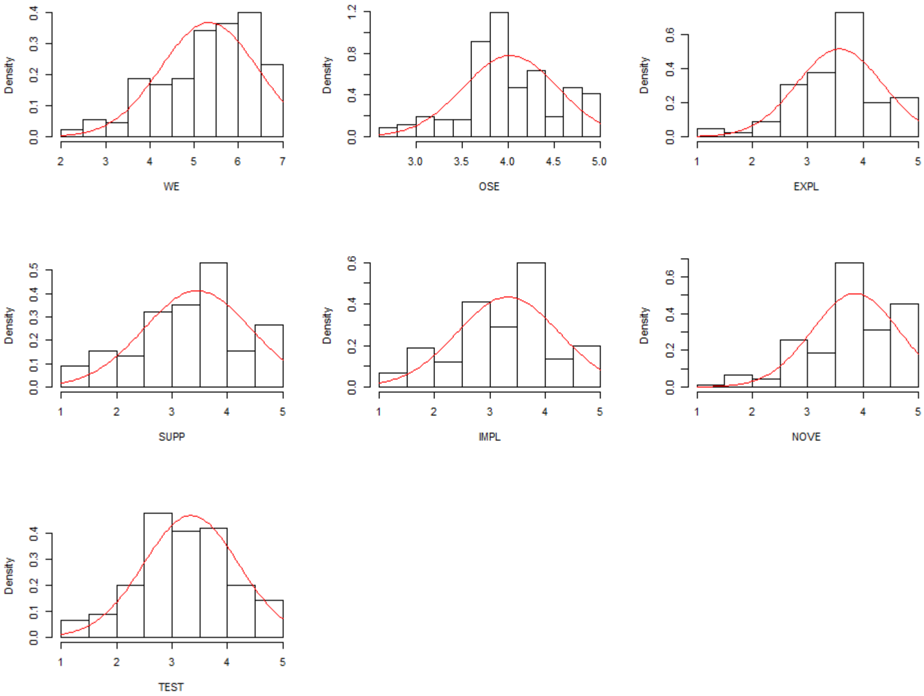

Figure 3: Univariate histograms of observed variables.

4.5.2 Detection of Outliers and Influential Observations

For the detection of possible univariate outliers, we looked which observations of standardized variables are greater than absolute value of three. Only NOVE and EXPL variables had such observations, for NOVE observation No.102 and for EXPL – No.36.

After calculating Mahalanobis distance (MD), we checked for extreme values higher than the selected threshold of 8.5. Such value was selected by the 68–95–99.7 rule, see [27], by multiplying the mean of the Mahalanobis Distance results by the extremeness degree k, where $k = 2.0 * sd(MD)$. Two outlier observations No.94 and No.99 were detected.

We fitted the initial selected model (see section 4.4) with and without removing outliers. No difference for model fit indices or parameter estimates were detected, therefore, the decision was made to keep the outliers in the dataset.

4.6 Influence of demographic variables in the model

As information on several demographic variables were collected during the data collection, before proceeding to test the mediation model of innovative work behaviour, the regression was performed to test the effect of demographic variables on the dependent variables. If demographic variables are to be significant in the regression, that would mean that they should be treated as confounding variables and should be included in the SEM model to

Table 3: Regressions with demographic variables

		NOVE	EXPL	TEST	SUPP	IMPL
Standardized β	Gender2	0.022	**0.329**	**0.331**	**0.372**	0.244
	Age	0.008	0.009	-0.012	-0.019	-0.008
	Education2	0.283	-0.109	0.035	0.199	0.420
	Education3	-0.216	-0.373	-0.166	0.095	-0.893
	Education4	-0.402	-0.404	**-0.849**	**-0.774**	**-0.690**
	Education5	0.184	0.219	-0.503	0.048	-0.080
	Experience_yrs	-0.011	-0.016	0.009	0.033	0.006
	Position2	**-0.440**	**-0.413**	**-0.472**	**-0.605**	**-0.696**
R^2		0.11	0.14	0.12	0.14	0.17
F		2.58	3.4	2.97	3.5	4.5
p-value		0.01	0.001	0.004	0.001	0.000

*Note. Estimates with p<0.01 are in bold.

control for their effect on the mediation (they might enhance or suppress the effect of WE as the mediator).

The results of the regressions for each dependent variable included in our SEM model can be seen in table 3.

Here, gender2 represents males vs. females, education2 – higher non-university education, education3 – vocational education, education4 – secondary education, education5 – unfinished secondary education vs. higher university education, position2 – non-managers vs. managers.

Checking R^2, we can see that demographic variables explain a very small part of various innovative work behaviours – from 10% to 17%. Although, a couple of variables, gender and secondary education, are significant predictors for some dependent variables, only position has been a significant predictor for all types of innovative work behaviours. All β coefficients being negative indicate that non-managerial positions having employees express less innovative work behaviour compared to managers. However, it is important to note that the groups for different demographic variables were unequal and quite small to have confidence in regression results. It may only be an indication of a possibility and should be explored further in future works with bigger sample sizes. Currently, as demographic variables explain a small part of the variance of the dependent variables and have unequal sizes, they will not be used in our model.

4.7 Model estimation

In the following subsections we will discuss the model estimation process and the results of model estimates and fit.

4.7.1 Initial model fit

We started by estimating the model described in section 4.4. with traditional ML estimator. The initial model does not show a good fit with χ^2 being 62.16 with p=0.000 and 13 *df*, meaning that the model does not fit the data well. The same conclusion is confirmed by the model fit indices: RMSEA=0.145 with p=0.000, CFI=0.92, SRMR=0.05.

We may hypothesize that the χ^2 was inflated and RMSEA, that has a straightforward relation to the Maximum-Likelihood fitting function and *df*, penalised a correctly specified model due to a fair degree of non-normality present in the distribution of the data. To test this, we applied Yuan-Bentler estimator, a maximum likelihood estimation with robust standard errors and a scaled test statistic in order to account for the effect of non-normality and looked at the changes in statistics and fit indices. However, even though, it corrected the χ^2 for inefficiency of the ML estimator for non-normally distributed data to some degree, producing $\chi^2 = 54.19$, the hypothesis that observed and reproduced matrices are equal was still rejected, with p=0.000, indicating that the constructed model does not fit the data, in addition, corrected RMSEA=0.132, that also indicates a poor model fit.

Looking at standardised residual covariation matrix (table 4), for relationships among variables, we can see that the relationship between NOVE and WE is highly underestimated and the one between SUPP and WE is overestimated. This fact raises serious doubts about the overall fitting of the model.

Therefore, further modifications to these two relationships were made and the model was once again evaluated.

