# Abstract

Self-report-based research on traffic behavior is most often carried out with the instrumental goal of predicting traffic accidents in mind, rather than out of inherent interest in how people behave, think or feel in traffic. Therefore, nomological relationships of traffic behaviors and accidents are of central importance to the researcher. The most commonly used analysis method of self-report data is factor analysis, followed by the calculation of unit-weighted average scores of the frequencies of the behaviors that load on the factors. However, recent research (Mattsson 2012, Mattsson et al., 2015) has shown that the factor models of the commonly-used Driver Behavior Questionnaire lack the property of measurement equivalence across subgroups of respondents. This has the unfortunate consequence of rendering the meanings of the average scores group-specific. On the other hand, this may not as big a problem as it first seems, as the average scores are not relevant for the nomological relationships, which are quantified using some measure of association (such as a correlation coefficient or another). In this contribution I pursue the idea of modelling drivers’ self-reported behaviors, thoughts and self-perceptions as an interrelated nomological network rather than as reflections of in principle unobservable latent variables, and suggest that the previously noted lack of measurement equivalence reflects the fact that postulating latent variables as an additional level of abstraction is unnecessary in self-report-based traffic research. Further, I examine the pairwise associations between nodes of the nomological network and being involved in a traffic accident.

# Introduction

**[Reasonin kelat: kognitiiviset ominaisuudet selittää onnettomuuksien syntymistä]**

To err is human, and human errors are important predictors of accidents. Therefore, to prevent accidents, we need to understand the ways that cognitive mechanisms fail when accidents happen. One influencal view on the nature of cognitive failures is the Generic Error Modeling System (GEMS) of Reason (1990). A central distinction in GEMS is whether or not an individual was actively trying to solve a problem when an error occurred (p. 56). If not, errors are often related to performance of routine activities, and they are referred to *slips* and *lapses* in the GEMS error taxonomy. Slips are errors involving paying either too little or too much attention to the task at hand, while lapses are primarily errors of forgetting where an individual was located in a goal-oriented action sequence. Errors related to problem solving, on the other hand, are referred to as mistakes, and they can be analyzed as being due to applying otherwise good rules in an inappropriate situation (*rule-based mistakes*), or an individual being forced by the situation to come up with a novel solution to a problem and failing in the process (*knowledge-based mistakes*).

**[Pyrkimys toteuttaa Reasonin keloja liikennetutkimuksessa: DBQ-tutkimus]** The Driver Behavior Questionnaire (DBQ) was developed as a self-report instrument aimed at collecting information on the occurrence of *slips*, *lapses*, *mistakes* (two types of mistakes, rule-based and knowledge-based, were mentioned but were not differentiated when formulating the items) and, in addition, *unintended* and *deliberate violations* of rules, laws, norms of operating procedures. In other words, the measurement model (REF) of the DBQ involved each item as a measurement of on of the five different types of ”aberrant[[1]](#footnote-1)” behavior. The principal components analysis that was performed on the DBQ failed to support the measurement model[[2]](#footnote-2), which lead to the prompt dismissal of the measurement model, and to replacing it with the tripartite typology of *violations*, *dangerous errors* and *trivial slips and lapses*. Subsequent studies (REF Parker) built on this typology (saiko ne jotain aikaan?), and the dimension of *aggressive violations* was later added to the measurement model (REF Lawton). Since then, numerous versions of the instrument have been developed, with the number of items ranging from ten to over a hundred (REFs).

**[Reasonin kelojen toteuttamisen haasteet: mittausekvivalenssin puute, vaikeus löytää yksittäisiä kognitiivisia toimintoja heijastelevia osioita (monet osiot ristiinlatautuu voimakkaasti useissa tutkimuksissa)]**

In addition to the original DBQ failing to measure what it was intended to measure, subsequent studies have shown that it is difficult to formulate questionnaire items that would be unequivocally related to the failure of a single cognitive process (relationship is assumed causal, note here!). This is evidenced by

1) different factor structures being obtained for the same version of the instrument. For instance, the often-used 27-item questionnaire is thought to reflect the failures of two, three or four different psychological processes;

2) typically high cross-loadings of items on factors;

3) the necessity to specify correlated error variances in confirmatory factor analysis (CFA) studies. CFA models are based on assuming the observed variables to be conditionally independent, interchangeable indicators of the latent variable being measured. The assumption of conditional independence explicitly prohibits direct associations among the observed variables: all correlations among pairs of variables are assumed to be due to the effect of the latent variable. For instance, tailgating and speeding are assumed to correlate because they are both measurements of the underlying psychological property of “proneness to violate rules”. Further, assuming the indicators to be interchangeable is related to how variance in indicators is portioned in latent variable models into reliable (due to the latent variable) and unreliable (due to measurement error). Under these conditions, when one knows the expected value of one indicator, (e.g. tailgating as an indicator of violations), none of the other indicators contain any additional information on the individual’s position on the latent continuum of proneness to violate rules (Cramer, Borsboom, LordNovick, Jöreskog 1971). Even though this seems counterintuitive psychologically, it is a bullet that one must bite when assuming a latent variable model of driver behavior.

4) the complex factor structures needed to adequately fit the data (either by specifying second-order factors or a general factor) and

5) Failures of the test of measurement equivalence across some subgroups of respondents (Mattsson, 2012, Mattsson et al. 2015, Australia). In short, there is evidence of different factor structures needed across genders and age groups in Finland; In Australian data, factor structures differed for the youngest and oldest age groups and professional vs. non-professional drivers (REFs). On the other hand, tests of measurement equivalence produced similar results when comparing men and women or two middle age groups in Australian data (REF). Comparing Finnish and Irish data produced mixed results in that the two factors related to violations were quite different across these countries, while conditional strong equivalence was obtained for the factors of slips and lapses (tarkista vielä).

These results are all problematic for latent variable models (Fig 1), which attribute causal power to latent variables, with the observed variables functioning as inert reflections of the latent *measuranda*.

**[Verkostomallien perustelu]**

In this contribution I propose that the problems related to factor models of the DBQ are explained by there existing direct causal relationships – contra the assumptions of the factor models – between the behaviors, thoughts and emotions encoded into the DBQ variables. For instance, instead of both speeding and driving too close to the car in front both being interchangeable measurements of the driver’s proneness to violate rules, it may be that speeding causes one to end up driving too close to the car in front and having difficulties stopping in time. Speeding, or the other violations, may also well increase the probability of the behaviors that have traditionally been considered slips of attention or memory lapses.

