A new perspective on the role of attitudes in explaining travel behavior: A psychological network model

Maarten Kroesen⁎, Caspar Chorus

Delft University of Technology, Faculty of Technology, Policy and Management, P.O. Box 5015, 2600 GA Delft, the Netherlands

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ABSTRACT

Psychological factors are generally thought to play an important role in the prediction of individual variations in travel behavior and travel related choices. To assess their effects in statistical models, three assumptions are typically made, namely: (1) the psychological factors influence behavior/choices and not vice versa, (2) psychological factors can be conceptualized as latent variables measured by observed indicators and (3) estimated between-person relationships are indicative of within-person relationships. Recent research has shown that each of these assumptions is conceptually and empirically problematic. This paper introduces to the field of travel behavior research an alternative modeling approach which has its roots in the emerging field of Network Psychometrics. This so-called psychological network model avoids the above mentioned problematic assumptions, by modeling the relationships between attitudinal and behavioral indicators as dynamic causal systems which can be operationalized as a network. We illustrate the new insights that may be gained from this approach in a travel behavior context. In particular, we estimate between-person and within-person network models using data from a (two-wave) panel survey containing indicators regarding travel modality use and related attitudes. Our results indicate that the extent to which the use of a mode is considered convenient is most strongly connected to the actual use of the corresponding mode, and that the convenience of using the car takes a central position in the attitude-behavior network. At the within-person level, no strong connections between attitudes and behaviors seem to exist. This latter finding serves as a warning against the practice, embodied in many popular travel behavior models, of interpreting associations between attitudes and (travel) behaviors as causal within-person relations.

1. Introduction

It is generally believed that psychological factors (attitudes and perceptions) play an important role in explaining individual differences in travel behavior and travel-related choices. For example, they figure prominently in social-psychological theories, such as the Theory of Planned Behavior (Ajzen, 1991) which has been used extensively to explain individual variations in travel behavior (Bamberg, 2006; Bamberg et al., 2003; de Groot and Steg, 2007; Heath and Gifford, 2002). Furthermore, an increasingly popular strand of econometric –so called Hybrid Choice– models includes psychological factors into the utility functions of the considered alternatives. In short, these psychological factors are presumed to capture the inner workings of the behavioral decision process, leading to a more behaviorally realistic representation thereof (Ben-Akiva et al., 2002; Walker and Ben-Akiva, 2002; Vij and Walker, 2016).

⁎ Corresponding author.

E-mail addresses: m.kroesen@tudelft.nl (M. Kroesen), c.g.chorus@tudelft.nl (C. Chorus).

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Typically, the models of travel behavior described above are estimated using data from cross-sectional surveys, the psychological factors being conceptualized as latent variables and operationalized using multi-item scales. To test the resulting measurement structure a confirmatory factor model is usually estimated. Once the validity of the measurement model is established, the structural model is estimated, which specifies the relationships between the assumed psychological factors and the travel choices/behavior(s) under investigation. (Note that these two estimation steps can also be executed jointly.)

Usually, the psychological factors are found to explain large portions of the variance resulting from individual differences in behavioral outcomes (in social-psychological models) and to help predict choices over and above the influences of the included objective attributes of alternatives (in hybrid choice models). As such, the results of the analyses are often used to inform ‘soft’ transport policies which are focused on altering the psychological factors such that they influence behavior in desirable directions. However, the estimated models and the validity of the conclusions derived from them rest on three crucial assumptions: (1) the psychological factors influence behavior and not vice versa (i.e., the relationships are unidirectional); (2) psychological factors which are conceptualized as latent variables represent ‘common causes’ underlying (sets of) observed indicators; and (3) the estimated between-person relationships (i.e., between psychological factors and behaviors) are similar to and thereby indicative of within-person relationships. As will be discussed in the next section, these three assumptions are increasingly regarded as problematic, both from a conceptual and an empirical point of view.

