

# Validating a Mindset Scale

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### **Popular abstract**

Mindset theory explains two different types of mindset, or core reasoning behind one's beliefs and actions, an individual can have. A fixed mindset believes that mindsets are fixed and cannot change throughout one's life. On the other hand, growth mindset believes that mindset can be developed and changed throughout one's life; one can also change from fixed to growth mindset through appropriate intervention and education. Mindset scale then measures whether a person has a fixed or a growth mindset. Since mindset scale is a crucial tool before any mindset interventions, it is important to study whether the mindset scale is functioning properly and producing reliable results. Moreover, it is also crucial to test whether the mindset scale is functioning the same across different population, such as for males and females. Therefore, this study aims to test the validity of the mindset scales used by a Norwegian company, Made to Grow, and see whether the scale is functioning the same for different gender groups.

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#### Abstract

Mindset theory is a steady growing theory in education first developed by Carol Dweck (1999). Since it focuses on the human development aspect, it is seen as offering more flexibility for school systems. Made to Grow is a Norwegian company that adopts this theory of fixed and growth mindset and offers resources to help Norwegian students develop from fixed to growth mindset. Using the mindset scale, Norwegian students can test where they stand on the mindset spectrum. To examine the psychometric properties of the mindset scale Made to Grow used, reliability and the evidence for crafting a validity argument have been considered. Confirmatory factor analysis (CFA) and testing for measurement invariance across genders were methods used to assess the validity of the mindset scales. Moreover, network models were used to gain indepth information on individual items within mindset scales. As a result, mindset scales showed to be producing reliable results and functioning equally for both genders.

*Keywords*: fixed and growth mindset, confirmatory factor analysis, measurement invariance, network models, validation, psychometric

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#### Validating a mindset scale

### Introduction

The Merriam-Webster (n.d.) dictionary defines 'mindset' as such: "a fixed state of mind" or "a mental attitude or inclination". Dweck and Yeager (2019) states that mindset is an important attribute in one's life; it is the functioning core that supports one's beliefs, personality, motivation, and ability. Thus, mindset plays a crucial role in shaping one's actions towards relationships and achievement in life (Dweck & Yeager, 2019). However, Dweck (2008) disagrees with Merriam-Webster's definition and argues that there are two types of mindsets. The first type is the fixed theory of mindset, which theorizes one's intelligence or personalities as fixed and not changeable (Dweck, 2008). The second type, or the malleable theory of mindset, also known as the growth mindset, then theorizes that people's personal qualities can constantly be developed and changed (Dweck, 2008).

Over time, mindset has been studied not only from psychological, but also neurological and educational perspective with a focus on individual growth (Dweck & Yeager 2019). Especially when Dweck (2017) found that these different mindsets already start to form in children at a young age, guiding children and helping them form a malleable growth mindset have become of importance. As a result, various interventions to help students develop growth mindset started to form (Shan et al., 2021). Mindset scales were also created to test and measure people's mindsets before interventions took place.

In Norway, a company called Made to Grow has been working with mindset scales to promote growth mindset not only in students but also adults. The company offers online platform for people to learn more about fixed and growth mindset and train oneself to have a growth mindset (Made to Grow, n.d.). Recently, the company also launched an app to provide easier access to their customers. Through these online platforms, the company also has collected data on which type of mindset students have. The data is based on a questionnaire containing questions about life behavior, health, motivation and more.

Mindset interventions like those from Made to Grow have been proven to be successful in providing positive effects, such as improvement in motivation and educational achievement (Blackwell et al., 2007; Bostwick et al., 2017; Limeri et al., 2020). However, there are other studies that proved effects of mindset interventions to be weaker or produced inconclusive results (Ingebrigtsen, 2018; Napolitano et al., 2021). Nonetheless, the growing popularity of mindset theory emphasizes the need to carefully measure the effect of these interventions. Since mindset scales are used as an important source alongside with mindset interventions, it is also vital that these scales are able to measure mindsets in a reliable way and that the results are valid (Ingebrigtsen, 2018).

This study used 11 items related to fixed and growth mindset from the data compiled by Made to Grow company. Psychometric properties such as validity of the mindset scales were studied to see whether the items measure fixed and growth mindset. Moreover, functioning of the items was tested to see whether they show measurement invariance across gender. Therefore, we formulate the research questions of this study in two.

- 1. How are the mindset scales connected to fixed and growth mindset?
- 2. Are the mindset scales functioning the same for both female and male students?

The data was analyzed through confirmatory factor analysis (CFA). Once a model was selected accordingly through model fit indices, measurement invariance based on this CFA model across gender groups were tested. Lastly, network models were also created to gain a deeper knowledge into different interaction between items beyond the latent variable of mindset.

This study is divided into 5 sections. First, previous research related to mindset scale will be discussed. Various topics connecting mindset theory with education and how mindset scale has been statistically analyzed based on factor analysis will be shown. Since this study uses both factor analysis and network models which is not often done using mindset scales, why these two statistical approaches were specifically chosen will be explained. Then, the methods section goes into depth about item variables and the statistical process to assess these variables. Results based on descriptive statistics, confirmatory factor analysis, measurement invariance across gender groups, and network models will be provided. Discussion section uses these results to answer the study's research questions and compare them to previous research. Then, limitations and possible future directions will be shortly discussed. A short conclusion will follow to summarize what can be learnt through this study.

### **Previous research**

Linking previous studies of mindset theory and education emphasizes why mindset theory has progressed to take place in the educational world. Moreover, reliability and measurement invariance related to mindset scale that has been researched in other studies are shown compare how the results of this study is relatable.

### Mindset theory and education

During the 20<sup>th</sup> century, the importance of intelligence quotient (IQ) on individual development and the importance of testing IQ began to arise (Shan et al., 2021). Since then, high IQ level was central for an individual to show high achievement in school and develop successfully. Alfred Binet, who created a scale to measure IQ in 1905, strongly believed that IQ could not be improved or changed during one's lifetime (Shan et al., 2021). This led to a fixed

mindset-like belief especially in teachers and schools which led to stagnant education systems and formation of stereotypes against low IQ students (Shan et al., 2021).

However, the introduction of Dweck's fixed and growth mindset became a turning point for many students and schools. Instead of high IQs, developing growth mindset with positive and flexible attitude towards learning became the new objective. Moreover, Rosenthal and Jacobson (1968) found that students with low IQ could improve their academic achievement after they have received growth mindset intervention. Yeager et al. (2019) found similar results in which a high school classroom that adopted a growth mindset grading model resulted in weak-performing students with improved academic performance. Researchers such as Blackwell et al. (2007) and Shan et al. (2021) also found results that growth mindset interventions improved academic achievements.

On the other hand, this was not the result found by Sisk et al. (2018). The researchers conducted a meta-analysis on the relationship between growth mindset and academic achievement; the result they found was that the relationship was much weaker than anticipated. Although some correlation was found between mindset interventions and improved academic achievement for high-risk students such as from low socioeconomic households, the researchers concluded that it may be better for schools to allocate their resources on other things than mindset interventions (Sisk et al., 2018). Leach (2015) also reported that high performing students did not show much difference in academic achievement compared to before and after mindset interventions (Leach, 2015). However, they did not show much difference in their attitude towards learning since they already had adopted and acted based on growth mindset (Shan et al., 2021).

