Chapter 14
The Integration of Work and Learning: Tackling the Complexity with Structural Equation Modelling

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Abstract Researching professional learning within the paradigm of the integration of work and learning is interesting as it captures the complexity of workplace learning. However, it does require advanced statistical techniques that are able to model this complexity. Structural equation modelling (SEM) is one of the techniques that enable the examination of more complex relations. This book chapter aims at providing a basic introduction to SEM without using mathematical formulas and going into all the specific technicalities while at the same time staying true to the complexity of the presented analysis.

The current book chapter starts with a general and conceptual presentation of SEM, including the advantages and disadvantages of the technique. The goal of this introduction is to address the questions of why and when SEM should be used and which conditions need to be fulfilled for a valid application of this technique. After a discussion of the fit indices that are used to evaluate the models, the analyses of different types of models are presented by means of an authentic dataset. More specifically, data regarding employees' approaches to learning at work were used to illustrate confirmatory factor analysis (including measurement invariance across groups), path analysis, and the analysis of a full SEM model. The chapter concludes by discussing several possible extensions of SEM and their relevance for researching professional learning.

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14.1 Introduction

Throughout this book, the integration of learning and working takes a central role. Research into the learning potential of the workplace and the characteristics that promote or impede learning has already offered interesting insights (e.g. Hurtz & Williams, 2009; Kyndt & Baert, 2013; Lohman, 2000). Billett (2001) states that the workplace has to be designed in a way that people are invited and stimulated to learn. In addition, Tynjälä (2008) rightly pointed out that learning results from the interaction between the workplace and the individual: 'While the organisation of work sets the context and conditions for learning, it continues to be the reciprocal interaction between the individual and the workplace that determines learning' (Tynjälä, 2008, p. 141). When investigating professional learning, it is therefore important to pay attention to possible interactions and reciprocal and mediating relationships. Researching professional learning within the paradigm of the integration of work and learning is interesting as it captures the complexity of workplace learning. However, it does require more advanced statistical techniques that are able to model this complexity. Structural equation modelling (SEM) is one of the techniques that enable the examination of more complex relations. This book chapter aims at providing a basic introduction to SEM without using mathematical formulas and going into all the specific technicalities while at the same time staying true to the complexity of the presented analysis.

The current book chapter will start with presenting SEM at a conceptual level. We will present why and when SEM could be used, what the advantages and disadvantages are in comparison with regression analysis and which different types of models can be analysed with SEM. Subsequently, the analyses will be illustrated on a dataset that was collected to investigate the approaches to learning of employees in relation with their work motivation, perceived workload and choice independence. Furthermore, several applications of SEM within the research of professional learning will be discussed. Finally, the main conclusions will be summarised.

14.2 Structural Equation Modelling (SEM)

Structural equation modelling denotes a family of multivariate techniques including and combining factor analysis and path analysis in which the focus lies on theoretical constructs represented by latent factors (Hox & Bechger, 1998). Latent factors are unobserved constructs that are reflected by a set of observed variables. Within this section we will first focus on why and when SEM could be used. The different models within SEM will be introduced, and the assumptions of the analysis along with the conditions for conducting SEM will be discussed. Following, the fit indices used to evaluate the models are presented, and the use of modification indices for model improvement is considered.

The core of the SEM analysis involves specifying a theoretical model and subsequently testing whether this model is plausible given the sample data. This comparison is based on the comparison of the variance-covariance matrix of the theoretical model to the variance-covariance matrix that is observed in the sample data (Crockett, 2012). Therefore, SEM is sometimes also known as covariance structure analysis. SEM thus examines a model that represents the linear relationships among variables. Because SEM is based on the analysis of covariances, a SEM model in itself cannot establish causal effects (see Sect. 14.5).

14.2.1 Why and When Should We Use SEM?

The main reason for applying SEM instead of traditional regression analysis is the flexibility and ability to model more complex relationships between constructs. With SEM it is possible to specify 'path models with intervening variables between the independent and dependent variables, and latent factor as well' (Hox & Bechger, 1998, p. 6). Although the method of Baron and Kenny (1986) offers an alternative for assessing whether or not a variable mediates the relationship between two other variables, from a statistical point of view, analysing the different paths simultaneously will yield better results (Iacobucci, 2009). The estimates of the strength of the relationships are more precise, and there is less bias as each effect is estimated together with the other effects (Iacobucci, 2009). In other words, the same variance cannot be estimated twice, as it is the case when separate regression analyses are applied.

Chin (1998) states that for any given SEM model, alternative models that fit the data as well as the proposed model can be found that potentially provide substantially different explanations of the data. Therefore, it is important to note that SEM is traditionally not recommended for exploratory purposes. Clear hypotheses about the structure of the data both in terms of factors as in terms of paths between constructs are needed for sound and replicable applications (Hox & Bechger, 1998). The paths included in the model should be theoretically justified (Chin, 1998). Additionally, the more complex the specified model is, the higher the requirements in terms of sample size become. This issue will be discussed within the section focusing on the conditions that need to be fulfilled for the analysis.

SEM models comprise a measurement model and structural model. The measurement model relates the observed or manifest variables to the latent constructs while the structural or path model denotes the paths/relationships between the constructs. Fitting a measurement model is also known as confirmatory factor analysis (Hox & Bechger, 1998; Iacobucci, 2009). Full SEM models combine the two into one model. When performing SEM analyses, it is always convenient to start by drawing a path diagram; it can guide the analysis. Within this chapter, the generally accepted notation for representing SEM models will be used (Tacq, 1997). Within this notation, boxes represent the observed variables (e.g. the items in your questionnaire) and circles depict the latent constructs (e.g. the underlying construct

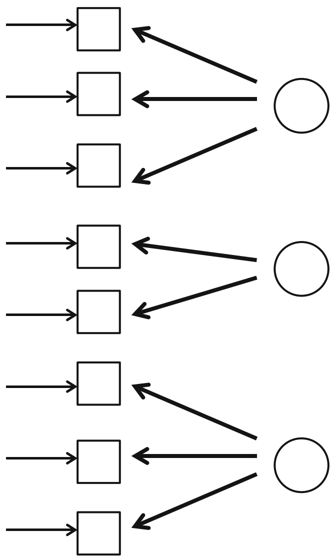

Fig. 14.1 Conceptual model for a confirmatory factor analysis

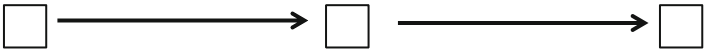

Fig. 14.2 Conceptual model for a path analysis with single mediation between two observed variables

you are trying to measure using different items). Within the measurement model, the arrows originate from the latent construct and point to the observed variables. The underlying idea is that the latent construct gives rise to or is reflected in the observed variables (Chin, 1998; Hox & Bechger, 1998; Iacobucci, 2009). Within the path model the single-headed arrows reflect the directional relationship between two constructs; double-headed arrows depict covariances.

Figure 14.1 represents a measurement model with three latent constructs and eight observed variables. The arrows on the left side of the observed variables indicate the residual error term originating from the fact that the observed variation is not completely explained by the latent construct.

Figure 14.2 depicts a conceptual model for a path analysis. The illustration shows a simple mediation model in which one variable mediates the relation between two other variables. Within a full SEM model (see below), the paths would connect latent constructs. A path analysis reflects the directional relations between observed variables (Cohen, Manion, & Morrison, 2011).

Figure 14.3 shows a full SEM model in which the measurement and the structural model are combined into one analysis.

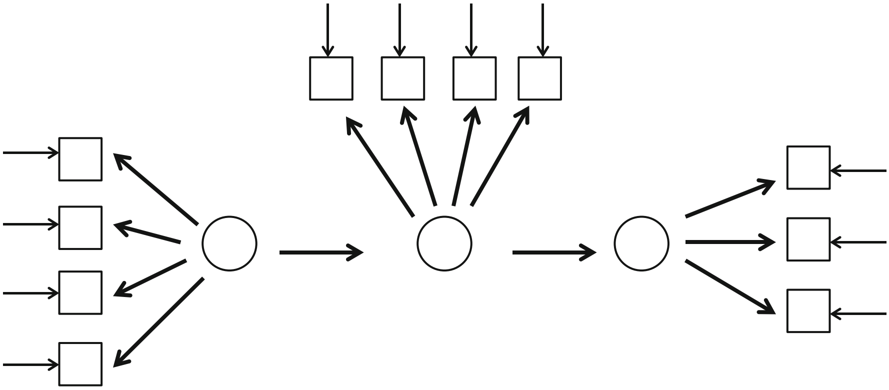

Fig. 14.3 Conceptual model for a full SEM model

14.2.2 Which Conditions Should Be Fulfilled?

When applying SEM and making inferences based on the analysis, it is important to consider the underlying assumptions of the analysis. First, SEM imposes the same statistical assumptions on the data as traditional regression analysis. In addition, *multivariate normality* is assumed. Secondly, SEM assumes that the correct model has been specified, meaning that no relevant variables are missing and that the directional relationships are specified correctly. A correct *model specification* foremost depends on the theoretical grounds of the research at hand. Moreover, the observed variables in SEM are assumed to reflect the latent construct and not to cause it (Kline, 2012). This also explains why the arrows in Figs. 14.1 and 14.3 point from the latent construct towards the observed variables and not vice versa. Changes in the latent construct should be reflected in all observed variables as they are conceptually related to each other. The observed variables in the SEM model cannot be indicators that compensate each other to form an artificial index or composite score (Kline, 2012). In the latter case of *formative indicators,* a change in one observed variable could cause a change in the construct but does not necessarily result in a change in the other observed variables. An example of a formative measure is when the success of an organisation is measured through the combination of an organisation's annual profits, the increase in number of staff members and an indication of the popularity of the company. It could be that the company grows more popular and at the same time a decrease in number of staff members occurs. The profits, number of staff members and popularity of the company might be good indicators, but they do not reflect a latent construct, as they are conceptually unrelated.

After the model has been specified, it is important to check whether the model can be identified, that is, 'whether a unique solutions to the model can be generated' (Crockett, 2012, p. 36). *Model identification* can be executed by following two guidelines developed by Bollen (1989 in Crockett, 2012). First, the structural model should be recursive; this means that all relationships within the structural model are unidirectional and no feedback loops are included. In other words, the dependent variables in the model cannot be a cause and an effect at the same time (Crockett, 2012; Kline, 2012). In addition, the observed variance-covariance matrix must contain more unique elements than the number of parameters that need to be estimated (i.e. factor loadings, latent constructs, paths between latent constructs, etc.). The number of unique elements in the variance-covariance matrix can be calculated using $p(p+1)/2$, where p equals the number of observed variables. The latter guideline is also known as the t rule (Crockett, 2012).

The invalidating effect of violating the statistical assumptions that SEM makes can be reduced by fulfilling conditions regarding sample size and missing values.