Driven (at least partly) by the desire to address these assumptions, the field of network psychometrics has been developing, which, broadly speaking, provides a less theory-driven, but more exploratory and dynamic approach to understanding the relationships between (items of) psychological factors and behaviors. In this research we aim to introduce the field of network psychometrics to the field of travel behavior research and to show its potential to provide an understanding of attitudes and choices that does not rest on the above-mentioned overly restrictive and problematic assumptions. In particular, to illustrate the potential new insights to be gained, we estimate psychological network models at the between-person as well as at the within-person level, using both behavioral outcomes reflecting the use of three modes (public transport, the car and bicycle) and psychological items reflecting the corresponding attitudes towards the use of these modes. Data to estimate the resulting networks are obtained from a large representative sample of Dutch adults who completed a mobility survey in both 2013 and 2014 (N = 1376).\(^1\) Before presenting these models (Section 3) and the results that are obtained on our dataset (Section 4), the following section will first discuss in more detail the problematic assumptions of existing social psychological models and provide an introduction to the field of network psychometrics.

### 2. Assumptions embedded in current models of travel behavior

#### 2.1. The direction of causation

In general, hybrid choice models as well as (structural equation) models inspired by social-psychological theories assume that the latent psychological factors –mostly attitudes and perceptions– influence behavior and not vice versa. Yet, there are good reasons to believe that reverse effects may exist in real-life behavioral processes. For example, based on the experiences gained during the use of a mode, certain attitudes or perceptions may be updated. Or, a person may post-hoc rationalize the decision of using a certain mode and therefore alter a psychological factor. And thirdly, based on the theory of cognitive dissonance (Festinger, 1962), which posits that any dissonance between behavior and certain psychological factor may be resolved by either changing the behavior or the psychological factor, one can expect effects from psychological factors to behavior as well as vice versa.

Early research in the domain of travel behavior (Tardiff, 1977; Tischer and Phillips, 1979) as well as more recent empirical studies using panel data (Thøgersen, 2006; Kroesen et al., 2017; Kroesen and Chorus, 2018) show that the respective relationships between the attitudes toward the use of a mode and the actual use of that mode are indeed bidirectional; i.e. attitudes influence (future) behavior, but behavior also influences (future) attitudes. This means that the assumption of unidirectional causation embodied in many travel behavior models is overly strict and misleading and that, if the goal is to better understand how psychological variables interact with travel behavior, it is necessary to relax it.

#### 2.2. Psychological factors as latent common causes

An assumption which is typically not reflected upon in travel behavior research, but which is increasingly under attack in general psychological research, is the ‘common cause’ model of psychological factors. This model presumes that a psychological factor represents the latent cause behind –and thereby constitutes the (only) source of co-variation among– the set of observed indicators used to measure the factor. Related to this notion is the so-called local independence assumption, which states that, conditional on the latent variable, the residual associations between the indicators are zero (i.e., non-significant).

In many empirical applications, however, residual associations between indicators remain after controlling for the latent variable, which likely originate from direct causal paths between the indicators. A compelling example provided by Borsboom and Cramer (2013) relates to the construct of depression. Amongst others, typical items of scales to measure this latent construct consist of aspects such as ‘insomnia’, ‘fatigue’ and ‘concentration problems’. It seems obvious here that, irrespective of a person’s latent level of depression, there is also a direct causal chain linking these ‘symptoms’; i.e. someone who sleeps poorly will be more fatigued and will likely experience concentration problems (Borsboom and Cramer, 2013). In a similar fashion, direct causal pathways may exist with

\(^1\)The used data are freely available to academic researchers (http://www.lissdata.nl/).
respect to items of attitudinal factors related to travel behavior; for example, someone who believes cycling is relaxing is likely to experience cycling as pleasant, simply because that person enjoys activities that are relaxing. In such cases, there is no benefit or need associated with invoking the presence of a latent variable like an ‘attitude toward cycling’ to account for any empirical association between items.

In addition to this empirical critique leveled by psychologists at the local independence assumption, the conceptualization of psychological factors as underlying common causes of sets of observed items has also been criticized on fundamental theoretical grounds. The heart of that theoretical critique relates to the notion that for the common cause model to hold, the cause (i.e., the latent psychological factor) must be separately identifiable from the observed effects (i.e., the scores on the indicators), which is a straightforward but crucial condition for establishing a causal relationship. As argued by Borsboom and Cramer (2013), this assumption behind the common cause model does make sense for medical (biological) diseases; for example, a person suffering from a viral infectious disease (e.g., a cold) may experience both coughing and run a fever. These symptoms are separately identifiable from the cause (i.e., the infection), in the sense that the symptoms can be observed directly, but also in the sense that one may imagine a medical test to detect the infection directly. In principle, the cause may also be present without the symptoms being present and the symptoms could exist due to other causes. Moreover, physical (biological) causal mechanisms may be identified linking the cause to its symptoms.