**[Verkostomallien yhteensopivuus liikennepsykologisten motivaatioteorioiden kanssa]**

When comparing the network model and the latent variable model of traffic behavior, the network model seems prima facie better compatible with theories of driver motivation (Summala, Fuller, Wilde REF) that view driving as a self-paced activity. First, the speed choices of a driver have a special status in these theories, and if speed choices are treated as an indicator of a latent variable, the direct relationship of speed choice with other traffic behaviors cannot be assessed[[3]](#footnote-3). In the zero-risk theory the criterion is distance to collision, while in the task-difficulty theory it is the difficulty of the task. Further, according to the zero risk model, speeding is caused by an “extra motive” of one kind or another, such as thrill seeking, enjoying speed, competing with others etc. Importantly, different violations of traffic rules or social rules, such as speeding and tailgating, may involve different causes and effects, supporting the use of network models. Indeed, studies investigating the effects of attitudes, social norms and perceived behavioral control on intentions to commit violations focus on specific violations instead of on a person violating rules in general (Parker, Manstead, Stradling, Reason & Baxter, 1992; Lawton et al. 1997, self-reported attitude towards speeding and its possible consequences in five different road contexts). Further, speeding may lead to information-processing overload at least when speeding leads to drivers exceeding their time-to-collision comfort zones (Summala, 2007). In the case of the DBQ, some of the attention-related slips can be thought of reflecting such information overload: for instance, not noticing pedestrians / cyclists may be related to drivers not having enough time to direct their attention to where it is needed. Especially for the relatively inexperienced drivers of the current sample, directing attention correctly and thus perceiving hazards is likely to be a procedure that necessitates conscious control of action.

Further, I propose that the behaviors intended as measurements of inattentive slips are too heterogeneous to arise from the malfunctioning of a single cognitive process. For instance, misjudging the speed of an oncoming vehicle depends on (the malfunctioning of) a different cognitive process than not noticing pedestrians when turning to a side street: the latter depends on top-down control of attention, while the former is a more basic perceptual process (kai? Miten se idea visuaalisista kulmista, tau-suureesta ja objektin representation koon muutoksista menikään?). Factor models of traffic behavior, on the other hand, view all attention-related errors (or slips, as they were originally called) as measurements of the underlying latent variable. This leads to thinking of their causes and effects as identical, which does not seem realistic. Similar considerations are likely to apply to memory lapses (see also Mattsson, 2012).

**[Verkostomallien taustafilosofia]**

Network models have recently been applied in research on various forms of psychopathology (such as depression, post-traumatic stress disorder and schizophrenia) and in research on the structure of personality (REFs). The central idea in psychopathology networks is that mental disorders arise as a result of direct causal associations between symptoms, and latent disorders need not be assumed as an explanation of the covariation of the symptoms. These models have been either explicitly or implicitly based on viewing the phenomena under investigation as dynamical systems that may end up in different states: for instance, the network of depression symptoms (e.g. sleeplessness, lack of energy, depressed mood) can be characterized as being in a depressed or non-depressed state. If, for an individual, the depression symptoms are tightly connected so that, say, one sleepless night activates the symptom of lack of energy, the individual may end up in a depressed state more easily than someone in whose case the connection between these symptoms is weaker. The depression networks exhibit properties such as a non-random topology, with certain nodes being more tightly connected than others, and the property of hysteresis, which refers to how the network reacts to the effect of an external stressor: it first undergoes a state change to the depressed state, but does not return to the non-depressed state even after the stressor is removed.

Interestingly, it has been proposed that habits can be analyzed as stable states in networks of behaviors, thoughts and emotions (REF), and as is well-known, driving is to a large extent habitual activity (Summala REF). Perhaps the network model of the DBQ may function as a first approximation (albeit a crude one) of such a model of driving behavior.

**[Verkostomallien yhteensopivuus tutkijoiden intuitioiden kanssa]**

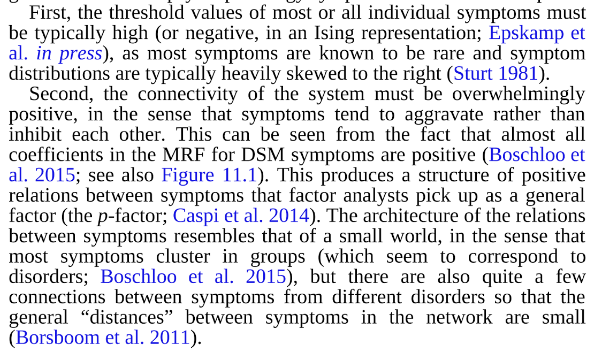
One important benefit of the network models is that they are compatible with researchers’ intuitions concerning cause-effect relationships. For instance, Davey, Wishart, Freeman & Watson (2007) investigated the traffic behavior of Australian professional drivers using the DBQ. They calculated scale mean scores based on PCAs that they refer to as factor analysis, but discuss the causes and effects of individual driving behaviors such as speeding, tailgating and crossing junctions when the light has turned red. They present an entirely believable analysis of how the time pressures facing professional drivers may be a likely cause, and reflect on the social norms related to speeding (i.e. that slight speeding is likely socially acceptable). The causal models that the authors propose can be summarized as *time pressure 🡪 speeding* and *time pressure 🡪 frustration 🡪 aggression 🡪 tailgating*, which seem entirely natural – and better compatible with network models than latent variable models.

Interestingly for the present concerns, a previous study investigated the relationships between individual driver behaviors and being involved in self-reported accidents using data obtained from Finland, Greece, Sweden and Turkey (Wallen Warner et al. (2011) <http://www.sciencedirect.com/science/article/pii/S1369847811000453>). The study was based on the DBQ, and variables with the greatest mean differences between countries were used as predictors together with age, gender and mileage in a forward selection regression analysis. After pooling data from all countries, speed choices on residential roads and highways, showing anger, overtaking from the inside, pulling out of a junction so that others need to yield and getting into a wrong lane before a roundabout or a junction were included as predictors of the number of accidents. Interestingly, the more the drivers reported speeding on a motorway and the more often they erroneously chose the wrong lane, the fewer accidents they were involved in; the other predictors were positively associated with the number of accidents. None of the DBQ variables (Finland, Sweden) or fewer of them (Greece, Turkey) were included in the model in within-country analyses. The idea of using individual DBQ items as independent variables in a regression analysis is certainly relevant for the present concerns. On the other hand, limiting the analyses on variables with greatest mean differences between countries does not necessarily result in the best predictors within countries; further, the forward selection algorithm is known to overfit models to the data at hand. The present study also involves predicting the number of accidents from the DBQ variables, but the analysis is based on LASSO estimation (described in more detail in the Methods section) that performs variable selection and estimation simultaneously and does not similarly capitalize on chance variation (REF).

