All happy emotions are alike but every unhappy emotion is unhappy in its own way: a network perspective to academic emotions

Markus Mattsson*, Telle Hailikari^a, Anna Parpala^a

^aCentre for University Teaching and Learning (HYPE), University of Helsinki, Helsinki, Finland

*Correspondence:

Markus Mattsson, Maskuntie 3 A 14, 00280 Helsinki, Finland

Tel: +358407689406

E-mail: markus.mattsson@helsinki.fi

Abstract

Research into the nature of academic emotions has thus far been dominated by factor analyses of self-report questionnaire data. Recently, network analysis has arisen as an alternative method of conceptualizing the nature and composition of psychological phenomena such as emotions. In this contribution we assess the structure and functioning of a Finnish questionnaire of academic emotions using both network analysis and factor analysis on cross-sectional data obtained during a single course. In network analysis the correlational structure of the questionnaire is understood as consisting of local interactions among the items. Our results show that items related to individual emotions such as boredom appeared as tightly connected clusters in the network. Items related to anger and boredom were positively related. Those relationships, explained in previous research by positing the underlying latent variable of frustration, can also be understood as family resemblance between the semantic contents of the respective items in the network model. From the theoretical point of view, network analysis is most naturally compatible with perceiving emotions as wholes arising out of the interactions among their component parts. From the practical point of view, the present study offers a critical perspective on the use of self-report measures in the study of academic emotions, focusing especially on currently prevailing practices of data analysis.

Keywords: network model, factor model, academic emotions

1 Introduction

The emotional experiences of students have been the topic of intensive research efforts during the previous 15 years. The term “academic emotions” was introduced to refer to emotions that arise in different academic settings and that are directly linked to academic learning, instruction and achievement (Pekrun, Goetz, Titz, & Perry, 2002). Quantitative research on academic emotions was made possible with the development of questionnaire instruments, such as the Academic Emotions Questionnaire (AEQ; Pekrun, Goetz, Frenzel, Barchfeld, & Perry, 2011), Academic Emotions Scale (AES; Govaerts & Grégoire, 2008) and the Student Experience of Emotions Inventory (SEEI; Trigwell, Ellis, & Han, 2012). The questionnaires are intended to provide a means of measuring the variety of academic emotions such as enjoyment, hope, pride, anger, anxiety, shame, hopelessness and boredom that may arise in different contexts. The contexts may include, e.g., preparing for a test, classroom activities or studying alone (Pekrun et al., 2002; Govaerts & Grégoire, 2008). The current emphasis on the importance of emotions across contexts is a recent development: academic emotions were a largely neglected topic in educational research until the 21st century, except for research on test anxiety (for a review, see Zeidner, 1998).

Emotions are often analyzed using the two concepts of valence and activation. Valence refers to the distinction between positive and negative or pleasant versus unpleasant emotions (e.g., Pekrun et al., 2002). The other dimension, activation, has physiologically activating emotions as one pole and deactivating emotions as the other one (Pekrun et al. 2011; Feldman Barrett & Russell, 1998; Linnenbrink, 2007). Both positive and negative emotions may be activating or deactivating, and thus affect student learning in various ways (Feldman Barrett & Russell, 1998; Pekrun et al., 2002). According to one view, known as the circumplex model, discrete emotions can be reduced to positions on these dimensions, while according to another, valence and activation function merely as convenient categories that can be used in classifying discrete emotions (Lindquist, Siegel, Quigley, & Barrett, 2013). We do not wish to take part in this “100 years emotion war”, as Lindquist et al. call it, and remain open to both interpretations of valence and activation.

The third way of classifying emotions is through the concept of motivation (approach / avoidance; for a good review in the context of self-report instruments, see Harmon-Jones, Bastian, & Harmon-Jones (2016). Approach motivation may be defined as the direction and energization of behavior towards positive stimuli whereas in avoidance motivation the direction of behavior is away from negative stimuli (Elliot, 2006). In addition, emotions can be typical ways for a person to react across situations (trait emotions) or specific to a given situation (state emotions), Harmon-Jones et al., (2016). Furthermore, as mentioned, academic emotions may occur in different contexts, at different times (i.e. before, during or after being immersed in a given context) and they may comprise affective, cognitive, physiological and motivational components (Pekrun et al., 2002).

The multitude of dimensions along which emotions can be categorized leads naturally to thinking of the practical challenge of constructing the questionnaire items – with the contents of the items affecting the kinds of conclusions that can be drawn using the instrument in question. For instance, considering the number of emotions to be investigated (8 or 9), components of emotions (4), time (3) and context (3) as suggested by Pekrun et al. (2002) together with the fact that in a factor analysis context it is desirable to have 4 items / factor, we end up with $8*4*3*3*4 = 1152$ potential questionnaire items. In this respect it is understandable to omit one or the other dimension or to focus on only some of the dimensions at a time. For instance, Govaerts & Grégoire (2008) have suggested dropping the category of *motivation* when classifying the emotions; also, it is possible to concentrate on only one context at a time. Even with these simplifications, however, hundreds of potential combinations of items remain. Further, whatever else may be mentioned in the items will naturally have an effect on how the respondents interpret the items: It is a well-known fact that the concrete formulations given to the individual items will influence how they are interpreted and, *a fortiori*, the correlational structures that will be observed among them. Commonly, some variant of factor analysis is used for analyzing such data, and the results of factor analysis may well reflect the effects of such unintended factors (for discussion, see e.g. Elson, in press).

In the present study our central aim is to show that network analysis offers a novel, useful perspective for understanding the relationships among items intended to measure academic emotions. Some of these relationships may be causal in nature, such as when the questionnaire comes to comprise items related to trait emotions and state emotions – in this situation, the former can be thought of as the causal antecedent of the latter. On the other hand, the network perspective may offer hints on the existence of completely unintended causal variables driving the correlations. Further, the relationships found using network analysis can perhaps be understood as non-causal in nature, being related to the fact that certain (emotion-laden) experiences are likely to co-occur in a society structured the way ours is. In short, we claim that network analysis is helpful in disentangling the above-mentioned dimensions when assessing the relationships among the questionnaire items.

1.1 Ontological and causal assumptions in modeling academic emotions

Using a psychometric questionnaire in a cross-sectional research design produces correlational data, and when analyzing such data, a central task for the researcher is to explain why the variables vary together the way they do. It is naturally preferable to express the explanation as a formal statistical model, and the researcher has traditionally been equipped with two main kinds of models to choose from: the *reflective measurement model* and the *formative measurement model* (Borsboom, Mellenbergh, & Van Heerden, 2003; Edwards & Bagozzi, 2000). Both are based on the idea that the object of the study is a latent variable that is in principle unobservable in nature. Still, the models conceptualize the relationship between the latent and observed variables quite differently, making different assumptions concerning the causal and ontological status of the observed and latent variables. In addition to these two types of models, in recent years a third alternative, the network model, has been developed for representing the relationships of the observed variables (Borsboom & Cramer, 2013; Schmittmann et al., 2013). It is important to choose a statistical model whose causal and ontological assumptions mesh with the theoretical description of academic emotions. In what follows, a brief summary of the main properties of the three alternatives is given.