However, the ‘common cause’ model has also been applied to psychological disorders like depression and to psychological factors in general. On the surface, this makes sense; since the symptoms of depression empirically cluster together, it indeed seems logical to assume that—similar to medical diseases—there is an underlying root cause (depression). In this case, however, the cause ‘depression’ cannot be separately identified from its symptoms. For example, there is no medical test to directly assess a person’s level of depression. Moreover, it is very difficult to imagine situations where the cause (depression) is present, but the symptoms (e.g. a high score on the statement ‘I feel blue’) are not, or vice versa. And finally, it is hard to imagine—let alone detect— the psychological causal mechanisms through which depression supposedly causes its symptoms. In short, the cause (depression) cannot be separately identified from its symptoms, instead the symptoms ‘make up’ or constitute the depression (Borsboom and Cramer, 2013).

This analogy similarly applies to (travel related) psychological factors. For example, there is no test to directly measure a factor like the ‘attitude towards cycling’. Moreover, it is difficult to imagine a person having a positive attitude towards cycling who at the same does not enjoy cycling and/or find it relaxing (or vice versa). And here as well, it would difficult, if not impossible, to identify any psychological causal mechanisms through which the ‘attitude towards cycling’ (as a separate psychological entity) affects its indicators. Hence, similar to psychological disorders, the items directly make up or constitute the psychological factor; as such, separately invoking the presence of underlying psychological factors does not seem to make much sense.

It should be noted finally that the critique on the ‘common cause’ assumption is related yet distinct from the discussion regarding general and specific attitudes in the travel behavior literature (De Vos, 2018; Kroesen and Chorus, 2018). For example, De Vos (2018) and also the authors of the present paper (Kroesen et al., 2017) make a case for measuring specific attitudes towards various modes, but do not question the aggregation of such (specific) attitudes in a single overall score. This step implicitly assumes there is a latent factor underlying/causing the individual scores, i.e. an overall (specific) attitude towards a mode.

2.3. The equivalence of between-person and within-person relationships

Thirdly, since models of travel behavior generally rely on cross-sectional data, the implicit assumption is made by modelers that estimated between-person relationships reflect those at the within-person level (Chorus & Kroesen, 2014). While this assumption might seem reasonable initially, compelling examples illustrate that it may not be realistic. One such example is provided by Hamaker (2012) who considers the relationship between typing speed (i.e., the number of words typed per minute) and the percentage of typos being made. Cross-sectionally (i.e., at the between-person level) a negative relationship will likely be found; more experienced typists type faster and make fewer mistakes. Yet, this result does not hold at the within-person level, i.e. if any particular person would be forced to type faster than he/she is normally used to, that person would be actually expected to make more mistakes, not less. Hence, the relationship at the within-person level may be different from and, in this example, even be opposite to, the relationship at the between-person level. Similar examples have been provided by other authors, for example, considering the relation between general intelligence (IQ) and alcohol use (Kievit et al., 2013).

Linking the above discussion to travel behavior and its relationship with psychological factors, it becomes clear that insofar psychological factors indeed cause behavior, their influences reflect individual psychological processes and therefore operate at the within-person level by definition. Hence, ideally these effects should also be estimated at this level. Of course, the fact that relationships may potentially differ at the within and between-person level, does not automatically mean that this will always be the case in all travel behavior contexts and for all relevant psychological factors. But since most of the models estimated in the field are based on cross-sectional data, it is simply unknown if the interpretation of effects at the within-person level is justified or not. And even in those cases where panel data have been used, the estimated models do not necessarily separate within- and between-person effects. For example, the studies of Thøgersen (2006) and Kroesen et al. (2017) were based on panel data, but the estimated (cross-lagged) panel models did not separate between- and within person co-variation. For this distinction to be made, other (more sophisticated) models have to be estimated, such as those recently developed by Hamaker et al. (2015) and Allison et al. (2017); but these models require more than two waves of data collection.
2.4. Network psychometrics

As mentioned in the introduction, the field of network psychometrics, initially pioneered by Borsboom and Cramer (2013) and Schmittmann et al. (2013), has been developing as a way to relax the problematic assumptions described above. While the approach is centered around providing an alternative to the ‘common cause’ model of psychological factors, it also avoids the first and third assumption.