Based on these observations, in the present contribution I will explore the idea of modeling the driving behaviors reported in the DBQ as an interrelated network rather than as a reflection of some unobserved latent variables causing variation in the items. Still, this approach is compatible with forming different summated scales based on the DBQ variables, perhaps based on driving behaviors forming tightly coupled clusters in the network model. In fact, clusters of interconnected nodes in a network correspond to variables loading on a single factor in a latent variable model, with the most central node in the cluster corresponding to the variable having the highest factor loading (stateofaRt). One natural interpretation for the central node would then be that it is the one causing variation in the others. For various definitions of node centrality, please see the methods section. Interestingly, these ideas are also compatible with the idea of formative measurement models, i.e. the idea of forming weighted sum scores as indices that may consist of various different kinds of variables as long as predictive validity is maximized, without the need of assuming that a common psychological characteristic is being measured as in reflective measurement models.

In this study I will specifically concentrate on pairwise associations between the DBQ variables, conditioned on all other variables included in the 27-item version of the instrument. This step of the analysis is equivalent to creating the measurement model when building a structural equation model (SEM). In an additional analysis step, I include certain other DBQ variables into the network model to show how network models can be used as a tool of investigating modified versions of a commonly-used questionnaire instrument. Next, I will return to using the commonly-employed 27-item version of the instrument, but this time include a variable related to the drivers’ self-image in the network (i.e. a variable related to whether the drivers perceive themselves as better or worse than other drivers). As a final step in the analysis, I include a variable indicating being involved in an accident in the network to test the idea of predicting being involved in an accident from the individual traffic behaviors and the self-image variable.

# Method



# Borsboom in: Philosophical Issues in Psychiatry IV: Psychiatric Nosology

## Data

This study is based on the archival data set described in Wells et al. (2008) and recently used by Rowe, Roman, McKenna et al. (2015) and de Winter, Dodou & Stanton (2015). The data set is based on a random sample of 128,000 practical driving test candidates from the UK, with the overall response rate being 33 %. The response rate of females was 40 %, and that of males 26 %. Those who passed their driving test were more likely to respond than those who didn’t (39 % and 29 %, respectively). In the final sample, the youngest age group (17 – 19 year-olds) were slightly over-represented, with the 40+ age group slightly under-represented in comparison to the sampling frame. Still, age-wise the data set was quite representative of the population of new drivers in the UK. For full details of the data, please consult the report Wells et al. (2008).   
  
Formation of the analysis data set and the variables used

In addition to modeling the DBQ data, it was of interest to examine the interrelationships of the driver’s self-image and accident involvement with the driver behaviors encoded in the DBQ. The ordinal variables (DBQ variables and self-image variables were analyzed as they were, without recoding the variables as done in, for example, Mattsson (2012). The accident variable (number of non-low speed at-fault accidents on public roads during the past six months) was recoded so that those not involved in an accident were coded as “0” and those involved in an accident as “1”. This accident variable was chosen because the more minor accidents that the respondents were inquired about were perhaps of less interest from the traffic safety perspective.

## Statistical analyses

In the present study, self-reported traffic behaviors, the self-image of the drivers and their involvement in an accident was analyzed as an interrelated network of behaviors, perceptions and events. As the structure of the network of traffic behaviors is currently not known, it had to be estimated based on sample data. The network graphs of the present contribution depict pairwise associations among the variables in the dataset, controlling for the effects of all other variables, i.e. partial correlations. The variables are represented as the nodes of the network, while the strengths of the partial correlations correspond to width and saturation of the edges. Positive partial correlations are drawn in green, negative in red.

However, choosing a suitable estimation method for the partial correlations involves two challenges: first, it is possible that at the population level, many of the nodes are conditionally independent given the other nodes (i.e. their partial correlations are zero), whereas in the sample, the partial correlations are likely to deviate from zero due to sampling variation alone (REF state of the art); second, the choice of correlation coefficient is a non-trivial matter when the variables correspond to rare events, which is the case with the DBQ and accidents. The first question can in principle be solved in many ways, such as calculating p-values for all partial correlations and then applying a correction for multiple comparisons, such as the Bonferroni correction. As is well known, this would, however, result in a loss of power of the analysis; in the present case, potentially important edges might fail to be drawn in the networks with this procedure. An elegant alternative to applying such a correction is to perform the analysis based on the graphical lasso as implemented in the qgraph package (REF). The basic idea of lasso estimation in the context of least squares regression analysis is to apply a penalty to each estimated regression coefficient to shrink them toward zero, and to shrink small coefficient to exactly zero. Stated in other words, lasso estimation performs variable selection simultaneously to regularization. The graphical lasso is a modified version of the basic lasso procedure and it results directly in a regularized inverse covariance matrix (for details, see chapter 17 ESL\_II or Friedman, Tibshirani & Hastie, 2007). When using the lasso methods, the amount of regularization to apply needs to be chosen using a principled criterion. While cross-validation is often used, the method implemented in qgraph is based on using the Extended Bayesian Information Criterion (EBIC, REF). That method, based on trying 100 different lambda (regularization parameter) values and then choosing the one minimizing the value of the EBIC was used in the present study.

This procedure attempts to uncover a graph known as a Gaussian Graphical Model, the central idea of which is that each node of the graph is independent of those in the rest of the network given the values of the immediately neighboring nodes (these properties of the network are described by the Markov properties). The network graphs were drawn using the Fruchterman-Rheingold –algorithm, which places nodes that are strongly connected and have many edges in common close to one another.

To solve the second challenge, the choice of a suitable correlation coefficient, a small simulation study was carried out. Choosing the method of quantifying the associations that is most suitable for the data at hand is an important decision before commencing with the data analysis. For instance, using Pearson correlations or polychoric correlations when the association between the variables is non-linear would not produce accurate results.