Despite the diverse results from different studies, it is important for teachers and educators to be aware of different mindset theories and move away from IQ tests. IQ tests encourage fixed mindset and cannot be changed, whereas different mindsets can change; growth mindset can even be learnt and educated. Being aware of fixed and growth mindset could even improve the intelligence of students (Shan et al., 2021). Moreover, younger students that received early intervention related to growth mindset showed long-lasting effects of higher academic achievement than those who have not received interventions (Blackwell et al., 2007).

These interventions are especially crucial for adolescent students who are at an age "which declines in achievement are common and can have important consequences for future life success" (Dweck & Yeager, 2019, p. 7). Therefore, school is an important stage to teach students about different mindset theories – for we can teach students about self-esteem and "to value learning over the appearance of smartness, to relish challenge and effort, and to use errors as routes to mastery" (Dweck, 2000, p. 4). In conclusion, mindset theories have come to playing a crucial role in educational fields not only to improve academic achievement, but also long-term individual growth and development for students.

#### Mindset scale and reliability

The original mindset scale was originally created by Dweck (2000), known as the Implicit Theories of Intelligence scale. This 6-item scale consists of both fixed and growth mindset items and specifically ask questions that are related to intelligence such as "To be honest, you can't really change how intelligent you are" (Dweck, 2000, p. 178). The scale offers 6-likert scale ranging from 1 ("strongly disagree") to 6 ("strongly agree").

Researchers found that for these mindset scales, the reliability numbers were relatively high. Levy et al. (1998) reported high internal reliability between 0.93 and 0.95 with test-retest

reliabilities of 0.82 of a week's interval. Blackwell et al.(2007) tested the internal reliability of 6 items from the intelligence scale and reported a lower reliability value of 0.78. Test-retest reliability of 2-week interval was 0.77. On the other hand, Midkiff et al.(2018) reported a higher reliability value of 0.90, although the reliability was tested only for 4 items out 6 from Dweck's intelligence scale (2000). In general, the mindset scale proved to have relatively high reliability.

### Mindset scale and factor analysis

There were several studies using factor analysis to test for number of factors present in the mindset scale. Especially in the beginning of the mindset theory development, Dweck (2000) argued that fixed and growth mindset was on a single continuum and should be seen as a single variable (Lüftenegger & Chen, 2017). Since then, the number of dimensions and factors for mindset theory has been a subject of matter.

However, the idea of mindset theory as a unidimensional entity has been constantly been argued against by many researchers (Ingebrigtsen, 2018; Tempelaar et al., 2014). Dupeyrat and Mariné (2005) found through exploratory factor analysis that the mindset scales consisted of two factors rather than one single factor. Ingebrigtsen (2018) used measurement models of exploratory factor analysis and confirmatory factor analysis to test his mindset scale. He found evidence that mindset scale was not a single factor but a bifactor model. De Castella and Byrne (2015) started their research out by testing between single factor and bifactor model using confirmatory factor analysis and structural equation modelling. The researchers also found evidence that their mindset scales were based on a bifactor structure. Though there is more evidence that the mindset scale can be defined through a bifactor model, we will test this hypothesis once again by comparing a single factor model and a bifactor model.

### Mindset scale and measurement invariance

To ensure that a measurement scale is functioning the same for different sample groups, measurement invariance is important to test once a statistical model for the measurement scale has been specified (Limeri et al., 2020). Using the mindset scale, different sample groups were tested for measurement invariance in various studies. For instance, Bostwick et al. (2017) tested for growth mindsets and academic achievements in mathematics using confirmatory factor analysis and structural equation modelling. The researchers also tested for measurement invariance for different sample groups such as gender, school grade and socioeconomic status. They found that all different sample groups achieved measurement invariance.

Napolitano et al. (2021) tested measurement invariance of the mindset scale for different gender groups of Indian adolescents. They found that measurement invariance had been achieved. However, when they further researched for measurement invariance for different cultural groups between American adolescents and Indian adolescents, the result was inconclusive. Measurement variance was found when using the Bayesian method, but a weak invariance in the configural model was identified when using a subsampling statistical approach. The researchers concluded that further investigation was needed for analysis on cross-cultural sample.

On the other hand, Limeri et al. (2020) tested the relationship between growth mindset and academic achievement for undergraduate students. The researchers found measurement invariance for the mindset scale across different timelines, using a longitudinal data. This test was to ensure that the mindset scale had high validity and reliability. The researchers found measurement invariance achieved on their longitudinal model and concluded that the mindset scale was reliable enough to go further with their research.

### **Statistical approaches**

To study the psychometric properties of the mindset scale, confirmatory factor analysis was used (CFA). CFA is especially useful since it allows us to test the reliability of the scale before we specify models, which is essential for validity testing (Ingebrigtsen, 2018). Moreover, CFA allows model testing and comparing model fit, such as single factor and bifactor models. Testing for measurement invariance between different sample groups is also a great benefit of CFA. Thus, CFA has long been used for multifactorial models.

Despite the benefits CFA has, however, it also has some shortcomings. One of the weakness CFA has is that it has a strong assumption on local independence (Epskamp et al., 2017). This indicates that items are assumed to be independent from each other, and that the latent variable is the only common explanation the items share. When this assumption is violated, however, then there is a great risk of model specification being biased using CFA (Epskamp et al., 2017).

The risk of violating local independence may especially be higher when interpreting personality or any behavioral traits (Costantini et al., 2015; Epskamp et al., 2017). This is especially when personality and behaviors are shown through number of characteristics interacting with each other, creating an 'ecosystem' (Costantini et al., 2015). This hypothesis is based on network perspective of psychology (Cramer et al., 2010), which theorizes that: noticeable macroscopic behavior – the co-occurrence of aspects of psychology such as cognitive abilities, psychopathological symptoms, or a set of behaviors – is hypothesized to not be due to influence of unobserved common causes such as general intelligence, psychopathological disorders, or personality traits, but rather to emergent behavior in a

network of interacting psychological, sociological, and biological components. (Epskamp et al., 2017, p. 904)

If personalities and behavioral traits have a causal relationship with each other, this then violates the CFA assumption of local independence (Costantini et al., 2015; Cramer et al., 2010; Epskamp et al., 2017). Moreover, there is a risk that using only CFA provides an incomplete portrayal of relationship between item and the common variable rather than the whole complexity of network between items. However, using only network model can also be risky, for many of the personality or behavior related questionnaires are built so that it can easily be interpreted using factor analysis (Costantini et al., 2015).

To create a stronger model with less possibility of bias, both CFA from factor analysis and Gaussian graphical model (GGM) from network models are used for this study. GGM does not focus on the common variance like the CFA and assumes that covariances between items (or observed variables) are not caused by any latent variable (Epskamp et al., 2017). Based on this assumption, it draws a network between the items based on partial correlation and describe the unique relations they have, independent of any latent variables. Since both CFA and GGM are built from covariance structures, both are in fact, closely related and can be built to be used along each other (Epskamp et al., 2017).

Moreover, Residual network models (RNM) is also used alongside GGM since it also provides ways to improve interpretation of items from the mindset scale. While both network models aim to describe the unique relationships between items, GGM creates network based on observed items and RNM creates a network after taking under consideration that some items may have a common variance such as fixed or growth mindset. Therefore, this provides a clearer picture on how residuals interact beyond possible cross-loadings that explanations CFA or GGM might provide (Epskamp et al., 2017). RNM also does not change the structure from the latent variable created by CFA, which indicates that RNM is adding more detailed information even if the CFA assumption of local independence has been violated and has specified a biased model. GGM and RNM can also be tested for model fit, which is also helpful in specifying the model further.

