FACULTY OF SCIENCE
DEPARTMENT OF MATHEMATICS
MASTER OF STATISTICS AND DATA SCIENCE
STRUCTURAL EQUATION MODELING

Assignment

Van den Broeck Sebastiaan (r0902562)

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1 Introduction

It has been noted that almost one in six individuals in the United States will experience a depressive disorder. Consequently, considerable personal, social and economic loss can be attributed to this type of illness. Although there is clearly a very large societal impact of depression, little is known about its relationship with personality and social functioning. In this report I will test a hypothesis related to depression that has been proposed by Tse et al. (2011). Specifically, they proposed that harm avoidance and self-directedness are indirectly linked to depression through social functioning. Moreover, there should be a direct effect of self-directedness on depression. On the one hand, a behaviour can be classified under harm avoidance if it is done to avoid novelty and punishment. Self-directedness, on the other hand, is a form of self-determination and ability to regulate behaviour to suit goals and values. The authors have tested this hypothesis on a sample of university students, which limits the interpretability of their findings. By testing their hypothesis on a larger and more representative sample, I hope to contribute to the literature on depression. The dataset will be discussed next. Afterwards, a structural equation model has been used to test the hypothesis and will be discussed as well. Lastly, the results and implications thereof will be considered.

2 Data

The data treated in the report is the Midlife in the United States (MIDUS) series. It is a national longitudinal study of health and well-being, created by a team of multi-disciplinary researchers. Currently, there are three waves in the study, which were collected via phone interviews, surveys and by bringing participants into clinical settings to facilitate collecting biological data. All three waves cover the contiguous United States in its entirety. The first wave was collected in 1995 and 1996, while the second wave was collected in 2004 and 2005. The most recent and third wave was collected in 2013 and 2014. In this analysis, the second and third wave have been combined to create a bigger dataset. It was not possible to incorporate the first dataset, since a lot of variables changed between the first and second and third waves (Radler, 2014). In this section I will discuss the variables that have been used in the analysis.

An important reason for choosing this dataset is that it contains a lot of documentation for which variables form certain latent constructs such as depression or social anxiety. Since I am not too familiar with the field of psychology this would allow me to test a hypothesis that is better grounded in theory. First, depression is the most important latent variable in this work. It has been measured through seven questions during which the respondent reflects over the last two weeks. For example, the questions include losing interest, becoming tired, having trouble falling asleep or thinking about death. The responses have been recoded such that a higher score equates a higher level of depression. Specifically, each variable which measures this latent construct has been coded such that a 1 reflects a yes answer. As could be expected, a 0 the means a respondent has answered no.

Table 1: Depresssion indicators

Construct	Code	Question
Depression	PA63	During those two weeks, did you lose interest in most things?
	P164	Thinking about these same two weeks, did you feel more tired out or low on energy?
	PA65	During those same two weeks, did you lose appetite?
	PA66	Did you have more trouble falling asleep than you usually do during those two weeks?
	PA67	During that same two week period, did you have a lot more trouble concentrating than usual?
	PA68	People sometimes feel down on themselves, no good, or worthless. During that two-week period, did you feel this way?
	PA69	Did you think a lot about death - either your own, someone else's or death in general - during those two weeks?

Second, another important aspect in this report is harm avoidance. It has been described as an inheritable tendency for inhibiting behaviours to avoid novelty and punishment (Tse et al., 2011). Since

Table 2: Depresssion indicators distribution

Construct	Code	Count	
		0	1
Depression	PA63	126	479
	P164	51	554
	PA65	263	342
	PA66	172	433
	PA67	88	517
	PA68	222	383
	PA69	229	376

it cannot be measured directly, four questions were asked to get an idea about this construct. First, interviewees were asked whether they would enjoy experiencing an earthquake or learning to walk the tightrope. These two variables were reverse recoded such that a 4 reflects not agreeing with the statement at all (harm avoidance), while a 1 indicates fully agreeing (no avoidance). Second, interviewees were presented with two scenario's twice. For each question, one scenario corresponds to a harmful situation, while the other scenario's is harmless. Again, there was a recoding such that a higher score on these two variables indicates avoiding harm.