## Characterizing the networks

The strength of the connection (edge in the network) between two variables (nodes in the network) was estimated as defined above (statistical analyses). In characterizing the networks, the concepts of *distance* and *path* are of importance. In a weighted network, the distance between adjacent nodes is defined as the reciprocal of the strength of the connection between them. Further, a *path* is a sequence of nodes and edges, with no repetitions of either. The global structure of the network was assessed by calculating the strength distribution, average path length between nodes, the diameter of the network and the weighted global clustering coefficient. The diameter of the network is simply the longest path in the network. The global clustering coefficient describes the overall tendency of the nodes to cluster together in the network. In this contribution, I used the generalization to weighted networks based on the arithmetic mean method. It has a large value if the edge weights of nodes in closed triplets are high in relation to edge weights in all triplets (open or closed). The method is described in more detail in REF. Further, I also calculated the ratio of the weighted and unweighted global clustering coefficients to investigate whether triplets involving strong edges are more likely to be closed than those involving weak edges.

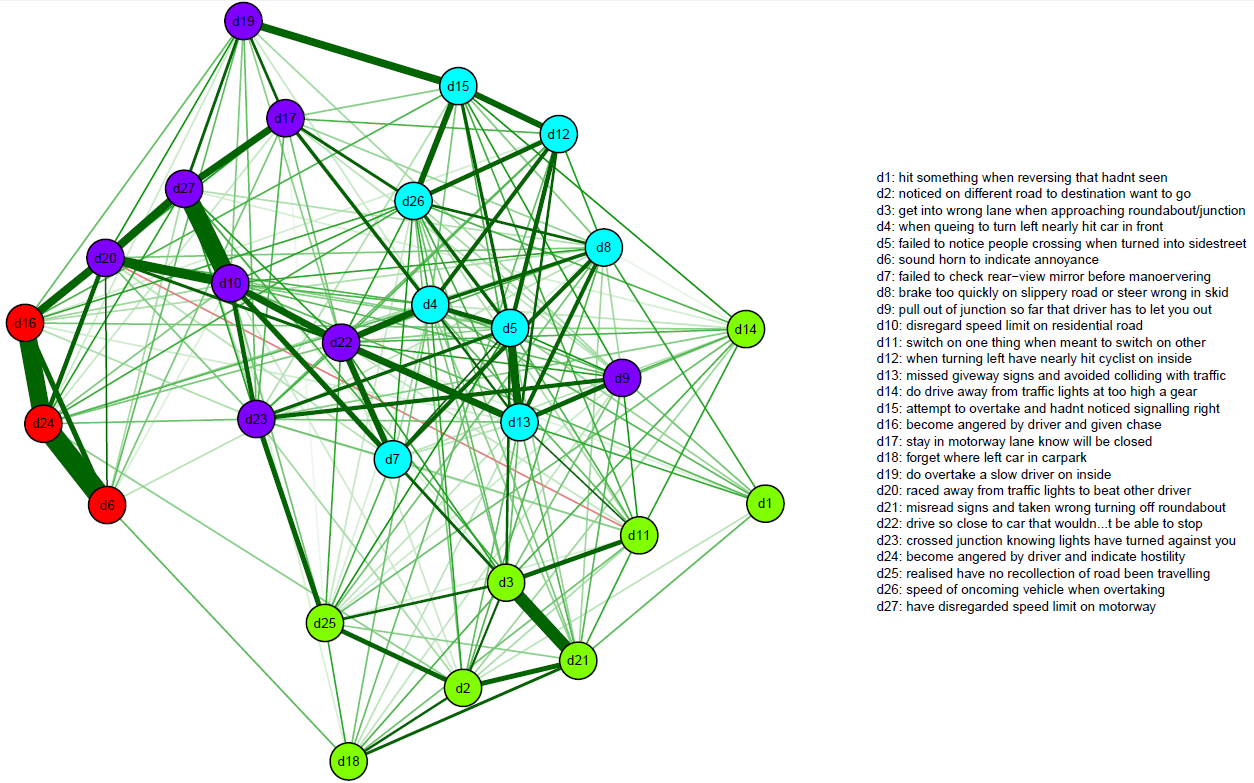
The local structure of the network was assessed by calculating the strength centrality, betweenness centrality, and closeness centrality. Further, the generalization of Zhang’s local clustering coefficient (REF) to signed networks (REF) was calculated. The coefficient of local clustering can be interpreted as an index of the redundancy of the node, and in the case of regularized partial correlation networks, it is important to take the sign of the connections into account. The generalization of Zhang’s coefficient was used rather than the generalization of Onnela’s coefficient as the former is more sensitive to the presence of weak edges (see Figure 1 in).

The strength centrality of a focal node is defined as the sum of the absolute values of the weights of the edges connected to the focal node. If the strength of a node is high, a change in its value will have a large direct effect on the nodes to which it is directly connected, i.e. on its neighborhood. Closeness centrality was calculated by first finding the sum of distances from a focal node to all other nodes, and then taking the reciprocal of the sum. A node that has a high closeness centrality is likely to be easily affected by changes in the values of nodes that are directly or indirectly connected to it (Costantini et al., 2015). The betweenness centrality of a node is obtained by calculating the number of shortest paths between two nodes that pass through the focal node. The perhaps most natural way of interpreting betweenness centrality is to think of what would happen if a node high in betweenness centrality were removed from the network: that would either increase the distances between pairs of nodes or even separate them completely (if the only path between a pair of nodes passes through the focal node). This idea invites thinking of the networks as dynamic entities, and asking questions such as: “What would happen to the connectivity of the network if this node was removed?” The values of the centrality indices were standardized to ensure comparability between networks and between studies.