4.7.2 Modification and estimation of the model

In this section we will discuss the performed model modification to obtain a better fit to the data. In addition, we will evaluate the model-fit of the modified model and discuss the obtained parameters,

Model modification. In order to compensate for the over and under estimation of

Table 4: Standardised residual covariation matrix

	NOVE	EXPL	TEST	SUPP	IMPL	WE	OSE
NOVE	0.000						
EXPL	1.994	0.000					
TEST	-0.309	0.814	0.000				
SUPP	-1.993	-0.705	-0.271	0.000			
IMPL	0.251	-1.352	-0.163	1.342	0.000		
WE	**3.024**	0.830	-1.531	**-2.493**	1.007	0.000	
OSE	-1.769	0.460	0.589	1.038	-1.102	0.000	0.000

the two relations, we removed the SUPP variable as an indicator of IWB dependent latent variable within the mediation, considering that WE is not a mediating variable for it and there is only a direct relationship between OSE and SUPP, this way hopefully correcting the overestimation of the relationship between SUPP and WE. In order to compensate for underestimation of WE and NOVE relationship we included additional covariation between them, assuming that the two share some bias not common with the other indicators of IWB. See the graphical representation of the model in figure 4.

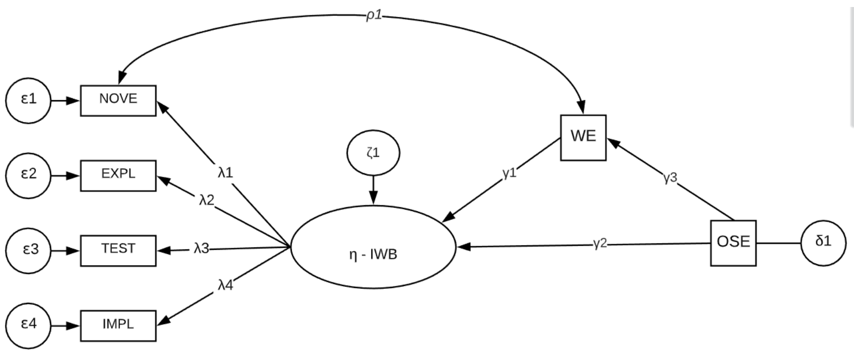

Figure 4: Modified model.

Model fit. The results show that model fit increased, with ML estimator $\chi^2 = 13.95$, RMSEA=0.074, in addition, p-values for both were over 0.05, respectively 0.052 and 0.208, meaning that the null hypothesis of model fit to the data was accepted. Applying Yuan-Bentler estimator decreased χ^2 to 12.93 with p=0.074 and RMSEA=0.068 with p=0.253, which also indicates a good model fit to the data. SRMR and CFI indices were the same for both estimators, respectively, 0.032 and 0.99, also indicating a good model fit.

Model parameter summary. Having a good fitting model, it is then important to have a closer look at the standardized parameter estimates (see table 5 for reference). We can see that all of the estimates have $p<0.05$. We can also see that all std. estimates for indicators satisfy the condition of minimum 0.4 to attribute it as an indicator of the latent factor and even more so, each indicator is a relatively strong measure of IWB, with EXPL being the most saturated (i.e., having the strongest factir loading) and NOVE being the least saturated. All indicators have a big part of variance explained by the latent variable (communality), NOVE having the smallest. In addition, it is visible that all of the regressors are positively related to its' dependent variable. The variances section gives the error variances of the endogenous variables.

Mediation. To test the mediation effect, bootstrapping mediation by Preacher & Hayes (2008) was used (in more detail described in section 3.7). From the obtained results (see table 6) it is evident that all indicated associations between dependent and independent variables are significant ($p<0.05$). Every increase in OSE by 1 results in 0.44 increase in IWB, similarly every increase in WE by 1 results in 0.32 increase in IWB, and an increase of 1 in OSE results in 0.38 increase in WE. In addition, by looking at significant mediation effect, we can say that increases in OSE were associated with increases in IWB indirectly through increases in WE. Specifically, for every 0.38 unit increase in the association between OSE and WE, there was a 0.121 increase in IWB. Importantly, a bias-corrected bootstrapped confidence interval with 10.000 samples was above zero – 95% CI [0.15, 0.54].

4.8 Comparison of estimators and overall model evaluation

In this study we estimated a model with two different estimators: maximum likelihood and Yuan-Bentler. The evaluation process of the performance of each estimator was conducted along Muthén & Muthén (2002) guidelines, who argue that Monte Carlo method is the best way to do such evaluation.

In Monte Carlo studies, data are generated from a population with calculated parameter values. A large number of samples are drawn, a model is estimated for each sample and then parameters are averaged over the samples.

The number of replications should be increased until stability of the results is achieved. The value of the seed determines the starting point for the random draws of the samples. More than one seed should be used, and the results for the different seeds should be checked for stability.

In this study, the number of replications started from 1000 and were increased until 10000. The stability was reached at 5000 replications. Different seeds provided identical results for

Table 5: Model summary

	Std.Est	Std.Err	p(>|z|)	Communality
Indicators:				
IWB=~NOVE	0,642	0,042	0	0,412
IWB=~EXPL	0,825	0,04	0	0,681
IWB=~TEST	0,798	0,045	0	0,637
IWB=~IMPL	0,818	0,048	0	0,669
Regressions:				
IWB~OSE	0,44	0,192	0	
IWB~WE	0,317	0,087	0	
WE~OSE	0,381	0,145	0	
Covariances:				
NOVE~~WE	0,286	0,049	0,001	
Variances:				
NOVE	0,511	0,038	0	
EXPL	0,319	0,028	0	
TEST	0,364	0,037	0	
IMPL	0,33	0,041	0	
WE	0,855	0,108	0	
IWB	0,6			
Mediation:	0,121	0,09	0,001	

Table 6: Bootstrapping mediation results with bias-corrected CIs

Parameter	Std.Est	Std.Err	P-value	CI.lower	CI.upper
IWB~OSE (a)	0,440	0,192	0,000	0,741	1,492
IWB~WE (c)	0,317	0,087	0,000	0,203	0,543
WE~OSE (b)	0,381	0,145	0,000	0,538	1,106
Mediation (bc)	0,121	0,090	0,002	0,149	0,536

the selected number of replications that implies the stability of results.

As MLR estimator uses standard error correction to accomodate for non-normal data, standard error biases will be compared for the two estimators. Parameter estimate and standard error bias, coverage, Type I error rate and power was used as a criteria for overall model evaluation.

4.8.1 Comparison of estimators

Standard error bias. To compare models with different estimators we evaluated the degree of potential for standard error bias. We compared mean standard errors in the generated data sets to the empirical standard errors for each parameter estimate, see equation (24).

$$RB_{SE} = \frac{\overline{SE}_{est} - SE_{emp}}{SE_{emp}}. \tag{24}$$

Here, SE_{emp} is the true standard error value and $\overline{SE}_{est}$ is the average estimated value of the standard errors across all replications. Acceptable standard error estimates had to be within 5% of the population standard error, see [21].