The main idea in a reflective measurement model is that the latent variable causes the observed variables (i.e. questionnaire items) to correlate, and there is no other reason for the observed variables to vary together; in particular, direct pairwise relationships between the observed variables are not allowed in the prototypical reflective model. In other words, the observed variables are assumed to be conditionally independent given the latent variable. This idea is central to reflective measurement models, and it is known as the assumption of local independence (e.g., Bollen, 2002). Further, the observed variables are assumed to be qualitatively similar, interchangeable indicators of the latent variable in that it does not matter which particular variables one chooses to use in a given study (Bollen & Bauldry, 2011). When it comes to the ontology of the

latent variables, the reflective model is most naturally compatible with a stance known as entity realism. According to this idea, the latent variables exist independently of the actions of the researcher and are capable of affecting things in the world; in other words, they are causally efficacious, or have causal power (Borsboom et al., 2003). A further corollary of this idea is that manipulating the observed variables should have no effect on the latent variable.

Reflective measurement models have been previously used in studying academic emotions: both the AEQ (Pekrun et al., 2011) and the AES (Govaerts & Grégoire, 2008) were constructed based on factor analyses in which the latent variables were conceptualized as separate continuous variables¹. If we assume entity realism, the latent variables, for instance *hopelessness*, are taken as real entities capable of affecting the observed variables: for instance, the question items *studying the materials of this course feels hopeless* and *I feel like I cannot make it through this course* are assumed to correlate because they are both affected by a common latent variable. The assumption seems reasonable at least in this case, but there are other properties of the reflective model that seem less so: for instance, the two items do not seem quite interchangeable as they are related to different aspects of *hopelessness*. Further, in other cases the assumption of local independence seems overly restrictive: for instance, if the questionnaire contains an item related to a feeling of despair and another one related to losing hope of making it through the course, it would seem natural to think that feeling despair causes one to lose hope (or perhaps vice versa), rather than both being caused by a latent variable.

Formative models are in many ways conceptualized as the opposite of reflective models. In formative models, variation in the observed variables brings about change in the latent variable in the sense that the latent variable is formed as a weighted sum of the observed variables (Borsboom et al., 2003; Edwards & Bagozzi, 2000). An often-used example is that of socio-economic status, which is formed as a function of the salary, education level and occupational prestige of a person. The observed variables are not interchangeable in the sense that they are thought to represent different aspects of the phenomenon of interest: none of them can be left out without altering the latent variable (Bollen & Bauldry, 2011). Conditional independence of the indicators, given the latent variable, is not assumed, and no assumptions concerning the correlational structure among the observed variables are made. In further contrast with the reflective model, the formative model is compatible with a constructionist, operationalist or instrumentalist ontological view of latent variables (Borsboom et al., 2003). Lastly, when formative latent variables are used in structural equation models, they are said to suffer of interpretational confounding, even though the issue has been the topic of intense debate lately (Bainter & Bollen, 2014; Markus, 2014). Interpretational confounding refers to a situation in which empirical meaning is assigned to a latent variable in a way that was not intended by the researcher; in this case that may happen because formative latent variables that figure in a

¹ Rather than basing the analysis on the orthogonal latent dimensions of valence, activation (and perhaps motivation) – such a model could also have been derived from previous research on emotions.

structural equation model need to be identified by regressing a dependent variable on them, and the dependent variable may be chosen in different ways.

The *principal components analysis model*, which was employed by Trigwell et al. (2012) when constructing the SEEL, is one type of a formative model; specifically, one which assumes that the measurement error term involved in regressing the latent variable on the observed ones is zero (Edwards & Bagozzi, 2000). The attractive property of this model is that the questionnaire items can be thought of as representing different aspects of the academic emotions: for instance, two students may end up having identical levels of boredom through different combinations of the observed variables (such as boredom with course assignments and boredom with the course in general). Further, the PCA model does not suffer from interpretational confounding (Howell, Breivik, & Wilcox, 2007). On the other hand, the fact that the formative model is not directly compatible with the realist interpretation of latent variables weighs against it in at least some cases: for instance, there are certain biologically-based core components of emotions, expressions related to which are reliably recognized across cultures (Elfenbein & Ambady, 2002). If we assume the latent variables related to emotions to be socially constructed entities, observations such as this are difficult to explain.

Recently, network analysis has emerged as a third alternative for examining the relationships among the observed variables (Schmittmann et al., 2013). A network model (Epskamp, Maris, Waldorp, & Borsboom, in press) consists of direct relationships between the observed variables that obtain when controlling for the effects of all the other variables in the network. Similarly to the formative measurement models, the individual observed variables are seen as causally efficacious entities. Latent variables, however, are best understood as emergent properties produced by the local interactions between the observed variables. For example, when investigating academic emotions, the emotion of test anxiety (the latent variable) could be conceptualized as being formed when anxious thoughts (“I am going to fail the exam”) interact with the affective state characteristic of anxiety, with the bodily feeling of not getting enough air and with the motive to withdraw from the situation. In a network model, the relationship of the observed variables to the emergent latent variable is that of parts to a whole, i.e. mereological composition (Markus, 2008) rather than one of measurement (Borsboom & Cramer, 2013). Still, the network models can accommodate the equivalent of a latent variable in a *community* of nodes: a group of nodes having strong pairwise links with one another, and only weak links to outside the community. Entity realism is an in principle viable option also in a network model of emotions, even though ontological questions related to the relationships of parts and wholes will by necessity be faced (such as “Is the whole more than the sum of its parts?”)

The connections among the observed variables in a network model may signify different things. Some of the connections may occur because one of the variables acts as the cause and the other as the effect; on the other hand, it is possible that the pairwise connections reflect the existence of an unobserved variable not included in the network that influences both. In addition, a connection between

variables in a network model may indicate a logical relationship of entailment between the two variables.

The fact that the spreading of activation is a central idea in network models (e.g. (Borsboom, Cramer, Schmittmann, Epskamp, & Waldorp, 2011) makes them a *prima facie* plausible model of emotions: the affects, cognitions, physiological reactions and motivations that make up emotions are in a constant flux. Indeed, network models have been used as a representation of the dynamic interactions among emotions across time (Bringmann et al., 2016) and in describing the relationships of emotion concepts in the Finnish language (Toivonen et al., 2012). In this contribution, we perform a network analysis on data obtained using a Finnish questionnaire of academic emotions, and compare the interpretations and insights with those obtained using a more traditional analysis based on using a reflective measurement model (an exploratory factor analysis).

The manuscript is organized as follows. First, we introduce certain background concepts related to using network models. Second, we report the results of performing an exploratory factor analysis (EFA) on our data set. Third, we analyze our data set using a network model and calculate associated centrality indices for the nodes of the network. The experiences that are found central in this sense are important determinants of the other emotions and thus prime targets for interventions aimed at enhancing the well-being of academic students. Fourth, we compare the ways that the phenomenon of academic emotions becomes conceptualized when analyzed using a network model vs. a factor model; similarly, we assess the kinds of practical conclusions and suggestions that it is possible to draw based on either model. We also interpret our results from the point of view of the various dimensions that can be used in analyzing the phenomenon of emotions. Finally, we conclude by offering certain recommendations and suggestions for further research.