The stability and accuracy of the centrality indices was assessed by bootstrap analyses using the bootnet package. Epskamp, S., Borsboom, D., & Fried, E. I. (2017a). Estimating psychological networks and their accuracy: A tutorial paper. Behavior Research Methods

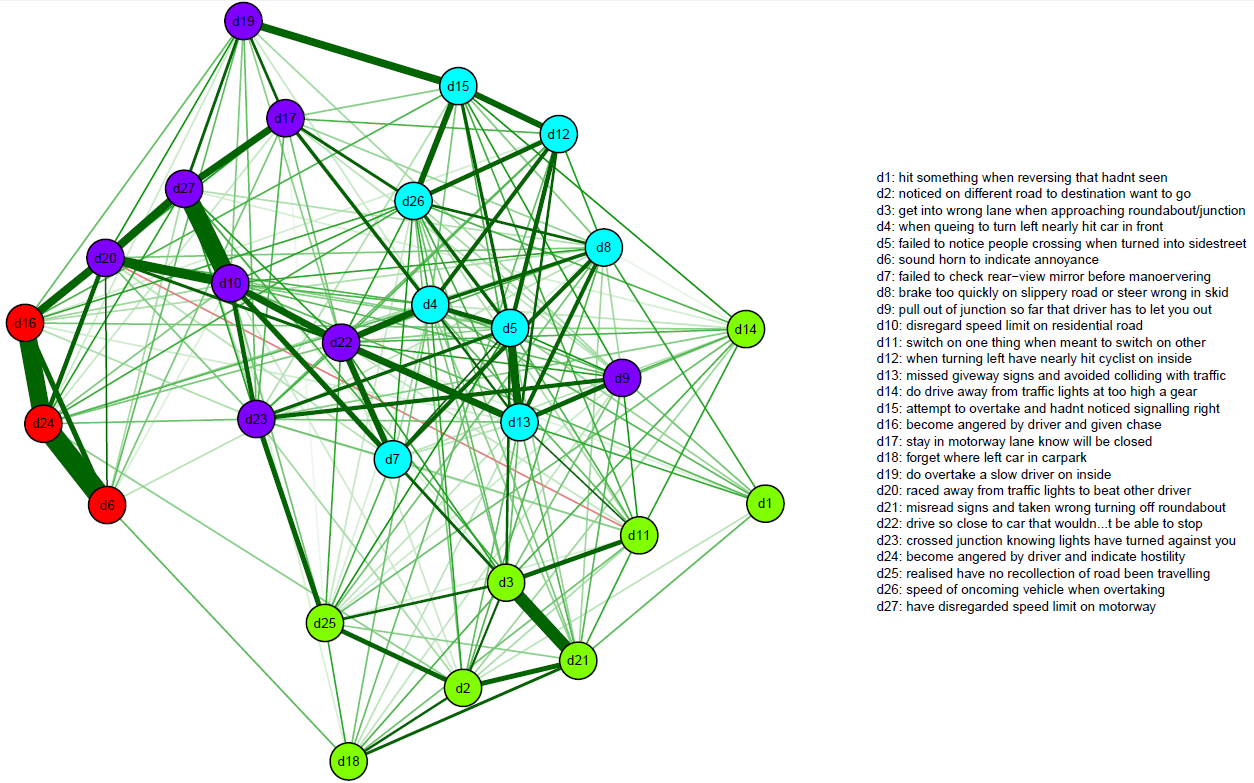
(http://dx.doi.org/10.3758/s13428-017-0862-1).

# Results

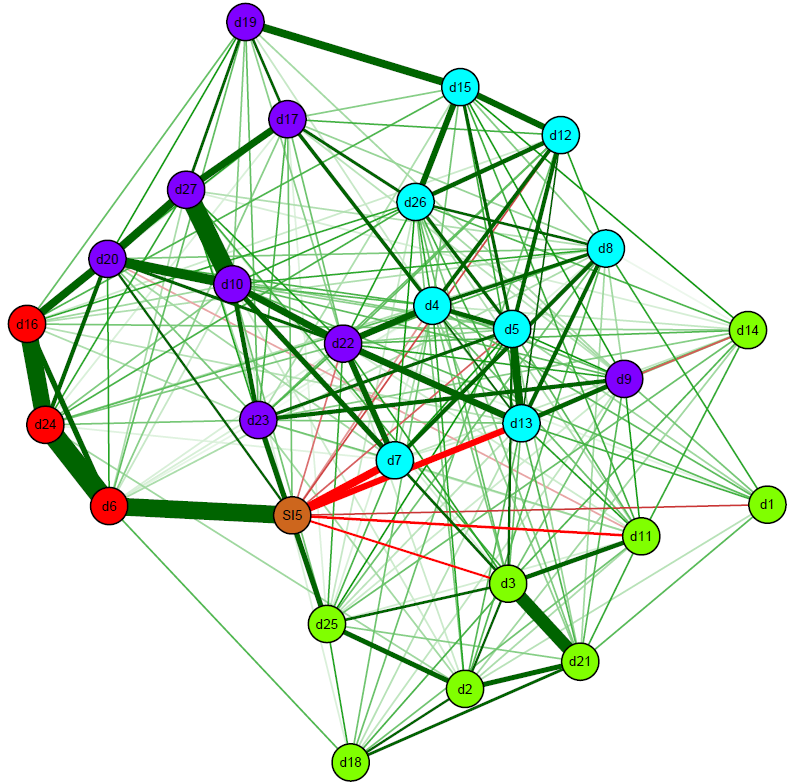


* Aggressio vaikuttaa melko yksiulotteiselta ilmiöltä
  + Kaikki yhteydessä liikennevaloista kiihdyttelyyn (20)
  + puskurissa roikkuminen (16) ja kiukustuminen (24)
  + Torvensoitto (6) yhteydessä auton paikan unohtamiseen (18) ??
* Rikkomukset ei vaikuta homogeeniselta ryhmältä:
  + Osa tiiviissä yhteydessä aggressioon: kisailu (20), punaisia päin ajaminen (23), ylinopeudetkin
  + Toisaalta suljettavalla kaistalla pysyminen (17) vähemmän yhteydessä aggressioon.
  + Lisäksi sisäpuolelta ohittelu (19), kaistalla roikkuminen (17), puskurissa roikkuminen (22) ja liikennevirtaan tunkeminen (9) yhteydessä slipsi-osioihin
    - Nämä voivat olla sellaisia, että niitä tehdään vähintäänkin osaksi vahingossa (17,22,9)
    - Toisaalta 19 on yhteydessä toiseen ohitteluitemiin (15), joten kyse voi olla ylipäätään siitä, kuinka paljon tyyppi ohittele. Tai metodivarianssista.
* Slipsien taustalla voi olla faktoreita, kausaaliselitykset ei tunnu uskottavilta
  + Tarkkaavaisuuden suuntaaminen 15, 12, 26, 5 (ei huomannut ohitettavan olevan kääntymässä, ei huomannut fillaristia, arvioi väärin vastaantulijan nopeuden, ei huomannut jalankulkijoita)