Results for comparison can be found in table 7. As it can be seen the relative standard error bias is higher for MLR estimator and varies from 0 to 18% which is above the 5% accepted norm. Most factor loadings tend to be downward biased meaning that they are on average smaller than the empirical standard deviations of the associated parameter estimates. Meanwhile, standard error bias for ML estimate seems to be within norms varying from 0 to 2.2%. Therefore, it seems that ML provides less biased standard error for the model with given sample size.

When an estimator is more stable from sample to sample, one can have greater confidence that the parameter estimates obtained from a particular sample are fairly close to their population values, therefore, in our case, ML is a more efficient estimator.

The obtained results can be confirmed by the study conducted by Nalbantoğlu-Yılmaz(2019), who evaluated the performance of both estimators for non-normal data for various sample sizes. MLR estimator had biggest standard error bias, 10% for smallest sample (N=300) and decreased with the increase of the sample size. As our sample size is even smaller than mentioned in the study, the bias is even higher. The small standard error bias provided by ML estimator could be explained by small data non-normality, that does not exceed the margins indicated in the studies, beyond which it starts affecting the efficiency of ML estimator.

Table 7: Standard error bias comparison

Parameter	St. Error bias for ML	St. Err. bias for MLR
IWB=~NOVE	0,000	-0,176
IWB=~EXPL	0,000	-0,149
IWB=~TEST	-0,022	-0,021
IWB=~IMPL	0,000	0,000
IWB~OSE	0,011	0,031
IWB~WE	0,011	0,035
WE~OSE	-0,007	-0,039
Mediation	0,022	0,000

Considering all of the above we chose ML as the most efficient estimator and will proceed to evaluate the model with maximum likelihood estimator in the next section.

4.8.2 Model evaluation

As ML provides less biased standard error values, the following model evaluation is based on the model estimated with maximum likelihood estimator. Parameter estimate bias, standard error bias and coverage values are provided in Appendix D.

Parameter estimate bias. First, we evaluated the degree of bias in the parameter estimates. Specifically, we examined the mean parameter estimates (i.e., factor loadings and regressive paths) across simulations in comparison to the specified population values. This index of relative parameter bias (RB_{PE}) was derived by subtracting the population value from the mean estimated value and dividing by the population value, following Muthén and Muthén (2002) as per equation (25)

$$RB_{PE} = \frac{\overline{\theta}_{est} - \theta_{emp}}{\theta_{emp}}. \tag{25}$$

Here, θ_{emp} is the true parameter value and $\overline{\theta}_{est}$ is the average estimated value of the parameter across all replications. Consistent with other references, we consider estimates to be substantially biased if $|RB_{PE}| < 0.10$, for example, see [32]. Parameter estimate bias in this study is low and varies from 0 to 0.6% for different parameters.

Coverage. Coverage gives the proportion of replications for which the 95% confidence interval contains the true parameter value. According to Muthén and Muthén (2002) coverage between 91% and 98% is considered acceptable. Coverage for the model analysed varies from 93.8% to 94.8%, which is well within the norms, meaning that for above 90% of replications 95% confidence interval contained the true parameter value.

Type I error rate. Empirical Type I error at $\alpha = 0.05$ is defined as the proportion of converged replications that generated a p value less than 0.05, i.e. the proportion of replications that were falsely evaluated as a misspecified model. Type I error rate for ML model is at 8.7%.

Model power. Once the bias and coverage conditions are satisfied one can proceed to estimate the power of the selected estimation method to reject null hypothesis when it is false. As we saw previously, Type I error rate was well controlled, allowing for a power examination.

To determine the model power, we compared a correct population model, for which we do not wish to reject the null hypothesis of good model fit (the one described in 4.7.2) and an incorrect population, for which we wish to reject the null hypothesis of good model fit. A cut-off was created from a correct population, and the data was created from the alternative model that we wish to reject. Finally, we determined the proportion of replications simulated from a model with serious misspecification rejected by the cut-offs (i.e., statistical power). A commonly accepted value for sufficient power is above 0.8, see [21]. Investigating power would help us evaluate whether the sample size is sufficient to yield enough confidence about the detection of significant parameter values.

Our model with ML estimator has a strong power to detect a misspecified model equal to 91%. The graphs of model fit indices for both correctly specified and misspecified models are provided in Appendix E. The red line indicates cut-off values used based on correctly specified model.

As expected, we see the fit indices obtained from the data from the misspecified model indicating worse fit than the fit indices from the correct model. Hence, our model is able to confidently reject misspecified model.

4.9 Discussion of the results

Having done the analysis on the relationships among innovative work behaviour, occupational self-efficacy and work engagement, it is safe to say that these three constructs are related. Both occupational self-efficacy and work engagement predict innovative work behaviour. It has also been found that work engagement is a partial mediator between occupational self-efficacy and innovative work behaviour, meaning that there are not only direct predictive relationships among those three constructs, but also an indirect effect.

If we are to go into more details of our results, then first, our model shows that being an employee with stronger beliefs about the ability to cope with work related tasks and problems, is an important predictor of innovative work behaviour, which is indicated by interest in novelty, exploration and creation of ideas, idea testing and evaluation and idea implementation. This confirms the research done by other authors about the relationship between occupational self-efficacy and one-dimensional innovative work behaviour, see [60] and occupational self-efficacy and idea creation, see [49] but also brings new knowledge about the relationship between occupational self-efficacy and more broad range of innovative work behaviours, e.g. idea testing and evaluations, interest in novelty. Based on social-cognitive theory, see [42], every person before setting a goal for themselves and working on achieving it, first evaluates his or her ability of successfully reaching it and therefore is prone to choose and dedicate their efforts to the task that matches their evaluation of their own abilities. Based on social-cognitive theory, we can assume that people with strong beliefs about their ability to do work related tasks will be more confident about their abilities to innovate and, therefore, more prone to expressing such behaviour by being more sure of successfully accomplishing it in the organisation. In addition, employees with high occupational self-efficacy are likely to dedicate more effort, less likely to give up when faced with difficulties, hence more likely to successfully reach the set goal, i.e. demonstrate innovative behaviour: will be interested in novelty, create and explore ideas, test and evaluate them, and implement.

Second, work engagement did predict innovative work behaviour as well. These results add to the research about the predictive relationship between work engagement and general innovative work behaviour, see [52] but also shed new light on the predictive relationship between work engagement and specific innovative work behaviour indicators. Work engagement is defined as positive emotional-motivational work-related state of mind that is characterized by high levels of energy and mental resilience while working, the willingness to invest effort in one's work, persistence, sense of significance, enthusiasm, inspiration, pride and being fully concentrated, see [62]. These characteristics show a higher degree of connection between the employee and his/her work and predict the organisational citizenship behaviour, that although is not directly related to the official job description, adds value to the organisation, see [55]. Work engagement as a motivational state increases initiative behaviour and people with high levels of initiative search and find new challenges, which by itself promotes innovative work behaviour, see [63].