This study's statistical approach starts with the reliability coefficient of the McDonald's omega reliability to show the validity of the mindset scales. Then, CFA was used to specify and compare models between a single factor model and a bifactor model. Various model fit indices were used to compare models. With the final chosen model, measurement invariance between genders was studied. Furthermore, GGM and RNM from network models was used to study interaction between items and gain a deeper insight into the measurement scale items.

#### Methods

#### **Descriptive statistics**

### Sample

Data has been collected from students in Norway from 2018 to 2020 (n = 266) from five different schools. There were more female respondents (59.8%) compared to male respondents (40.2%) in this study. Participants from year 2018 and 2019 were students from grade 7 to 13, with grade 8 (29.6%) and grade 10 (26.6%) showing the highest participation rate. In 2020, data was collected on students from private schools that did not belong to specific grades. Due to this change, the age of all participants in the study varied from 13 to 55 from year 2018 to 2020 (M = 20.15, SD = 9.03 years). Age 16 students had the highest participation rate (25.19%) with age 14 students the second highest in participation rate (21.8%) and age 17 students the third (12.4%).

2018 had the highest participation rate (38.7%) and 2019 being the next highest (37.6%). In 2020, the participation rate was slight lower compared to previous years (23.7%).

The questionnaire consisted of 134 total number of items, in which they were divided into 14 different categories such as flourishing and well-being, adaptability, epistemic curiosity, mindset and health. The questionnaire was also updated over the years, and therefore did not contain data from all participants for all questions. For future research, the same questionnaire was provided more than once for selected students. Therefore, the dataset consisted of longitudinal data. However, since this research aim is to test the validity specifically only of the mindset scales, data available only for this purpose was utilized of 11 items in mindset scale.

### Measures

For this study, mindset scale used by Made to Grow company was studied. Unlike Dweck's original Implicit Theories of Intelligence Scale of 6-items scale, the company updated a new scale based on Dweck (2000) and Blackwell's research (2007). Therefore, the new scale consisted of 11 items with 7-likert scale response and measures whether one has a fixed or growth mindset.

Table 1 shows the 11 mindset scale items divided into fixed mindset (FM) and growth mindset (GM); 6 items were related to fixed mindset and 5 items to growth mindset (see Appendix 1 for Norwegian version). Participants used a 7-point Likert scale ranging from 1 ("Strongly disagree"), 2 ("Quite disagree"), 3 ("Slightly disagree"), 4 ("Either agree or disagree"), 5 ("Slightly agree"), 6 ("Quite agree") to 7 ("Strongly agree"). The mindset scale showed a reliability value of  $\omega$ =0.86. Dividing the mindset scale into growth and fixed, growth mindset scales showed a reliability value of  $\omega$ =0.79 and fixed scales showed reliability value of  $\omega$ =0.86.

# Table 1

Mindset scales used by Made to Grow

Mindset	Items	Mean (SD)				
	1. You can learn new things, but you can't really change	3.40 (1.69)				
	your basic intelligence.					
	2. Your intelligence is something about that you can't	3.13 (1.62)				
	change very much.					
	3. You have a certain amount of intelligence and you can't	2.69 (1.47)				
	really do much to change it.					
Fixed (FM)	8. Everyone is a set type of person, and there is not much	2.82 (1.47)				
	they can do to change it.					
	10. To tell the truth, when I work hard with something, it	3.79 (1.57)				
	makes me feel like I'm not very smart.					
	13. Only a few people can really be good, whether in	2.92 (1.63)				
	sports, music, art a school subject or something else – you					
	have to be born with the talent.					
Growth (GM)	4. No matter how much intelligence you have, you can	5.10 (1.44)				
	always change it quite a bit.					
	5. Everyone, no matter who they are, can change one's	5.00 (1.51)				
	basic intelligence level considerably.					
	9. When there is something difficult, I wish to work more	3.89 (1.57)				
	with it and not less.					

11. If you work hard at something, you will likely perform	4.93 (1.60)
well, no matter how smart you are.	
12. I like work that I can learn from even if I make a lot of	4.67 (1.42)
mistakes.	

### **Statistical Analyses**

### Model specification and model fit

Statistical analyses were first conducted using CFA to test for the first research question. To account for the skewness of the item distribution and accommodate for deviations from a normal distribution, robust Maximum Likelihood (MLR) was used to estimate the models. Moreover, full-information Maximum Likelihood (FIML) was also used to account for random missing values of the data. Based on CFA, three models were specified. The first model was a single factor model with all 11 items under one factor of 'MINDSET'. The second model then, was specified as a bifactor model with items divided accordingly to fixed and growth following the supporting evidence of bifactor model from previous studies. The final model was a bifactor model with specified covariances based on modification indices. All analyses were conducted using the statistical program R.

The three models were also evaluated of model fitness using the Comparative Fit Index (CFI), Root Mean Square Error of Approximation (RMSEA) and the Standardized Root Mean Square Residual (SRMR). The standard criteria of good model fit were used as CFI  $\geq$  0.95, RMSEA < 0.08 and SRMR < 0.08 (Marsh et al., 2004). Once the models' goodness of fit was conducted, Akaike's information criteria (AIC), model fit and chi-square values from one-way

Analysis of Variance (ANOVA) test were used to compare between models and choose the best fitting model.

### Measurement invariance

To answer for the second research question, various measurement invariance testing models were constructed between gender groups. Based on the best fitting model from CFA, 4 different models of configural, metric, scalar and strict models were additionally tested. The *configural model* assumes the same overall factor; there are same number of factors with same number of fixed and free parameters between female and male students (Steinmetz et al., 2008). Then, the *metric model* constrains the factor loadings, whereas *scalar model* constrains the item intercepts of the CFA model for both genders (Steinmetz et al., 2008). Lastly, the *strict model* constrains the item uniqueness, or residuals, for the models of each gender group (Scherer et al., 2016). Once these four models were specified, ANOVA was used to compare model fit indices of AIC and chi-square value differences. Through the ANOVA test, the models were then judged whether measurement invariance had been achieved or not for different gender groups.

#### Interaction between items

To gain deeper insight into the interaction of items, model fit for both GGM and RNM were looked at. Same model fit indices from CFA of CFI, RMSEA, AIC and chi-square values were studied. Then, the models were plotted by extracting their matrices, which revealed the partial correlations of various items. GGM was used to see whether items had unique relationships without accounting for any common variance, and RNM was used to see if there were any residual interactions between items after accounting for some common variance such as mindset. 4 aspects of centrality indices of expected influence, strength, betweenness and closeness were considered to study different interactions of items based on the GGM (Epskamp et al., 2018). Centrality indices measure the importance of an item and what roles each item plays in the whole scale. Therefore, strength indicates how much weight an item has, or how much influence it has on other items directly (Costantini et al., 2015). Then, closeness indicates how close one item is from each other, or how fast it can be affected directly or indirectly by the answers in other items. Betweenness indicates how important the item plays as a role as a medium, or delivering influence on other items from one point to another (Costantini et al., 2015). Combining the information from these three centrality indices then provide the information of expected influence. Lastly, clustering coefficient is also studied for the network models, which provides information on how many connections each item holds with other items(Costantini et al., 2015). Based on these information, one can observe a bigger network interaction based on the items for the mindset scale.