Table 3: Harm avoidance indicators

Construct	Code	Question
Harm avoidance	SE7D	It might be fun and exciting to be in an earthquake.
	SE7V	It might be fun learning to walk a tightrope.
	SE8	Of these two situations, I would dislike more: Situation 1: Riding a long stretch of rapids in a canoe; Situation 2: Waiting for someone who's late.
	SE9	Of these two situations, I would dislike more: Situation 1: Being at the circus when two lions suddenly get loose down in the ring; Situation 2: Bringing my whole family to the circus and then not being able to get in because a clerk sold me tickets for the wrong night.

Table 4: Harm avoidance distribution

Construct	Code	Count			
		1 (harm)	2	3	4 (no harm)
Harm avoidance	SE7D	33	92	91	389
	SE7V	25	79	69	432

Table 5: Harm avoidance distribution

Construct	Code	Count	
		0 (harm)	1 (no harm)
Harm avoidance	SE8	335	270
	SE7V	276	329

Third, we should not forget about self-directedness, which has been measured through three variables. It measures the amount of self-determination and ability a respondent has in order to regulate behaviour to achieve goals and values (Tse et al., 2011). Making plans for the future, knowing what to want out of life and setting goals are important for this dimension. Again, the variables were reverse coded such that a higher score reflects agreeing more with the statement. The data indicates that most participants agree somewhat or fully what the three statements.

Table 6: Self-directedness indicators

Construct	Code	Question
Self-directedness	SE14O	I like to make plans for the future.
	SE14R	I know what I want out of life.
	SE14P	I find it helpful to set goals for the near future.

Fourth, the latent variable social functioning has been used in the analysis. Seven questions related to this dimension were asked. The variables SE1BB, SE1D, SE1I and SE1V were reverse coded such that a

Table 7: Self-directedness distribution

Construct	Code	Count			
		1	2	3	4
Self-directedness	SE14O	48	140	241	176
	SE14R	67	144	235	159
	SE14P	47	149	228	181

higher score indicates a higher degree of social functioning. The dataset counts 601 observations after deleting rows with missing values. A missingness at random principle is therefore assumed.

Table 8: Social functioning indicators

Construct	Code	Question
Social functioning	SE1BB	People would describe me as a giving person, willing to share my time with others.
	SE1D	Most people see me as loving and affectionate.
	SE1HH	I have not experienced many warm and trusting relationships with others.
	SE1J	Maintaining close relationships has been difficult and frustrating for me.
	SE1I	I think it is important to have new experiences that challenge how you think about yourself and the world.
	SE1P	I often feel lonely because I have few close friends with whom to share my concerns.
	SE1V	I enjoy personal and mutual conversations with family members and friends.

Table 9: Social functioning distribution

Construct	Code	Count						
		1	2	3	4	5	6	7
Social functioning	SE1BB	4	7	16	36	70	207	265
	SE1D	5	14	23	68	74	225	196
	SE1HH	75	71	69	34	51	113	192
	SE1J	67	88	106	57	52	94	141
	SE1I	7	14	14	57	124	175	215
	SE1P	71	82	80	51	50	103	168
	SE1V	14	14	17	26	82	159	293

Lastly, the relationships between the variables will be considered. In the context of structural equation modeling, convergent and discriminant validity are important concepts. On the one hand, convergent validity means that indicators which load on the same factor should be strongly related to each other (Brown, 2015). Inspecting Figure 1, it is clear that this requirement is not always satisfied. Specifically, the variables that are related to depression do not seem to have high intercorrelations. On the other hand, discriminant validity assesses whether indicators of different constructs are not highly correlated. It is possible that some cross-loadings should be allowed in the model, since some high correlations exist between indicators that load on different factors.