In essence, instead of invoking the presence of latent variables, the psychological network approach assumes that the items of a psychological factor function as autonomous entities which causally influence each other within a (dynamic) system that can be formalized as a network consisting of nodes (i.e., the items) and edges (i.e., the causal relations between the items). Hence, the items are no longer conceived of as ‘passive’ indicators of certain latent common causes, but as ‘active’ causal entities functioning autonomously within the system. By implication, the research aim then shifts from revealing the latent psychological factors (and subsequently their relations to behavior) towards discovering the structure of the psychological network and the role of each item within that network.

The concepts behind the psychological network approach have initially been developed in the field of psychopathology to better understand the structure of mental diseases. In this context, for example, it has provided a new perspective on the concept of comorbidity. This concept relates to the phenomenon that certain mental disorders are empirically linked to one another, for example, general anxiety disorder and major depression. While the lack of separability poses a problem in the latent variable approach (as indicators cannot uniquely be linked to distinct factors) this issue can be handled and understood within the network approach, by explicitly acknowledging that the boundaries between mental constructs are partly overlapping. Any symptoms that are related to both networks (i.e., disorders) may then be labelled and understood as ‘bridge symptoms’, capturing pathways that empirically connect different mental disorders.

In addition to psychopathology the network approach has been successfully applied to various other (psychological) fields, for example, cognitive development (Van Der Maas et al., 2017), substance abuse (Rhemtulla et al., 2016), personality psychology (e.g., Costantini et al., 2015), health-related Quality of Life (Kossakowski et al., 2016), and attitude research (Dalege et al., 2016). The final application domain is most strongly linked to the present study and will be discussed briefly in the following.

Dalege et al. (2016) have proposed the so-called Causal Attitude Network (CAN) model, which posits that people generally try to achieve cognitive consistency, but also have a desire to maintain accurate beliefs. The presence of such a trade-off implies, Dalege et al. (2016) suggest, that attitude networks show clustering, meaning that different sets of items will be highly interconnected internally, but will have weak connections with items of other clusters. While the notion that people make trade-offs between the degree of cognitive consistency and belief accuracy may seem a bit bold initially, it makes intuitive sense upon closer inspection, especially when considering the two extremes. That is, if people would only strive towards having consistent beliefs/feelings all evaluative reactions should be perfectly aligned. In such a world it would be impossible for a person who is generally positive towards a certain object (or behavior) to believe or feel anything negative with respect to the object (or behavior), which seems quite unlikely. Alternatively, if a person would only strive towards having accurate beliefs this may lead to many unaligned evaluative reactions. It seems unlikely that people would maintain multiple conflicting positions over prolonged periods of time. To conclude, the cognitive consistency / accuracy trade-off does appear theoretically plausible. Yet, empirical evidence in favour of this notion is still scarce. The present study aims to make a contribution in this respect, besides its core contribution which is to introduce the psychological network modeling approach to the field of travel behavior research and show its potential to analyze and understand attitude-behavior relations.

2.5. Estimating psychological networks

As stated above, the general aim of network psychometrics is to discover the structure of a psychological network and the role of individual items within that network. Depending on the available data, different types of models exist to estimate and reveal psychological networks. When only cross-sectional data are available, the most popular method is the undirected network based on partial correlation coefficients (Schmittmann et al., 2013). Whereas directed networks (i.e. path models) are typically difficult to identify because models with different structures (parameters) may lead to equal model fit, undirected networks have the advantage that they are well identified and easily parameterized by using partial correlation coefficients. The underlying idea behind the use of partial correlations is that, while controlling for all other indicators in the network, these correlations provide the strongest empirical evidence possible, of a causal effect between any two indicators (in either direction or in both directions).