Sample size. The debate about the appropriate *sample sizes* for SEM is ongoing. For every 'rule of thumb' that exists, another occurs. In general, the rule is that the more complex the model, the more parameters that need to be estimated, the larger the sample size needs to be and, of course, larger is better (Iacobucci, 2010). The most correct and accurate method to assess the sample size is to assess the power of the analysis, as sample size depends on the specifications of the SEM model at hand (Chin, 1998). More information on power analysis can be found in MacCallum, Browne and Sugawara (1996). Iacobucci (2010) argues that the vague rule of thumb that the sample needs to be larger than 200, which was commonly accepted a while ago, is conservative and oversimplistic. In her article, she therefore argues that small samples of 50–100 could suffice. However, we would like to emphasise that this is only the case when you are testing a simple model with strong effects. One could wonder whether these simple models depict the true effects in an accurate way. The literature does offer some interesting rules of thumb that give an indication of an appropriate *sample size* in which the number of constructs or estimated parameters are taken into account. For the measurement model, the ratio of the sample size to the number of observed variables should at least be 10:1 (Hair, Black, Babin, Anderson, & Tatham, 2006). Bentler and Chou (1987) recommend that the ratio between the sample size and the number of parameters that need to be estimated should also be 10:1 or higher. More information on conducting SEM with small samples can be found in the article of Bentler and Yuan (1999). In addition, alternative estimation methods such as partial least squares (PLS) exist that are appropriate for small samples (see Sect. 14.4).

Missing values. By default, SEM only uses the data of participants without missing values. This approach assumes that if the dataset contains *missing values*, these values are missing completely at random. If this is not the case, one could adopt more advanced methods for handling missing values. For more information on this topic, the reader is referred to Allison (2003).

There is some evidence that SEM is robust to violations of the statistical assumptions if the sample size is large (more than 200 independent observations) and there are no missing values (Hsu, Chen, & Hsieh, 2006; Hu, Bentler, & Kano, 1992; Yuan & Bentler, 1999; Yuan & Zhong, 2013). However, with highly discrete and/or skewed data, especially if sample size is small or moderate, it is recommended to apply more robust estimation techniques and alternative statistics (for more information on these alternatives, see Bentler & Yuan, 1999; Jung, 2013; Kline, 2012; Satorra, 1990).

14.2.3 Fit Indices

A wide variety of *fit indices* have been proposed to evaluate the proposed model in terms of goodness of fit and simplicity of the model. Some fit indices emphasise the fit of the model to the data, while others take into account whether the model is parsimonious (Hox & Bechger, 1998; Iacobucci, 2010). In general, there is some agreement on which fit indices should be reported. First, there is the chi-square test, which is the only inferential measure. The null hypothesis of the chi-square test is that the model fits the data, meaning that to conclude that your model fits the data the chi-square test should not be significant. However, the chi-square test is very sensitive to sample size (Hox & Bechger, 1998). As a consequence, when working with large samples, the statistical test will be significant in almost all real data applications (Hox & Bechger, 1998; Iacobucci, 2010). One might think that it would be advisable not to work with large samples; however, this is not a valid advice, as a sufficiently large sample size is necessary to support the precision of the parameter estimation (Iacobucci, 2010). Alternatively, it has been suggested that fit is acceptable when the *ratio of the chi-square test statistic to the degrees of freedom* is not larger than 3: $\chi^2/\mathrm{df} \leq 3$ (Iacobucci, 2010).

Due to the sensitivity of the chi-square test, the fit of the model is always evaluated based on *multiple alternative indices*. Because all goodness-of-fit indices are some function of the chi-square test, the majority of these indices are also subjected to the sample size but to a much smaller degree than the chi-square test (Hox & Bechger, 1998). As the following indices are not inferential, no statistical hypothesis testing is involved, only guidelines or 'rules of thumb' can be offered (Hu & Bentler, 1999; Iacobucci, 2010). Table 14.1 summarises the different guidelines that are offered in the standard methodological literature. Below we will describe the most commonly used cut-off values. In general, authors are advised to report the *comparative fit index* (*CFI*) that captures the relative goodness of fit in comparison to a simpler model. In a sense it indicates whether making your model more complex actually pays off. Preferably, the CFI is close to or higher than .95 (Hu & Bentler, 1999; Iacobucci, 2010), but values starting from .90 are considered acceptable (Iacobucci, 2010). Some authors also report the Tucker-Lewis Index (TLI) also known as the Non-normed Fit Index (NNFI), which follows the same rules of thumb as the CFI. Next to the chi-square test and CFI, the *SRMR* or *Standardised Root Mean square Residual* is usually reported. The SRMR actually indicates to what extent your model does not fit the data. The higher the value, the worse the model fit. This SRMR largely depends on the factor loadings in the measurement model and is less

Table 14.1 Cut-off values for fit indices

Type fit index	Fit index	Adequate fit index
Absolute fit indexes	Standardised Root Mean Square Residual (SRMR)	SRMR $\leq$ .08 (Hu & Bentler, 1999; MacCallum et al., 1996) SRMR $\leq$ .05 = good (Byrne, 2001; Jaccard & Wan, 1996)
	Jöreskog-Sörbom Goodness-of-Fit Index (GFI)	CFI $\geq$ .95 (Browne & Cudeck, 1993; Hu & Bentler, 1999)
	Adjusted Goodness-of-Fit Index (AGFI)	AGFI $\geq$ .95 (Hu & Bentler, 1999)
Incremental fit indexes/ comparative fit indexes/ relative fit indices	Bentler Comparative Fit Index (CFI)	CFI $\geq$ .95 (Hu & Bentler, 1999) CFI $\geq$ .90 (Bentler, 1992; Byrne, 2001)
	Normed Fit Index (NFI)	NFI $\geq$ .95 (Hu & Bentler, 1999)
	Tucker-Lewis index (TLI) = NNFI: Non-normed Fit Index	TLI $\geq$ .95 (Hu & Bentler, 1999)
Parsimony-adjusted fit indexes	Root Mean Square Error of Approximation (RMSEA)	RMSEA $\leq$ .06 (Hu & Bentler, 1999) RMSEA .06 $\rightarrow$ .08 = reasonable error (Browne & Cudeck, 1993) RMSEA .08 $\rightarrow$ 1 = reasonable error (MacCallum et al., 1996)

prone to violations of the distributional assumption. The maximum value of this index equals 1 and (very) low values are preferred. Values below .08 indicate an acceptable model. Finally, most researchers also report the *Root Mean Square Error of Approximation* (*RMSEA*) and its 90 % confidence interval. The RMSEA was developed to provide an indication of the extent to which the model does not match the true model. Small values indicate a good match. An RMSEA smaller than .06 is advised, although a value lower than .08 can also be considered acceptable (Browne & Cudeck, 1993; MacCallum et al., 1996).

14.2.4 Modification Indices

When the model fit is not satisfactory, a researcher could choose to modify his model. This modification can be based on the parameter estimates (e.g. removing nonsignificant paths or observed variables with low loadings) or on the *modification indices* that indicate which parameter(s) should be added to the model to improve the model fit and how much the chi-square statistic is expected to minimally decrease when that parameter would be added (Hox & Bechger, 1998; Iacobucci, 2009). There is some debate on the use or misuse of *modification indices* (Hox & Bechger, 1998; Iacobucci, 2009). At first glance, these modification indices appear to be very helpful. Often these modification indices are used to improve the model fit sequentially, up till the point that the model meets the requirements. A strong advice regarding the use of the modification indices for improving the model fit is that alterations to the hypothesised model based on the data should only be done when there are theoretical grounds that support these alterations (Chin, 1998; Hox & Bechger, 1998). However, some researchers seem to be very creative in evaluating the theoretical justification post hoc, leading to potentially incorrect models or models that are difficult to cross-validate because they rely too much on the data of the sample at hand (Hox & Bechger, 1998; Iacobucci, 2009). It is therefore proposed to use modification indices prudently and to compare different a priori constructed models (Hox & Bechger, 1998).

14.3 Analysing and Interpreting Data

Within this section the goal is to offer some guidelines for making decision about the data and the steps that could be followed within the analysis, as well as the interpretation of the results. However, bear in mind that how the model is built and the decisions taken within this process need to be theory driven. Crockett (2012) describes five sequential steps within SEM. The first two steps were discussed above: model specification and model identification. Subsequently, the model is estimated. Different estimation procedures can be used for the estimation of the variance-covariance matrix of the model, within this chapter the maximum likelihood estimation will be used. For an introduction into the different estimation methods, we refer the reader to Crockett (2012). Below, we will foremost focus on the fourth and fifth step: model testing and model modification. Model testing involves the evaluation of the plausibility of the theoretical model given the sample data (Crockett, 2012). This evaluation is based on multiple fit indices (cf. infra). The final step of model modification was already shortly introduced above and will also be illustrated below.

14.3.1 Illustration: Concept and Sample

The analyses will be illustrated with a data set that was collected to investigate the relationship between employees' approaches to learning at work and their work motivation, perceived workload and choice independence.

14.3.1.1 Concepts and Measurement Instruments

Within the literature three approaches to learning at work are distinguished: a deep approach, a surface-rational approach and a surface-disorganised approach. A deep approach to learning refers to the combination of an eagerness to learn and the use of integrative strategies that contribute to personal understanding. The surface-rational approach reflects a preference for orderly, accurate and detailed work achieved by using surface learning strategies such as memorisation and a step-by-step approach. Finally, the surface-disorganised approach is considered a nonacademic orientation in combination with surface motives. It is associated with feeling overwhelmed and a sense of incompetence when executing task. These approaches to learning at work were measured by means of the *Approaches to learning at Work Questionnaire* (Kirby, Knapper, Evans, Carty, & Gadula, 2003).

Work motivation was conceptualised from the perspective of the self-determination theory. Within this study the focus lied on the reasons why someone does a particular job and a distinction between autonomous and controlled motivation is made. Work motivation was measured with the *Motivation at Work Scale* (Gagné et al., 2010). Perceived workload and choice independence were measured with the *Workplace Climate Questionnaire* (Kirby et al., 2003). The complete theoretical background, the rationale and the results of the actual study can be found in the article of Kyndt, Raes, Dochy and Janssens (2013).

14.3.1.2 Sample

The *sample* consisted of 358 employees from diverse companies (59 % female). The majority of the participants were employed in profit organisations (52 %), and 38 % were employed in nonprofit or social profit organisations (e.g. healthcare). The remaining 10 % of the participants were employed within the public sector. Participants were between 20 and 64 years old ($M = 37.85$, $SD = 10.64$); on average they had 11.22 years of seniority ($SD = 10.16$). Most respondents had a permanent full-time contract (83 %); others worked part time (14 %) or had a temporary contract (3 %). Finally, participants' initial level of education was diverse: '1 % did not obtain a diploma or finished elementary school, 25 % obtained a secondary degree, 40 % obtained a bachelor's degree (professional or academic), and 34 % obtained a master's degree' (Kyndt et al., 2013, p. 278).