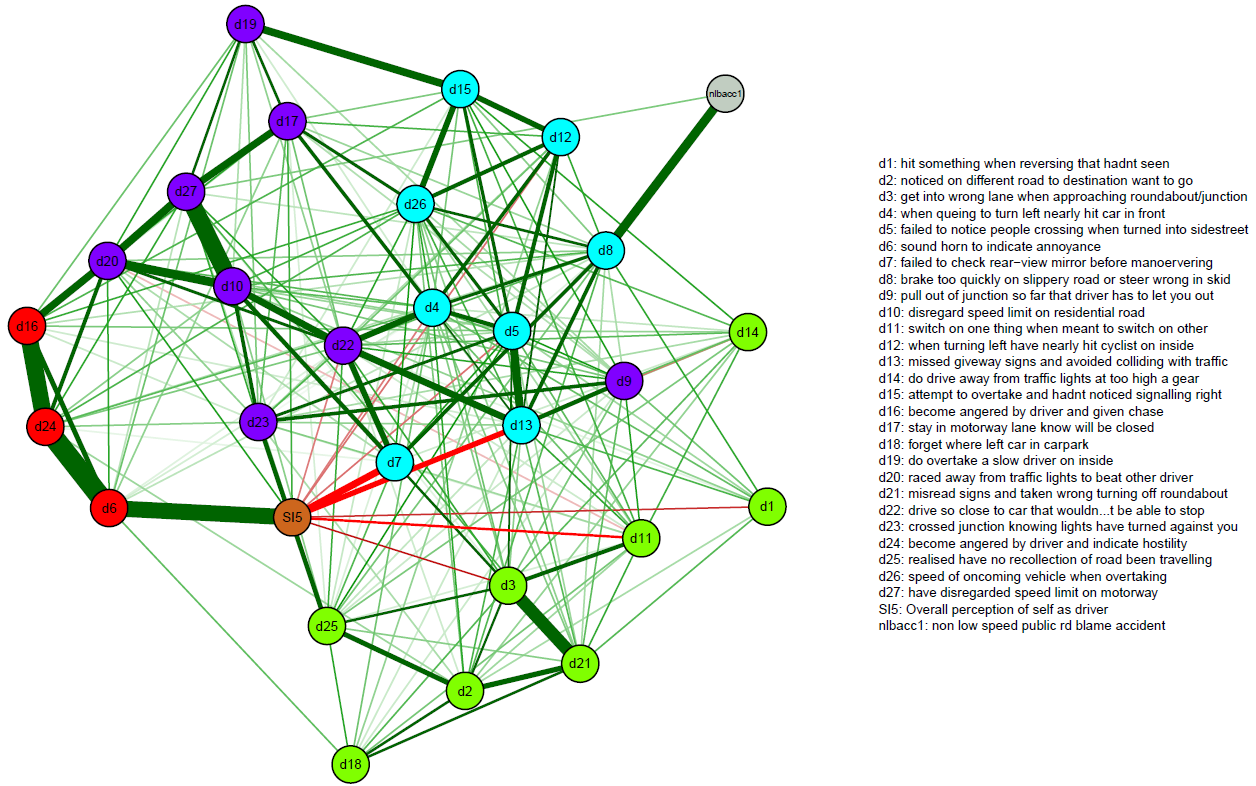
Self-image muodostuu verkoston keskeiseksi noodiksi, se välittää informaatiota muiden välillä. Torvensoitto: itsellä on taitavampana kuskina etuoikeus kulkea? Tai koska on itse taitava, on varaa kritisoida muita. Ei muistikuvaa tiestä: uppoutuu ajamiseen? Ajaa punaisia päin: tietää kuinka kauan voi. Läheltäpititilanteiden kokeminen on voimakkaimmin yhteydessä siihen, että kokee itsensä huonoksi kuskiksi. Samoin se, että unohtaa katsoa peruutuspeiliin ennen ohjaamista. Ehkä tästäkin on seurannut läheltäpititilanteita? Kontrollien kanssa sählääminen, jotain päin peruuttaminen, väärän kaistan valinta



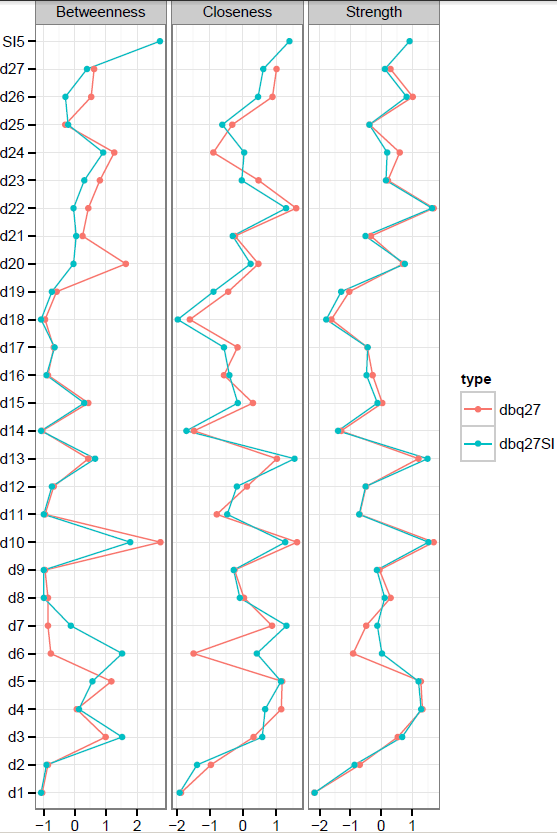
Measurement graph



Graph with self-image



Accident graph



# Discussion

DISKUSSIOON POHDINTAA SIITÄ, MITÄ MALLIIN VAIKUTTAVAT STRESSORIT VOISIVAT OLLA. Esim. aggression herääminen jonkin pienen ärsytyksen seurauksena joissain autoilijoissa tai se, miten onnettomuus tai läheltä piti –tilanne voi vaikuttaa (tai olla vaikuttamatta) käyttäytymisverkostoon (Rajalin & Summala). Se, että näin vakavat tapahtumatkaan eivät välttämättä vaikuta verkostoon, kertoo siitä kuin syvässä tottumukset istuvat.