While cross-sectional data only allows estimation of undirected networks that capture between-person relationships, panel data containing multiple observations from the same individuals over time allow the researcher to estimate directed networks and to separate between-person from within-person co-variation. With respect to the latter benefit, a straightforward way to estimate a within-person network is by calculating (for each person and for each wave) deviation scores from the individual means (which then function as fixed effects) (Ep skamp et al., 2018b). Based on these deviation scores, a within-person network can subsequently be estimated using the same method as is used for cross-sectional data, i.e. using partial correlation coefficients. The associations within this network then represent within-person contemporaneous relationships; they show whether, at the individual level, an increase in one item (compared to the expected score for that person) is associated with an increase or decrease in another item. In principle, this estimation procedure described above can already be applied when as few as two waves of panel data are available.

With panel data it is also possible to estimate (lagged) directional relationships, for example, by estimating a vector autoregressive (VAR) model. Basically, in this model, each variable at a certain moment in time is predicted by itself and all other variables in the
network at a previous moment in time; this results in a set of autoregressive and cross-lagged parameters, which can be used to visualize a temporal directional psychological network. This model can also be extended to a so-called Graphical VAR model (Wild et al., 2010; Epskamp et al., 2018b), in which the error structure of the VAR model is again modelled using a network of partial correlation coefficients leading, in turn, to an undirected contemporaneous (between-person) network in addition to the temporal directed network. Another extension, proposed by Bringmann et al. (2013), is the multi-level VAR model, in which a random effect is included for each parameter of the VAR model. Hence, this model is able to separate within-person from between-person influences, and simultaneously assesses the direction of causation over time between items in the network. However, this latter procedure requires many observations per individual.

In the present application we will estimate an undirected between-person network based on cross-sectional data and an undirected within-person network based on deviation scores from the mean. Hence, the empirical application will not address the assumption of unidirectional causation. The reason is that we already addressed this assumption in earlier work using the same data (Kroesen et al., 2017).

3. Method

3.1. Data and measures

To illustrate the network approach, data are used from a mobility survey which has been administrated twice (in July 2013 and July 2014) to the Longitudinal Internet Studies for the Social (LISI) sciences panel. In total, 1376 respondents completed both surveys and are considered in the present analysis. As mentioned above, the data have previously been used to study the (lagged) bidirectional relationships between mode-related attitudes and behaviors. Similar to that study three modes will be considered here, namely car (as driver), public transport and bicycle. The sample distributions of the socio-demographic characteristics were found to correspond well with population distributions obtained from the central statistics agency in the Netherlands. For details related to these descriptive statistics we refer to Kroesen et al. (2017). In the following, we briefly re-iterate the operationalizations of the behavioral and attitudinal variables.

To assess people's travel behavior, the following open question was formulated: ‘how many kilometers do you travel (approximately) in a regular week, using the following modes of transport?’. It should be noted that this open-answer question may be affected by (random) measurement errors (especially related to car use). Yet we considered it the most efficient and parsimonious way to capture the relative amount of travel by each mode. Since the network model can only be based on one type of correlation matrix the decision was made to recode the travel behavior variables into 5-point ordinal scales. With respect to car and bicycle use thresholds were chosen that divided the sample into five more or less equally sized categories. For public transport use this was not feasible since a large portion did not use this mode at all. For this mode, we therefore chose the same thresholds as for the car.

In line with the recommendation of Ajzen and Fishbein (1977), the attitudes were operationalized to correspond one-on-one with the considered behaviors. Hence, we measured respondents' specific attitudes towards driving the car, cycling and using public transport. For each mode, six items were measured on 5-point scales ranging from 1 (totally disagree) to 5 (totally agree).

1. [Driving by car / Using PT / Cycling] is convenient
2. [Driving by car / Using PT / Cycling] is relaxing
3. [Driving by car / Using PT / Cycling] is fun
4. [Driving by car / Using PT / Cycling] is healthy
5. [Driving by car / Using PT / Cycling] is safe
6. [Driving by car / Using PT / Cycling] is environmental friendly

The items were formulated such that they cover the most important motivations for using the different modes, covering both instrumental aspects (items 1, 4, 5 and 6) and affective ones (items 2 and 3) (Anable & Gatersleben, 2005). In previous research, both types of motivations have been found to correlate with behavioral outcomes (Anable & Gatersleben, 2005; Steg et al., 2001; Steg, 2005; De Vos, 2018).