Third, work engagement was confirmed to act as a partial mediator between occupational self-efficacy and innovative work behaviour. Therefore, occupational self-efficacy not only directly predicts innovative work behaviour, but also through work engagement. The results add to the research about the work engagement as an important factor between personal resources and work related behaviour, for example, between proactive behaviour, reflective behaviour and self-efficacy and organisational citizenship behaviour and work-related behaviour, see [53], between rest and proactive behaviour, see [64], between self-efficacy, confidence, optimism and financial gain, see [57]. The results of current study add to the existing research that work engagement acts as a mediator between occupational self-efficacy and innovative work behaviour as well. According to the JD-R theory (job demands and resources), see [44], described motivational process, the resources that an employee has (in this study it would be occupational-self-efficacy) increases both, internal motivation by increasing the wish for competence and autonomy, and external motivation to complete the task by the increased belief about the ability to deal with job demands, see [65]. Both external and internal motivation results in increased engagement at work, which in turn results in positive outcomes as engaged people tend to demonstrate higher levels of energy, enthusiasm, concentration and dedication, giving the resources to complete extra-role tasks.

The only indicator of innovative work behaviour that work engagement did not act as a mediating factor for, was search for support. Meaning that it does not matter whether a person with high occupational self-efficacy will be highly engaged in his work or not engaged at all, his/her search for support will not be affected by it. It might be hypothesized that the association between variables requires an additional moderator, which when present in the relationship makes work engagement a significant mediator between occupational self-efficacy and the search of support. For example, some studies confirm the importance of emotional intelligence, see [66]. Emotional intelligence is related to the ability to regulate emotions and recognise and evaluate emotions of others, which leads to more successful social interactions, see [67]. Therefore, by being a predictor of work engagement it might also act as a moderator between work engagement and search for support.

To sum up, the study confirmed that occupational self-efficacy and work engagement predict innovative work behaviour, work engagement mediated the relationship between occupational self-efficacy and innovative work behaviour, and that all variables but one, search for support variable, are indicators of innovative work behaviour in the mediation. Meaning that organisations, which want to improve innovative work behaviour, could employ a strategy to strengthen work engagement of the employees. In addition, strengthening employee occupational self-efficacy, would not only strengthen employee work engagement, but also innovative work behaviour, with employees being more interested in novelties, more prone to idea creation and evaluation, idea testing and its' implementation. However, if the support aspect of innovative work behaviour is wanted to be strengthened, other strategies should be employed.

4.10 Limitations

We recognize there are limitations with the current study. It is important to understand them in order to see how it may have impacted the results. First of all, the sample was collected using questionnaire on the internet, therefore, there was an imbalance in different groups and sample was not representative of the population. Such results should not be generalised to the population, but is rather an indication of a possibility. Another drawback of the internet questionnaire is the lack of the presence of the researcher who might have answered the questions and concerns. Even though the participants could have written a question via email, it is not as convenient and they might have chosen to just fill the questionnaire as per their understanding, which might have been inaccurate.

5 Conclusions

Several conclusions can be made in the thesis.

Structural equation modelling revealed that first, occupational self-efficacy and work engagement have a positive effect on innovative work behaviour. Meaning that people with strong beliefs about their ability to do work related tasks will be more confident about their abilities to innovate and, therefore, more prone to expressing such behaviour in the organization. They will be interested in novelty, will be likely to create and explore ideas more, test and evaluate them and implement. Also, work engagement as a motivational state increases initiative behaviour and people with high levels of initiative search and find new challenges, which by itself promotes innovative work behaviour.

Second, work engagement acts as a mediating factor between occupational self-efficacy and innovative work behaviour. The resources that an employee has, i.e. higher occupational-self-efficacy, increases motivation, that results in an increased engagement at work, which in turn results in positive outcomes as engaged people tend to demonstrate higher levels of energy, dedication, enthusiasm, concentration and dedication, giving the resources to complete extra-role tasks.

Third, interest in novelty, exploration and creation of ideas, idea testing and evaluation, and idea implementation are strong indicators of innovative work behaviour in the mediation model, except for search for support. It infers that it does not matter whether the person with high occupational self-efficacy will be highly engaged in his work or not engaged at all, his or her search for support will not be affected by it.

In addition, Monte Carlo simulations showed that maximum likelihood estimator is better suited for our model, having smaller sample size and close to normal distribution, compared to Yuan-Bentler estimator.

To sum up, it can be concluded that organisations, which want to improve innovative work behaviour, could employ a strategy to strengthen work engagement of the employees or strengthen occupational self-efficacy, which would not only result in increased employee work engagement, but also innovative work behaviour, with employees being more interested in novelties, more prone to idea creation and evaluation, idea testing and its' implementation.

6 References

[1] Finney, S. J., & DiStefano, C. (2013). *Non-normal and categorical data in structural equation modelling.* In G.R. Hancock & R.O. Mueller (Eds.). A second course in structural equation modelling (2nd ed., pp. 439-492). Charlotte, NC: Information Age.

[2] Newsom, J. (2018). *Practical approaches to dealing with non-normal and categorical variables.* http://web.pdx.edu/ newsomj/semclass/ho_estimate2.pdf . Retrieved November, 12, 2019.

[3] Ullman, J. B. (2006). *Structural Equation Modeling: Reviewing the Basics and Moving Forward.* Journal of Personality Assessment, 87, 35-50.http://dx.doi.org/10.1207/s15327752jpa8701_03

[4] Bentler, P.M., & Wu, E.J.C. (2002). *EQS for Windows user's guide.* Encino, CA. Multivariate Software, Inc.

[5] Yu, C. (2002). *Evaluating Cutoff Criteria of Model Fit Indices for Latent Variable Models with Binary and Continuous Outcomes.* https://www.statmodel.com/download/Yudissertation.pdf . Retrieved November, 12, 2019.

[6] Foss, T., Jöreskog, K. G., & Olsson, U. H. (2011). *Testing structural equation models: The effect of kurtosis.* Computational Statistics and Data Analysis, 55, 2263–2275.

[7] Beauducel, A., & Herzberg, P. Y. (2006). *On the performance of maximum likelihood versus mean and variance adjusted weighted least squares estimation in CFA*. Structural Equation Modeling: A Multidisciplinary Journal, 13, 186–203

[8] Ge Jiang, & Ke-Hai Yuan (2017). *Four New Corrected Statistics for SEM With Small Samples and Nonnormally Distributed Data.* Structural Equation Modeling: A Multidisciplinary Journal, DOI: 10.1080/10705511.2016.1277726

[9] Satorra, A., & Bentler, P. M. (1988). *Scaling corrections for chi-square statistics in covariance structure analysis.* In American Statistical Association 1988 Proceedings of Business and Economics Sections (pp. 308–313). Alexandria, VA: American Statistical Association.

[10] Hu, L. T., Bentler, P. M., & Kano, Y. (1992). *Can test statistics in covariance structure analysis be trusted?* Psychological Bulletin, 112, 351–362.