“Changing a habit of not fulfilling promises, for example, is more likely to be difficult because to change that component, there are many others that may need to be changed as well (e.g. sympathize more with other people ’ s needs and learning to finish things)” Cramer Personality

[Different causes and effects on each node, even those specified to measure the same unobserved variable. ]

The addition of the single variable related to the driver’s self-image as a driver had a profound impact on the network. As evidenced by the extremely high values of the centrality coefficients (especially betweenness centrality), it connected forms of behavior that were otherwise unconnected, such as sounding the horn and errors related to controlling the vehicle (hitting something reversing, switching on the wrong thing etc.) or sounding the horn and attention-related errors (missing give-way signs, failing to direct attention to rear-view mirror). The causal chain might run from these driving errors and attention-related errors to self-image, with error-prone drivers perceiving themselves as worse drivers than others. In fact, missing give-way signs and avoiding a collision may well be the kind of memorable event that drivers are able to report using a self-report instrument such as the DBQ (Lajunen & Özkan kirja).

On the other hand, driver’s inflated self-image might be most naturally thought as an antecedent to aggressive behavior (d6), crossing junctions against red lights (d23), or racing from traffic lights (d20). This may be so because perceiving one’s self as better than others may lead one to think that he is entitled to certain things, such as the possibility to proceed unimpeded in traffic (sounding horn, crossing junctions against red lights and speeding). Interestingly, the item related to lack of awareness of one’s current whereabouts (item 25), also had a strong positive association with inflated self-image. If it is the case that drivers with an inflated perception of themselves are not quite aware of their surroundings, they might also be prone to committing the above-mentioned attention-related errors.

And: they may then also be more likely to report not committing the slips and attention-related errors, irrespective of whether they commit them or not. 🡪 Experiment providing information on whether people commit the behaviors that they report (or fail to report) in DBQ would be in order.

And, in fact, the direction of causation might also be from self-image toward attention-related errors, but explaining why this might be so requires introducing the concept of mindfulness in driving.

One interesting explanation for this pattern of results draws on the recent body of research related to the role of mindfulness in driving. By mindfulness, I refer to the idea of curious, dispassionate, non-judgmental, compassionate awareness directed towards one’s surroundings (Brown, Ryan & Creswell, 2007). On the other hand, perceiving oneself as better than others is by definition in conflict with the idea of paying mindful attention one’s surroundings, as it entails an essential value judgement. The concept of mindfulness is difficult to exactly define in scientific terms, as it has its roots in Buddhist philosophy in which exact definitions are not used; still, Brown et al. (2007) offer a balanced discussion on the difficult subject.

One characteristic of the mindful state that is especially relevant for traffic behavior is the clear awareness of one’s surroundings, thoughts, emotions and perceptions at a given moment. This can be contrasted with “mindlessness” (Abdul Hanan, King & Lewis, 2011), which the authors define as lack of attention or concern for one’s behavior or its’ outcome. The authors give the example of driving on a familiar route and not recalling anything about the journey upon arrival. Interestingly, the present results show that this is one of the behaviors associated with an inflated image of self as a driver.

Another idea central to mindfulness is the intent of perceiving the self, other people and the world at large as they are, in a non-conceptual manner, and to avoid judging one’s self, other people or events as inherently good or bad. In a word, this type of open-mindedness can be described as an “empirical stance toward reality” in which judgment is deferred until the relevant facts are known (Brown et al., 2007). I do not wish to tackle the difficult philosophical questions related to the possibility of non-conceptual perception in this context, but rather to suggest that the concept of mindfulness might offer promise in forming a unifying framework for explaining the present findings: perceiving oneself as better than others entails the idea of judging others to be in some sense worse in comparison to oneself, and judgments such as these might lead one to behave aggressively toward others, as seen in the present study.

Finally, similar ideas have been recently framed using concepts from academic cognitive psychology in the study by Lennon and Watson (2015). The authors found that driver’s attributional style was related to their level of driving-related anger. By this they mean that perceiving other drivers as unskilled, dangerous or intentionally lead to the driver himself responding in an aggressive manner. On the other hand, remaining open to the interpretation that others’ irritating driving behavior might be due to them lacking necessary skills or them not realizing they are behaving in an irritating manner was associated with lower levels of angry responses by the driver himself. This type of non-judgmental awareness that remains open to different interpretations is a hallmark of mindfulness, even though the ideas were described using different concepts in the study. The results naturally lead to asking: “Which kinds of interventions might lead to lower levels of driving anger?” The question is at least partly answered in the study of Deffenbacher (2015) in which he compares mindfulness-based interventions with those based on ideas from cognitive and behavioral therapy. He concludes that the interventions are mostly deemed equally effective, with some evidence (of regrettably low methodological quality) favoring mindfulness-based interventions.

In summary, then, I offer the tentative interpretation for the present results related to drivers’ view of themselves as better than others as being related to their lack of mindful attention to the driving task. This interpretation would explain the negative association between self-image and attention-related errors, the positive association between self-image and lack of awareness of one’s immediate surroundings, and, importantly, the strong positive association between self-image and aggressive behavior.

# Notes to self

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Complexity scores from FA (no of factors needed).

Encourages thinking of the dynamics of the network: how to influence the individual behaviors, that’s what’s central to traffic safety after all.

Yksittäiseen noodiin vaikuttaminen 🡪 muutokset muissa; vain verkostomallissa.

Tiiviisti konnektoitu malli: pienillä muutoksilla on suuret vaikutukset (anopin soitto depressiomallissa); harvasti konnektoitu: vain isoilla muutoksilla on vaikutusta.

Latenttien muuttujein alaan kuuluvat ilmiöt heterogeenisia, kukaan ei tee kaikkia näitä juttuja, ja yksittäiset käyttäytymiset ovat lainmukaisissa (?) suhteissa toisiinsa muodostane klustereita.

Verkostoanalyysin puutteet: samoin kuin CFAt, nekin voivat kärsiä mtitausainvarianssin puutteesta: ehkä kaikki otoksen henkilöt eivät koe samalla tavalla asioiden yhteyskisä, ja ne voivat välittyä useiden kausaalisten polkujen kautta, kuten Mattsson (2012) esittää. Verkoston tilastollienn sopivuus aineistoon on myös toistaiseksi avoin kysymys (Fried depression article).

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Mahdollisesti diskussioon:

Itsearviointi-instrumenttien käyttö deindividuaation ja ajokäyttäytymisen tarkastelussa?