Table 1 presents an overview of the descriptive statistics of the travel behavior variables and the attitudinal items in the first wave (2013). Before moving on the results it is relevant to note that in our previous analysis of these data (Kroesen et al., 2017), the 6 items loaded uniquely on a respective latent variable for that mode, which could be labelled as the attitude towards the use of that mode. Here, in line with the network approach, we no longer assume that such latent variables exist but that the attitudinal items, along with behavioral ones, exert influences on each other within a causal system.

3.2. Network model estimation

The between-person and within-person network with 21 nodes (i.e., 3 mode use variables plus 3*6 attitudinal variables) were estimated using the EBIC graphical LASSO procedure (Foygel and Drton, 2010). The applied LASSO regularization is aimed at limiting the number of spurious edges, resulting in a more parsimonious network. The between-person network was based on the
cross-sectional data of the first wave (2013). For the within-person network we applied the procedure described above, i.e. calculating (for each wave) the deviation scores from the individual means. The network models were estimated using JASP (version 0.10.2).

Since the data are all ordinal, polychoric correlations were used as input. The resulting edge weight matrix can be used to visualize the network. This was done by the Fruchterman–Reingold algorithm that places nodes (indicators) with stronger and/or more connections closer together and the most central nodes into the center (Epskamp et al., 2018a).

Following the principles of network theory, an additional way to interpret the role of individual items in the network is by calculating centrality indices, which indicate the centrality of a node in the network. For weighted networks (including psychological networks) Opsahl et al. (2010) have specifically developed the metrics of node strength, closeness and betweenness. Node strength (also called degree) is equal to the sum of absolute partial correlation coefficients between the respective node and all other nodes, betweenness is equal to the number of the shortest paths between two nodes that go through the node in question and closeness is equal to the inverse of the sum of all the shortest paths between one node and all other nodes. It should be noted that these centrality indices are also used in certain transport studies (e.g., studies analyzing airline networks like Wang et al., 2011), but (up till now) not in travel behavior studies.

It should be noted that there is some debate on the suitability of different measures to interpret the centrality of an item within a psychological network. In particular, Bringmann et al. (2018) argue that the use of the closeness and betweenness index stand on conceptually weak ground. The authors do consider node strength to be an appropriate measure though. In a simulation experiment, the measure of strength was also found to be more stable compared to the measures of closeness and betweenness (Epskamp et al., 2018a). Nevertheless, for the sake of comparison we choose to calculate and report all three measures.

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Table 1
Descriptive statistics of mode use and attitudes in wave 1 (N = 1376).

<table>
<thead>
<tr>
<th>Mode use</th>
<th>Car</th>
<th>%</th>
<th>Public transport</th>
<th>%</th>
<th>Bicycle</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Distance travelled in a regular week (kilometer)</td>
<td>0</td>
<td>21</td>
<td>0</td>
<td>77</td>
<td>0</td>
<td>19</td>
</tr>
<tr>
<td>1–20</td>
<td>16</td>
<td>1–20</td>
<td>9</td>
<td>1–10</td>
<td>29</td>
<td></td>
</tr>
<tr>
<td>21–50</td>
<td>15</td>
<td>21–50</td>
<td>4</td>
<td>11–20</td>
<td>15</td>
<td></td>
</tr>
<tr>
<td>51–200</td>
<td>27</td>
<td>51–200</td>
<td>6</td>
<td>21–40</td>
<td>16</td>
<td></td>
</tr>
<tr>
<td>&gt;200</td>
<td>21</td>
<td>&gt;200</td>
<td>4</td>
<td>&gt;40</td>
<td>21</td>
<td></td>
</tr>
<tr>
<td>Attitudes towards mode use</td>
<td>mean</td>
<td>SD</td>
<td>mean</td>
<td>SD</td>
<td>mean</td>
<td>SD</td>
</tr>
<tr>
<td>1. [Driving by car / Using PT / Cycling] is convenient</td>
<td>4.3</td>
<td>1.0</td>
<td>2.9</td>
<td>1.3</td>
<td>4.4</td>
<td>1.0</td>
</tr>
<tr>
<td>2. [Driving by car / Using PT / Cycling] is relaxing</td>
<td>3.5</td>
<td>1.1</td>
<td>3.0</td>
<td>1.2</td>
<td>4.3</td>
<td>0.9</td>
</tr>
<tr>
<td>3. [Driving by car / Using PT / Cycling] is fun</td>
<td>3.8</td>
<td>1.0</td>
<td>2.8</td>
<td>1.1</td>
<td>4.3</td>
<td>1.0</td>
</tr>
<tr>
<td>4. [Driving by car / Using PT / Cycling] is healthy</td>
<td>2.3</td>
<td>1.0</td>
<td>2.6</td>
<td>1.1</td>
<td>4.6</td>
<td>0.7</td>
</tr>
<tr>
<td>5. [Driving by car / Using PT / Cycling] is safe</td>
<td>3.2</td>
<td>1.0</td>
<td>3.4</td>
<td>1.0</td>
<td>3.6</td>
<td>1.0</td>
</tr>
<tr>
<td>6. [Driving by car / Using PT / Cycling] is environmental friendly</td>
<td>2.0</td>
<td>0.9</td>
<td>3.2</td>
<td>1.1</td>
<td>4.7</td>
<td>0.6</td>
</tr>
</tbody>
</table>