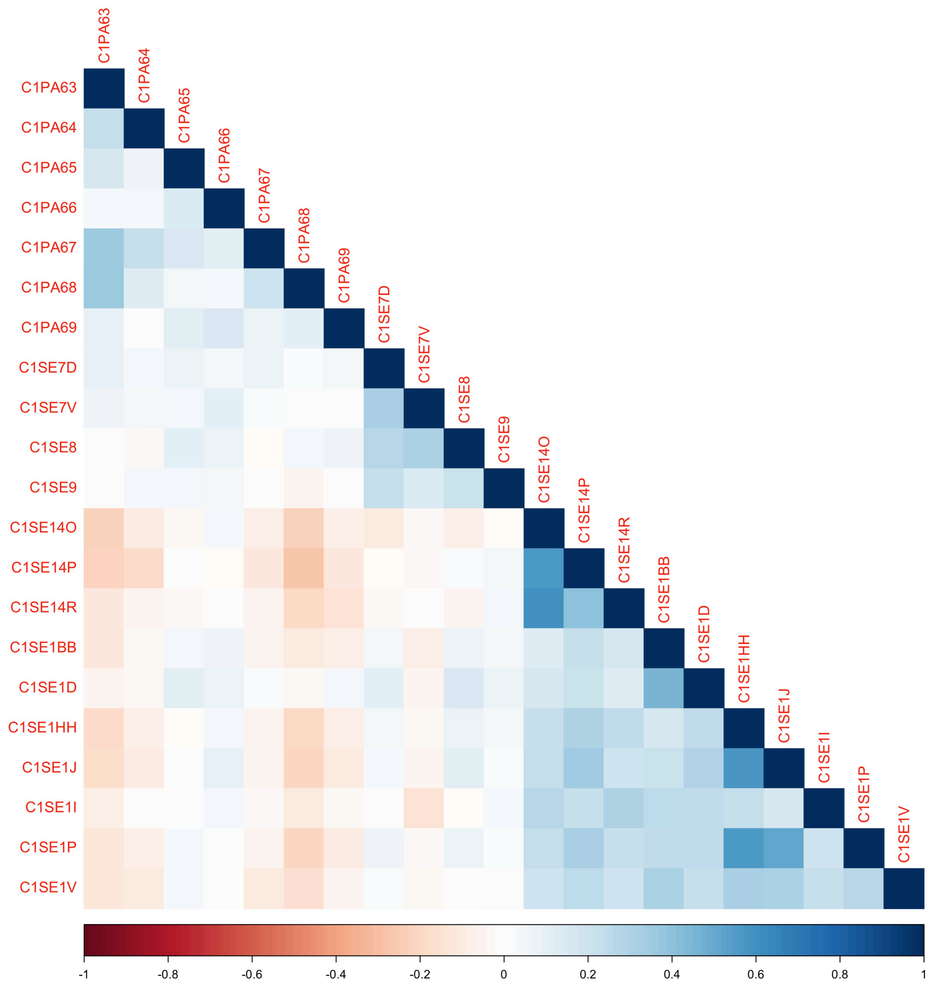

Figure 1: Correlation plot

3 The base model

Next, the base model will be discussed. Based on the work of Tse et al. (2011), it has been concluded that depression can be explained through the constructs harm avoidance, self directedness and social functioning. In other words, there are four latent variables which are related to each other through a structural model. Harm avoidance and self-directedness have an effect on social functioning. Social functioning, then, has an effect on depression. Moreover, it was estimated that there is also a direct effect of self-directedness on depression. Hence, there should be no direct effect of harm avoidance on depression.

In the previous section it became clear that ordinal variables have been used in the analysis. Model identification and estimation will therefore be discussed first. The measurement model indicates how variables are related to their latent constructs and will be discussed next. Afterwards, a closer look will be taken at the structural model, since an important aspect in this work is the relationships between latent variables. Lastly, the model fit will be evaluated through fit measures and further inspected using modification indices.

3.1 Model identification and estimation

First and foremost, model identification and estimation will be discussed. A structural equation model is said to be identified if every latent variable has its scale identified and the models degrees of freedom is zero or greater. To that end, the scale of the first indicator of every latent variable has been fixed to one. The model contains 92 parameters that should be estimated. Specifically, there are 17 (21 -

4) loadings, 4 regression parameters, 66 thresholds (more about this later), 1 latent covariance and 4 latent variances. The degrees of freedom of the model therefore equals 276 (23*24/2) - 92 = 184. The following assumptions have been made on the equations shown in 1. The measurement errors δ are supposed to have an expected value of 0. It is assumed that they have constant variance across observations and are mutually uncorrelated. There should be a covariance of zero between these errors and the latent variables.