“Anonymity, diffused responsibility, group activity, altered temporal perspective, emotional arousal, and sensory overload are some of the input variables that can generate deindividuated reactions,” he says in the International Encyclopedia of Psychiatry, Psychology, Psychoanalysis, and Neurology. Sano Zimabardo

Itsearviointimenetelmien hyödyllisyys nimenomaan kuljettajien itsereflektiokyvyn lisääjinä

DBQ:n päivityksessä voisi olla hyvä kysyä:

* erilaisista emootioista (positive behaviors scale on jo kokeiltukin)
* uskomuksista (tyyliin pyöräilijät ovat maanvaiva) ja tarkastella niiden yhteyksiä pyöräilijöiden havaitsemiseen
* habits: mikä pitää tottumukset elossa
* asenteista
* Mihin pitäisi keskittyä? Mitä uutta tietoa kuljettajan käyttäytymisen tutkiminen voi edes tuottaa? Kaikki tekevät harmittomia virheitä, joo, mutta lähes kukaan ei joudu kolareihin. Pitäisikö keskittyä ”on social delinquents”
* Laajemmat yhteydet yhteiskuntaan? Pyöräily ja käveleminen on hyväksi ihmiselle?
* It is questionable whether self-report research produces information relevant to accident prevention, and whether it produces information on anything we did not know already (ref RUOTSI)
  + Perhaps self-report research should focus on investigating why people spend so much time stuck in traffic jams, which is bad for their own health and for the environment (<https://www.psychologytoday.com/blog/minding-the-body/201509/how-stress-less-in-traffic-jam>)
* Being easily bored should be an item: it leads to distraction (the driver chooses to attend to something else than the road)
  + Autoihin sisäänrakennetaan lisää ja lisää distraktioita ([https://s3.amazonaws.com/academia.edu.documents/40554420/Human\_Factors\_Engineering\_and\_Ergonomics\_-\_A\_Systems\_Approach\_2nd\_ed\_-\_Stephen\_J.\_Guastello\_CRC\_\_2014.pdf?AWSAccessKeyId=AKIAIWOWYYGZ2Y53UL3A&Expires=1512151321&Signature=F3MeiQmhGHiEf1kdz9rvIMk40%2F0%3D&response-content-disposition=inline%3B%20filename%3DHuman\_Factors\_Engineering\_and\_Ergonomics.pdf](https://s3.amazonaws.com/academia.edu.documents/40554420/Human_Factors_Engineering_and_Ergonomics_-_A_Systems_Approach_2nd_ed_-_Stephen_J._Guastello_CRC__2014.pdf?AWSAccessKeyId=AKIAIWOWYYGZ2Y53UL3A&Expires=1512151321&Signature=F3MeiQmhGHiEf1kdz9rvIMk40%2F)) Kirjan luku 14.

Itsearviointien validiteetti: Sen sijaan että lasketaan monimutkaisia validiteetti-indeksejä esim. discriminant validity / concurrent validity, voisi vain laskea korrelaation raportoidun käyttäytymisen ja todellisen käyttäytymisen väliltä:

When thinking of whether the behaviors included in the DBQ correlate with real-world driving behaviors, it is of interest to examine the results of an earlier traffic behavior study (West et al., 1993). The authors examined correlations between self-reported behaviors and those actually observed and noted that self-reported speeding and that actually observed correlated strongly (the correlation was in the order of magnitude of .6). Even though the study did not employ the DBQ specifically, the result increases confidence in the ability of drivers to report at least some aspects of their traffic behavior realistically.

A further result from the Zhao et al. (2012) study pertains to thinking of the nature of the assumed latent DBQ variables. Interestingly, the authors proposed that high lapse scores reflect the drivers paying too little attention to the driving task and / or trouble when performing a dual tasks while driving. Reason et al. (1990) originally intended slips to measure facets of attention to driving, so if the interpretation given by Zhao et al. (2012) is correct, the items related to lapses rather than slips would be those reflect the functioning of attentional processes. Of course, accepting the previously-mentioned multicausal perspective that comes naturally with the network perspective is relevant in this context as well.

Selityksiä havainnoille: Considering the causal psychological mechanisms that have been posited to have effects on the various DBQ items, it is of interest to summarize findings from still some more previous studies. Åberg & Rimmö (REF) put forward the idea of “some slips and lapses” being related to the driver’s amount of experience, because the frequency of committing these presumably depends on how fully automatized the behaviors are. On the other hand, they mentioned a different subset of slips that might be related to the amount of top-down attention the driver has directed at the task at hand, and that the consequences of not doing so might be catastrophic. In their view there are attention-related slips that increase with age and experience. A subset of the items assumed to measure slips in the presently-used 27-item version of the DBQ are the ones that loaded on the factor of inattention errors in the study of Åberg and Rimmö. Because of this, it is likely that some of the items (such as misreading signs, taking the wrong route) share variation due to a common cognitive process (the amount of top-down attention directed at the driving task) influencing them.

Finally, the postulated latent variables thought to underlie the DBQ responses were originally defined at such a high level of abstraction that common causal pathways to all behaviors thought to fall under a particular factor would have been unlikely to be found. The definition of violations was already discussed above. The ideas in themselves were reasonable, the level of abstraction was just too high. For instance, the conceptual framework for thinking about attention-related errors presented in Trick (ref) might be of the correct level of granularity for analyzing the phenomenon of attention in traffic. Similarly, different time scales of the behaviors should be taken into account, because different types of cognitive processes are at play when planning the trip and when performing the individual, highly automatized driving behaviors. These issues are discussed at length in Mattsson (2012) and Mattsson (2014). In this context it is worthwhile to remember the simple observation made by Lajunen & Parker (2001): Aggressive driver behavior is a complex phenomenon with a range of psychological causes. Similarly, the other driver behaviors probed in the DBQ are likely to be caused by many sorts of different processes, psychological and otherwise, and to be in complex relationships with one another.

1. Quotation marks are used because most of the behaviors described in the DBQ are not at all uncommon or deviant: the word “aberrant” conveys a moralistic sense that is foreign to science. [↑](#footnote-ref-1)
2. Reason et al. considered principal component analysis as a form of factor analysis. [↑](#footnote-ref-2)
3. Not that researchers would not have tried, REF. [↑](#footnote-ref-3)