#### Results

### **Descriptive statistics**

Figure 1 shows the distribution of all 7 responses for each mindset scale items. While most of the items showed a moderate level of skewness, items such as GM9 and FM10 showed normal distribution. On the other hand, items FM3 (0.86) and FM8 (0.74) showed higher level of skewness. Next, figure 2 shows the correlation between different items. Some items indicated moderate correlation with other items which may occur since they share similar traits of growth or fixed mindset. However, items GM9 and GM12 showed noticeably high correlation of 0.87.

Distribution and correlations were used as a guidance to improve the mindset scales and statistical model in the next steps.

### **Confirmatory Factor Analysis (CFA)**

For CFA, three different models were created for mindset scales. The first model was a single factor model with one factor of 'MINDSET' with all items in the equation. Factor variance was also included in the model specification (figure 3). The fit indices for the first model showed a bad fit ( $\chi^2(44) = 359.22$ , CFI = 0.685, RMSEA = 0.165, SRMR = 0.12, AIC = 10076.44). CFI was under the cut-off value of 0.95 indicating a bad fit. Both RMSEA and SRMR also showing a larger value than 0.08 indicated a bad model fit. Since all the model fit indices showed bad fit, we moved onto model 2 without going deeper into interpretation of the first model.

In the second model, all items were now divided accordingly to fixed and growth mindset. Factor variance and covariance was also accounted for in the model specification as seen in figure 4. Model fit indices showed slightly improved values compared to model 1 ( $\chi^2(43) = 275.19$ , CFI = 0.768, RMSEA = 0.143, SRMR = 0.11, AIC = 9994.4). CFI, RMSEA and SRMR showed improved values compared to model 1, but the values were still not acceptable and did not satisfy the good model fit values. Although chi-square values and AIC were lower than model 1 indicating a better fitting model in comparison, bad CFI, RMSEA and SRMR proves that the model needs to be improved. Since this model is the original two factor model with items divided into growth and fixed mindset, each item's statistical significance and R-square values were investigated. Modification indices were used to specify covariance relationship between the mindset scales.

To begin with, the model summary showed that GM9 (0.192, p = 0.220) does not have a statistically significant effect in the two-factor model. Although FM10 was statistically significant, the factor loading showed a low value of 0.232 (p=0.01) compared to other items. Studying the R-square for all the items, we saw that GM9 explains 2.2% of the factor, and that FM10 only explains 3.7% of the factor. Since these two variables showed low power in explaining the factors, we proceeded to remove them from the model.

Next, modification indices were used to identify covarying relationship between items. Four modification indices values of  $GM9 \sim GM12$  (MI: 91.528),  $GM11 \sim GM12$  (27.652),  $GM11 \sim FM13$  (34.453) and  $FM1 \sim FM2$  (26.510) indicated that there was high covarying relationship between these items. Since GM9 would be be removed from the model, a third improved model with these 3 covariances without GM9  $\sim GM12$  were specified.

Figure 5 shows the plot and model specifications for model 3. Fit indices now indicated that model 3 was a better fit ( $\chi^2(23) = 35.344$ , CFI = 0.985, RMSEA = 0.045, SRMR = 0.048, AIC = 7955.4). CFI has greatly improved compared to the previous 2 models and were well above the cut-off value of 0.95 to be a good model. Moreover, RMSEA and SRMR also dropped tremendously compared to the previous models and showed values under the cut-off value of 0.8. In general, third model was concluded to be a good model fit. Therefore, mindset scale was decided to be a bifactor model with correlations between items GM11 and GM12, GM11 and FM13, and FM1 and FM2 for this study.

### Measurement invariance across gender

Using model 3, we tested for measurement invariance across gender. The first *configural model* showed that the model is an okay fit ( $\chi^2(46) = 67.626$ , CFI = 0.975, RMSEA = 0.060,

SRMR = 0.062, AIC = 7967.7). CFI showed a value higher than the cut-off value of 0.95 which indicated a good fit. RMSEA and SRMR were below the cut-off value of 0.08, indicating that the model was a good fit. In conclusion, measurement invariance in the configural model for gender had been achieved; the overall factor structure functions similarly for both female and male students.

Next, measurement invariance for the *metric model* was tested. The model fit also indicated that this model was a good fitting model ( $\chi^2(53) = 72.352$ , CFI = 0.985, RMSEA = 0.053, SRMR = 0.073, AIC = 7958.4). CFI showed a higher value than the configural model, and RMSEA also showed improvement compared to the configural model by showing a value beneath the cut-off value of 0.08. Although SRMR was higher than the configural model, the value still indicated a good fit of under 0.80. Chi-square was higher than the configural model, but AIC is lower than the configural model. Overall, measurement invariance was also achieved for metric model; mindset scale had the same factor loadings for both female and male students.

To see whether there is an improvement of fit in the configural and metric model, an ANOVA test was conducted to compare chi-square values between the two models. The ANOVA test indicated there was no statistically significant difference in chi-square values between configural and metric model (table 2). Since this indicated that there was measurement invariance in the configural or metric model, measurement invariance was further tested.

The third model was the *scalar model*, which also indicated a good model fit ( $\chi^2(60) =$  77.371, CFI = 0.980, RMSEA = 0.047, SRMR = 0.074, AIC = 7949.446). CFI was well above the cut-off value and both RMSEA and SRMR was below the cut-off value, indicating that this model was a good fit. Since scalar model was a good fit in general for both genders, this showed that measurement invariance was again achieved; factor loadings and item intercepts are similar

for both female and male students. ANOVA test was conducted to test for significant differences in chi-square values for all three models of configural, metric and scalar. The values showed there was no statistically significant difference in chi-square values between the models. Thus, the fourth model was tested for measurement invariance.

The *strict model* which tests for similar residuals between female and male students showed a good model fit ( $\chi^2(69) = 84.598$ , CFI = 0.982, RMSEA = 0.041, SRMR = 0.073, AIC = 7938.674). CFI indicated a good fit by being above the cut-off value; RMSEA and SRMR also indicated a good fit. An ANOVA test was used to see whether there is statistically significant difference in the chi-square and AIC for all four models. As seen in table 2, the results showed that there was no statistically significant difference. This proves that measurement invariance has been achieved for both gender groups.

### Table 2

	$\chi^2(df)$	$\Delta \chi^2 (\Delta df)$	$Pr(\chi^2)$	RMSEA	SRMR	CFI	AIC
Configural	67.63 (46)			0.060	0.062	0.975	7967.7
Metric	72.35 (53)	3.38 (7)	0.80	0.053	0.073	0.985	7958.4
Scalar	77.37 (60)	4.90 (7)	0.67	0.042	0.074	0.98	7949.4
Strict	84.60 (69)	3.97 (9)	0.91	0.041	0.073	0.982	7938.7

Test results for measurement invariance across gender groups

### **Network models**

### Gaussian Graphical Model (GGM)

Now that models have been studied through CFA modelling, network modelling was used to gain additional insight to the mindset scale items. Before interpreting network between items, model fit with modification of the model was first looked at. The model fit indicated a good fit ( $\chi^2(23) = 26.69 \text{ CFI} = 1.0$ , RMSEA = 0.025, AIC = 7946.75).

Using the specified GGM, partial correlation between items were then studied. Network plot in figure 7 showed that all items are interacting at least with more than one items, either directly or indirectly. However, some of these values were too low, indicating that the interaction has low power to be statistically significant (Epskamp et al., 2018). The highest correlated items were FM2 and FM3 with a value of 0.76. This coincides with the high covariance values in the CFA model, which was accounted for in the final CFA model. GGM network plot, however, indicated that these two items had the second highest covariance with a value of 0.52. The highest correlation of 0.74. Next, although not the highest negative correlation, figure 7 also showed that GM11 and FM13 had a strong negative relationship between them. Network plot also indicated that these two items have a strongest negative covariance interaction with each other. The relationship between these two items have also been accounted for in the CFA model.