[11] Gana, K., & Guillaume, B. (2019). *Structural Equation Modeling.* In K. Gana & B. Guillaume (Eds.). Structural Equation Modeling with lavaan (1st ed., pp.1-51). Hoboken, USA: John Wiley & Sons, Ltd. DOI: 10.1002/9781119579038.ch1

[12] Jöreskog, K.G., & Sörbom, D. (1989). *LISREL 7: A Guide to the Program and Applications.* Scientific Software International, Chicago.

[13] Boomsma, A. (1982). *Robustness of LISREL against small sample sizes in factor analysis models.* In K. G. Joreskog, & H. Wold (Eds), Systems under Indirection Observation: Causality, Structure, Prediction (Part I), North Holland, Amsterdam.

[14] Kline R.B. (2016). *Principles and Practice of Structural Equation Modeling*, 4th edition, Guilford Press, New York.

[15] Bentler, P.M. (1995). *EQS Structural Equations Program Manual*, Multivariate Software, Encino.

[16] Jackson, D.L. (2003). *Revisiting sample size and number of parameter estimates: some support for the N: q hypothesis.* Structural Equation Modeling, vol. 10, pp. 128–141.

[17] In'nami, Yo & Koizumi, Rie. (2013). *Review of Sample Size for Structural Equation Models in Second Language Testing and Learning Research: A Monte Carlo Approach.* International Journal of Testing. 13. 10.1080/15305058.2013.806925.

[18] Hu, Li-tze, and Peter M. Bentler. (1998). *Fit indices in covariance structure modeling: Sensitivity to underparameterized model misspecification.* Psychological methods 3.4, 424.

[19] Kim, K. H. (2005). *The Relation Among Fit Indexes, Power, and Sample Size in Structural Equation Modeling.* Structural Equation Modeling, 12, 368-390. doi: 10.1207/s15328007sem1203_2.

[20] Palomo, J., Dunson, D.B., & Bollen, K. (2007). *Bayesian Structural Eqution Modeling.* Handbook of latent variable and related models, pp.163-188.

[21] Muthén, L. K., & Muthén, B. O. (2002). *How to use a Monte Carlo study to decide on sample size and determine power.* Structural Equation Modeling, 9, 599–620.

[22] Mardia, K.V. (1970). *Measures of Multivariate Skewness and Kurtosis with Applications Measures of Multivariate Skewness and Kurtosis with Applications.* Biometrika, 57(3), 519. doi: 10.2307/2334770.

[23] Browne, M. W., & Cudeck, R. (1992). *Alternative ways of assessing model fit.* Sociological Methods & Research, 21, 230–258.

[24] Hildreth, L. (2013). *Residual analysis for structural equation modeling.* Graduate Theses and Dissertations. 13400. https://lib.dr.iastate.edu/etd/13400

[25] Wu, H., & Leung, S-O. (2017). *Can Likert Scales Be Treated as Interval Scales?* Journal of Social Service Research 43/4: 527–32.

[26] Mahalanobis, P. Ch. (1936). *On the generalised distance in statistics.* Proceedings of the National Institute of Sciences of India. 2 (1): 49–55.

[27] G. Gallego, C. Cuevas, R. Mohedano, & García, N. (2013). *On the Mahalanobis Distance Classification Criterion for Multidimensional Normal Distributions.* In IEEE Transactions on Signal Processing, vol. 61, no. 17, pp. 4387-4396. doi: 10.1109/TSP.2013.2269047

[28] Geležinytė, R., & Bagdžiūnienė, D. (2016). *Inovatyvus Elgesys Darbe: Kai Kurie Psichometriniai Lietuviškojo Klausimyno Rodikliai.* Psichologija, 53, 59–77.

[29] Leth-Steensen, C., & Gallitto, E. (2016). *Testing Mediation in Structural Equation Modeling: The Effectiveness of the Test of Joint Significance.* Educational and psychological measurement, 76(2), 339–351. doi:10.1177/0013164415593777

[30] Gunzler, D., Chen, T., Wu, P., & Zhang, H. (2013). *Introduction to mediation analysis with structural equation modeling.* Shanghai archives of psychiatry, 25(6), 390–394. doi:10.3969/j.issn.1002-0829.2013.06.009

[31] Preacher, K.J., & Hayes, A.F. (2008). *Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models.* Behav Res Methods 40:879–891. https://doi. org/10.3758/BRM.40.3.879 62.

[32] Rhemtulla, M., Brosseau-Liard, P.É., & Savalei, V. (2012). *When can categorical variables be treated as continuous? A comparison of robust continuous and categorical SEM estimation methods under suboptimal conditions.* Psychol. Methods 2012, 17, 354–373. DOI: 10.1037/a0029315

[33] Maydeu-Olivares, A. (2017) *Maximum Likelihood Estimation of Structural Equation Models for Continuous Data: Standard Errors and Goodness of Fit.* Structural Equation Modeling A Multidisciplinary Journal. DOI: 10.1080/10705511.2016.1269606

[34] Nalbantoğlu-Yılmaz, F. (2019). *Comparision of Different Estimation Methods Used in Confirmatory Factor Analyses in Non-Normal Data: A Monte Carlo Study.* International Online Journal of Educational Sciences, 11 (4), 131-140

[35] Yuan KH, & Bentler PM. (1998). *Structural Equation Modeling with Robust Covariances.* Sociol Methodol 28:363 – 396

[36] Newman, D. A. (2014). *Missing Data.* Organizational Research Methods, 17(4), 372–411. doi:10.1177/1094428114548590

[37] Grewal, R., Cote, J. A., & Baumgartner, H. (2004). *Multicollinearity and Measurement Error in Structural Equation Models: Implications for Theory Testing.* Marketing Science, 23(4), 519–529. doi:10.1287/mksc.1040.0070

[38] Zhu, Y. (2013). *Individual Behavior: In-role and Extra-role.* International Journal of business Administration, 4(1), 23-27. doi:10.5430/ijba.v4n1p23

[39] de Jong, J. P. J. (2007). *Individual innovation. The Connection Between Leadership and Employees' Innovative Work Behavior.* Amsterdam: University of Amsterdam. Unpublished doctoral dissertation. Paimta iš http://ondernemerschap.panteia.nl/pdf-ez/r200604.pdf

[40] Janssen, O. (2000). *Job Demands, Perceptions of Effort-Reward Fairness, and Innovative Work Behavior.* Journal of Occupational and Organizational Psychology, 73(3), 287-302. doi: 10.1348/096317900167038

[41] Kanter, R. (1988). *When a Thousand Flowers Bloom: Structural, Collective, and Social Conditions for Innovation in Organizations.* Iš B. M. Staw, & L. L. Cummings (Eds.), Research in Organizational Behavior (pp. 169–211). Greenwich, CT: JAI Press. Paimta iš http://tinyurl.com/zghaf7g