14.3.1.3 Software and Output

For this illustration the analyses were performed with the *lavaan* package of R (Rosseel, 2012). *R* is a free software for statistical computing that can be downloaded from www.R-project.org (R Development Core Team, 2012). Figure 14.4 was plotted by means of the *qgraph* package (Epskamp, Cramer, Waldorp, Schmittmann, & Borsboom, 2012). The R code of this example can be found in the appendix. SEM analysis can also be performed with the AMOS package (Extension of SPSS; Arbuckle, 2011), SAS Calis procedure (SAS Institute Inc, 2008), Mplus (Muthén & Muthén, 1998–2010), EQS (Bentler, 2004) or Lisrel (Jöreskog & Sörbom, 1997). For this illustration, we chose to present the output as given by R so that the reader would recognise these output when undertaken the analysis themselves. This output presents more information than discussed

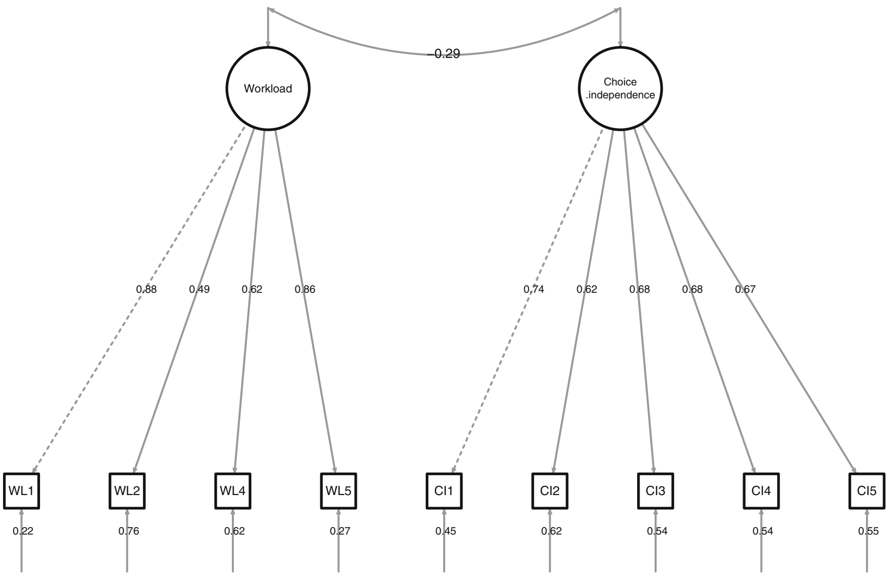

Fig. 14.4 Measurement model with standardised coefficients

within this introductory chapter; therefore, we have marked the values on which the interpretations are based. When performing the analysis in R, the first steps that need to be undertaken are setting a working directory, loading the data and installing the necessary packages.

14.3.2 Measurement Model: Confirmatory Factor Analysis

We will illustrate the *confirmatory factor analysis* with the simplest measurement that was included within the study, that is, the measurement of perceived workload and perceived choice independence of the employee (Kirby et al., 2003). Both constructs were measured by five items (i.e. observed variables) that were scored on a five-point Likert scale (see Table 14.2).

14.3.2.1 Confirming the Model

The results of the CFA show that the hypothesised measurement model fits the data reasonably well (Output 1). Although the chi-square test is statistically significant ($\chi^2 = 98.223$, df = 34, $p < .001$), the ratio between the test statistic and degrees of freedom (98.223/34 = 2.89) is below 3. In addition, the *CFI* and *TLI,* respectively, equal .94 and .92, which is above the proposed cut-off of .90. The *SRMR* and *RMSEA* are rather high (SRMR = .075, RMSEA = .073, CI 90 % [.056, .09]), but both are acceptable, although it is not a good sign that the values within the confidence interval exceed .08.

```
lavaan (0.5-12) converged normally after  31 iterations

Used       Total
  Number of observations                           354        359

  Estimator                                         ML
  Minimum Function Test Statistic               98.223
  Degrees of freedom                                34
  P-value (Chi-square)                           0.000

Model test baseline model:

  Minimum Function Test Statistic             1176.569
  Degrees of freedom                                45
  P-value                                        0.000

Full model versus baseline model:

  Comparative Fit Index (CFI)                    0.943
  Tucker-Lewis Index (TLI)                       0.925

Loglikelihood and Information Criteria:

  Loglikelihood user model (H0)              -4804.185
  Loglikelihood unrestricted model (H1)      -4755.074

  Number of free parameters                         21
  Akaike (AIC)                                9650.371
  Bayesian (BIC)                              9731.626
  Sample-size adjusted Bayesian (BIC)         9665.005

Root Mean Square Error of Approximation:

  RMSEA                                          0.073
  90 Percent Confidence Interval          0.056  0.090
  P-value RMSEA <= 0.05                          0.013

Standardized Root Mean Square Residual:

  SRMR                                           0.075


Parameter estimates:

  Information                                 Expected
  Standard Errors                             Standard


                   Estimate  Std.err  Z-value  P(>|z|)   Std.lv  Std.all
Latent variables:
  Workload =~
    WL1               1.000                               1.006    0.875
    WL2               0.611    0.063    9.686    0.000    0.615    0.512
    WL3               0.197    0.061    3.218    0.001    0.199    0.181
    WL4               0.769    0.062   12.432    0.000    0.774    0.633
    WL5               0.961    0.057   16.854    0.000    0.967    0.859

  Choice.independence =~
    CI1               1.000                               0.809    0.743
    CI2               0.815    0.079   10.353    0.000    0.659    0.619
    CI3               0.892    0.079   11.263    0.000    0.721    0.680
    CI4               0.808    0.072   11.240    0.000    0.653    0.678
    CI5               0.836    0.075   11.173    0.000    0.676    0.674

Covariances:
  Workload ~~
    Choic.ndpndnc    -0.231    0.054   -4.259    0.000   -0.284   -0.284

Variances:
    WL1               0.310    0.050                      0.310    0.234
    WL2               1.061    0.084                      1.061    0.737
    WL3               1.166    0.088                      1.166    0.967
    WL4               0.896    0.075                      0.896    0.600
    WL5               0.332    0.048                      0.332    0.262
    CI1               0.529    0.056                      0.529    0.447
    CI2               0.698    0.061                      0.698    0.616
    CI3               0.605    0.057                      0.605    0.538
    CI4               0.500    0.047                      0.500    0.540
    CI5               0.549    0.051                      0.549    0.546
    Workload          1.013    0.106                      1.000    1.000
    Choic.ndpndnc     0.654    0.089                      1.000    1.000
```

Output 1 CFA all items

Table 14.2 Items measurement model

Scale	Item nr.	Question
Workload	WL1	The workload here is too heavy
	WL2	It sometimes seems to me that my job requires me to do too many different things
	WL3	In this organisation you're expected to spend a lot of time learning things on your own
	WL4	There seems to be too much work to get through here
	WL5	There's a lot of pressure on you as an employee here
Choice independence	CI1	There is a real opportunity in this organisation for people to choose the particular tasks they work on
	CI2	The organisation really seems to encourage us to develop our own work-related interests as far as possible
	CI3	We seem to be given a lot of choice here in the work we have to do
	CI4	This organisation gives you a chance to go about your work in ways which suit your own way of learning
	CI5	Employees here have a great deal of choice over how they learn new tasks

Table 14.3 Model fit without item WL3

Instrument	χ^2/df	CFI	TLI	RMSEA 90 % CI	SRMR
Workload and choice independence	2.40	.97	.95	.063 [.043; .083]	.052

In sum, the measurement model shows an acceptable fit, but there is room for improvement. Because the SRMR is rather high, it could be interesting to examine the factor loadings of the different items and delete item(s) with low factor loadings. Ideally the standardised values of the factor loadings (see std.all in output) are around or above .50 (Hair et al., 2006; Maruyama, 1998). Within this solution, only item WL3 has a factor loading below .50. If we look at the questions in Table 14.2, we can observe that WL3 focuses on a different aspect in comparison with the other four items. WL3 is the only item that considers learning. Therefore, we decided to test a second measurement model in which item WL3 was excluded. The results show an improved fit (Table 14.3 and Output 2).

```
lavaan (0.5-12) converged normally after  31 iterations

                                                  Used       Total
  Number of observations                           355         359

  Estimator                                         ML
  Minimum Function Test Statistic               62.391
  Degrees of freedom                                26
  P-value (Chi-square)                           0.000

Model test baseline model:

  Minimum Function Test Statistic             1128.760
  Degrees of freedom                                36
  P-value                                        0.000

Full model versus baseline model:

  Comparative Fit Index (CFI)                    0.967
  Tucker-Lewis Index (TLI)                       0.954

Loglikelihood and Information Criteria:

  Loglikelihood user model (H0)              -4286.378
  Loglikelihood unrestricted model (H1)      -4255.182

  Number of free parameters                         19
  Akaike (AIC)                                8610.755
  Bayesian (BIC)                              8684.326
  Sample-size adjusted Bayesian (BIC)         8624.049

Root Mean Square Error of Approximation:

  RMSEA                                          0.063
  90 Percent Confidence Interval          0.043  0.083
  P-value RMSEA <= 0.05                          0.136

Standardized Root Mean Square Residual:

  SRMR                                           0.052


Parameter estimates:

  Information                                 Expected
  Standard Errors                             Standard


                   Estimate  Std.err  Z-value  P(>|z|)   Std.lv  Std.all
Latent variables:
  Workload =~
    WL1               1.000                               1.009    0.878
    WL2               0.604    0.063    9.590    0.000    0.609    0.508
    WL4               0.765    0.062   12.403    0.000    0.771    0.632
    WL5               0.954    0.057   16.700    0.000    0.962    0.855


  Choice.independence =~
    CI1               1.000                               0.806    0.742
    CI2               0.815    0.079   10.315    0.000    0.658    0.617
    CI3               0.893    0.079   11.242    0.000    0.720    0.679
    CI4               0.809    0.072   11.230    0.000    0.653    0.678
    CI5               0.837    0.075   11.155    0.000    0.675    0.673
```

Output 2 CFA without WL3

```
Covariances:
  Workload ~~
    Choic.ndpndnc    -0.237    0.054   -4.357    0.000   -0.291   -0.291

Variances:
    WL1               0.302    0.051                      0.302    0.229
    WL2               1.068    0.084                      1.068    0.742
    WL4               0.895    0.074                      0.895    0.601
    WL5               0.340    0.049                      0.340    0.268
    CI1               0.531    0.056                      0.531    0.450
    CI2               0.702    0.061                      0.702    0.619
    CI3               0.605    0.057                      0.605    0.539
    CI4               0.499    0.047                      0.499    0.540
    CI5               0.549    0.051                      0.549    0.547
    Workload          1.017    0.107                      1.000    1.000
    Choic.ndpndnc     0.650    0.088                      1.000    1.000
```

Output 2 (continued)

Table 14.4 Measurement invariance for males and females

Model					Model comparison			
	χ^2 (df)	CFI	RMSEA	BIC		$\Delta\chi^2$ (Δdf)	p-value	Δ CFI
Model 1	88.810** (52)	.966	.063	8833.54				
Model 2 (equal loadings)	100.039** (59)	.962	.063	8803.69	Model 1 vs. 2	11.228 (7)	.129	.004
Model 3 (+equal intercepts)	103.398** (66)	.965	.057	8765.96	Model 2 vs. 3	3.359 (7)	.850	−.003
Model 4 (+equal errors)	113.432*** (68)	.958	.061	8764.25	Model 3 vs. 4	10.034 (2)	<.01	.007

*$p<.05$; **$p<.01$; ***$p<.001$

Because both models show an acceptable fit, both could be accepted. The decision for the most appropriate measurement model should foremost be guided by theory. In this case, one could consider whether or not investing time in learning is an important aspect of the construct of perceived workload. In addition, you could also test which model is superior in a statistical sense. Because the first model can be considered an extension of the second model (i.e. the models are nested), the *chi-square test for model comparison* can be applied. By using a simple formula in Excel (=CHIDIST(Δ*chi-statistics*[1]; Δ*degrees of freedom*)), you can calculate whether the difference between the chi-square statistics of both models is statistically significant. In this example, the difference between the chi-square statistics equals 98.223−62.391 = 35.832, and the difference between the degrees of freedom equals 34−36 = 8. The significance test reveals that this difference is statistically significant ($p<.001$) indicating the second model is statistically superior to the first (a smaller chi-square value indicates a better fit). From a theoretical point of view, the conclusion is also supported because the emphasis within perceived workload lies on general workplace conditions, regardless of the fact that the effort had to be undertaken for learning specifically. Figure 14.4 depicts the measurement model.