4 aspects of the centrality indices of expected influence, strength, closeness and betweenness were further studied for the GGM model for detailed information on each item. In general, centrality indices plot (figure 8) showed that item FM2 had the highest value in all centrality indices – thus, the highest expected influence. Regarding strength centrality, FM2 showed a value of 1.4 and had the most influence on other items directly without using other nodes as mediation. Moreover, closeness (0.020) and betweenness (22) was also the highest; FM2 could quicky be affected by changes from other items (closeness), but also played an important role in acting as the medium for other items to influence each other (betweenness) (Epskamp et al., 2018). Therefore, FM2 had the highest expected influence out of 9 items. Then, FM3 had the second highest strength centrality value of 1.0. Closeness and betweenness centrality for FM3 were also the second highest, with 0.019 for closeness and 18 for betweenness. Expected influence was then calculated as 0.6. Thus, FM3 has the second highest expected influence; it has second most connections to other items.

Next, clustering coefficients were studied to see which item could be redundant in giving similar information and were connected many items that are directly related to each other (Costantini et al., 2015). Usually, items from the same subscale can be connected to each other in clusters, which can cause that special item to have more redundant information. In our case, the clustering plot in figure 9 showed that FM3 had the highest clustering coefficient, with FM2 and GM4 following closely behind.

Regarding the fact that FM3 was also the second highest with expected influence, this could be interpreted as FM3 having many connections with similar items that give similar information as FM3 does, such as items that are related to fixed mindset. Similar interpretation could go for FM2, which had the highest expected influence. However, this could only be inspected through the RNM, to see whether similar information comes from a common variable or some other unknown factor. Thus, studying the RNM was used for further investigation.

#### Residual network model (RNM)

Before interpreting the network between residual of items, model fit indices showed that the model was a great fit ( $\chi^2(22) = 22.26$  CFI = 1.0, RMSEA = 0.007, AIC = 7944.32). After plotting for residual network model, four residual covariance relationships between items were identified. FM1 and FM2 had the highest positive correlation coefficient of 0.43 (p < .000) and GM12 and GM11 the second highest positive residual correlation of 0.31 (p < .000). The highest negative residual correlation was shown between GM11 and FM13 of -0.35 (p < .000). FM1 and GM12 showed the lowest residual correlation of 0.14 (p < .012). Apart from FM1 and GM12, 3 of these covariance interactions coincided with the residual covariance relationships that were identified in the CFA model and was accounted for (figure 5).

Other than these, none of the other items indicated an interaction strong enough to be shown on the plot in figure 10. FM3 that had the highest clustering coefficient and second highest expected influence did not have any residual interactions with other items now. FM2 on the other hand, had a high interaction with FM1. Since RNM is the leftover interactions of the items after accounting for the common latent structure, all of these 4 interactions between items could be concluded as an interaction beyond the common variable of fixed or growth mindset.

#### Discussion

In general, mindset scales showed high reliability coefficients of 0.86. For fixed and growth mindset separately, fixed mindset showed a reliability coefficient value of 0.86 while growth mindset showed 0.79. To answer research question 1, the study successfully specified a bifactor model which clearly indicated that the mindset scales are related to fixed and growth mindset. Like the results that Dupeyrat and Mariné (2005), Ingebrigtsen (2018) and Tempelaar et al. (2014) found, the mindset scale was a bifactor model instead of a single factor. Most items also showed high factor loadings that indicated they were related to either fixed or growth mindset, with high reliability value for the whole mindset scale separate scales of fixed and growth mindset scale.

However, there were several items that showed low factor loadings. Moreover, these had covariance between items from within or between different mindsets. This suggests that there

could be relations between items that are not captured by the two factors of growth and fixed mindset. Using the network models for further investigation, three interactions between 6 items were concluded to have an interaction beyond the common variable of fixed or growth mindset. Both CFA and network models identified 3 residual covariance interactions between FM1 ~~ FM2, GM11 ~~ GM12, and GM11 ~~ GM13. Therefore, 3 interactions are concluded to be caused by unobserved factor(s).

The network model also indicated that FM2 and FM3 had the most connection between other items. This proved that these two items have the highest expected influence over other items. Therefore, item FM2 and FM3 held most direct influence over other items, but also acted as a bridge as an indirect influence over other items too. Although FM1 and FM2 had the highest covariance values in the GGM network plot, RNM network plot additionally explained the reason behind this high interaction between the two items; there might be more than one factor that enhances the interaction between the two items. This means that other than the common mindset variable, FM1 and FM2 was likely to have an additional interaction from an unobserved factor. Therefore, FM2 and FM3 are the items that act as the most crucial items in the mindset scales. Depending on what the respondent answers for FM2 and FM3, these answers are likely to have influence on how individuals answer other items related to both fixed and growth mindset. High R-square values from CFA for both FM2 (73.1%) and FM3 (79.2%) also supported the conclusion that these two items play a crucial role in the mindset scale.

Next, research question 2 related to measurement invariance was answered through four models of configural, metric, scalar and strict. Model fitting indices and ANOVA testing of these four models indicate that measurement invariance has been achieved for both genders. This was a similar result as found by Bostwick et al. (2017) and Napolitano et al. (2021) that showed

measurement invariance between different gender groups. Since measurement invariance had been achieved for the highest level of measurement invariance testing of strict model, the mindset scale is concluded to be functioning the same without measurement variance for both gender groups.

### Limitations and future directions

One of the limitations of this study is the small sample size. Although the results of this study showed similar results with previous researches by achieving measurement invariance between gender groups and bifactor model for the mindset scale, the small sample size also shows weakness in this study. Therefore, the results have shortcomings regarding generalization for larger population. Since the sample size was small, other sample groups than gender was not possible to be tested. Moreover, huge variation in age group also decreased the strength of any possible results the study could have produced regarding different age groups.

Small sample size also brought limits to statistical approach when analyzing the data. Increasing the number of sample size could also open up possibility for other methodological approach such as item response theory (IRT); this approach would give another explanation and insight to the mindset scale items. Items such as GM9 and GM10 that were initially included in the mindset scale but was removed in the final model specification process during CFA, would now be fully explained why they had to be removed through IRT. At this point however, the study was not able to offer more explanation behind these two items.

Another limitation is the possibility of misinterpretation of the mindset scale. Since the original mindset scale is written in English, the mindset scale used by Made to Grow had to be translated into Norwegian. Although there is a Norwegian version of the mindset scale translated from English to Norwegian, there is no official mindset scale created for the Norwegian

population (Ingebrigtsen, 2018). Therefore, there is always the possibility of certain words or phrases being interpreted or accepted differently due to difference in culture by Norwegian students. Since there are not many studies done on the Norwegian population regarding the mindset scale, the results of this study are specifically unique for Norwegian students and cannot be generalized to other cultural population. This is especially important regarding the research results from Napolitano et al. (2021), in which measurement invariance was inconclusive when it came to cross-cultural sample groups.

Despite its shortcomings, this study opens up possibilities of few future directions. To overcome the shortcomings this study holds of small sample size, a bigger sample population should be collected. Since the company Made to Grow is currently still working with their online platform and providing their services to the Norwegian population, there will be a bigger sample size for future studies. This will provide possibilities for testing measurement invariance on different sample groups than gender. Moreover, this will also increase the strength of the study and provide the possibility of generalization of the results of the studies.