[42] Bandura, A. (2001). *Social Cognitive Theory: An Agentic Perspective.* Annual Review of Psychology, 52(1), 1-26. doi: 10.1111/1467-839x.00024

[43] Gist, M. E., & Mitchell, T. R. (1992). *Self-efficacy: A theoretical analysis of its determinants and malleability.* Academy of Management Review, 17(2), 183–211. doi: 10.5465/AMR.1992.4279530

[44] Schaufeli, W.B., & Bakker, A.B. (2004). *Job Demands, Job Resources, and Their Relationship with Burnout and Engagement: a Multi-Sample Study.* Journal of Organizational Behavior, 25(3), 293315. doi: 10.1002/job.248

[45] Skaalvik, E. M., & Skaalvik, S. (2014). *Teacher Self-Efficacy and Perceived Autonomy: Relations with Teacher Engagement, Job Satisfaction, and Emotional Exhaustion.* Psychological Reports, 114(1), 68-77. doi:10.2466/14.02.PR0.114k14w0

[46] Mache, S., Vitzthum, K., Wanke, E., Groneberg, D. A., Klapp, B. F., & Danzer, G. (2014). *Exploring the Impact of Resilience, Self-Efficacy, Optimism and Organizational Resources on Work Engagement.*

[47] Kumar, R., & Uzkurt, C. (2011). *Investigating the effects of self-efficacy on innovativeness and the moderating impact of cultural dimensions.* Journal of International Business and Cultural Studies, 4, 1-15. Taken from http://jupapadoc.startlogic.com/manuscripts/10631.pdf

[48] Noordewier, M. K., & van Dijk, E. (2016). *Interest in complex novelty.* Basic and Applied Social Psychology, 38(2), 98-110. doi: 10.1080/01973533.2016.1153474

[49] Zhao, H., Seibert, S. E., & Hills, G. E. (2005). *The Mediating Role of Self-Efficacy in the Development of Entrepreneurial Intentions.* Journal of Applied Psychology, 90(6), 1265–1272. doi: 10.1037/00219010.90.6.1265

[50] Speier, C., & Frese, M. (1997). *Generalized Self-Efficacy as a Mediator and Moderator Between Control and Complexity at Work and Personal Initiative: A Longitudinal Field Study in East Germany.* Human Performance, 10(2), 171–192. doi: 10.1207/s15327043hup1002_7

[51] Park, Y. K., Song, J. H., Yoon, S. W., & Kim, J. (2014). *Learning Organization and Innovative Behavior. The Mediating Effect of Work Engagement.* European Journal of Training & Development, 38(1/2), 75-94. doi:10.1108/EJTD-04-2013-0040

[52] Aryee, S., Walumbwa, F. O., Zhou, Q., & Hartnell, C. A. (2012). *Transformational Leadership, Innovative Behavior, and Task Performance: Test of Mediation and Moderation Processes.* Human Performance, 25(1), 1–25. doi:10.1080/08959285.2011.631648

[53] Mastenbroek, N. J. J. M., Jaarsma, A. D. C., Scherpbier, A. J. J. A., van Beukelen, P., & Demerouti, E. (2014). *The Role of Personal Resources in Explaining Well-Being*

and Performance: A Study Among Young Veterinary Professionals. European Journal of Work and Organizational Psychology, 23(2), 190–202. doi:10.1080/1359432X.2012.728040

[54] Saks, A. M. (2006). *Antecedents and Consequences of Employee Engagement.* Journal of Managerial Psychology, 21(7), 600-619. doi: 10.1108/02683940610690169

[55] Salanova, M., & Schaufeli, W. B. (2008). *A cross-national study of work engagement as a mediator between job resources and proactive behaviour.* The International Journal of Human Resource Management, 19(1), 116-131. doi: 10.1080/09585190701763982

[56] Salanova, M., Agut, S. and Peiro, J.M. (2005). *Linking organizational resources and work engagement to employee performance and customer loyalty: the mediation of service climate.* Journal of Applied Psychology, Vol. 90, pp. 1217-1227. doi: 10.1037/0021-9010.90.6.1217

[57] Xanthopoulou, D., Bakker, A.B., Demerouti, E., & Schaufeli, W.B. (2009). *Work Engagement and Financial Returns: A Diary Study on the Role of Job and Personal Resources.* Journal of Occupational and Organizational Psychology, 82(1), 183–200. doi: 10.1348/096317908X285633

[58] Bakker, A. B., & Bal, M. (2010). *Weekly Work Engagement and Performance: A Study Among Starting Teachers.* Journal of Occupational and Organizational Psychology, 83(1), 189–206. doi: 10.1348/096317909x402596

[59] Agarwal, U. A., Datta, S., Blake-Beard, S., & Bhargava, S. (2012). *Linking LMX, Innovative Work Behaviour and Turnover Intentions. The Mediating Role of Work Engagement.* Career Development International, 17(3), 208-230. doi:10.1108/13620431211241063

[60] Hsiao, H. C., Tu, Y. L., Chang, J. C., & Chen, S. C. (2011). *The influence of teachers' self-efficacy on innovative work behavior.* In International Conference on Social Science and Humanity IPEDR, 5, 233-237. doi: 10.7763/ijssh.2011.v1.6

[61] Bandura, A. (2009). *Socialiniai minties ir veiksmo pagrindai. Socialinė kognityvi teorija.* Vilnius: VU Specialiosios psichologijos laboratorija.

[62] Ventura, M., Salanova, M., & Llorens, S. (2015). *Professional Self-Efficacy as a Predictor of Burnout and Engagement: The Role of Challenge and Hindrance Demands.* The Journal of Psychology, 149(3), 277-302. doi:10.1080/00223980.2013.876380

[63] Hakanen, J.J., Perhoniemi, R., & Toppinen-Tanner, S. (2008). *Positive Gain Spirals at Work: From Job Resources to Work Engagement, Personal Initiative, and Work-Unit Innovativeness.* Journal of Vocational Behavior, 73(1), 78-91. doi: 10.1016/j.jvb.2008.01.003

[64] Sonnentag, S. (2003). *Recovery, Work Engagement, and Proactive Behavior: a New Look at the Interface between Non-Work and Work.* Journal of Applied Psychology, 88(3), 518-28. doi: 10.1037/00219010.88.3.518

[65] Hakanen, J. J., & Roodt, G. (2010). *Using the Job Resouces-Demands Model to Predict Engagement: Analysing a Conceptual model.* From A. B. Bakker, & M. P. Leiter (Eds.). Work engagement: A handbook of essential theory and research. Psychology Press.