[1] **Δ** = difference.

14.3.2.2 The Stability of the Model: Measurement Invariance

Recently, more and more attention has been given to the stability of the measurement model (Boeve-de Pauw, Jacobs, & Van Petegem, 2012; Coertjens, Donche, De Maeyer, Vanthournout, & Van Petegem, 2013). If the goal is to compare the constructs across groups and/or over time – which is often the case – it is important to determine whether a questionnaire measures the same constructs with the same structure across groups and/or over time. When *measurement invariance* is established, it can be accepted that different groups of participants (e.g. males and females) or the same participants across different measurement moments (longitudinal measurement invariance) interpret the individual questions and underlying constructs in a similar way.

Different levels (less to more demanding) of measurement invariance are described: configural, metric, scalar, and strict invariance. Configural invariance (Model 1) refers to the fact that the basic model structure is invariant across groups (Boeve-de Pauw et al., 2012). It shows that the participants conceptualise the constructs similarly. It basically shows that the same structure – the same items belong to the same construct – holds for both groups or both measurement moments. Configural invariance, however, does not ensure that the separate items are interpreted similarly because the factor loadings of the items can be different across groups or measurement moments.

To test whether metric invariance is achieved, one can compare the configural model to a model in which the factor loadings are constrained (Model 2) to be equal for each group or at each measurement moment. If constraining the factor loadings does not result in a significantly less good fit of the model, metric invariance can be claimed. A model is considered as good as the previous model if the difference between the *CFI*s of both models is smaller than .01. Ideally the difference in the chi-square test is also not significant; however, it is known that the chi-square statistic is sensitive to the size of the sample (Iacobucci, 2010).

Metric invariance indicates that the items are interpreted in a similar way across groups or measurement moments. When the aim is to compare means of the latent constructs across groups, it is necessary to achieve scalar invariance. Scalar invariance indicates that differences in means of the observed items are a consequence of the differences in means of the latent constructs. To identify scalar invariance, the model in which both the loadings and the intercepts of the items are constrained to be equal across groups or measurement moments (model 3) is compared to the model in which only the loadings (model 2) are constrained. When the model with constrained loadings and intercepts results into a too large decrease of the CFI, one could explore the option of freeing some of the intercepts and achieving partial intercept invariance. Advanced statistical models such as multiple-indicator growth analysis in case of longitudinal analysis can take these intercept variances into account (e.g. Coertjens et al., 2013). Finally, one can also check for invariance in error variances (strict invariance). However, in practice full measurement invariance is rarely achieved nor necessary (Boeve-de Pauw et al., 2012).

Measurement invariance *across groups* can be tested relatively easy in R with the *semTools* package (Pornprasertmanit, Miller, Schoemann, & Rosseel, 2013). The specific commands can be found in the Appendix.

```
Measurement invariance tests:

Model 1: configural invariance:
   chisq       df    pvalue      cfi     rmsea      bic
  88.810   52.000     0.001    0.966     0.063 8833.541

Model 2: weak invariance (equal loadings):
   chisq       df    pvalue      cfi     rmsea      bic
 100.039   59.000     0.001    0.962     0.063 8803.685

[Model 1 versus model 2]
  delta.chisq      delta.df delta.p.value     delta.cfi
       11.228         7.000         0.129         0.004

Model 3: strong invariance (equal loadings + intercepts):
   chisq       df    pvalue      cfi     rmsea      bic
 103.398   66.000     0.002    0.965     0.057 8765.959

[Model 1 versus model 3]
  delta.chisq      delta.df delta.p.value     delta.cfi
       14.588        14.000         0.407         0.001

[Model 2 versus model 3]
  delta.chisq      delta.df delta.p.value     delta.cfi
        3.359         7.000         0.850        -0.003

Model 4: equal loadings + intercepts + means:
   chisq       df    pvalue      cfi     rmsea      bic
 113.432   68.000     0.000    0.958     0.061 8764.254

[Model 1 versus model 4]
  delta.chisq      delta.df delta.p.value     delta.cfi
       24.622        16.000         0.077         0.008

[Model 3 versus model 4]
  delta.chisq      delta.df delta.p.value     delta.cfi
       10.034         2.000         0.007         0.007
```

Output 3 Measurement invariance

Within our illustration, we checked whether males and females interpreted the items and constructs in a similar way. In other words the measurement invariance across males and females was tested. The results can be found in Output 3 and are preferably reported by means of a table (see Table 14.4). The results in Table 14.4 show that the measurement of perceived workload and choice independence reaches scalar invariance. The differences between the *CFI*s are below .01 and the chi-square test for model comparison show that the different models do not differ significantly from each other.

Establishing *longitudinal measurement invariance* follows the same procedure as establishing measurement invariance over groups:

- Testing configural invariance
- Constraining factor loadings to be equal and comparing this to the configural invariance model (metric invariance)
- Constraining factor loadings and intercepts to be equal and comparing this to the metric invariance model (scalar invariance)

However, the difference with establishing measurement invariance across groups is that longitudinal measurement invariance is assessed for each scale separately and not the instrument as a whole (Coertjens, Donche, De Maeyer, Vanthournout & Van Petegem, 2012). Currently, longitudinal measurement invariance cannot be assessed by means of an R-package. This type of analysis is foremost executed with the Mplus

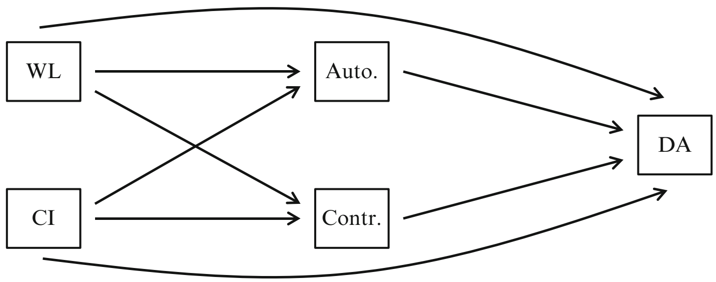

Fig. 14.5 Path diagram illustration path analysis (*Note*: *WL* workload, *CI* choice independence, *Auto.* autonomous motivation, *Contr.* controlled motivation, *DA* deep approach)

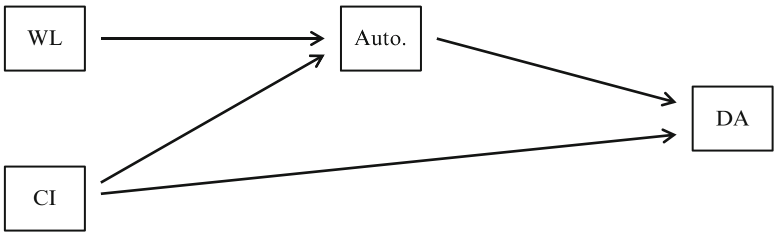

Fig. 14.6 Path diagram illustration path analysis without nonsignificant paths

software (Muthén & Muthén, 1998–2010). In our article on the development of a self-assessment instrument for the generic competences of vocational education students, an example of longitudinal measurement invariance testing relevant for the field of professional learning can be found (Kyndt et al., accepted).

14.3.3 Structural Model: Path Analysis

An illustration of a model including the two motivational scales as mediating variables is provided below. Figure 14.5 represent the path diagram of the model under examination.

The *path analysis* including the two mediating variables shows a fit that is not optimal. Moreover, because the model includes almost every possible relationship, the model cannot be considered parsimonious. The poor model fit is evident from a ratio between the chi-square and degrees of freedom that is too large (χ^2/df = 5.92) and an *RSMEA* of .12 which is also too large. Simplifying the model by excluding nonsignificant paths could be a solution to this problem. Based on the output (Output 4), we decided to exclude the path between controlled motivation and a deep approach to learning, and the path between workload and autonomous motivation. Because the interest lies in predicting employees' deep approach to learning and controlled motivation was inserted as a mediator between the perception of workload and choice independence, the paths from workload and choice independence to controlled motivation were also removed (Output 5). The new model that will be tested is represented by a path diagram in Fig. 14.6.

```
lavaan (0.5-12) converged normally after  19 iterations

  Number of observations                           359

  Estimator                                         ML
  Minimum Function Test Statistic                5.923
  Degrees of freedom                                 1
  P-value (Chi-square)                           0.015

Model test baseline model:

  Minimum Function Test Statistic              249.403
  Degrees of freedom                                 9
  P-value                                        0.000

Full model versus baseline model:

  Comparative Fit Index (CFI)                    0.980
  Tucker-Lewis Index (TLI)                       0.816

Loglikelihood and Information Criteria:

  Loglikelihood user model (H0)              -5099.399
  Loglikelihood unrestricted model (H1)      -5096.438

  Number of free parameters                         11
  Akaike (AIC)                               10220.798
  Bayesian (BIC)                             10263.515
  Sample-size adjusted Bayesian (BIC)        10228.617


Root Mean Square Error of Approximation:

  RMSEA                                          0.117
  90 Percent Confidence Interval          0.041  0.215
  P-value RMSEA <= 0.05                          0.069

Standardized Root Mean Square Residual:

  SRMR                                           0.029

Parameter estimates:

  Information                                 Expected
  Standard Errors                             Standard

                   Estimate  Std.err  Z-value  P(>|z|)   Std.lv  Std.all
Regressions:
  DA ~
    Autonomous        0.266    0.062    4.313    0.000    0.266    0.219
    Controlled        0.085    0.056    1.535    0.125    0.085    0.071
  Autonomous ~
    WL                0.067    0.049    1.349    0.177    0.067    0.063
    CI                0.529    0.051   10.400    0.000    0.529    0.485
  Controlled ~
    WL                0.242    0.055    4.410    0.000    0.242    0.227
    CI                0.181    0.056    3.208    0.001    0.181    0.165
  DA ~
    WL                0.199    0.059    3.347    0.001    0.199    0.155
    CI                0.488    0.069    7.115    0.000    0.488    0.369

Variances:
    DA               20.246    1.511                     20.246    0.711
    Autonomous       14.805    1.105                     14.805    0.768
    Controlled       18.208    1.359                     18.208    0.931
```