Fig. 1. Between-person (cross-sectional) relationship, and within-person and between-person relationships between number of words per minute and percentage of typos (\(\cdot\)).
Source: Hamaker, 2012

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2 An additional between-person network was also estimated using data from the second wave (2014), which yielded similar results as the first wave network. The average absolute difference in the parameter estimates (i.e. the partial correlations) was found to be very small (< 0.02).
4. Results

Estimation of the between-person network yielded 135 nonzero edges out of 210 possible edges with 21 nodes (the full weight matrix is included in Appendix A). The visualized network (Fig. 1) clearly shows the existence of three clusters reflecting the attitudes towards each of the three modes. The mode use variables form a separate (fourth) cluster. Note that the colors of the nodes are defined by the researcher.

Within the mode use cluster, a negative edge was found between car and public transport use (reflecting substitution), while a positive edge was found between bicycle use and public transport use (reflecting complementary). No edge was revealed between car and bicycle use, suggesting that these modes are used independently from each other.

Interestingly, for each mode, the attitude reflecting the extent to which the use of the mode is considered ‘convenient’ (i.e., C1, B1 and PT1) is most strongly connected to the actual use of the corresponding mode. Convenience, in turn, is most strongly linked with the extent to which the use of the mode is considered ‘fun’ and ‘relaxing’. It can be observed that these three items form separate sub-clusters. In a similar fashion, the perceptions of safety, healthiness and environmental friendliness also form sub-clusters for each mode. Yet, they have a more distant position in relation to the actual use of each mode, suggesting that these are secondary reasons for mode use.

The existence of the two sub-clusters can be visualized more clearly by adjusting the colors of the nodes, which is done in Fig. 2.

Interestingly, the (empirically revealed) clusters do not align entirely with the conceptual categories. In particular, convenience—an instrumental motivation—clusters together with the two affective motivations (relaxing and fun), while the other three instrumental reasons (health, safety and environment) form a second cluster (for each mode). This raises the question as to why convenience, as an instrumental reason to use a mode, clusters together with the two affective items and not with the other instrumental reasons.

To answer this question, we can follow the argument of Dalege et al. (2016) (discussed in Section 2.4) and interpret the observed clustering as a means to reduce cognitive dissonance, while maintaining belief accuracy. In this particular case, as confirmed by the sample means (see Table 1), most people agree with the statements that driving is convenient, relaxing and fun, but at the same time, most do not believe that driving is environmentally friendly, healthy or (particularly) safe. Based on the CAN-model one may reason that by keeping these items in separate clusters, the beliefs that the use of the car is not environmentally friendly, healthy or safe can be maintained (belief accuracy), while cognitive dissonance between these items and the endorsed items (car use is convenient, relaxing and fun) can (mostly) be avoided because they form separate sub-clusters.

While this line of reasoning seems plausible another (or additional) explanation may be that convenience is actually regarded as an affective aspect. In Dutch the word we used in the survey was “het gemak”, which can be translated as “convenience” but also as “easiness”, which has a more affective connotation. At this point it seems difficult to draw hard lines between the conceptual categories.