[66] Akhtar, R., Boustani, L., Tsivrikos, D., & Chamorro-Premuzic, T. (2015). *The engageable personality: Personality and trait EI as predictors of work engagement.* Personality and Individual Differences, 73, 44-49. doi:10.1016/j.paid.2014.08.040

[67] Mayer, J. D., Salovey P, & Caruso, D. R. (2008). *Emotional intelligence: New ability or eclectic traits.* American Psychologist, 63(6), 503–517. doi: 10.1037/0003-066x.63.6.503

[68] West, M. A., & Altink, W. M. (1996). *Innovation at Work: Individual, Group, Organizational, and Sociohistorical Perspectives.* European Journal of Work and Organizational Psychology, 5(1), 3-11. doi:10.1080/13594329608414834

[69] Petkovska, T. (2015). *The Role And Importance Of Innovation In Business Of Small And Medium Enterprises.* Economic Development, 17(1/2), 55-74. From http://tinyurl.com/zkaahbd

[70] Anderson, N., Potočnik, K., & Zhou, J. (2014). *Innovation and Creativity in Organizations: a State-of-theScience Review, Prospective Commentary, and Guiding Framework.* Journal of Management, 40(5), 1297-1333. doi:10.1177/0149206314527128

[71] Agarwal, U. A. (2014). *Linking justice, trust and innovative work behaviour to work engagement.* Personnel Review, 43(1), 41-73. doi: 10.1108/PR-02-2012-0019

[72] Rich, B., Lepine, J., & Crawford, E. (2010). *Job engagement: Antecedents and Effects on Job Performance.* Academy of Management Journal, 53(3), 617-635. doi: 10.5465/AMJ.2010.51468988

[73] Veenendaal, A., & Bondarouk, T. (2015). *Perceptions of HRM and their effect on dimensions of innovative work behaviour: Evidence from a manufacturing firm.* Management revue, 26(2). doi: 10.1688/mrev2015-02-Veenendaal

[74] Hu, L., & Bentler, P. M. (1999). *Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives.* Structural Equation Modeling: A Multidisciplinary Journal, 6(1), 1–55. doi:10.1080/10705519909540118

7 Appendices

7.1 Appendix A

1. Ar užimate vadovaujančias pareigas? Taip ☐ Ne ☐

2. Kiek metų užimate dabartines pareigas? (*įrašykite*) ___

3. Jūsų lytis: ☐ Moteris ☐ Vyras

4. Jūsų amžius (*įrašykite*): ____

5. Jūsų išsilavinimas:

☐ Aukštasis universitetinis

☐ Aukštasis neuniversitetinis / aukštesnysis

☐ Profesinis

☐ Vidurinis

☐ Nebaigtas vidurinis

Figure 5: Examples of demographic questions.

14. Žemiau pateikiami teiginiai apie Jūsų savijautą dirbant. Pasirinkite Jums tinkamiausią atsakymo variantą.

0	1	2	3	4	5	6
Niekada	Beveik niekada / keletą kartų per metus ar rečiau	Retai / kartą per mėnesį ar rečiau	Kartais / keletą kartų per mėnesį	Dažnai / kartą per savaitę	Labai dažnai / keletą kartų per savaitę	Visada / kasdien

Šis darbas mane įkvepia.	☐ 0	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5	☐ 6
Kai dirbu, visiškai užsimirštu.	☐ 0	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5	☐ 6
Ryte atsikėlęs (-usi) noriu eiti į darbą.	☐ 0	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5	☐ 6

Figure 6: An example of work engagement questionnaire.

15. Perskaitykite pateiktus teiginius ir pasirinkite Jums tinkamiausią atsakymo variantą.

1	2	3	4	5
Visiškai nesutinku	Nesutinku	Nei sutinku, nei nesutinku	Sutinku	Visiškai sutinku

Jei darbe man iškyla problemos, dažniausiai aš surandu išeitį.	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
Įgyta darbo patirtis gerai paruošė mane darbui ateityje.	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5

Figure 7: An example of occupational self-efficacy questionnaire.

18. Toliau pateikiami teiginiai yra susiję su naujų idėjų darbe paieška, kūrimu, plėtojimu ir vertinimu. Įvertinkite, kaip dažnai Jūs savo darbe elgiatės pagal toliau pateiktus būdus (kai kurie teiginiai yra panašūs, tačiau prašome įvertinti juos visus).

1	2	3	4	5
Niekada	Retai	Kartais	Dažnai	Labai dažnai / visada

Domiuosi organizacijoje diegiamomis naujovėmis.	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
Sugalvoju naujų ir praktiškų būdų, kaip išspręsti darbo problemas.	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
Prieš įgyvendindamas (-a) darbe naujas idėjas pirmiausia patikrinu, kaip jos veikia praktikoje.	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5

19. Toliau pateikiami teiginiai yra susiję su naujų idėjų pateikimu kitiems ir įgyvendinimu. Įvertinkite, kaip dažnai Jūs savo darbe elgiatės pagal toliau pateiktus būdus (kai kurie teiginiai yra panašūs, tačiau prašome įvertinti juos visus).

Aktyviai pristatau savo idėjas kitiems (pavyzdžiui, vadovui, bendradarbiams).	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5
Sudarau konkrečius savo idėjų įgyvendinimo planus.	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5

Figure 8: Examples of innovative work behaviour questionnaire.

7.2 Appendix B

Table 8: Descriptive statistics for observed variables

Variable	N	Mean	Median	SD	min	max	% Missing	VIF
OSE	181	4.02	4.00	0.51	2.62	5	0	1.15
WE	181	5.34	5.44	1.09	2.22	7	0	1.15
NOVE	181	3.86	4.00	0.78	1.33	5	0	
EXPL	181	3.58	3.60	0.77	1.20	5	0	
TEST	181	3.35	3.25	0.85	1.00	5	0	
SUPP	181	3.46	3.50	0.97	1.00	5	0	
IMPL	181	3.33	3.40	0.92	1.00	5	0	