2 Method

2.1 Participants and data

The data consisted of Bachelor students studying in the field of technology and engineering. The participants took a lecture course that consisted of lectures, homework, midpoint exam and final exam. A total of 350 students enrolled on the course, of which 323 students were active (they returned at least one homework assignment). A total of 241 responses were obtained. A single student responded to all Likert scale items using the response option “1” and the data of this student was discarded. Another student had responded twice and only one of these responses was included. Finally, one respondent had omitted all the emotion items, leaving the final number of usable responses at 238. The students had an incentive to take part in the study: movie tickets were raffled among the respondents and in addition the respondents were awarded an extra point that was added to the points they received from their homework.

The course is known to be extremely demanding and many students fail to pass it. Therefore, many students are forced to repeat the course. 171 students (72 % of participants) took part on the course for the first time, 43 (18 %) for the second time and 25 (10 %) for the third time or more. 87 % of the respondents were male, 13 % female, while 49 % were first year students and 23 % second year students. The rest had begun their studies earlier. The teachers claim that because of the demanding content the students have negative attitudes and emotions towards the course. Therefore, different emotions were expected to arise during this particular course. The data was obtained using an electronic questionnaire focusing on their academic emotions during the course, just before the midpoint exam.

2.2 Development of the questionnaire

The questionnaire measuring academic emotions was translated and modified from several instruments measuring academic emotions. First, the Students Experience of Emotions Inventory (SEEI; Trigwell et al. 2012) was taken as a basis for the instrument as it focuses on course level emotions among university students. The SEEI was based on the Academic Emotions Scale (AES) developed by Govaerts and Gregoire (2008), which focused on state academic emotions occurring in a specific context. As the instrument by Trigwell et al (2012) has only two items measuring the anxiety, an item measuring anxiety in relation to homework was included from the original work by Govaerts and Gregoire (2008). In addition, SEEI does not include items measuring the experiences of joy and despair, which are also shown to emerge in an academic context (Pekrun et al., 2002). Therefore, items related to these emotions were added using the items from Achievement Emotions Questionnaire (AEQ; Pekrun et al., 2011) as a basis. The items were first translated into Finnish and modified to suit the course context. In this process items referring to the final test were modified to focus on the midpoint and final exam as there were many test situations during the course.

After the first round of modifying the items a focus group interview was conducted. Students participating in the focus group were asked to fill in the questionnaire and after this they were interviewed. In the interview they were asked to evaluate each item and their content in the light of their study context. If the students felt that the item did not suit the context of their studying the item was remodified. In this process it became clear that the emotion of anger was considered a negative emotion of such intensity that students did not report experiencing it during their studies. Therefore, items mentioning *anger* were replaced with items containing milder expressions such as *irritation*. Moreover, *being proud* is an academic emotion rarely expressed in the Finnish context, because it carries a strong connotation of self-importance. For this reason mentions of *pride* were replaced with expressions such as *satisfaction*. This modification process was done among the experts in university pedagogy and students studying behavioral sciences bearing in mind the Finnish context. The original items and back-translated versions are presented in Table 1. The back-translations are literal translations from Finnish into English. They are provided to readers not proficient in the Finnish language as examples of the

kind of expressions that are used when referring to emotion-laden experiences in Finnish. Simultaneously, they highlight the difficulty of creating exact, literal translations from one language to another.

Table 1. Questionnaire items used in the present study

Item in Finnish	Item no.	Item in English (translated by the lead author)	Corresponding item in original	Item code in original*	Latent variable in original
Kurssin sisältöjen opiskelu on minusta innostavaa	1	I find studying the course contents inspiring	I am motivated to go to this class because it's exciting*	P11, CJOM1B	Enjoyment
Olen toiveikas sen suhteen, että olen valmistautunut välikokeeseen riittävän hyvin	2	I feel optimistic about my preparation for the exam in this course	I feel optimistic about my preparation for the assessment in this course	T9	Positive emotions
Olen todella tyytyväinen oppimiseeni tällä kurssilla	3	I am extremely happy with my learning on this course	I feel proud of my progress in this course	T25	Positive emotions
Tämän kurssin tehtävien tekeminen ärsyttää minua	4	Completing the assignments on this course irritates me	I get angry with this course*	T15	Anger-Boredom
Työstystyn tällä kurssilla	5	I am bored by this course	I am bored by this course	T3	Anger-Boredom
Tämän kurssin materiaalin opiskelu tuntuu toivotomalta	6	Studying the materials of this course feels hopeless	I feel hopeless when I think about studying	P95, LHLA1B	Hopelessness
Olen todella tyytyväinen siihen, miten olen suoriutunut kurssin kotitehtävistä	7	I am extremely happy with the way I have done with the homework in this course	I get a feeling of pride as a result of my work on this course	T21	Positive emotions
Tämän kurssin sisällöt tympivät minua	8	I am fed up with the contents of this course	The content of this course irritates me*	T7	Anger-Boredom
Minusta tuntuu, etten voi selvittää tästä kurssista	9	I feel like I cannot make it through this course	I start to think that no matter how hard I try I won't succeed on the test*	P185, THLC3D	Hopelessness
Minua hävettää se, etten ole panostanut tähän kurssiin tarpeeksi	10	I feel ashamed not having prepared better for this course	I feel ashamed not having prepared better for this course	T17	Anxiety-Shame
Ahdistun tehdessäni tämän kurssin kotitehtäviä	11	I feel anxious when I am doing the homework assignments on this course	I feel anxious when I am doing exercises for the math exam	G5	Anxiety
Minua hävettää se, etten ehkä ole valmistautunut tämän kurssin välikokeeseen riittävästi	12	I feel ashamed thinking I might have not prepared adequately for the exam in this course	I feel ashamed thinking I might have not prepared adequately for the assessment in course	T5	Anxiety-Shame
Tämän kurssin sisällöt ja tehtävät saavat minut pahantuntuiseksi	13	The contents and the assignments on this course make me unhappy	I feel annoyed when trying the learning activities for this course*	T23	Anger-Boredom
Kun ajattelen tätä kurssia, ahdistun	14	When I think about this course, I become anxious	When I think about this course, I become panicky	T8	Anxiety-Shame
Nautin uusien asioiden oppimisesta kurssilla	15	I enjoy learning new things on this course	I enjoy acquiring new knowledge	P139, LJOA3D	Enjoyment
Olen varma, että opiskelu sujuu hyvin tällä kurssilla	16	I am sure that I will do well on this course	I am sure that everything is going well in this course	T18	Positive emotions
Kurssin tentistä suoriutuminen on minusta mukava haaste	17	I find the course exam a pleasant challenge	For me the test is a challenge that is enjoyable	P204, TJOC3D	Enjoyment
Kurssiin liittyvät tehtävät eivät ole kiinnostavia	18	The learning activities for this course are not interesting	The learning activities for this course are not interesting	T19	Anger-Boredom
Minua nolottaa, jos en suoriudu kurssin kotitehtävistä	19	I am embarrassed when I cannot complete the homework assignments on this course	I am embarrassed when I cannot contribute to learning activities	T11	Anxiety-Shame
Minua ahdistaa kysyä tai osallistua keskusteluun tällä kurssilla	20	Contributing to discussions or asking questions on this course makes me anxious	Contributing to discussions in class makes me anxious	T29	Anxiety-Shame
Minua hävettää, jos kysyn kurssilla kysymyksen, johon muut jo varmasti tietävät vastauksen	21	If I ask a question in class that others already certainly know the answer to, I feel embarrassed	If I ask a question in class that others already understand, I feel embarrassed	T30	Anxiety-Shame
Kurssilla (esim. laskutavassa) tai kotitehtävissä tekemäni virheet nolostuttavat minua	22	Mistakes I make on the course (e.g. during the mathematical exercises) or when doing homework embarrass me	When I get an idea wrong in class I feel embarrassed	T24	Anxiety-Shame
Olen luopunut toivosta, että pystyisin pärjäämään välikokeessa hyvin	23	I have lost hope of doing well in the course exam	I have lost all hope that I have the ability to do well on the exam	P164, THLC1B	Hopelessness
Kurssin alkaessa luotin siihen, että tulen pärjäämään kurssilla	24	In the beginning of this course I was confident that I will do well on this course	I generally feel confident that I will do well when I begin a course	T22	Positive emotions
Olen todella tyytyväinen siihen, miten olen panostanut opiskeluun tällä kurssilla	25	I am extremely happy with the way I have invested my efforts in studying on this course	I am proud of the way I am contributing to this course	T16	Positive emotions