$$\begin{cases} \text{PA63} & = \lambda_{11}\text{depression} + \delta_{11} \\ \text{PA64} & = \lambda_{12}\text{depression} + \delta_{12} \\ \text{PA65} & = \lambda_{13}\text{depression} + \delta_{13} \\ \text{PA66} & = \lambda_{14}\text{depression} + \delta_{14} \\ \text{PA67} & = \lambda_{15}\text{depression} + \delta_{15} \\ \text{PA68} & = \lambda_{16}\text{depression} + \delta_{16} \\ \text{PA69} & = \lambda_{17}\text{depression} + \delta_{17} \\ \text{SE7V} & = \lambda_{21}\text{harm avoidance} + \delta_{21} \\ \text{SE7D} & = \lambda_{22}\text{harm avoidance} + \delta_{22} \\ \text{SE8} & = \lambda_{23}\text{harm avoidance} + \delta_{23} \\ \text{SE9} & = \lambda_{24}\text{harm avoidance} + \delta_{24} \\ \text{SE14O} & = \lambda_{31}\text{self-directedness} + \delta_{31} \\ \text{SE14P} & = \lambda_{32}\text{self-directedness} + \delta_{32} \\ \text{SE14R} & = \lambda_{33}\text{self-directedness} + \delta_{33} \\ \text{SE1BB} & = \lambda_{41}\text{social functioning} + \delta_{41} \\ \text{SE1D} & = \lambda_{42}\text{social functioning} + \delta_{42} \\ \text{SE1HH} & = \lambda_{43}\text{social functioning} + \delta_{43} \\ \text{SE1J} & = \lambda_{44}\text{social functioning} + \delta_{44} \\ \text{SE1I} & = \lambda_{45}\text{social functioning} + \delta_{45} \\ \text{SE1P} & = \lambda_{46}\text{social functioning} + \delta_{46} \\ \text{SE1V} & = \lambda_{47}\text{social functioning} + \delta_{47} \\ \text{social functioning} & = \beta_1\text{harm avoidance} + \beta_2\text{self-directedness} + \delta_1 \\ \text{depression} & = \beta_3\text{social functioning} + \delta_2 \\ \text{depression} & = \beta_4\text{self-directedness} + \delta_3 \end{cases} \tag{1}$$

A considerable problem arises when one considers the assumption of multivariate normality on the residuals δ. All observed variables are ordinal in nature, meaning that they are not continuous and should not be treated as such. Their means and (co)variances have no meaning, since they do not have origins or units of measurement (Jöreskog, 1994). The standard maximum likelihood machinery used in structural equation modeling is therefore not applicable. In this case, robust maximum likelihood or a least squares approach (unweighted least squares, diagonally weighted least squares or weighted least squares) can be used (Yang-Wallentin et al., 2010). The method of diagonally weighted least squares has been specifically developed for ordinal data and has been shown to yield better results when the sample size is not small (Li, 2016). It has therefore been applied here. First, polychoric correlations are estimated. Afterwards, the model parameters can be estimated.

First, the polychoric correlations should be estimated. A solution can then be obtained by assuming that a latent, normal variable x^* is responsible for the observed ordinal variables x. With $x = m$ I mean to say that x belongs to a category m. Generally, the mean and variance if x^* are not identified, since only ordinal information is available (Şimşek and Noyan, 2012). Thresholds are used to link the latent variable to its observed counterpart:

$$x = m \;\text{ if }\; \nu_m < x^* < \nu_{m+1}. \tag{2}$$

Also, if one assumes x^* is standard normally distributed:

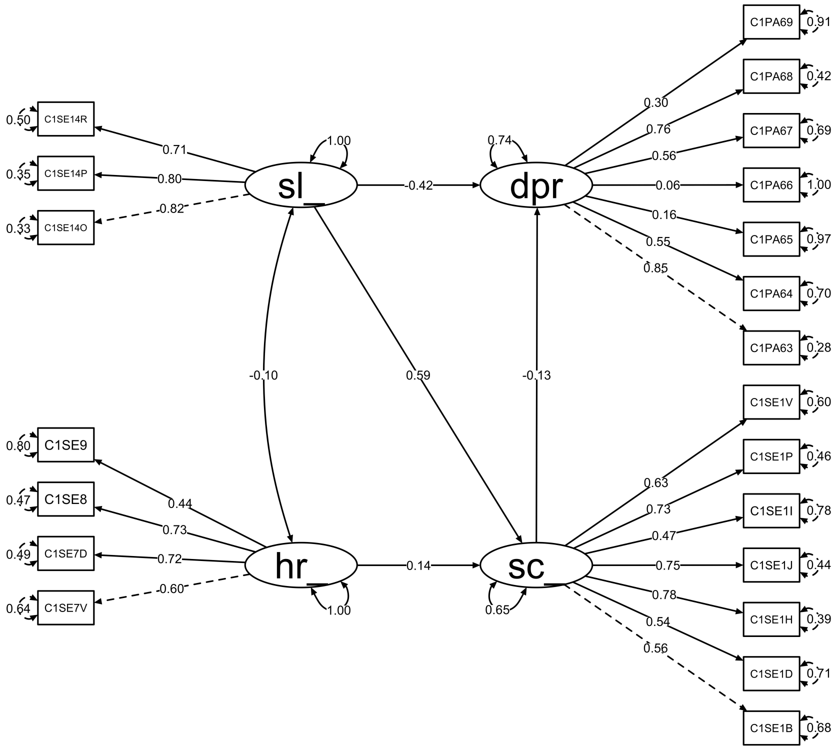

Figure 2: Summary of the (standardized) base model. hr_: harm avoidance, sl_: self-directedness, sc_: social functioning, dpr: depression

$$\pi_m = Pr[x = m] = Pr[\nu_m < x^* < \nu_{m+1}] = \int_{\nu_m}^{\nu_{m+1}} \Phi(u)du = \Phi(\nu_{m+1}) - \Phi(\nu_m). \tag{3}$$

In other words, a certain response m from the ordinal variable x is observed, if the response from its latent variable x^* falls between two thresholds. Hence, the thresholds are also parameters to be estimated. Second, the model parameters can be estimated using using a fit function. The ML and DWLS fit functions are defined as follows:

$$F_{ML} = \ln|S_{ML}| - \ln|\Sigma| + \text{trace}[(S_{ML})(\Sigma^{-1})] - p \qquad \text{(ML fit function)}$$
$$F_{DWLS} = [S_{DWLS} - \Sigma]' W_D^{-1} [S_{DWLS} - \Sigma]. \qquad \text{(DWLS fit function)}$$

S_{ML} is the covariance or correlation matrix and S_{DWLS} contains the polychoric correlations. Σ is the reproduced covariance or correlation matrix and depends on the models parameters. W_D^{-1} is a diagonal weight matrix, which are inversely proportional to the variances of the polychoric correlations (Yang-Wallentin et al., 2010). We can therefore conclude that the DWLS fit function is a weighted least squares approach.

```
base.model <- ”
    # measurement
    depression =~ C1PA63 + C1PA64 + C1PA65 + C1PA66 + C1PA67 + C1PA68 + C1PA69
    harm_avoidance =~ C1SE7V + C1SE7D + C1SE8 + C1SE9
    self_directedness =~ C1SE14O + C1SE14P + C1SE14R
    social_functioning =~ C1SE1BB + C1SE1D + C1SE1HH + C1SE1J + C1SE1I + C1SE1P + C1SE1V

    # structural
    social_functioning~harm_avoidance+self_directedness
    depression~social_functioning
    depression~self_directedness
”

base.fit <- cfa(base.model, data=data, ordered=TRUE)
summary(base.fit, standardized=TRUE, fit.measures=TRUE)
modindices(base.fit, sort=TRUE, maximum.number=20)

jpeg(file=”visualizations/base_model.png”, width=50, height=50, units=”cm”, res=400)
semPaths(base.fit, what=”diagram”, whatLabels=”stand”, layout=”tree2”, rotation=2,
         sizeMan=5, sizeMan2=3, sizeLat=10, sizeLat2=4, intercepts=FALSE,
         edge.color=”black”, thresholds=FALSE, label.scale=TRUE, asize=1.5,
         edge.label.cex=0.5, label.cex=1)
dev.off()
```

3.2 Measurement model

Second, we will take a closer look at the measurement model, which indicates how the variables relate to their latent constructs. The factor loading can be interpreted as the regression slope for predicting the indicator from the latent variable (Brown, 2015). The standardized loading is often more interesting, since it can then be interpreted as a correlation and one does not need to worry about the scale of the variables. By squaring the standardized loading the communality can be obtained, which indicates the proportion of the variance in the indicator that is explained by the latent variable. The residual variance then indicates the proportion of the variance that is not explained by the latent factor. Although there are no hard rules, a popular cut-off value for the communality appears to be 0.5 (Hair, 2010). Based on my observation, communalities that are a little bit lower are also acceptable, as long as there is a good theoretical justification for the relationship between the factor and indicator. The standardized loading should then be larger than 0.7, which means that the indicator does a good job at reflecting the latent construct.