Output 4 Path analysis with mediating variables

This more parsimonious model shows a good fit (χ^2/df = 1.82, CFI = .99, TLI = .98, RMSEA = 0.048, CI 90 % [0; .058], SRMR = .02). All included paths are significant, indicating that perceived workload and choice independence predict employee's deep approaches to learning significantly. In addition, autonomous motivation was found to mediate this relationship.

```
lavaan (0.5-12) converged normally after  16 iterations

  Number of observations                           359

  Estimator                                         ML
  Minimum Function Test Statistic                1.815
  Degrees of freedom                                 1
  P-value (Chi-square)                           0.178

Model test baseline model:

  Minimum Function Test Statistic              215.652
  Degrees of freedom                                 5
  P-value                                        0.000

Full model versus baseline model:

  Comparative Fit Index (CFI)                    0.996
  Tucker-Lewis Index (TLI)                       0.981

Loglikelihood and Information Criteria:

  Loglikelihood user model (H0)              -4071.179
  Loglikelihood unrestricted model (H1)      -4070.271

  Number of free parameters                          6
  Akaike (AIC)                                8154.358
  Bayesian (BIC)                              8177.658
  Sample-size adjusted Bayesian (BIC)         8158.623

Root Mean Square Error of Approximation:

  RMSEA                                          0.048
  90 Percent Confidence Interval          0.000  0.158
  P-value RMSEA <= 0.05                          0.355

Standardized Root Mean Square Residual:

  SRMR                                           0.020

Parameter estimates:

  Information                                 Expected
  Standard Errors                             Standard

                   Estimate  Std.err  Z-value  P(>|z|)   Std.lv  Std.all
Regressions:
  DA ~
    Autonomous        0.278    0.062    4.506    0.000    0.278    0.229
  Autonomous ~
    CI                0.520    0.051   10.287    0.000    0.520    0.477
  DA ~
    WL                0.219    0.058    3.776    0.000    0.219    0.170
    CI                0.497    0.068    7.336    0.000    0.497    0.376

Variances:
    DA               20.376    1.521                     20.376    0.717
    Autonomous       14.881    1.111                     14.881    0.772
```

Output 5 Path analysis mediating variables without nonsignificant paths

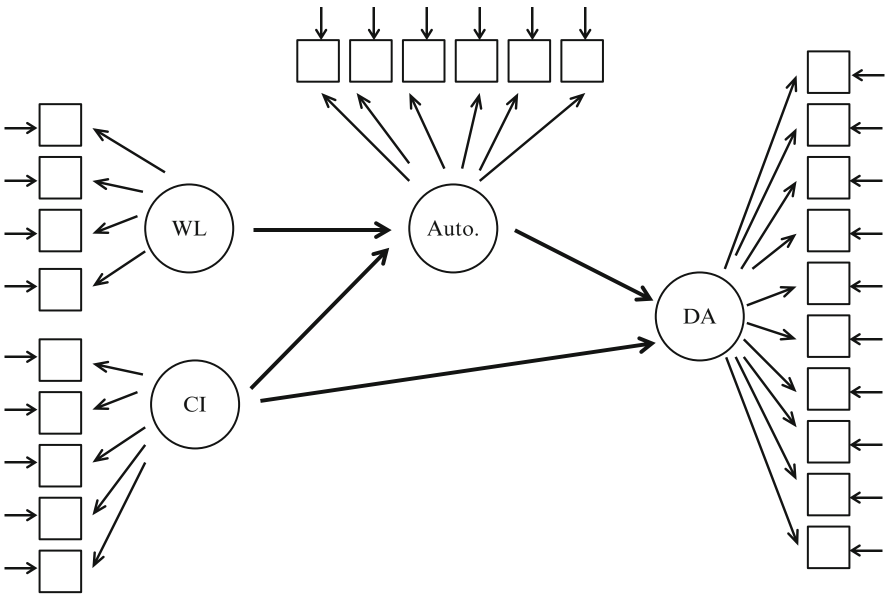

Fig. 14.7 Path diagram full SEM model

Full SEM Model

Finally, a *full SEM model* combines a measurement model and structural model that were presented above. As an illustration, the full SEM model of final path analysis will be examined (see Fig. 14.7).

The results show that this model does not adequately fit the data (χ^2/df = 2.47, CFI = .85, TLI = .84, RMSEA = 0.065, CI 90 % [.059; .071], SRMR = .075). The modification indices were checked to examine whether the model could be improved (Output 6).

```
lavaan (0.5-12) converged normally after  41 iterations

                                                  Used       Total
  Number of observations                           346         359

  Estimator                                         ML
  Minimum Function Test Statistic              665.646
  Degrees of freedom                               270
  P-value (Chi-square)                           0.000

Model test baseline model:

  Minimum Function Test Statistic             3011.588
  Degrees of freedom                               300
  P-value                                        0.000

Full model versus baseline model:

  Comparative Fit Index (CFI)                    0.854
  Tucker-Lewis Index (TLI)                       0.838

Loglikelihood and Information Criteria:

  Loglikelihood user model (H0)             -11147.345
  Loglikelihood unrestricted model (H1)     -10814.522

  Number of free parameters                         55
  Akaike (AIC)                               22404.690
  Bayesian (BIC)                             22616.244
  Sample-size adjusted Bayesian (BIC)        22441.768

Root Mean Square Error of Approximation:

  RMSEA                                          0.065
  90 Percent Confidence Interval          0.059  0.071
  P-value RMSEA <= 0.05                          0.000

Standardized Root Mean Square Residual:

  SRMR                                           0.075

Parameter estimates:

  Information                                 Expected
  Standard Errors                             Standard

                   Estimate  Std.err  Z-value  P(>|z|)   Std.lv  Std.all
Latent variables:
  Workload =~
    WL1               1.000                               1.004    0.873
    WL2               0.613    0.064    9.593    0.000    0.615    0.515
    WL4               0.762    0.063   12.171    0.000    0.765    0.631
    WL5               0.962    0.059   16.390    0.000    0.966    0.856
  Choice.independence =~
    CI1               1.000                               0.796    0.735
    CI2               0.839    0.080   10.543    0.000    0.667    0.628
    CI3               0.897    0.079   11.363    0.000    0.714    0.680
    CI4               0.804    0.072   11.200    0.000    0.640    0.669
    CI5               0.815    0.075   10.908    0.000    0.649    0.651
  Deep.approach =~
    ALWD1             1.000                               0.521    0.446
    ALWD2             0.559    0.132    4.243    0.000    0.292    0.292
    ALWD3             0.463    0.104    4.461    0.000    0.241    0.312
    ALWD4             0.350    0.107    3.260    0.001    0.182    0.213
    ALWD5             0.778    0.132    5.873    0.000    0.405    0.471
    ALWD6             1.065    0.162    6.588    0.000    0.555    0.590
    ALWD7             0.773    0.134    5.785    0.000    0.403    0.459
```

Output 6 Full SEM model

```
    ALWD8             1.160    0.181    6.417    0.000    0.605    0.557
    ALWD9             0.691    0.126    5.498    0.000    0.360    0.422
    ALWD10            1.046    0.170    6.153    0.000    0.545    0.513
  Autonomous.motivation =~
    Intrins1          1.000                               0.883    0.903
    Intrins2          0.970    0.042   23.369    0.000    0.857    0.916
    Intrins3          0.631    0.051   12.330    0.000    0.557    0.597
    Ident1            0.426    0.063    6.771    0.000    0.376    0.361
    Ident2            0.342    0.070    4.900    0.000    0.301    0.267
    Ident3            0.716    0.052   13.800    0.000    0.632    0.648

Regressions:
  Deep.approach ~
    Workload          0.093    0.032    2.901    0.004    0.180    0.180
    Choic.ndpndnc     0.387    0.069    5.573    0.000    0.591    0.591
    Autonms.mtvtn     0.163    0.044    3.706    0.000    0.276    0.276
  Autonomous.motivation ~
    Choic.ndpndnc     0.579    0.071    8.208    0.000    0.522    0.522

Covariances:
  Workload ~~
    Choic.ndpndnc    -0.211    0.053   -3.948    0.000   -0.264   -0.264

Variances:
    WL1               0.316    0.052                      0.316    0.239
    WL2               1.048    0.084                      1.048    0.735
    WL4               0.886    0.075                      0.886    0.602
    WL5               0.339    0.050                      0.339    0.266
    CI1               0.540    0.054                      0.540    0.460
    CI2               0.685    0.060                      0.685    0.606
    CI3               0.593    0.055                      0.593    0.538
    CI4               0.505    0.046                      0.505    0.552
    CI5               0.573    0.051                      0.573    0.577
    ALWD1             1.093    0.089                      1.093    0.801
    ALWD2             0.909    0.071                      0.909    0.914
    ALWD3             0.540    0.042                      0.540    0.903
    ALWD4             0.703    0.054                      0.703    0.955
    ALWD5             0.576    0.048                      0.576    0.778
    ALWD6             0.577    0.052                      0.577    0.652
    ALWD7             0.608    0.050                      0.608    0.789
    ALWD8             0.811    0.071                      0.811    0.689
    ALWD9             0.599    0.048                      0.599    0.822
    ALWD10            0.833    0.071                      0.833    0.737
    Intrins1          0.176    0.025                      0.176    0.184
    Intrins2          0.141    0.023                      0.141    0.161
    Intrins3          0.560    0.045                      0.560    0.643
    Ident1            0.944    0.073                      0.944    0.869
    Ident2            1.180    0.090                      1.180    0.928
    Ident3            0.552    0.045                      0.552    0.580
    Workload          1.007    0.108                      1.000    1.000
    Choic.ndpndnc     0.633    0.086                      1.000    1.000
    Deep.approach     0.120    0.034                      0.442    0.442
    Autonms.mtvtn     0.567    0.059                      0.728    0.728
```

Output 6 (continued)