*Our item has no directly equivalent item in the original questionnaire; this is the closest equivalent

*Item codes: T = item from Trigwell et al. (2011); P = item from Pekrun et al. (2005); G = item from Govaerts & Gregoire (2008). Numbers are the item numbers from the original, the sequence of letters and numbers additional codes from the original.

2.3 Analysis

2.3.1 Factor analysis

An exploratory factor analysis was performed using the psych package (Revelle, 2014) in R (R Core Team, 2016). The analysis was based on calculating polychoric correlations and factor analyzing them using the method of minimum residuals (Harman & Jones, 1966), followed by oblique rotation using the oblimin method. A parallel analysis based on the factor analysis method was performed to assess the number of latent variables in the data.

2.3.2 Network analysis

All network analyses were performed using the qgraph package (Epskamp, Cramer, Waldorp, Schmittmann, & Borsboom, 2012) in R (R Core Team, 2016). The networks represent the partial polychoric correlations among the variables, with the connection weights determined using the graphical lasso method as implemented in qgraph. The graphical lasso applies a penalty to the absolute values of the elements of the inverse covariance matrix, constraining small values to zeroes (Friedman, Hastie, & Tibshirani, 2008). This is useful as the procedure implements model selection and parameter estimation simultaneously, thus avoiding, for instance, the necessity of calculating p-values and correcting them for multiple comparisons. Other benefits of using the lasso

include avoiding overfitting models to the sample of data at hand, and the increase in interpretability that results from constraining small values of partial covariances to exact zeroes. For a detailed summary of the lasso estimation method in the context of network modeling, see (Epskamp & Fried, 2016).

In the network graphs in this study, the width and saturation of the edges (connections) among the nodes (individual variables) illustrate the strengths of the lasso-estimated partial polychoric correlations. Edges drawn in green color represent positive associations, while those drawn in red dashed lines represent negative associations.

Positioning the nodes of the network on a two-dimensional surface in a way that optimally reflects their interrelationships is not a trivial problem. In qgraph, this problem is solved by applying the Fruchterman-Reingold algorithm (Fruchterman & Reingold, 1991), which places strongly connected nodes close to each other. Further, nodes that have the overall strongest connections in the network are positioned centrally in the graph, while nodes with weaker connections appear closer to the periphery of the graph (Epskamp et al., 2012).

The resulting networks can be described using the global and local indices that are commonly used in the description of network graphs, such as measures of distance, centrality and clustering. In this contribution, we focus on measures of centrality (Opsahl, Agneessens, & Skvoretz, 2010). The centrality of the emotion-laden experiences reflects the importance of the individual experiences in the emotional ecosystem of the students. Below, we describe some of the commonly used centrality measures.

2.3.2.1 Centrality measures

Three measures that are commonly used in characterizing the properties of a network graph are briefly summarized below. These indices are known as *strength*, *closeness centrality* and *betweenness centrality*. More in-depth information on their properties and examples of their use can be found, e.g., in (Costantini et al., 2015; Opsahl et al., 2010).

2.3.2.1.1 Strength

The strength index describes the absolute values of the weights of the connections to a focal node. When a node is strongly connected to its neighborhood, a change in the value of the node will have a large effect on the nodes in its neighborhood.

2.3.2.1.2 Closeness centrality

In a weighted network, the distance between a pair of nodes is defined as the inverse of the absolute value of their connection weight. Metaphorically, the idea can be described by thinking of the two nodes as cities and the weight of the connection as the size of the road connecting them: if the cities are connected by a highway (a large weight), they can be considered to be close to one another (in travel time), whereas if they are connected by a rural road (a small weight), they can be considered further apart. The closeness centrality of a focal node is defined as the inverse of the sum of its distances to other nodes in the network. A

node with a high closeness centrality is easily affected by changes in the values of the other nodes in the network.

2.3.2.1.3 Betweenness centrality

The betweenness centrality of a focal node is defined as the number of shortest paths between two other nodes that pass through that node. A node with a high betweenness centrality is important for the smooth flow of information through the network: if a node with a high betweenness centrality value were removed from the network, the distances between other nodes would increase considerably.

2.3.2.2 Network community structure detection

Network community detection is a process of determining groups of nodes in the network that are densely interconnected and have only relatively few connections to nodes outside the group (Fortunato, 2010). Many different community detection algorithms have been developed for different types of networks, such as weighted, directed and signed ones. In this study, we used the spinglass algorithm which is suitable for community detection in weighted and signed networks such as the present one. Further, the spinglass algorithm has been shown to perform well with quite high values of the mixing parameter, which describes the proportion of connections from a focal node to other nodes outside its own community (Yang, Algesheimer, & Tessone, 2016). It is conceivable that in the present application this proportion quite high, since there are likely a multitude of reasons for the questionnaire items to correlate. Furthermore, when the network size (represented as the number of nodes) is small, the spinglass algorithm is known to reliably detect the correct number of communities in the data (Yang et al., 2016).

The spinglass algorithm was run using the default values in igraph (Csardi & Nepusz, 2006) in R (R Core Team, 2016), with start temperature = 1, stop temperature = 0.01, cooling factor = 0.99, gamma = 1 and gamma^{*} = 1. Due to the stochastic nature of the simulated annealing algorithm that is used in the spinglass community estimation, 1000 repetitions of the analysis were run. We report the most frequently obtained community structure.

2.3.2.3 Illustration of a network model with simulated data

In the present study, data analyses were based on using both network analysis and factor analysis. Either the factor model or the network model may prove to be the correct representation for the data that was collected for this study. However, in a real-life data-analysis situation the true data-generating mechanism remains necessarily unknown, unlike when using simulated data. For this reason, simulations are a useful tool for illustrating the ideal situation of analyzing data that is known to conform to a given model. Therefore, we simulated data based on a four-factor model with no cross-loadings of the items on the factors, with weak to moderate positive and negative correlations among the factors, and analyzed the resulting data using a network model that was built similarly to the ones used in analyzing the empirical data in this study.