Inspecting Table 10, it is evident to see that some indicators have a low communality. First, the variables PA64, PA65, PA66, PA67 and PA69 load on the latent variable depression and have a unique variance that is too high. The indicators PA64, PA65 and PA66 assess feeling low on energy, a loss of appetite and trouble falling asleep. PA66 and PA67 evaluate trouble falling asleep and concentrating. Using PA69 it was asked whether the participant often thinks about death. A simple way to improve the model fit may be to reduce the number of variables that load on depression. However, this action would lead to a decline of the theoretical support and validity of the model as well (Hair, 2010). Since these variables were specifically designed by the authors of the dataset to measure depression I have decided against doing so.

Next, the harm avoidance construct, which measures whether a behaviour is done to avoid novelty and punishment, plays a central role in the model. It is measured using four indicators: SE7V, SE7D, SE8 and SE9. Unfortunately, we have to again conclude that some of the indicators have a low communality. On the one hand, SE7V evaluates whether the participant believes it could be fun to experience an earthquake. On the other hand, through SE9 the respondent has to choose between a harmful and a safe situation. These variables have a communality of 0.379 and 0.201, respectively. Since these variables have been specifically designed by the authors of the dataset I will also not be deleting them from the model.

Table 10: Measurement model

Variable	Loading	Standard error	z-value	p-value	St. loading	Communality	Unique var.
PA63 (λ_{11})	1.000				0.847	0.718	0.275 (δ_{11})
PA64 (λ_{12})	0.646	0.108	5.974	<0.001	0.548	0.300	0.700 (δ_{12})
PA65 (λ_{13})	0.194	0.082	2.384	0.017	0.165	0.027	0.973 (δ_{13})
PA66 (λ_{14})	0.068	0.085	0.806	0.420	0.058	0.003	0.997 (δ_{14})
PA67 (λ_{15})	0.657	0.096	6.810	<0.001	0.556	0.309	0.691 (δ_{15})
PA68 (λ_{16})	0.896	0.108	8.321	<0.001	0.760	0.578	0.422 (δ_{16})
PA69 (λ_{17})	0.357	0.088	4.076	<0.001	0.303	0.092	0.908 (δ_{17})
SE7V (λ_{21})	1.000				0.604	0.365	0.635 (δ_{21})
SE7D (λ_{22})	1.186	0.153	7.754	<0.001	0.716	0.513	0.487 (δ_{22})
SE8 (λ_{23})	1.203	0.158	7.600	<0.001	0.726	0.527	0.473 (δ_{23})
SE9 (λ_{24})	0.733	0.116	6.322	<0.001	0.442	0.195	0.795 (δ_{24})
SE14O (λ_{31})	1.000				0.817	0.667	0.333 (δ_{31})
SE14P (λ_{32})	0.984	0.048	20.3655	<0.001	0.805	0.648	0.352 (δ_{32})
SE14R (λ_{33})	0.866	0.047	18.5985	<0.001	0.708	0.501	0.499 (δ_{33})
SE1BB (λ_{41})	1.000				0.563	0.317	0.683 (δ_{41})
SE1D (λ_{42})	0.952	0.072	13.3028	<0.001	0.536	0.287	0.713 (δ_{42})
SE1HH (λ_{43})	1.385	0.097	14.2430	<0.001	0.779	0.607	0.303 (δ_{43})
SE1J (λ_{44})	1.331	0.092	14.4760	<0.001	0.749	0.561	0.484 (δ_{44})
SE1I (λ_{45})	0.843	0.079	10.6372	<0.001	0.474	0.225	0.775 (δ_{45})
SE1P (λ_{46})	1.303	0.085	15.2614	<0.001	0.733	0.537	0.463 (δ_{46})
SE1V (λ_{47})	1.117	0.091	12.2490	<0.001	0.629	0.396	0.604 (δ_{47})

Third, self-directedness has been described as a form of self-determination and ability to regulate behaviour to suit goals and values (Tse et al., 2011). The variables that load on this construct evaluate whether the respondent likes to make plans for the future, knows what to want out of life and finding it helpful to set goals for the near future. The standardized loadings are high (0.817, 0.805 and 0.708) and indicate a high correlation between the indicators and latent variable.

Lastly, we can observe that some of the indicators that share a loading on social functioning have a low communality. Specifically, the variables SE1D and SE1I are problematic cases. Using SE1D the respondent has to answer whether he or she believes that other people see him or her as loving and affectionate. SE1I evaluates whether the participant thinks that it is important to have new experiences that challenge how you think about yourself and the world.