Made to Grow is also collecting data for future research using longitudinal data. Once enough data has been collected for a longitudinal study, the study could test for measurement variance across different times and how long effects of growth mindset resources and interventions offered by the company last. This will also give answers to how effective these growth mindset interventions are and emphasize the importance of these interventions. Once these results have been found, these could bring focus to involving more schools and even policymakers to adopt growth mindset in societal systems.

#### Conclusion

This study aimed to assess the psychometric properties of a mindset scale used by Made to Grow, a company that provides online resources for people to get acquainted with mindset theories and develop growth mindset. As a tool to study psychometrics properties, reliability value of McDonald's omega was looked at, with various model specifications using CFA and model fitting indices to test for measurement invariance. Network models were further used to investigate a broader network of mindset scale items.

The mindset scale was found to be reliable found through McDonald's omega test. The study was able to gain insight into psychometric properties through CFA. Moreover, this CFA model was found to achieve measurement invariance between male and female students. Although mindset scale items indicated they were related to fixed or growth mindset, the network models also indicated the possibility of interactions between items beyond the common variable of mindset.

These results show that the Norwegian version of mindset scales used by Made to Grow is successful in assessing students regarding fixed and growth mindset. This will provide a strong starting point for students before receiving growth mindset interventions. Moreover, the validity of mindset scales will help more Norwegian students and schools spread knowledge about fixed and growth mindset in Norway.

Although the study found some residual covariance between several items, the result from CFA and measurement invariance suggests that this additional network between items does not interfere in providing a valid and reliable result from the mindset scales in this study. Nonetheless, the existence of an interaction between certain items from unobserved factor should be acknowledged. Due to the small number of sample size in this study, results from the network model suggests possible research topics in the future with a larger sample size.

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Histogram of the mindset scale items



Correlation plot of the mindset scale items



Single factor model for MINDSET (Model 1)





MINDSET ~~ MINDSET

Bifactor model with FIXED and GROWTH mindset (Model 2)





Bifactor model with additional covariance between items (Model 3)



$GROWTH = \sim GM4 + GM5 + GM11 + GM12$
$FIXED = \sim FM1 + FM2 + FM3 + FM8 + FM13$
$GM11 \sim \sim GM12$
$GM11 \sim \sim FM13$
$FM1 \sim ~FM2$
GROWTH ~~ GROWTH
$GROWTH \sim \sim FIXED$
$FIXED \sim \sim FIXED$

Correlation plot for GGM in network models



Network plot for GGM



# Centrality indices of GGM



# Clustering plot for GGM



Network plot for RNM



### Appendix

### Appendix I. GDPR documents & Ethical approval

Reference number to Made to Grow case file: 58892

# NOTIFICATION FORM (ENGLISH TRANSLATION) - NSD

NB! First draft Personal data Types of data Project Information Responsibility Sample and Criteria Third Persons Documentation Other approvals Processing Information Security Duration of project Additional Information Send in

### Which personal data will be processed?

Name **No** 

National ID number or other personal identification number No

Date of birth **No** 

Address or telephone number **No** 

Email address, IP address or other online identifier No

Photographs or video recordings of persons **No** 

Audio recordings of persons No GPS data or other geolocation data **No** 

Demographic data that can identify a natural person

Genetic data **No** 

Biometric data **No** 

Other data that can identify a natural person If you think that you will be processing personal data but cannot find a suitable alternative above, indicate this here. **No** 

# Will special categories of personal data or personal data relating to criminal convictions and offences be processed?

Racial or ethnic origin **No** 

Political opinions No

Religious beliefs No

Philosophical beliefs No

Trade Union Membership **No** 

Health data **No** 

Sex life or sexual orientation **No** 

Criminal convictions and offences **No** 

### **Project Information**

Edit project Register new project Chose existing project under 'Register new project':

### Title

Validating a mindset scale

### **Project description**

Made To Grow is an education platform that offers an app with services such as online courses that initiates motivations and for people to learn and improve oneself. Using their online education platform, one can test and improve one's mindset into growth rather than fixed. This study is testing the validity of mindset scales related to growth mindset and whether it is working in equal ways across different groups such as age groups and gender.

### Subject area

### Social sciences

Will the collected personal data be used for other purposes, in addition to the purpose of this project? No.

Explain why it is necessary to process personal data. It is necessary to access data to see how different students in different schools or regions are.

### **Project description**

Chose file...

### **External funding**

• Public authorities

### Type of project

• Student project, Master's thesis

### **Responsibility for data processing**

Data controller Sissel Naustdal

Project leader (research assistant/ supervisor or research fellow/phD candidate) Name Sissel Naustdal Position Leader at Made To Grow Email address sissel@madetogrow.no Telephone number 922 90 902

Will the responsibility for processing personal data be shared with other institutions (joint data controllers)? **No** 

Joint data controllers Institution

### Whose personal data will be processed?

### Sample 1

Describe the sample Middle school and high school students in various districts

Recruitment or selection of the sample The school decides to partake in the program from Made to Grow.

Age 14-55

Will you include adults (18 år +) who do not have the capacity to consent? No

# Types of personal data - sample 1

GPS data or other geolocation data

### Methods /data sources - sample 1

Select and/or describe the method(s) for collecting personal data and/or the source(s) of data Schools will decide whether they will partake in a survey, and additional information will be provided through app that is run by the company, Made to Grow.

### Information - sample 1

Will you inform the sample about processing their personal data? Yes

How? Written information (on paper or electronically) Oral information

Information should be given in writing or electronically. Only in special cases is it applicable to give oral information, if a participant asks for this. See what you must give information about. Upload information letter Upload copy of oral information Yes No

Explain why the sample will not be informed about the processing of their personal data. + Add sample

### **Third persons**

No

### Documentation

Total number of data subjects in the project

(Data subjects: persons whose personal data you will be processing)

• 100-999

How can data subjects get access to their personal data or how they can have their personal data corrected or deleted?

### **Other approvals**

Will you obtain any of the following approvals or permits for the project?

- Ethical approval from The Regional Committees for Medical and Health Research Ethics (REC)
- Confidentiality permit (exemption from the duty of confidentiality) from the Regional Committees for Medical and Health Research Ethics (REC)
- Approval from own management for internal quality-assurance and evaluation of health services (intern kvalitetssikring) (The Health Personnel Act § 26)
- Confidentiality permit (exemption from the duty of confidentiality) from the Norwegian Directorate of Health, for quality-assurance and evaluation of health services (kvalitetssikring) (The Health Personnel Act § 29b)
- Biobank
- Confidentiality permit (exemption from the duty of confidentiality) from Statistics Norway (SSB) Statistics Norway has the authority to grant a confidentiality permit for the data that they manage, e.g. data about population, education, employment and social security.
- Approval from The Norwegian Medicines Agency (Statens legemiddelverk, SLV) E.g. for a clinical drugs trial
- Confidentiality permit (exemption from the duty of confidentiality) from a department or directorate
- Other approval E.g. from a Data Protection Officer

Indicate which approval Upload document (oppdragsdokument) Chose file... Upload approvals Chose file...

### Processing

Where will the personal data be processed?

- Computer belonging to the institution responsible for the project
- Mobile device belonging to the data controller
- Physically isolated computer belonging to the data controller
- External service or network
- Private device

Upload guidelines/approval for processing personal data on private devices Upload

Who will be processing/have access to the collected personal data?