Figure 1. illustrates what a network graph would look like if the population-level data-generating mechanism were really a four-factor model. The graph is based on population-level data (sampling variation not taken into account), and the actual sample-level model would likely be less clear. However, the graph helps to interpret the results of the present contribution in providing an ideal reference point with which to compare the network model formed on the basis of actually collected data. The simulations were carried out using the `sim.structure` function from the `psych` package (Revelle, 2014).

Figure 1. Ideal population level network structure for data generated based on a four-factor model (correlated factors).

3 Results

3.1 Missing data

The maximum number of missing values in any single questionnaire item was two, and it appeared that the missing values were inadvertent omissions of questionnaire items. Because of this, it was assumed that the missing data mechanism was *missing completely at random* (MCAR, Schafer & Graham, 2002)

and the missing values were dealt with by calculating the polychoric correlation matrices with pairwise deletion of missing values.

3.2 Factor analysis

Parallel analysis of the emotion items showed that four factors should be extracted. Therefore a minimum residual factor analysis (Harman & Jones, 1966) was performed based on the matrix of polychoric correlations among the emotion items. Four factors were extracted and the oblimin oblique rotation was applied to the resulting factor matrix. The tentative interpretations of the factors are given in the column headings of Table 2. The complexity scores of the individual items indicate that considerable cross-loadings were present for many of the items. The communality values and the related uniqueness values are shown in the remaining two columns of Table 2.

In the four-factor solution, the first factor comprised items related to anxiety and hopelessness together with items describing propositional attitudes related to learning on the course. The factor was named *anxiety and hopelessness*. Furthermore, the different items loading on this factor were perhaps also related to the student's initial knowledge level concerning the subject matter of the course: For instance, if the topics are not familiar, the student is unlikely to feel confident about performing well on the course (item 16) and is likely to feel unable of making it on the course (item 9).

Items related to boredom and lack of interest had high loadings on the second factor, with negative loadings on items related to enjoying the course. The factor was thus dubbed *boredom and anger*. A common denominator for all the items might be the difficulty level of the course for the individual student: if the student knows the course material well enough, the course may become boring, and if there are enough new and interesting things to learn, it will remain interesting (items 1 and 15).

Items reflecting various positive and negative emotions loaded on the third factor. The common denominator for the items was the amount of effort expended on the course and the emotions resulting from this. The fourth factor comprised items related to negative emotions (embarrassment, shame and anxiety) in social situations.

Table 2. Exploratory factor analysis of the emotion items

Item	Item no.	anxiety and hopelessness	boredom and anger	amount of effort	negative social em.	h ²	u ²	com
I feel like I cannot make it through this course	9	0.84	-0.09	0.00	0.01	0.63	0.37	1.0
I feel anxious when I am doing the homework assignments on this course	11	0.80	0.12	0.11	0.11	0.72	0.28	1.1
I have lost hope of doing well in the course exam	23	0.76	-0.05	-0.15	0.13	0.71	0.29	1.1
When I think about this course, I become anxious	14	0.76	0.19	0.01	0.11	0.79	0.21	1.2
The contents and the assignments on this course make me unhappy	13	0.71	0.25	0.07	0.06	0.73	0.27	1.3
I am sure that I will do well on this course	16	-0.71	0.08	0.39	0.11	0.78	0.22	1.6
Studying the materials of this course feels hopeless	6	0.66	0.26	0.15	0.02	0.61	0.39	1.4
In the beginning of this course I was confident that I will do well on this course	24	-0.52	0.18	0.15	0.06	0.27	0.73	1.4
I find the course exam a pleasant challenge	17	-0.45	-0.17	0.11	0.25	0.39	0.61	2.0
I feel optimistic about my preparation for the exam in this course	2	-0.44	0.01	0.43	0.15	0.49	0.51	2.2
I am bored by this course	5	-0.13	0.86	-0.02	0.04	0.65	0.35	1.1
The learning activities for this course are not interesting	18	0.00	0.82	-0.09	0.03	0.72	0.28	1.0
I am fed up with the contents of this course	8	0.19	0.77	0.04	0.04	0.77	0.23	1.1
I find studying the course contents inspiring	1	-0.07	-0.74	0.10	0.15	0.65	0.35	1.1
I enjoy learning new things on this course	15	-0.10	-0.51	0.20	0.07	0.42	0.58	1.4
Completing the assignments on this course irritates me	4	0.42	0.49	0.02	0.02	0.62	0.38	2.0
I am extremely happy with the way I have invested my efforts in studying on this course	25	0.10	-0.12	0.88	0.02	0.75	0.25	1.1
I feel ashamed not having prepared better for this course	10	-0.01	0.10	-0.71	0.24	0.67	0.33	1.3
I feel ashamed thinking I might have not prepared adequately for the exam in this course	12	0.10	-0.03	-0.68	0.27	0.68	0.32	1.3
I am extremely happy with my learning on this course	3	-0.36	-0.12	0.52	0.18	0.60	0.40	2.2
I am extremely happy with the way I have done with the homework in this course	7	-0.11	-0.01	0.50	-0.10	0.34	0.66	1.2
Mistakes I make on the course (e.g. during the mathematical exercises) or when doing homework embarrass me	22	0.08	-0.05	-0.18	0.73	0.64	0.36	1.2
If I ask a question in class that others already certainly know the answer to, I feel embarrassed	21	0.08	-0.03	0.00	0.61	0.40	0.60	1.0
Contributing to discussions or asking questions on this course makes me anxious	20	0.25	0.14	-0.05	0.61	0.58	0.42	1.5
I am embarrassed when I cannot complete the homework assignments on this course	19	-0.17	-0.05	-0.04	0.61	0.38	0.62	1.2
Factor correlations								
		anxiety and hopelessness	boredom and anger	amount of effort	negative social emotions			
	anxiety and hopelessness	1.00						
	boredom and anger	0.53	1.00					
	amount of effort	-0.39	-0.22	1.00				
	negative social emotions	0.17	0.07	-0.20	1.00			

h²: communality; u²: uniqueness, com: complexity (the degree of cross-loadings)

3.3 Network analysis

The network graph corresponding to the lasso-estimated partial correlations is shown in Figure 2. The edges drawn in green color correspond to positive correlations and those in red dashed lines to negative correlations. The width and saturation of the line indicate the strength of the correlation. The colors of the nodes were chosen based on the factor analysis reported above.

When interpreting the graph it may be beneficial to compare Figure 2 with the graph that would correspond to an ideal four-factor simple structure (Figure 1). If a factor model were the data-generating mechanism, we would expect all the items intended to measure a single factor to be interrelated with one another. Further, we would expect them to have only weak associations with items

related to the other factors. In sample data, we do not even expect to encounter such a clear structure because of sampling variation, which is the prime reason for creating the graphs using the lasso estimation method.