3.3 Structural model

Third, the structural model is of great interest in this work, since it allows us to make conclusions about the relationships between the latent constructs. First, we may consider the direct effect of harm avoidance (β_1) and self-directedness (β_2) on social functioning. Both parameters estimates are significant and indicate a positive relationship with social functioning. One the one hand, for one standardized unit increase in harm avoidance, it is estimated that there will be a 0.141 increase in social functioning. On the other hand, the standardized parameter estimate of 0.568 associated with self-directedness indicates a stronger relationship with social functioning. Next, following the theory proposed by Tse et al., 2011, we may expect there to be a significant effect of social functioning on depression. The results indicate that there is a negative pattern between the two in the sample, but this can not be estimated to the population. Lastly, the standardized direct effect of self-directedness on depression is -0.425. This highly significant ($p<0.001$) effect indicates that an increase of one standard deviation in self-directedness will lead to a decrease in depression of 0.425.

Strongly related to the structural model is the notion of discriminant validity. Discriminant validity gives an indication that theoretically different constructs should not be highly intercorrelated. In other words, if two latent variables are highly correlated they could represent the same construct and they could be merged into one latent variable to obtain a more parsimonious solution (Brown, 2015). The low and insignificant ($p=0.108$) standardized covariance of -0.1 between harm avoidance and self-directedness indicates that there is little evidence for poor discriminant validity.

$$\begin{cases} \text{social functioning} &= \beta_1 \text{harm avoidance} + \beta_2 \text{self-directedness} + \delta_1 \\ \text{depression} &= \beta_3 \text{social functioning} + \delta_2 \\ \text{depression} &= \beta_4 \text{self-directedness} + \delta_3 \end{cases} \qquad \text{(Structural model)}$$

Table 11: Structural model

Parameter	Coefficient	Standard error	z-value	p-value	Stand. coefficient
β_1	0.131	0.055	2.398	0.016	0.141
β_2	0.403	0.038	10.614	<0.001	0.568
β_3	-0.190	0.109	-1.748	0.080	-0.126
β_4	-0.441	0.084	-5.263	<0.001	-0.425

3.4 Goodness of fit

Fourth, the goodness of fit of the model will be evaluated. The χ^2 statistic is closely related to the fit of the model and is very popular in the literature, but it has received some important criticisms. It has been noted that in many instances the underlying distribution is not χ^2 distributed, which severely limits the interpretability. Moreover, it is inflated by sample size and it makes the stringent hypothesis that the sample covariance matrix and reproduced covariance matrix are equal (Brown, 2015). In this illustration, the test statistic of 589.88 is larger than the critical value of 216.65. Hence, the null hypothesis that this model is equal to a perfectly fitting model can be rejected and poor model fit is concluded. However, given the large sample size of 601 this conclusion should not be trusted.

Absolute fit indices have therefore been employed. They assess the quality of the solution without taking into account model parsimony. First, the standardized root mean square residual (SRMR) can be interpreted as the average standardized residual covariance (polychoric correlation). It can be calculated using the following equation, where p is the number of indicators and ϵ is the vector of the standardized residual covariances (Shi and Maydeu-Olivares, 2020). In this illustration a SRMR of 0.081 was obtained, which indicates borderline poor model fit as it is just above the target of 0.08.

$$SRMR = \sqrt{\frac{\epsilon\epsilon}{p(p+1)/2}} \tag{4}$$

Second, the root mean square error of approximation (RMSEA) takes into account the error of approximation in the population. The RMSEA takes values between zero and one and the fit of the model is acceptable if it falls under 0.05. A RMSEA of 0.065 has been obtained.

I have noticed that sometimes N or $N-1$ is used in the literature. For consistency I have chosen to use N.

$$RMSEA = \sqrt{\frac{\chi^2 - df}{N \times df}} \tag{5}$$

$$RMSEA = \sqrt{\frac{a(N-1)(\chi^2 - df) + b}{(N-1)df} - \frac{1}{N-1}} \tag{6}$$

CFI and TLI are two comparative fit indices that will be evaluated as well. This group of statistics is called comparative, since they make a comparison between a restricted null model and an alternative model supplied by the model-builder (Brown, 2015). The comparative fit index (CFI) and Tucker-Lewis index (TLI) have been shown below. Both measures have a range of possible values from zero to one and make a correction for complexity through the degrees of freedom. Values that are close to one imply a good model fit. Generally, 0.9 is taken as a target value. In this illustration the CFI and TLI are, respectively, 0.938 and 0.93. To sum up, the fit of this model is borderline good or bad, depending on which fit measures are taken into account.