The modification indices (Output 7) showed that the model could be improved by adding covariances between several observed variables. Only combinations of observed variables that reflected the same latent constructs were included because they can be considered in accordance with our theoretical model. For presentation purposes, only an excerpt of the output was included.

```
> modindices(FitSEMFull)
                         lhs op                         rhs     mi    epc sepc.lv sepc.all sepc.nox
1                   Workload =~                         WL1     NA     NA      NA       NA       NA
2                   Workload =~                         WL2  0.000  0.000   0.000    0.000    0.000
3                   Workload =~                         WL4  0.000  0.000   0.000    0.000    0.000
4                   Workload =~                         WL5  0.000  0.000   0.000    0.000    0.000
5                   Workload =~                         CI1  4.339  0.107   0.107    0.099    0.099
6                   Workload =~                         CI2  2.029  0.077   0.077    0.072    0.072
7                   Workload =~                         CI3  0.245 -0.025  -0.026   -0.024   -0.024
8                   Workload =~                         CI4 13.180 -0.171  -0.172   -0.180   -0.180
9                   Workload =~                         CI5  0.009  0.005   0.005    0.005    0.005
10                  Workload =~                       ALWD1  0.563 -0.047  -0.047   -0.041   -0.041

----------

100 Autonomous.motivation =~                       Ident3  0.000  0.000   0.000    0.000    0.000
101                      WL1 ~~                         WL1  0.000  0.000   0.000    0.000    0.000
102                      WL1 ~~                         WL2  1.644 -0.066  -0.066   -0.048   -0.048
103                      WL1 ~~                         WL4  0.000  0.001   0.001    0.001    0.001
104                      WL1 ~~                         WL5  5.857  0.248   0.248    0.191    0.191
105                      WL1 ~~                         CI1  0.025 -0.005  -0.005   -0.004   -0.004
106                      WL1 ~~                         CI2  0.079  0.010   0.010    0.008    0.008
107                      WL1 ~~                         CI3  0.111 -0.011  -0.011   -0.009   -0.009
108                      WL1 ~~                         CI4  2.462  0.047   0.047    0.043    0.043
109                      WL1 ~~                         CI5  0.410 -0.020  -0.020   -0.018   -0.018
110                      WL1 ~~                       ALWD1  0.299  0.023   0.023    0.017    0.017
111                      WL1 ~~                       ALWD2  2.124 -0.055  -0.055   -0.048   -0.048
112                      WL1 ~~                       ALWD3  0.040 -0.006  -0.006   -0.006   -0.006
113                      WL1 ~~                       ALWD4  0.018  0.004   0.004    0.004    0.004
114                      WL1 ~~                       ALWD5  1.139  0.033   0.033    0.033    0.033
115                      WL1 ~~                       ALWD6  0.238 -0.015  -0.015   -0.014   -0.014
116                      WL1 ~~                       ALWD7  2.483 -0.049  -0.049   -0.049   -0.049
117                      WL1 ~~                       ALWD8  0.061  0.009   0.009    0.007    0.007
118                      WL1 ~~                       ALWD9  4.256 -0.064  -0.064   -0.065   -0.065
119                      WL1 ~~                      ALWD10  0.649 -0.030  -0.030   -0.024   -0.024
120                      WL1 ~~                     Intrins1  3.911  0.040   0.040    0.036    0.036

----------

320                    ALWD2 ~~                      Ident3  4.251 -0.082  -0.082   -0.084   -0.084
321                    ALWD3 ~~                       ALWD3  0.000  0.000   0.000    0.000    0.000
322                    ALWD3 ~~                       ALWD4  6.804  0.088   0.088    0.133    0.133
323                    ALWD3 ~~                       ALWD5  0.026  0.005   0.005    0.008    0.008
324                    ALWD3 ~~                       ALWD6  0.618 -0.026  -0.026   -0.036   -0.036
325                    ALWD3 ~~                       ALWD7  0.134  0.012   0.012    0.018    0.018
326                    ALWD3 ~~                       ALWD8  2.855 -0.066  -0.066   -0.079   -0.079
327                    ALWD3 ~~                       ALWD9 25.463  0.162   0.162    0.246    0.246
328                    ALWD3 ~~                      ALWD10  2.638  0.063   0.063    0.077    0.077
329                    ALWD3 ~~                     Intrins1  1.622 -0.027  -0.027   -0.035   -0.035
330                    ALWD3 ~~                     Intrins2  1.203 -0.022  -0.022   -0.030   -0.030
331                    ALWD3 ~~                     Intrins3  6.572  0.078   0.078    0.109    0.109
332                    ALWD3 ~~                      Ident1  0.054  0.009   0.009    0.011    0.011
333                    ALWD3 ~~                      Ident2  0.138 -0.016  -0.016   -0.019   -0.019
334                    ALWD3 ~~                      Ident3  2.674  0.050   0.050    0.066    0.066
335                    ALWD4 ~~                       ALWD4  0.000  0.000   0.000    0.000    0.000
336                    ALWD4 ~~                       ALWD5  4.119 -0.073  -0.073   -0.099   -0.099
337                    ALWD4 ~~                       ALWD6  1.033 -0.038  -0.038   -0.047   -0.047
338                    ALWD4 ~~                       ALWD7  8.945  0.110   0.110    0.146    0.146
339                    ALWD4 ~~                       ALWD8  0.409 -0.028  -0.028   -0.030   -0.030
340                    ALWD4 ~~                       ALWD9  4.627  0.078   0.078    0.107    0.107
341                    ALWD4 ~~                      ALWD10  5.275  0.101   0.101    0.110    0.110
342                    ALWD4 ~~                     Intrins1  1.608 -0.030  -0.030   -0.036   -0.036
343                    ALWD4 ~~                     Intrins2  0.140 -0.008  -0.008   -0.010   -0.010
344                    ALWD4 ~~                     Intrins3  2.865  0.059   0.059    0.073    0.073
345                    ALWD4 ~~                      Ident1  0.913  0.042   0.042    0.047    0.047
346                    ALWD4 ~~                      Ident2  5.746 -0.118  -0.118   -0.122   -0.122
347                    ALWD4 ~~                      Ident3  0.311 -0.019  -0.019   -0.023   -0.023
348                    ALWD5 ~~                       ALWD5  0.000  0.000   0.000    0.000    0.000
349                    ALWD5 ~~                       ALWD6  0.702 -0.030  -0.030   -0.037   -0.037
350                    ALWD5 ~~                       ALWD7  4.588 -0.075  -0.075   -0.099   -0.099
351                    ALWD5 ~~                       ALWD8  2.701 -0.069  -0.069   -0.074   -0.074
352                    ALWD5 ~~                       ALWD9  0.207  0.016   0.016    0.021    0.021
353                    ALWD5 ~~                      ALWD10  0.215  0.019   0.019    0.021    0.021
354                    ALWD5 ~~                     Intrins1  1.153 -0.024  -0.024   -0.028   -0.028
355                    ALWD5 ~~                     Intrins2  0.744  0.018   0.018    0.022    0.022
356                    ALWD5 ~~                     Intrins3  0.001 -0.001  -0.001   -0.001   -0.001
```

Output 7 Modification indices full SEM model

```
357                ALWD5 ~~                   Ident1  0.382  0.025   0.025    0.028    0.028
358                ALWD5 ~~                   Ident2  0.805  0.041   0.041    0.042    0.042
359                ALWD5 ~~                   Ident3  0.013 -0.004  -0.004   -0.004   -0.004
360                ALWD6 ~~                    ALWD6  0.000  0.000   0.000    0.000    0.000
361                ALWD6 ~~                    ALWD7 10.839  0.121   0.121    0.147    0.147
362                ALWD6 ~~                    ALWD8  0.050  0.010   0.010    0.010    0.010
363                ALWD6 ~~                    ALWD9  0.667 -0.029  -0.029   -0.037   -0.037
364                ALWD6 ~~                   ALWD10  0.750 -0.038  -0.038   -0.038   -0.038
365                ALWD6 ~~                 Intrins1  0.196 -0.010  -0.010   -0.011   -0.011

-----------

400               ALWD10 ~~                 Intrins2  0.357  0.015   0.015    0.015    0.015
401               ALWD10 ~~                 Intrins3  2.201  0.058   0.058    0.059    0.059
402               ALWD10 ~~                   Ident1  3.023  0.087   0.087    0.078    0.078
403               ALWD10 ~~                   Ident2  2.416  0.087   0.087    0.072    0.072
404               ALWD10 ~~                   Ident3  1.036 -0.040  -0.040   -0.038   -0.038
405             Intrins1 ~~                 Intrins1  0.000  0.000   0.000    0.000    0.000
406             Intrins1 ~~                 Intrins2 22.639  0.195   0.195    0.213    0.213
407             Intrins1 ~~                 Intrins3  3.710 -0.049  -0.049   -0.053   -0.053
408             Intrins1 ~~                   Ident1  2.662 -0.047  -0.047   -0.046   -0.046
409             Intrins1 ~~                   Ident2  0.006  0.003   0.003    0.002    0.002
410             Intrins1 ~~                   Ident3  1.611  0.034   0.034    0.036    0.036
411             Intrins2 ~~                 Intrins2  0.000  0.000   0.000    0.000    0.000
412             Intrins2 ~~                 Intrins3  2.425  0.038   0.038    0.043    0.043
413             Intrins2 ~~                   Ident1 12.902 -0.099  -0.099   -0.102   -0.102
414             Intrins2 ~~                   Ident2 10.067 -0.096  -0.096   -0.091   -0.091
415             Intrins2 ~~                   Ident3  6.506 -0.066  -0.066   -0.072   -0.072
416             Intrins3 ~~                 Intrins3  0.000  0.000   0.000    0.000    0.000
417             Intrins3 ~~                   Ident1  4.778  0.088   0.088    0.091    0.091
418             Intrins3 ~~                   Ident2  1.755 -0.060  -0.060   -0.057   -0.057
419             Intrins3 ~~                   Ident3  0.078 -0.009  -0.009   -0.010   -0.010
420               Ident1 ~~                   Ident1  0.000  0.000   0.000    0.000    0.000
421               Ident1 ~~                   Ident2 46.922  0.392   0.392    0.334    0.334
422               Ident1 ~~                   Ident3  7.649  0.112   0.112    0.110    0.110
423               Ident2 ~~                   Ident2  0.000  0.000   0.000    0.000    0.000
424               Ident2 ~~                   Ident3  0.000 -0.001  -0.001   -0.001   -0.001
425               Ident3 ~~                   Ident3  0.000  0.000   0.000    0.000    0.000
426             Workload ~~                 Workload  0.000  0.000   0.000    0.000    0.000
427             Workload ~~      Choice.independence  0.000  0.000   0.000    0.000    0.000
428             Workload ~~            Deep.approach     NA     NA      NA       NA       NA
429             Workload ~~ Autonomous.motivation     0.285  0.025   0.028    0.028    0.028
430  Choice.independence ~~      Choice.independence  0.000  0.000   0.000    0.000    0.000
431  Choice.independence ~~            Deep.approach     NA     NA      NA       NA       NA
432  Choice.independence ~~ Autonomous.motivation     0.285  0.075   0.107    0.107    0.107
433        Deep.approach ~~            Deep.approach  0.000  0.000   0.000    0.000    0.000
434        Deep.approach ~~ Autonomous.motivation        NA     NA      NA       NA       NA
435 Autonomous.motivation ~~ Autonomous.motivation    0.000  0.000   0.000    0.000    0.000
436        Deep.approach  ~ Autonomous.motivation     0.000  0.000   0.000    0.000    0.000
437        Deep.approach  ~                 Workload  0.000  0.000   0.000    0.000    0.000
438        Deep.approach  ~      Choice.independence  0.000  0.000   0.000    0.000    0.000
439 Autonomous.motivation  ~           Deep.approach  0.285  0.285   0.168    0.168    0.168
440 Autonomous.motivation  ~                Workload  0.284  0.027   0.030    0.030    0.030
441 Autonomous.motivation  ~     Choice.independence  0.000  0.000   0.000    0.000    0.000
442             Workload  ~            Deep.approach  0.285  0.270   0.140    0.140    0.140
443             Workload  ~ Autonomous.motivation     0.285  0.044   0.039    0.039    0.039
444             Workload  ~      Choice.independence     NA     NA      NA       NA       NA
445  Choice.independence  ~            Deep.approach  0.284  0.811   0.531    0.531    0.531
446  Choice.independence  ~ Autonomous.motivation     0.285  0.132   0.147    0.147    0.147
447  Choice.independence  ~                 Workload     NA     NA      NA       NA       NA
```