Figure 2. Network graph with the node groups selected based on the results of factor analysis (top) with the related centrality indices (bottom). The green solid lines represent positive connections among the nodes while the dashed red lines represent negative connections.

When looking at Figure 2, the negative emotions experienced in social situations come closest to exhibiting the pattern of partial correlations that we would expect if the interrelationships among the items were indeed caused by an underlying latent variable. On the other hand, it is also possible that associations such as these arise because there exist central emotions that influence others in their immediate neighborhoods. When performing a factor analysis on the same data, such nodes would be represented as observed variables having high loadings on their respective factors. Among these four emotions, *being embarrassed by mistakes* (item 22) is the most central emotion when judging by strength centrality. It also has the highest factor loading on the respective factor as can be seen by examining Table 2.

When looking at the rest of the network graph, the similarly colored nodes do not form such clearly interconnected clusters. For instance, even though the items related to *boredom and anger* do form interconnected sub-clusters, not all of them are grouped together. Rather, these emotions might be best interpreted as bearing family-resemblance relations to one another, with strong connections between certain emotions and weak to non-existing ones between others. In this respect, it is of interest to note that the items intended to reflect boredom are strongly linked to one another (items 5, 8 and 18), while only one of them (item 8) has a strong link to the anger-related item 4.

Finally, when looking at the items colored in cyan close to the top of Figure 2, it is of interest to contrast the interpretation of the factor analysis with that of the network analysis. For instance, items 3, 7 and 25 loaded on the same factor (*effort*) and yet nodes 3 and 7 are only weakly connected in the graph. However, they both have strong connections with node 25, which may actually function as a common cause for both emotions: expending enough effort on the course may lead one to feel happy with one's performance.

The relative importance of the nodes in the network graph can be understood by examining the values of the centrality indices presented in the lower part of Figure 2. Looking at betweenness and closeness centrality, nodes 3 (happy with own learning on the course) and 16 (feeling sure of doing well on the course) are seen to be central for the flow of information in the network: they often lie on the shortest path between other nodes and are on average close to other nodes. These nodes are thus easily affected by changes in other nodes of the network, and, reciprocally, changes in them are likely to have a large effect on other nodes. Some of the connections among these items may also be causal in nature. For instance, feeling confident (item 16) may increase the chance of feeling happy with one's learning on the course (item 3).

Finally, we performed a springlass community detection analysis on the network graph. As described in the Methods section 2.3.2.2, we repeated the analysis for 1000 times because of the stochastic nature of the simulated annealing algorithm. Below, we report the most frequently obtained community structure, which the algorithm converged upon on 82.5 % of the repetitions. The next most frequent community structures occurred with probabilities of 7.4 %, 5.4 % and 2.9 %, with only few occurrences for other structures (eight other structures were found, each of them only 1–6 times during the 1000 repetitions). In the

most commonly obtained community structure, the items are grouped somewhat differently from the factor analysis. The most striking difference occurs with the positive emotions, which load on different factors but are grouped in the same community. Emotions related to anxiety and hopelessness form another community, with items related to boredom in a third. The four items related to negative emotions in social situations form a community of their own, with the remaining community consisting of the two extremely strongly connected items related to shame resulting from lack of effort.

Figure 3. Network graph with the node groups selected based on the results of the spinglass community detection algorithm

When looking at Figure 3, it appears that emotion 24 is far removed from the other positive emotions. One should not, however, put too much weight on interpreting the visual appearance of the graph, as projecting the multidimensional data structure on a two-dimensional plane cannot represent all relationships between the nodes equally well². For instance, if it were possible to examine the network model as a three-dimensional object, node 24 might appear close to the other nodes of its community in the third dimension. Further, it can be seen that the community detection algorithm groups together the two items arising from the feeling of shame due to lack of adequate preparation. This is understandable bearing in mind the definition of a community: the two nodes share an extremely strong connection, while most of their connections with

² For this reason, we encourage the reader to repeat our analyses based on the R code and the data set provided at the osf.io page related to the present contribution. This enables the reader to examine the actual connection weights among the items and obtain further insights on the data.

other nodes of the network are strongly or moderately negative or weakly positive.

4 Discussion

In this contribution we introduced a novel way of modeling academic emotions as a network of interrelated, emotion-laden experiences. We also performed an exploratory factor analysis on the same data with the aim of comparing the insights that can be obtained using the two methods. The network models and the factor models were constructed based on data obtained using a Finnish translation of the SEEI that was supplemented with items from the AES and the AEQ. The network graph depicts the pairwise associations among the observed variables that remain after controlling the effects of all the other variables in the network. Some of these associations may be given a causal interpretation (either a unidirectional or a bidirectional one), while others are likely due to unmodeled latent variables. Constructing a network model together with a factor model allows the researcher to formulate educated guesses on which of the connections among the observed variables are due to latent variables and which ones are potentially causal in nature. In a factor model it is assumed that all the connections are due to latent variables, whereas in a network model it is assumed that none of them are³. We believe the correct answer lies somewhere between these two extremes.

In addition to the factor analysis, the global structure of the associations between the observed variables was assessed using the spinglass community detection algorithm. While four factors were extracted, the community detection analysis showed that there were five aggregates of items. It is of interest that the community detection algorithm consistently grouped the positive emotions together as one community, while in the factor analysis the positive emotions were spread across factors with negative loadings on their respective factors. The result of the community detection algorithm accords with the human intuition that positive emotions belong together; simultaneously, it is congruent with the circumplex model of emotions, which reduces discrete emotions to positions on the two dimensions of valence and activation (Lindquist et al., 2013). The factor model expresses another aspect of the intercorrelations of the items, aggregating the positive emotions together with the negative emotions that they share strong negative correlations with. Neither of the results is more right or wrong in any well-defined mathematical sense, but there is one aspect of the factor analysis result that we would like to focus attention on: the negative loadings invite one to interpret the meanings of the items as their opposites to give the latent variable a congruent interpretation. This may be problematic from the practical point of view, however, as coming up with the opposite of a verbal statement is always to some degree a subjective decision. Further, it is an empirical question whether the correlation of the opposite verbal statement is

³ Actually, when thinking of the network model, it might also be possible to consider all nodes to represent a latent variable of their own: it is not the question item that is causally efficacious but the underlying psychological property.

In a similar vein, it is in our view beneficial to keep in mind the basic distinctions of activating / inhibiting emotions and the valence of the emotions. These ideas help interpreting the structure of the network when it comes to the emotions of anger and boredom. As the items related to these two emotions (partly) load on the same factor in our analysis they clearly do share some variation. In this respect our results bear a resemblance to those of Govaerts & Grégoire (2008) and Trigwell et al. (2012). Still, anger is by definition an activating emotion that is usually interpreted as negative in valence. Boredom, for its part, is a negative emotion that inhibits action (Pekrun et al., 2002). In light of the present results, this shared variation is perhaps best understood as family resemblance relations among these emotions and perceptions. For instance, perceiving the learning activities as uninteresting (item 18) is not directly related to getting irritated with the course assignments (item 4) or feeling unhappy about the course contents and assignments (item 13). Rather, item 18 is only related to these through its association with item 8, feeling fed up with the course contents. On the other hand, the three items clearly related to boredom (5, 8, 18) are closely associated, as can be seen looking at the right side of Figure 2. Finally, the network graph helps us understand the relationships that were represented as a correlation between the factors of boredom-anger and anxiety-hopelessness in the factor analysis. This correlation is largely driven by the close association between items 4 and 11.