- Project leader
- Student (student project)
- Internal co-workers
- External co-workers/collaborators inside the EU/EEA
- Data processor

### VALIDATING A MINDSET SCALE

• Others with access to the personal data

Which others will have access to the collected personal data?

Will the collected personal data be made available to a third party or international organisation outside the EEA? **No** 

Give the name of the institution/organisation Give the country of the institution/organisation On what basis will the collected personal data be transferred? Upload necessary safeguards Chose file... Next

### **Information Security**

Will directly identifiable personal data be stored separately from the rest of the collected data (in a scrambling key)? Yes

Explain why directly identifiable personal data will be stored together with the rest of the collected data.

Which technical and practical measures will be used to secure the personal data?

- Personal data will be anonymised as soon as no longer needed
- Personal data will be transferred in encrypted form
- Personal data will be stored in encrypted form
- Record of changes
- Multi-factor authentication
- Restricted access
- Access log
- Other security measures
- Indicate which measures

### **Duration of project**

Project period 2019-2021

Will personal data be stored beyond the end of project period?

- No, all collected data will be deleted
- No, the collected data will be stored in anonymous form
- Yes, collected personal data will be stored until
- Yes, collected personal data will be stored indefinitely.

For what purpose(s) will the collected personal data be stored?

- Research
- Other

Where will the collected personal data be stored?

- At the institution responsible for the project (data controller)
- Other

### **Additional information**

Will the data subjects be identifiable (directly or indirectly) in the thesis/publications for the project? If **No** 

### Appendix II. Data Management & Analysis code

library(lavaan) library(psych) library(semTools) library(semPlot) library(ggplot2) library(corrplot) library(networktree) library(ggpubr) library(ggrepel) library(readxl) library(polycor) library(psychonetrics) library(bootnet) library(qgraph) library(PerformanceAnalytics) library(GPArotation)

setwd("C:/Users/moni0/Downloads") MTG\_StudentData\_2018\_21\_03032021 <- read\_excel("MTG-StudentData-2018-21-03032021.xlsx")

abc <- MTG\_StudentData\_2018\_21\_03032021 abcsub <- subset(abc, select = c(1:9, 43:55, 254:266)) abcsub2 <- subset(abcsub, select = c(-15,-16,-28,-29)) abcsub2 <- as.data.frame(abcsub2)

##descriptives
table(abcsub2\$AGE)
table(abcsub2\$FEMALE)
table(abcsub2\$GRADE)
table(abcsub2\$WAVE)

```
psych::describe(abcsub2[c("GM4_T1", "GM5_T1", "GM9_T1", "GM11_T1", "GM12_T1", "FM1_T1", "FM2_T1", "FM3_T1", "FM8_T1", "FM10_T1", "FM13_T1")])
multi.hist(abcsub2[c("GM4_T1", "GM5_T1", "GM9_T1", "GM11_T1", "GM12_T1", "FM1_T1", "FM2_T1", "FM3_T1", "FM8_T1", "FM10_T1", "FM13_T1")],
density = TRUE)
```

chart.Correlation((abcsub2[c("GM4\_T1", "GM5\_T1", "GM9\_T1", "GM11\_T1", "GM12\_T1", "FM1\_T1", "FM2\_T1", "FM3\_T1", "FM8\_T1", "FM10\_T1", "FM13\_T1")]), method = c("pearson"))

S <- cor(abcsub2[10:20,10:20], method = "pearson") corrplot(S, type = "upper", order = "hclust", tl.col="black", tl.srt= 60, addCoef.col = "white", number.cex = 0.75, cl.cex=1, tl.cex=0.9) #reliability coefficient
omega(abcsub2[c("GM4\_T1", "GM5\_T1", "GM9\_T1", "GM11\_T1", "GM12\_T1", "FM1\_T1",
"FM2\_T1", "FM3\_T1", "FM8\_T1", "FM10\_T1", "FM13\_T1")])

omega(abcsub2[c("GM4\_T1", "GM5\_T1", "GM9\_T1", "GM11\_T1", "GM12\_T1")]) omega(abcsub2[c("FM1\_T1", "FM2\_T1", "FM3\_T1", "FM8\_T1", "FM10\_T1", "FM13\_T1")])

##################################CFA

##model 1 mindset <- ' MINDSET =~ GM4\_T1 + GM5\_T1 + GM9\_T1 + GM11\_T1 + GM12\_T1 + FM1\_T1 + FM2\_T1 + FM3\_T1 + FM8\_T1 + FM10\_T1 + FM13\_T1

MINDSET ~~ MINDSET'

mindsetfit <- cfa(mindset, data = abcsub2, estimator = "MLR", missing = "FIML", se = "robust.mlr") summary(mindsetfit, fit.measures = TRUE, standardized = TRUE, rsquare = TRUE)

##model 2 modelt1 <- ' GROWTH =~ GM4\_T1 + GM5\_T1 + GM9\_T1 + GM11\_T1 + GM12\_T1 FIXED =~ FM1\_T1 + FM2\_T1 + FM3\_T1 + FM8\_T1 + FM10\_T1 + FM13\_T1

GROWTH ~~ GROWTH GROWTH ~~ FIXED FIXED ~~ FIXED'

```
modelfit1 <- cfa(modelt1,
data = abcsub2,
estimator = "MLR", missing = "FIML", se= "robust.mlr")
```

summary(modelfit1,

fit.measures = TRUE, standardized = TRUE, rsquare = TRUE)

```
modindices(modelfit1)
```

semPaths(modelfit1, rotation = 2, layout = "tree2", what = "std", posCol = "black", edge.width = 1, style = "Lisrel", fade= T, edge.label.position = 0.55)

anova(mindsetfit, modelfit1)
anova(modelfit11m, ggm.mod)

## Modified modelt11m <- ' GROWTH =~ GM4\_T1 + GM5\_T1 + GM11\_T1 + GM12\_T1

anova(config.mod, metric.mod)

```
FIXED = FM1_T1 + FM2_T1 + FM3_T1 + FM8_T1 + FM13_T1
# residual covariances
GM11 T1 ~~ GM12 T1
GM11 T1 ~~ FM13 T1
FM1_T1 ~~ FM2_T1
# factor variance
GROWTH ~~ GROWTH
GROWTH ~~ FIXED
FIXED ~~ FIXED
modelfit11m <- cfa(modelt11m)
         data = abcsub2.
         missing = "FIML",
         se = "robust.mlr",
         estimator = "MLR")
summary(modelfit11m,
    fit.measures = TRUE,
    standardized = TRUE,
    rsquare = TRUE)
semPaths(modelfit11m, rotation = 2, layout = "tree2", what = "std", posCol = "black",
    edge.width = 1, style = "Lisrel", fade= T, edge.label.position = 0.55)
anova(mindsetfit, modelfit1, modelfit11m)
#configural model
config.mod <- sem(modelt11m, data = abcsub2,
        estimator = "MLR",
        missing = "FIML",
        se = "robust.mlr",
        group = "FEMALE")
summary(config.mod,
    rsquare = TRUE,
    fit.measures = TRUE, standardized = TRUE)
##metric model
metric.mod <- sem(modelt11m, data = abcsub2,
         estimator = "MLR", missing = "FIML", se = "robust.mlr",
         group = "FEMALE", group.equal = c("loadings"))
summary(metric.mod, rsquare = TRUE, fit.measures = TRUE, standardized = TRUE)
```