Output 7 (continued)

These modifications (Output 8) result in an acceptable model fit (χ^2/df = 1.94, CFI = .91, TLI = .90, RMSEA = 0.052, CI 90 % [.045; .059], SRMR = .064). When reporting on SEM analysis, it is not necessary to provide all coefficients of every model that was tested. It is however important that the reader gets an overview (with fit indices) of the different models that were tested. Only the coefficients of the final model should be reported. A table containing the coefficients, standardised coefficients, critical ratio and significance (level) is usually included. Table 14.5 provides an example of how the results of the final full SEM model could be presented.

```
lavaan (0.5-12) converged normally after  46 iterations

                                                  Used       Total
  Number of observations                           346         359

  Estimator                                         ML
  Minimum Function Test Statistic              505.367
  Degrees of freedom                               260
  P-value (Chi-square)                           0.000

Model test baseline model:

  Minimum Function Test Statistic             3011.588
  Degrees of freedom                               300
  P-value                                        0.000

Full model versus baseline model:

  Comparative Fit Index (CFI)                    0.910
  Tucker-Lewis Index (TLI)                       0.896

Loglikelihood and Information Criteria:

  Loglikelihood user model (H0)             -11067.206
  Loglikelihood unrestricted model (H1)     -10814.522

  Number of free parameters                         65
  Akaike (AIC)                               22264.411
  Bayesian (BIC)                             22514.430
  Sample-size adjusted Bayesian (BIC)        22308.231

Root Mean Square Error of Approximation:

  RMSEA                                          0.052
  90 Percent Confidence Interval          0.045  0.059
  P-value RMSEA <= 0.05                          0.288

Standardized Root Mean Square Residual:

  SRMR                                           0.064

Parameter estimates:

  Information                                 Expected
  Standard Errors                             Standard

                   Estimate  Std.err  Z-value  P(>|z|)   Std.lv  Std.all
Latent variables:
  Workload =~
    WL1               1.000                               1.011    0.879
    WL2               0.583    0.064    9.040    0.000    0.589    0.493
    WL4               0.738    0.063   11.694    0.000    0.746    0.615
    WL5               0.957    0.061   15.706    0.000    0.968    0.858
  Choice.independence =~
    CI1               1.000                               0.790    0.729
    CI2               0.854    0.080   10.623    0.000    0.674    0.634
    CI3               0.904    0.080   11.333    0.000    0.714    0.680
    CI4               0.810    0.073   11.171    0.000    0.640    0.669
    CI5               0.821    0.075   10.883    0.000    0.649    0.651
```

Output 8 Full SEM model after modification

```
  Deep.approach =~
    ALWD1             1.000                                  0.531    0.455
    ALWD2             0.566    0.129    4.385    0.000    0.301    0.302
    ALWD3             0.381    0.098    3.896    0.000    0.202    0.262
    ALWD4             0.274    0.103    2.670    0.008    0.146    0.170
    ALWD5             0.793    0.130    6.094    0.000    0.422    0.490
    ALWD6             0.981    0.151    6.501    0.000    0.521    0.554
    ALWD7             0.633    0.122    5.178    0.000    0.336    0.383
    ALWD8             1.156    0.176    6.580    0.000    0.615    0.567
    ALWD9             0.612    0.118    5.201    0.000    0.325    0.381
    ALWD10            1.018    0.164    6.225    0.000    0.541    0.509
  Autonomous.motivation =~
    Intrins1          1.000                                  0.770    0.788
    Intrins2          1.080    0.055   19.701    0.000    0.832    0.890
    Intrins3          0.736    0.074   10.006    0.000    0.567    0.608
    Ident1            0.739    0.094    7.858    0.000    0.569    0.547
    Ident2            0.500    0.092    5.467    0.000    0.385    0.342
    Ident3            0.802    0.072   11.170    0.000    0.618    0.634

Regressions:
  Deep.approach ~
    Workload          0.092    0.032    2.866    0.004    0.174    0.174
    Choic.ndpndnc     0.394    0.071    5.520    0.000    0.585    0.585
    Autonms.mtvtn     0.244    0.058    4.190    0.000    0.354    0.354
  Autonomous.motivation ~
    Choic.ndpndnc     0.546    0.067    8.095    0.000    0.559    0.559

Covariances:
  ALWD3 ~~
    ALWD9             0.168    0.034    4.888    0.000    0.168    0.285
  ALWD6 ~~
    ALWD7             0.140    0.038    3.648    0.000    0.140    0.220
  ALWD4 ~~
    ALWD7             0.126    0.037    3.389    0.001    0.126    0.184
  WL2 ~~
    WL4               0.195    0.059    3.276    0.001    0.195    0.196
  Intrins1 ~~
    Intrins2          0.121    0.043    2.843    0.004    0.121    0.472
  Ident1 ~~
    Ident2            0.271    0.060    4.500    0.000    0.271    0.294
  Intrins2 ~~
    Ident1           -0.198    0.039   -5.023    0.000   -0.198   -0.535
    Ident2           -0.105    0.030   -3.470    0.001   -0.105   -0.233
  Intrins1 ~~
    Ident1           -0.126    0.039   -3.256    0.001   -0.126   -0.241
    Ident3            0.095    0.027    3.460    0.001    0.095    0.209
  Workload ~~
    Choic.ndpndnc    -0.214    0.053   -3.998    0.000   -0.268   -0.268

Variances:
    WL1               0.302    0.056                      0.302    0.228
    WL2               1.080    0.086                      1.080    0.757
    WL4               0.915    0.077                      0.915    0.622
    WL5               0.335    0.053                      0.335    0.264
    CI1               0.549    0.054                      0.549    0.468
    CI2               0.675    0.059                      0.675    0.598
    CI3               0.593    0.054                      0.593    0.538
    CI4               0.505    0.046                      0.505    0.552
    CI5               0.573    0.051                      0.573    0.577
    ALWD1             1.082    0.089                      1.082    0.793
    ALWD2             0.903    0.071                      0.903    0.909
    ALWD3             0.557    0.043                      0.557    0.932
```

Output 8 (continued)

```
    ALWD4            0.715    0.055                            0.715    0.971
    ALWD5            0.563    0.047                            0.563    0.760
    ALWD6            0.613    0.054                            0.613    0.693
    ALWD7            0.658    0.053                            0.658    0.853
    ALWD8            0.798    0.070                            0.798    0.679
    ALWD9            0.623    0.050                            0.623    0.855
    ALWD10           0.837    0.071                            0.837    0.741
    Intrins1         0.361    0.053                            0.361    0.378
    Intrins2         0.181    0.047                            0.181    0.208
    Intrins3         0.548    0.046                            0.548    0.630
    Ident1           0.758    0.072                            0.758    0.701
    Ident2           1.122    0.089                            1.122    0.883
    Ident3           0.569    0.049                            0.569    0.598
    Workload         1.022    0.110                            1.000    1.000
    Choic.ndpndnc    0.624    0.086                            1.000    1.000
    Deep.approach    0.097    0.030                            0.344    0.344
    Autonms.mtvtn    0.408    0.062                            0.687    0.687
```

Output 8 (continued)

Table 14.5 Coefficients final full SEM model

	Regression weight	Standard error	Standardised regression weight	Critical ratio[a]
Measurement model				
Workload = ~				
WL1	1	[b]	.88	[b]
WL2	.58	.06	.49	9.04
WL4	.74	.06	.62	11.69
WL5	.96	.06	.86	15.71
Choice independence = ~				
CI1	1	[b]	.73	[b]
CI2	.85	.08	.63	10.62
CI3	.90	.08	.68	11.33
CI4	.81	.07	.67	11.17
CI5	.82	.08	.65	10.88
Deep approach = ~				
ALWD1	1	[b]	.46	[b]
ALWD2	.57	.13	.30	4.39
ALWD3	.38	.10	.26	3.90
ALWD4	.27	.10	.17	2.67
ALWD5	.79	.13	.49	6.09
ALWD6	.98	.15	.55	6.50
ALWD7	.63	.12	.38	5.18
ALWD8	1.16	.18	.57	6.58
ALWD9	.61	.12	.38	5.20
ALWD10	1.02	.16	.51	6.23
Autonomous = ~				
Intrins1	1	[b]	.79	[b]
Intrins2	1.08	.06	.89	19.70

(continued)

Table 14.5 (continued)

	Regression weight	Standard error	Standardised regression weight	Critical ratio[a]
Intrins3	.74	.07	.61	10.01
Ident1	.74	.09	.55	7.86
Ident2	.50	.09	.34	5.47
Ident3	.80	.07	.63	11.17
Structural model				
Deep approach ~				
Workload	.09	.03	.17	2.87[c]
Choice independence	.39	.07	.59	5.52
Autonomous	.24	.06	.35	4.19
Autonomous ~				
Choice independence	.55	.07	.56	8.10
Covariances				
ALWD3 ~ ~ALWD9	.17	.03	.29	4.88
ALWD6 ~ ~ALWD7	.14	.04	.22	3.65
ALWD4 ~ ~ALWD7	.13	.04	.18	3.39
WL2 ~ ~WL4	.20	.06	.20	3.28
Intrins1 ~ ~Intrins2	.12	.04	.47	2.84
Ident1 ~ ~Ident2	.27	.06	.29	4.50
Intrins2 ~ ~Ident1	−.20	.04	−.54	−5.02
Intrins2 ~ ~Ident2	−.11	.03	−.23	−3.47
Intrins1 ~ ~Ident1	−.13	.04	−.24	−3.26
Intrins1 ~ ~Ident3	.10	.03	.21	3.46
Workload ~ ~ Choice independence	−.21	.05	−.27	−4.00

Note: Estimation Method: Maximum Likelihood
[a]All critical ratios except b: $p < .001$
[b]Value fixed at 1.00 for model identification purpose; hence, no standard error was computed
[c]Critical ratio: $p < .01$

14.4 Extensions of SEM and Their Application in Research on Professional Learning

Confirmatory factor analysis, path analysis and structural equation modelling have been commonly applied by researchers in various fields, including the field on professional learning. ‘Basic’ SEM models already offer a variety of possibilities because different types of relationships can be modelled based on the theoretical foundations of the study. In addition various extensions or specific forms of SEM offer a wide range of possibilities. Within this section, these extensions will be presented accompanied by examples of how these analyses can be applied within the field of professional learning.