Figure 5. The community of items related to boredom and anger

The interpretation of the lower part of the network graph, which is related to the emotions of anxiety and hopelessness, can also be based on the idea of family resemblance relationships among the items. The two items clearly related to anxiety (11 and 14) are strongly connected. On the other hand, their relationships with items 13 and 6 seem to be driven by two facts: all items have negative valence and they mention the homework and / or contents of the course. So the overlapping content and the valence of the emotion seem to be the factors that explain the connections between these nodes. The remaining strong

connection obtains between items 23 and 9 (hopelessness), while both items are only weakly connected with the remaining item expressing hopelessness (6). This may be because the former are related to a more general, overwhelming feeling and the latter to course material specifically, driving its correlation with item 11, as noted above.

Figure 6. The community of items related to anxiety and hopelessness

Finally, let us turn our attention to the items at the top half of the network graph. They are all related to positive emotions, and are negatively connected to items expressing negative emotions. This is in keeping with the circumplex model of emotions in which positive and negative emotions occupy opposite ends of the dimension of valence.

Further, it is of interest to compare the results of the network analysis with those of the factor analysis. In the factor model, items 3 and 7 (*happy with own learning*) and 25 (*happy with own effort*) loaded on the same factor (effort) and yet nodes 3 and 7 were only weakly connected in the network graph. However, they both have strong connections with node 25, which may actually function as a common cause for both emotions: expending enough effort on the course may lead one to being happy with one's performance on homework and with one's own learning on the course. Other interpretations could be given for the observed result, but the data at least conform with interpreting these connections as causal. Importantly, potential causal relationships such as this would not be revealed if only factor analyses were performed.

Figure 7. The community of items related to positive emotions (nodes in cyan) and the community related to shame that is due to lack of effort (nodes in blue). Item 24 not shown.

One unique benefit of network analysis is that it enabled us to locate the emotions and cognitions that were central in the “emotional ecosystem” of the students. These emotions and cognitions are prime targets for interventions, because changes in them are likely to have large effects on the rest of the emotions felt by the students. We assessed the centrality of the emotions using the indices that are reported in the bottom of Figure 2. The optimism-related item *I am sure that I will do well on this course* (item 16) was on average close to the other nodes in the network and it had strong connections with the other nodes. The meaning of the item comes close to how self-efficacy is defined: “people’s beliefs about their capabilities to produce designated levels of performance that exercise influence over events that affect their lives” (Bandura, 1994) and how generalized self-efficacy is measured (e.g. with an item “When I make plans, I am certain I can make them work” (Judge, Erez, Bono, & Thoresen, 2002)). The network graph indicates that this node has positive links to nodes related to positive feelings arising from one’s own efforts on the course (items 2, 3 and 25) and negative links to feeling hopeless. These connections suggest that it might be beneficial to target future interventions at increasing the students’ self-efficacy, as these changes would have large effects on the other parts of the network of emotions.

When interpreting the results, it is beneficial to keep in mind that the questionnaire was intended to measure the eight emotions of enjoyment, hope, pride, anger, anxiety, shame, hopelessness and boredom. However, as noted

above, the community detection analysis indicated that the interrelationships among the items were best captured by five communities of items, while the factor analysis resulted in four factors. The careful examination of the network graph suggests that some of the interrelationships among the items were due to completely unexpected factors (e.g. the amount of effort), while some were apparently related to the non-emotion-laden content of the item, such as both items referring to the course materials in one way or another. Of course some of the subgroups (or *cliques*, Luce & Perry, 1949) of items within the communities were related to a single emotion as expected: the three boredom-related items 5, 8 and 18 are a case in point. These observations highlight the difficulty of formulating unambiguous wordings for the items and indicate ways in which the questionnaire could be improved in the future. For instance, the two anxiety-related items (11 and 14) could perhaps be supplemented with a still another one not related to social anxiety. On the other hand, at the end of this discussion, we propose an alternative response format for the academic emotions questionnaire that may avoid some of these problems of ambiguous wordings.

We would like to close with discussing certain theoretical and methodological points of view that are in common to all investigations of academic emotions. We will first consider ideas that are relevant within any given cultural group (or country) and then ideas related to the commensurability of the results across cultural groups or countries.

4.1 Examining the structure of emotions within and across cultures

Let us first reflect on the formidable challenge of construing a questionnaire instrument that is capable of capturing variation in the emotions that it is intended to⁴ within a certain culture. For instance, both the questionnaire used in the present study and the AEQ include question items related to embarrassment among the items intended to measure shame, which presupposes that embarrassment and shame are parts of the same emotion, perhaps only differing with regards to the intensity of the affect⁵. Empirical research, however, shows this not to be the case (Keltner, 1996; Tangney, Miller, Flicker, & Barlow, 1996) at least in the context of American university students. In case we consider it possible that similar distinctions might apply in Australia and the European countries in which the investigations of academic emotions have so far taken place, it would seem reasonable to take these results into account when considering the contents of the questionnaires.

⁴ Incidentally, the capability of an instrument to *capture variation in the attribute that it is supposed to* is the definition of validity espoused by Borsboom, Mellenbergh, & van Heerden (2004) and one we have also adopted in this contribution.

⁵ The distinction among embarrassment and shame functions here only as one example of the need to take the results of empirical investigations better into account when developing questionnaires related to the academic emotions. Similar considerations apply to the other emotions, but we do not intend to analyze them in detail in the present contribution.

Shame and embarrassment have been found to be qualitatively, not merely quantitatively, different emotions: they are both associated with specific kinds of precipitating factors, consequences, and the contexts in which they may be felt. Shame is an emotion signaling a moral transgression, unlike embarrassment, which is related to (perhaps more minor) social transgressions. Shame may be a potentially private emotion in contrast to embarrassment: while embarrassment may result in laughter and jokes, shame is more likely to lead to self-directed anger and apologies. Embarrassment is also more likely to involve physiological reactions such as blushing or increased heart rate than shame. Embarrassment is felt when the actor has no responsibility for the consequences and when others are likely to be amused by what happened – unlike shame (Keltner, 1996; Tangney et al., 1996). Further, the difference between shame and embarrassment has been shown not to be related to the intensity of the emotion; rather the differences are qualitative in nature (Tangney et al., 1996). Moreover, at least in the American context, shame has been found to be very rarely the consequence of cognitive shortcomings, unlike embarrassment (Keltner, 1996). The AEQ, however, involves items such as “I feel ashamed that I can’t absorb the simplest of details”, which is a cognitive shortcoming. If the above considerations generalize to Australia and the various European countries in which the investigations of academic emotions have so far taken place, it would seem like a reasonable option to aim at separating the emotions of shame and embarrassment in the questionnaire.