### VALIDATING A MINDSET SCALE

##scalar model scalar.mod <- sem(modelt11m, data = abcsub2,</pre> estimator = "MLR", missing = "FIML", se = "robust.mlr", group = "FEMALE", group.equal = c("loadings", "intercepts")) summary(scalar.mod, rsquare = TRUE, fit.measures = TRUE, standardized = TRUE) anova(metric.mod, scalar.mod, config.mod) ##strict model strict.mod <- sem(modelt11m, data= abcsub2, estimator = "MLR", missing = "FIML", se = "robust.mlr", group = "FEMALE", group.equal = c("loadings", "intercepts", "residuals")) summary(strict.mod, rsquare = TRUE, fit.measures = TRUE, standardized = TRUE) anova(config.mod, metric.mod, scalar.mod, strict.mod) ##Gaussian Graphical Model ggm.mod <- ggm(abcsub2[c("GM4\_T1", "GM5\_T1", "GM11\_T1", "GM12\_T1", "FM1\_T1", "FM2\_T1", "FM3\_T1", "FM8\_T1", "FM13\_T1")], estimator = "FIML") ggm.mod <- ggm.mod %>% runmodel ggm.mod %>% parameters ggm.mod <- ggm.mod %>% prune(adjust = "fdr", alpha = 0.05) ggm.mod %>% MIs ggm.mod <- ggm.mod %>% stepup(criterion = "bic", alpha = 0.05) ggm.mod %>% fit ggm.mod %>% print chart.Correlation((abcsub2[c("GM4\_T1", "GM5\_T1", "GM11\_T1", "GM12\_T1", "FM1\_T1", "FM2\_T1", "FM3\_T1", "FM8\_T1", "FM13\_T1")]), method = c("pearson"))G <- cor(abcsub2[c("GM4\_T1", "GM5\_T1", "GM11\_T1", "GM12\_T1", "FM1\_T1", "FM2\_T1", "FM3\_T1", "FM8\_T1", "FM13\_T1")], method = c("pearson"), use = "complete.obs") corrplot(G, type = "upper", order = "hclust", tl.col="black", tl.srt= 60, addCoef.col = "white", number.cex = 0.75, cl.cex=1, tl.cex=0.9)

```
layout = "spring",
           theme = "colorblind",
           groups = c("Growth mindset",
                   "Growth mindset",
                   "Growth mindset".
                   "Growth mindset",
                   "Fixed mindset",
                  "Fixed mindset".
                  "Fixed mindset".
                  "Fixed mindset",
                  "Fixed mindset"))
centrality (ggm.graph)
centralityPlot(ggm.graph,
        include = c("Strength", "Closeness", "Betweenness", "ExpectedInfluence"),
        orderBy= "Strength",
        scale = "raw")
clusteringPlot(ggm.graph, orderBy="default", scale = "raw")
####RNM
Lambda <- matrix(0, 9, 2) #9 items with 2 factors of growth/fixed mindset
Lambda[c(1:4),1] <- 1 #growth
Lambda[c(5:9),2] <- 1 #fixed
print(Lambda)
latents <- c("GROWTH", "FIXED")
rnm.cfa <- rnm(abcsub2[c("GM4_T1", "GM5_T1", "GM11_T1", "GM12_T1", "FM1_T1", "FM2_T1",
"FM3_T1", "FM8_T1", "FM13_T1")],
        lambda = Lambda,
        vars = c("GM4_T1", "GM5_T1", "GM11_T1", "GM12_T1", "FM1_T1", "FM2_T1", "FM3_T1",
"FM8_T1", "FM13_T1"),
        identification = "variance",
        latents = latents,
        estimator = "FIML")
rnm.cfa <- rnm.cfa %>% runmodel %>%
    prune(adjust = "fdr", alpha = 0.05) %>%
    stepup(criterion = "bic", alpha = 0.05)
rnm.cfa %>% parameters
rnm.cfa %>% fit
lambda3 <- getmatrix(rnm.cfa, "lambda")</pre>
psi3 <- getmatrix(rnm.cfa, "sigma zeta")
theta3 <- getmatrix(rnm.cfa, "sigma epsilon")
rnm.cfa.mod <- lisrelModel(LY = lambda3, PS = psi3, TE = theta3)
semPaths(rnm.cfa.mod,
     what = "std",
     "est",
     as.expression = "nodes", style = "lisrel",
```

```
residScale = 10,
     theme = "colorblind",
     layout = "tree2",
     cardinal = "lat cov",
     curvePivot = TRUE,
     sizeMan = 4,
     sizeLat = 10,
     edge.label.cex = 0.75)
rnm.cfa.graph <- qgraph(rnm.cfa@modelmatrices[[1]]$omega_epsilon,
             labels = c("GM4", "GM5", "GM11", "GM12", "FM1", "FM2", "FM3", "FM8", "FM13"),
              theme = "colorblind",
              vsize = 9,
              edge.labels = TRUE,
              layout = "circle",
              legend = TRUE,
              groups = c("Growth mindset",
              "Growth mindset",
              "Growth mindset",
              "Growth mindset",
              "Fixed mindset",
              "Fixed mindset",
              "Fixed mindset",
              "Fixed mindset",
              "Fixed mindset"),
              legend.cex = 0.6,
              palette = 'pastel',
              layout = averageLayout(ggm.graph))
```

anova(modelfit11m, ggm.mod, rnm.cfa.mod)

### Appendix III. Mindset scale items (in Norwegian)

FM1. You can learn new things, but you can't really change your basic intelligence. (Du kan lære nye ting, men du kan egentlig ikke endre din grunnleggende intelligens.)

FM2. Your intelligence is something about that you can't change very much. (Din intelligens er noe ved deg du ikke kan endre særlig mye.)

FM3. You have a certain amount of intelligence and you can't really do much to change it. (Du har en viss mengde intelligens og det er ikke særlig mye du kan gjøre for å endre det.)

GM4. No matter how much intelligence you have, you can always change it quite a bit. (Uansett hvor mye intelligens du har, kan du alltid forandre den ganske mye.)

GM5. Everyone, no matter who they are, can change one's basic intelligence level considerably. (Alle, uansett hvem de er, kan endre sine grunnleggende karakteristikker betydelig.)

FM8. Everyone is a set type of person, and there is not much they can do to change it. (Alle er en bestemt type person, og det er ikke mye de kan gjøre for å endre det.)

GM9. When there is something difficult, I wish to work more with it and not less. (Når noe er vanskelig får jeg lyst til å jobbe mer med det, ikke mindre.)

FM10. To tell the truth, when I work hard with something, it makes me feel like I'm not very smart. (Helt ærlig, når jeg jobber hardt med noe får det ikke meg til å føle meg veldig smart.) GM11. If you work hard at something, you will likely perform well, no matter how smart you are. (Dersom, du jobber hardt vil du mest sannsynlig prestere bra, uansett hvor smart du er.) GM12. I like work that I can learn from even if I make a lot of mistakes. (Jeg liker oppgraver jeg kan lære av, selv om det innebærer at jeg gjør mange feil.)

FM13. Only a few people can really be good, whether in sports, music, art a school subject or something else – you have to be born with the talent. (Bare noen få mennesker kan bli virkelig gode, uansett om det er innen idrett, musikk, kunst, et skolefag eller noe annet – du må ha et medfødt talent.)

(1: svært uenig, 2: ganske uenig, 3: litt uenig, 4: hverken enig eller uenig, 5: litt enig, 6: ganske enig, 7: svært enig).