Within the section on confirmatory factor analysis, we discussed the measurement invariance across groups. If this measurement invariance across groups is established, you could also investigate whether the SEM model is equal or different for different groups of participants. Establishing measurement invariance is important in this regard, as you would want to make sure that the differences that you find in the model reflect differences in the true constructs and relationships and not mere differences in measurement. With *multiple-group SEM*, it is possible to establish whether models are different for different groups of participants. The study of Hurtz and Williams (2009), for example, applied a multiple-group path analysis. This study examined attitudinal and motivational antecedents of employees' participation in development activities based on data collected within four organisations. A multiple-group path analysis was used to investigate whether the model differed for the four different organisations that were included in their study. They concluded that although the strengths of the different paths differed across organisations, the patterns were the same as the full SEM model that was based on the data from all four organisations (Hurtz & Williams, 2009). Within their study, they also examined whether their measurement was invariant across the groups and concluded that this was not the case. However, because the focus lied on identifying a general model looking at the relationship of the antecedents with participation and not on explaining organisational differences, Hurtz and Williams (2009) applied group-mean centring to remove organisational mean differences: they computed the difference between the employee score and the organisational mean of the scores and took this difference as their primary outcome variable. After applying this group-mean centring, measurement invariance was reached. However, it must be noted that no conclusions can be drawn regarding possible organisational differences. Alternatively to this approach, on the condition that metric invariance is achieved and the sample size is large enough, one could also adopt a full SEM model, sometimes also called multiple-indicator SEM model, because this allows the modelling of intercept variances. Multiple-group SEM analysis can also be applied to compare the models of males and females, high- and low-qualified employees, etc. In contrast, to multilevel SEM analysis (see below), multiple-group analysis does not require that the different groups are sampled at random. Multiple-group SEM can be conducted with the lavaan package (Rosseel, 2012).

Multilevel SEM requires a random sampling of groups because it assumes that the differences between organisations in terms of the intercept and slope are normally distributed around the average intercept or slope that holds for the population. For a basic introduction into multilevel analysis within professional learning, the reader is referred to Kyndt and Onghena (2014). In short, multilevel SEM combines multilevel analysis and SEM analysis. SEM analysis is not able to take the nested structure of the data into account (i.e. employees nested within organisations), while multilevel analysis is not able to examine more complex models. Multilevel analysis is comparable to regression analysis with regard to the type of relationships they investigate. In addition, multilevel analysis does not provide goodness-of-fit indices such as CFI, SRMR or RMSEA. One can only conclude that one model fits the data better in comparison with another model (Kyndt & Onghena, 2014). Within a multilevel SEM, the model is estimated while the organisational clustering is taken into account. Taking the organisational clustering into account is important because 'if the nested structure of the data is ignored, it is more likely that statistical relations are observed in the sample that are in fact not true (type-1 error), in addition it might be that it is concluded that a relationships holds for individuals when they are actually true for groups (ecological fallacy)' (Kyndt & Onghena, 2014, p. 339). Moreover, within multilevel SEM, predictors on the level of the organisation can be combined with predictors at the individual level. A final difference between multilevel SEM and multilevel analysis is that multilevel SEM can also predict outcomes at the organisational level, whereas in traditional multilevel analysis, the outcomes or dependent variables need to be situated at the lowest level, that is, the individual level. Sometimes this latter issue is resolved by aggregating the individual scores to the organisational level (after the within-group agreement has been checked); however, by doing this a lot of statistical power is lost as well as potentially interesting individual differences within organisations. To our knowledge it is not possible to conduct multilevel SEM with the R software, it is possible with Mplus (Muthén & Muthén, 1998–2010). More information on multilevel SEM can be found in the article of Kaplan and Elliott (1997). Within educational sciences and labour psychology, different examples of empirical studies using multilevel SEM can be found (e.g. Johnsrud, Heck, & Rosser, 2000; Mauno, Kiuru, & Kinnunen, 2011; Sebastian & Allensworth, 2012). However, we were not able to detect a specific example within the field of professional learning.

The two above-presented extensions of SEM have something in common that they add to the complexity of the model; as a consequence, both techniques usually require very large samples (many organisations and many employees within the organisations). However, *partial least squares* (*PLS*) might be an interesting alternative to SEM if the sample size requirements cannot be met. Where SEM combines factor analysis and path models, PLS combines principal component analysis and path models (Garthwaite, 1994; Goutis, 1996; Hoyle, 1999; Iacobucci, 2010). Principal component analysis does not aim at reflecting latent constructs; rather, it tries to predict the component as good as possible. Factor analysis most commonly uses the maximum likelihood estimation, which considers the variance the different observed variables have in common, while principal component analysis takes all variance into account when estimating the component (Garthwaite, 1994; Hoyle, 1999). Because the focus lies on maximising the prediction and capturing as much variance as possible from the dependent variable, PLS is better suitable for exploratory rather than confirmatory purposes (Hoyle, 1999; Iacobucci, 2010). The loadings tend to be overestimated and path coefficients underestimated (Goutis, 1996; Iacobucci, 2010). In addition, no goodness-of-fit indices are provided. Similarly to multilevel analysis, it can only be judged which model is more suitable in comparison with another model. However, it is an interesting approach when you want to explore complex models with a limited number of observations. Gegenfurtner (2013) illustrates the use of PLS in his study on the relationship between motivation to transfer, retention, transfer and attitudes.

14.5 Discussion

Throughout this chapter we have tried to introduce the reader to SEM by means of an illustration within the field of professional learning. The models that are tested within this chapter are solely for the purpose of illustrating the method and should not be used for interpreting the relationships between the constructs. These results and interpretations can be found in the publication of the empirical study in which the relationships including control variables were examined (Kyndt et al., 2013). SEM offers researchers a lot of possibilities to investigate complex models. Within the paradigm of the integration of work and learning, advanced techniques such as multiple-group and multilevel SEM might be especially relevant, because these techniques allow the simultaneous examination of individual and organisational differences. These techniques are interesting if the goal is to investigate professional learning conceptualised as a reciprocal interaction between individual and organisation (Tynjälä, 2008).

However, despite all the possibilities SEM offers, it also has its limitations and possible pitfalls. The two most evident limitations are the necessity for a strong theoretical basis and the large samples that are needed especially when comprehensive models with many variables need to be estimated. Although simple models can be estimated with moderate to small samples, the added value of SEM foremost lies in estimating complex models (Hox & Bechger, 1998).

One of the most common pitfalls of SEM is that many researchers are tempted to interpret SEM models as causal models due to the impression the direction of the paths give. However, merely applying SEM to your data does not provide proof for the causality of the relationship (Bollen & Pearl, 2013). A SEM model can however raise doubts about a causal theory; when the SEM model is correctly specified and the covariance structure does not support the theoretical causal structure, it seems less plausible that the causal relationships exists. One can say that establishing covariance or correlations between the variables is a necessary but not sufficient condition for establishing causality. To be able to prove the causality of the relationships empirically, data that allow this type of conclusions need to be collected (e.g. longitudinal or experimental data). If SEM is applied to correlational data, the SEM model cannot be interpreted as a causal model (Iacobucci, 2009).

The aim of the current book chapter was to introduce the reader with the possibilities that SEM can offer within the field of research on professional learning. Within the paradigm of the integration of work and learning, the possibility to analyse more complex models can contribute to the theory development and further understanding of how learning and working are intertwined.

Appendix: R Code Illustration

```
## Setting up working directory and loading data
setwd("/Users/evakyndt/Book chapter SEM")
data<-read.table("chapter SEM.csv",header=TRUE,sep=";")
```

```
## Loading packages
install.packages("lavaan")
library("lavaan")
install.packages("qgraph")
library("qgraph")
install.packages("semTools")
library("semTools")

## Measurement model: Confirmatory factor analysis (Output 1)
CFAModel1 <- 'Workload=~WL1+WL2+WL3+WL4+WL5
Choice.independence=~CI1+CI2+CI3+CI4+CI5'

Fit1 <- cfa(CFAModel1, data=data)
summary(Fit1, fit.measures=TRUE, standardized=TRUE)
modindices(Fit1)

## CFA without WL3 (Output 2)
CFAModel2 <- 'Workload=~WL1+WL2+WL4+WL5
Choice.independence=~CI1+CI2+CI3+CI4+CI5'

Fit2 <- cfa(CFAModel2, data=data)
summary(Fit2, fit.measures=TRUE, standardized=TRUE)

## Plot CFA model (Figure 4)
qgraph.lavaan(Fit1,layout="tree", vsize.man=5, vsize.
  lat=12, include=4, curve=-0.4, edge.label.cex=0.6,
  titles=F)

## Testing measurement invariance across groups (Output 3)
measurementInvariance(CFAModel1, data=data, group="Sex")

## Path analysis mediation (Output 4)
SEMModel2 <- 'DA ~ Autonomous + Controlled
Autonomous ~ WL + CI
Controlled ~ WL + CI
DA ~ WL + CI'

FitSEM2 <- sem(SEMModel2, data=data)
summary(FitSEM2, fit.measures=TRUE, standardized=TRUE)

## Path analysis mediation without non-significant paths
(Output 5)
SEMModel3 <- 'DA~Autonomous
Autonomous ~ CI
DA ~ WL + CI'

FitSEM3 <- sem(SEMModel3, data=data)
summary(FitSEM3, fit.measures=TRUE, standardized=TRUE)

## Full SEM model (Output 6)
FullModel <- 'Workload=~WL1+WL2+WL4+WL5
```

```
Choice.independence=~CI1+CI2+CI3+CI4+CI5
Deep.approach=~ALWD1+ALWD2+ALWD3+ALWD4+ALWD5+ALWD6+ALWD
  7+ALWD8+ALWD9+ALWD10
Autonomous.motivation=~ Intrins1+Intrins2+Intrins3+Iden
  t1+Ident2+Ident3
Deep.approach~Workload+Choice.independence
Deep.approach~Autonomous.motivation
Autonomous.motivation~Choice.independence'

FitSEMFull <- sem(FullModel, data=data)
summary(FitSEMFull, fit.measures=TRUE, standardized=TRUE)

## Modification indices (Output 7)
modindices(FitSEMFull)

## Full SEM model after modification (Output 8)
FullModel2 <- 'Workload=~WL1+WL2+WL4+WL5
Choice.independence=~CI1+CI2+CI3+CI4+CI5
Deep.approach=~ALWD1+ALWD2+ALWD3+ALWD4+ALWD5+ALWD6+ALWD
7+ALWD8+ALWD9+ALWD10
Autonomous.motivation=~ Intrins1+Intrins2+Intrins3+Iden
  t1+Ident2+Ident3
Deep.approach~Workload+Choice.independence
Deep.approach~Autonomous.motivation
Autonomous.motivation~Choice.independence
ALWD3~~ALWD9
ALWD6~~ALWD7
ALWD4~~ALWD7
WL2~~WL4
Intrins1~~Intrins2
Ident1~~Ident2
Intrins2~~Ident1
Intrins2~~Ident2
Intrins1~~Ident1
Intrins1~~Ident3'

FitSEMFull2 <- sem(FullModel2, data=data)
summary(FitSEMFull2,fit.measures=TRUE,standardized=TRUE)
## references
citation("lavaan")
citation("qgraph")
citation("semTools")
```

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