Furthermore, it is not self-evident that the complex emotions of pride, hope, anxiety, shame and hopelessness are similarly structured across cultures. Empirical studies on the recognition of facial expressions point toward the existence of certain universal, biologically-based core components of emotions that are similar across cultures. These include the fact that the emotions of anger, contempt, disgust, fear, happiness, sadness and surprise, together with the positive-negative dimension of emotion can be recognized quite well across cultures (Elfenbein & Ambady, 2002). But how similar are the complex emotions that are the focus of studies of academic emotions? For instance, even though rejection from a social group or a loss of something important is likely to produce similar emotions across cultures, there are notable differences across cultures in how emotions are expressed and displayed (Mesquita & Frijda, 1992). This observation has a direct bearing on the formulation and translation of the questionnaires related to academic emotions. For instance, even though Govaerts & Grégoire (2008) had included an item in their questionnaire related to expressing anger by throwing books out of the window, that item would have described uncommonly impulsive behavior in the Finnish context. Furthermore, even though shame and embarrassment have been shown to be distinct emotions in the American context, it is not necessarily the case that they can be so separated in the German, French, Finnish or Australian context. For instance, it is an empirical question whether, say, cognitive shortcomings result in shame in the German context in which the AEQ was developed, even if they are related to embarrassment in the American context as shown above; further, it may also be the case that shame and embarrassment are indeed distinct emotions in the American culture but not within the German one. If either of these is the case, a direct English translation of the questionnaire developed in the German context

might not work perfectly in the United States. Similar considerations apply to translating and modifying the questionnaires for use in different countries and cultures: behaviors that are considered funny (and thus potentially resulting in embarrassment) in one culture may be considered moral transgressions (and potentially resulting in shame) in another culture.

4.2 Response formats in questionnaires concerning academic emotions

Considerations such as those expressed in the previous section (section 4.1.) naturally lead one to think about the response format of the academic emotions questionnaires that are currently in use. They associate a given emotion with a given likely precipitating factor, even though other emotions could likely be felt under the same circumstances. For example, in the questionnaire used in the present study, there is an item that states “Contributing to discussions or asking questions on this course makes me anxious”, but no item related to feeling happy or enthusiastic about these things⁶. Instead of formulating items that conflate the presence of a precipitating factor (here: asking a question or taking part in a conversation) and experiencing a certain emotion (here: anxiety), another possible response format would be to ask the respondents to report the intensity of any emotion they may have felt in conjunction with the precipitating factor. Concretely, that would entail writing items such as:

When taking part in a conversation in which the whole class participates, I feel the following:

Anxiety

Annoyance

Boredom

Joy

...

with each emotion being associated with its own Likert response scale, and perhaps each emotion being reflected by a set of words (e.g. anger by “anger”, “mad”, “rage” and “pissed off” – words assumedly used by the participants themselves to refer to these emotions). A format similar to this has been used in the Discrete Emotions Questionnaire (Harmon-Jones et al., 2016). The relevant distinctions need to be made if this response scale is adopted: for instance, with respect to the course assignments, it might be necessary to differentiate, say, easy and demanding assignments and inquire about the emotions related to both. Other emotion-provoking experiences might include “expressing your ideas to all the other participants”, “Course arrangements (ease of registering on the course, suitability of classrooms etc.)”, “Teacher as a person” etc. This format would have the added benefit of not being sensitive to overlapping non-

⁶ This observation is by no means specific to the questionnaire used in the present study; rather, similar examples can be easily found in the AEQ, the AES and the SEEI.

emotional content that may have caused some of the associations in the questionnaire used in the present study as pointed out above.

An even more general consideration related to the use of self-report instruments as a tool for investigating emotional experiences is that they are only sensitive to what the respondent is able to consciously report. There may be emotion-laden experiences that no-one can express when a self-report instrument is used; furthermore, people are known to differ with respect to their abilities to describe their own inner states. One interesting future possibility for investigating the nature of academic emotions would be to combine Experience Sampling Methods (ESM) with measurement of physiological parameters such as skin electrical conductance and heart rate. These tools would enable examining causal chains that cannot be investigated using cross-sectional questionnaire research. For instance, we might be interested in showing empirically that a person with a high level of trait social anxiety is likely to blush in social situations, which embarrasses her, and her realization that she has blushed creates more anxiety at that moment. So, schematically, the hypothesized process might operate as follows:

Trait anxiety → Physical reaction (e.g. blushing) → Embarrassment → State anxiety

with the emotion of interest (here: embarrassment) being investigated using an ESM prompt on a cell phone. Investigations such as these could be used for instance in examining the difference between embarrassment and shame empirically: if the participants indeed experience embarrassment rather than shame in this situation, and shame in relation to a moral transgression, it would corroborate the idea that they are indeed distinct emotions. These results could then be taken into account when considering concrete recommendations of how to structure the academic teaching-learning environment so as to take into account the potential emotional reactions of the students. The network analysis method has been previously used in a study related to emotion dynamics based on ESM data (Bringmann et al., 2016).

4.3 Conclusions and ideas for further studies

In this contribution we have presented a novel way of modeling academic emotions as a network of emotion-laden experiences. We have also compared the kinds of inferences that can be drawn based on a network model to those derived from a factor model and suggested ways of developing questionnaires related to academic emotions further. We hope that the network perspective will provide useful insights into the dynamics of academic emotions in future research. In particular, the control value theory of academic emotions (Pekrun, 2006) seems to us compatible with the network perspective: it seems natural to us to think of emotions as interacting networks of affective, cognitive, motivational and physiological components. In addition, the network model provides us with interesting possibilities for modeling the phenomenon of academic emotions not afforded by either reflective or formative measurement models. For instance, the network representations of emotions may differ across

individuals, unlike the two types of measurement models: for one student, boredom and anger may occur together and be subsumed under the common rubric of frustration, while for another, boredom and anger may be distinct experiences. Longitudinal data is naturally needed in order to examine questions related to intra-individual variation such as these.

Network analysis has only recently been applied as a psychometric method, and the novelty of the method means that methodological and philosophical open questions remain. One important methodological question that needs to receive more attention in future studies concerns the most suitable method of carrying out community detection analysis within network psychometrics. Methodologically-oriented future studies will surely shed light on the issue and provide applied researchers with a set of recommendations on best practices in the use of community-detection analysis in this context. Further, intriguing philosophical questions remain to be solved. For instance: can latent variables as mereological sums be thought of as emergent properties either in the ontological or the epistemological sense (O'Connor & Wong, 2015), i.e. do the latent variables thus conceived have properties that are not shared by the observed variables? If they do, questions related to whole-part causation (top-down causation) arise, whereas it is characteristic for the network psychometrics literature as it currently stands to think of wholes composed of parts from the bottom up (for example when thinking of depression as a combination of symptoms, Fried, 2015). It is illustrative to consider that the same mental state, such as the state of feeling jealousy, may have multiple realizations as networks of interrelated variables. For instance, jealousy in one person may involve anger and violent intentions as component parts, whereas in someone else they may be replaced by intense sorrow; yet we speak of the same emotion. Perhaps, then, general psychological properties are determined by both local interactions among components parts (from the bottom up) and the global influence of the person in whom they occur functioning as the context in which they occur (the top-down influence).

All in all, intriguing substantive, methodological and philosophical questions remain to be investigated within the arising field of network psychometrics.

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