7.3 Appendix C

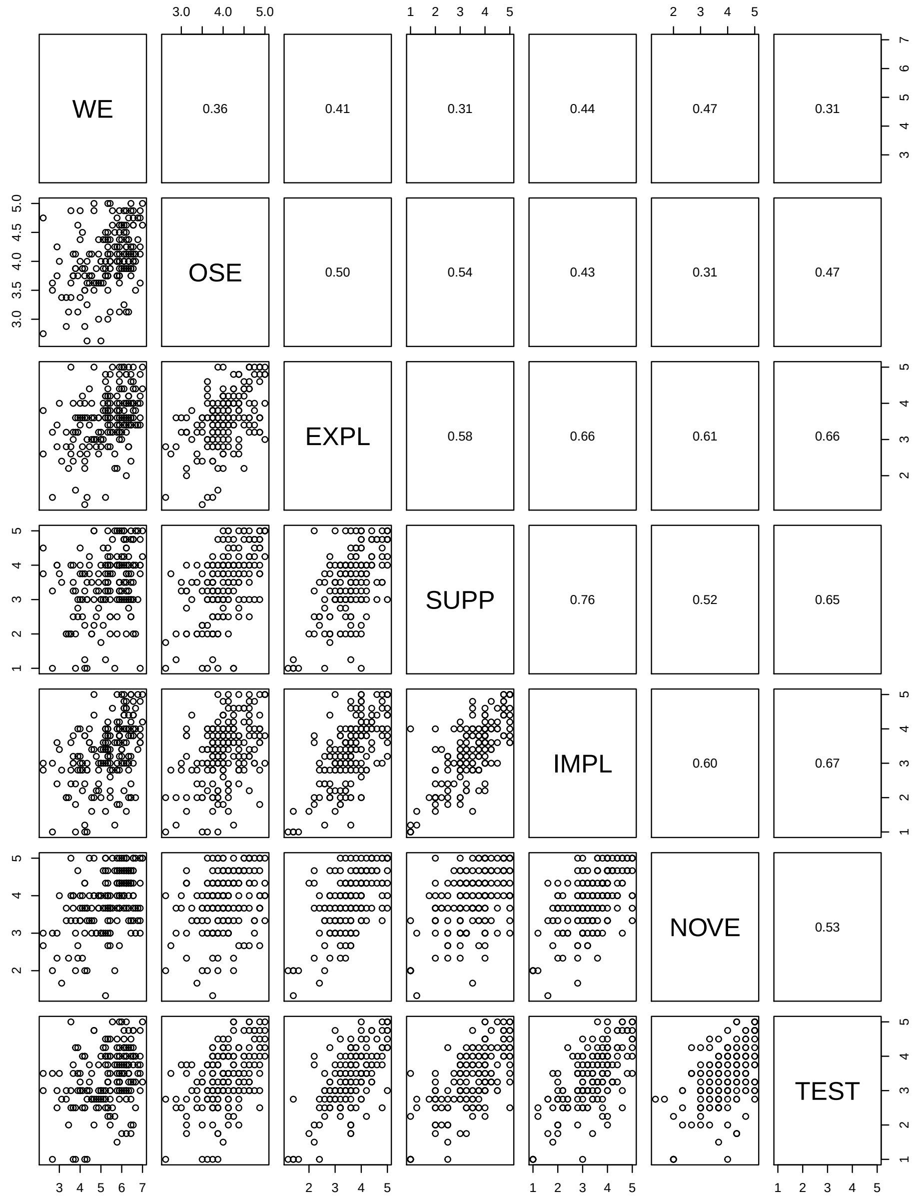

Figure 9: Correlations

*Note. p<0.001 for all correlations.

7.4 Appendix D

Table 9: Standardised estimate bias, standard error bias and coverage for ML estimator

Parameter	Std. Est. Bias	Std. Err. Bias	Coverage
IWB=~NOVE	0,002	0,000	0,939
IWB=~EXPL	0,000	0,000	0,938
IWB=~TEST	-0,001	-0,022	0,940
IWB=~IMPL	0,000	0,000	0,941
IWB~OSE	0,002	0,011	0,943
IWB~WE	-0,006	0,011	0,948
WE~OSE	0,003	-0,007	0,943
Mediation	0,000	0,022	0,943

7.5 Appendix E

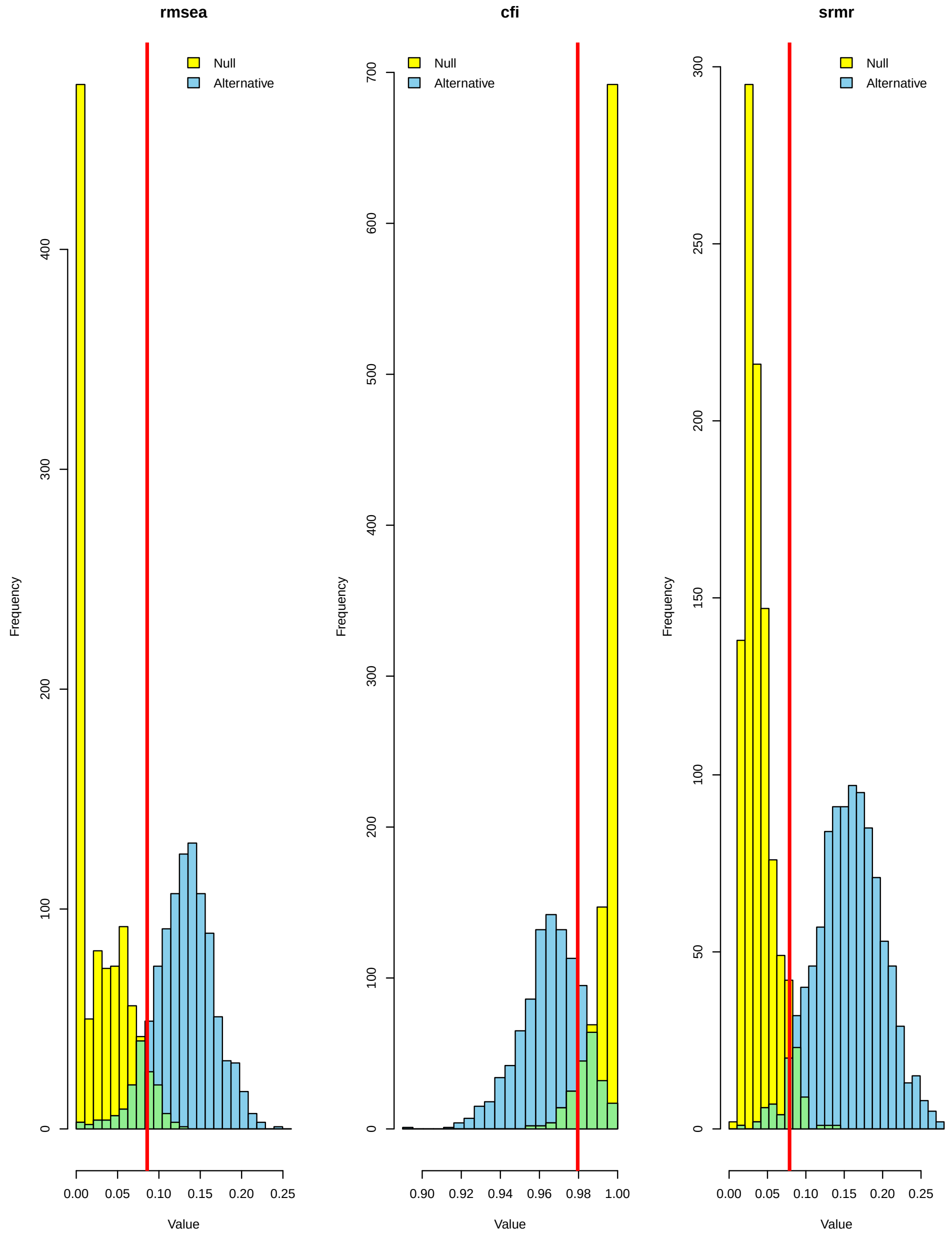

Figure 10: Power plots for model fit indices.