$$CFI = \frac{(\chi^2 - df)_{null} - (\chi^2 - df)_{alternative}}{(\chi^2 - df)_{null}} \quad (7)$$

$$TLI = \frac{(\chi^2/df)_{null} - (\chi^2/df)_{null}}{(\chi^2/df)_{null}} \quad (8)$$

Table 12: Test statistics

Statistic	Value	Target
χ^2	589.88	< 216.65
CFI	0.947	> 0.9
TLI	0.940	> 0.9
RMSEA	0.060	< 0.05
SRMR	0.081	< 0.08

Table 13: 10 highest modification indices of base model

Left hand side	Operation	Right hand side	Modification index	Expected parameter change	Stand. expected parameter change
C1SE1BB	correlation	C1SE1D	88.582	0.322	0.462
self-directedness	loading	C1SE1I	49.044	0.396	0.323
C1SE14O	correlation	C1SE14R	35.183	0.273	0.670
C1SE1BB	correlation	C1SE1HH	32.460	-0.278	-0.538
social functioning	loading	C1PA65	32.008	0.426	0.240
social functioning	loading	C1SE14P	27.723	0.516	0.290
C1SE1HH	correlation	C1SE1J	26.321	0.188	0.452
social functioning	loading	C1SE7V	26.143	-0.283	-0.159
C1SE14R	correlation	C1SE1I	25.824	0.197	0.317
social functioning	correlation	C1PA66	24.609	0.388	0.219

The modification indices can be used to further investigate sources of model misfit. They can be calculated for each fixed and constrained parameter in the model and indicate how much the model χ^2 would drop if the parameter was freely estimated. A good fitting model should then also produce modification indices that are small in magnitude. A modification index that is greater than 3.84 indicates that the model fit can be significantly improved if the parameter is freely estimated (Brown, 2015). Unfortunately, the summary shown in Table 13 indicates that there are various sources of badness of fit in the model.

First, there are some modification indices associated with the measurement model that can provide insight in sources of the badness of fit. It is estimated that the model fit can be improved dramatically by allowing a correlated error term between the variables 1SE1BB and SE1D, which load on social functioning. On the one hand, SE1BB assesses whether the respondent believes other people would describe him/her as a giving person. On the other hand, SE1D evaluates whether the respondent believes other people see him/her as loving and affectionate. Personally, I believe that it is very plausible that these two variables are related to one another. A correlation between these variables will therefore be allowed in the improved model.

Next, the modification indices indicate that the model fit would improve dramatically should a correlated error term be allowed between the self-directedness variables 1SE14O and 1SE14R. In 1SE14O and 1SE14R it is asked whether the respondent likes to make plans for the future and knows what to want out of life, respectively. Since I cannot see how these questions are directly related to each other, I will not allow a correlated error term between them in the improved model.

Another area where the model could be improved has to do with the variables 1SE1HH and 1SE1J, which load on social functioning. On the one hand, in 1SE1HH it is asked whether the participant has experienced many warm and trusting relationships. On the other hand, for 1SE1J it is asked whether he or she has difficulty maintaining close relationships. Clearly, if one has difficulty maintaining close relationships, one would also not have experienced many warm and trusting relationships. A correlated error term will therefore be allowed between these variables in the improved model.

It is estimated that the model fit can be improved drastically should a correlation error term be allowed between the variables 1SE1BB and 1SE1HH. Both variables have a loading on social functioning. 1SE1HH indicates whether the respondent has experienced many warm and trusting relationships. 1SE1BB assesses whether the respondent believes he or she would be described by others as a giving person, willing to share his or her time. Personally, I cannot see how both variables are directly related to each other. A correlated error term will therefore not be allowed.

Additionally, the modification indices indicate that the variables 1SE1HH and 1SE1P should share a correlation. 1SE1P indicates whether the respondent often feels lonely because he or she has few close friends with whom to share concerns. Since 1SE1HH assesses whether he or she has experienced many warm and trusting relationships, I believe such a correlation should be allowed.

Second, some modification indices indicate that the structural model is not plausible. The second and third largest modification specify that there should be a direct relationship between depression and self-directedness. Moreover, a drop of 27 in χ^2 can be achieved by allowing a direct relationship between depression and harm avoidance through a regression.

4 Expanding the base model

5 Conclusion