With only 76 nonzero edges, the within-person network was found to be much sparser than the between-person network, indicating that at this level the relationships among attitudes and between attitudes and behavior are generally weaker (the full weight matrix is again included in Appendix A). Fig. 3 presents the two-dimensional visualization of this network (again separately indicating the two sub-clusters for each mode). Interestingly, the sub-clusters identified in the between-person network are also found to exist at the within-person level, providing a form of cross-validation. Hence, for these associations, the assumption that the between-person relationships are more or less the same (albeit consistently weaker) as those at the within-person level seems to hold. Yet, this does not seem to be the case for the relationships between the attitudes and the behavioral items. Here only a few small edges (< 0.03) are found, controlling for all other nodes in the network. Hence, at the within-person level, changes in attitudinal items over time (e.g. an increase in agreeing to the statement ‘cycling is fun’) are not associated with changes in the actual uses of different modes (e.g. the level of cycling). This is a finding with potentially important implications for travel behavior research and practice, as we will discuss later.

![Fig. 2. Visualization of the between-person network.](image-url)
Table 2 presents the strength, betweenness and closeness measures (expressed in standardized scores) of both the between-person and within-person network. For the sake of completeness the raw (unstandardized) values are provided in Table 4 in the appendix. In the between-person network item C1 ‘driving by car is convenient’ takes the most central position in terms of all three indices, while PT6 ‘using PT is environmentally friendly’ has a consistently low score on all three centrality indices. In general, the behavioral items assume a less central position in the network compared to the attitudinal items. In terms of node strength, the within-person network shows a similar picture as the between-person network (the correlation between the respective strength indices is 0.70), providing again a form of cross validation of the structure of the network. Yet, item C1 forms a notable exception here, as it does not assume a very central position in the within-person network. The patterns in terms of betweenness and closeness are also quite different across both networks, which may also relate to the general instability of these measures (Epskamp et al., 2018a). In terms of betweenness, item B5 (cycling is safe) suddenly appears to take a central position, which is consistent with its position in the visualized network (see Fig. 4).

### Table 2
The centrality of each node in the between-person and within-person network in terms of strength, closeness and betweenness (expressed in standardized scores).

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>Between-person network</th>
<th>Within-person network</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Strength</td>
<td>Betweenness</td>
</tr>
<tr>
<td>CU</td>
<td>Car use</td>
<td>-2.20</td>
<td>-0.23</td>
</tr>
<tr>
<td>C1</td>
<td>Driving by car is convenient</td>
<td>1.35</td>
<td>2.31</td>
</tr>
<tr>
<td>C2</td>
<td>Driving by car is relaxing</td>
<td>0.66</td>
<td>-0.58</td>
</tr>
<tr>
<td>C3</td>
<td>Driving by car is fun</td>
<td>0.56</td>
<td>-1.15</td>
</tr>
<tr>
<td>C4</td>
<td>Driving by car is healthy</td>
<td>0.23</td>
<td>-0.23</td>
</tr>
<tr>
<td>C5</td>
<td>Driving by car is safe</td>
<td>0.02</td>
<td>0.69</td>
</tr>
<tr>
<td>C6</td>
<td>Driving by car is environmental friendly</td>
<td>0.12</td>
<td>-0.69</td>
</tr>
<tr>
<td>PTU</td>
<td>PT use</td>
<td>-0.62</td>
<td>0.00</td>
</tr>
<tr>
<td>PT1</td>
<td>Using PT is convenient</td>
<td>0.29</td>
<td>1.27</td>
</tr>
<tr>
<td>PT2</td>
<td>Using PT is relaxing</td>
<td>-0.01</td>
<td>-1.61</td>
</tr>
<tr>
<td>PT3</td>
<td>Using PT is fun</td>
<td>0.97</td>
<td>0.81</td>
</tr>
<tr>
<td>PT4</td>
<td>Using PT is healthy</td>
<td>-0.33</td>
<td>0.69</td>
</tr>
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<td>PT5</td>
<td>Using PT is safe</td>
<td>0.17</td>
<td>0.81</td>
</tr>
<tr>
<td>PT6</td>
<td>Using PT is environmental friendly</td>
<td>-1.35</td>
<td>-1.15</td>
</tr>
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<td>BU</td>
<td>Bicycle Use</td>
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<td>-1.38</td>
</tr>
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<td>Cycling is convenient</td>
<td>0.72</td>
<td>0.81</td>
</tr>
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<td>B2</td>
<td>Cycling is relaxing</td>
<td>0.28</td>
<td>0.46</td>
</tr>
<tr>
<td>B3</td>
<td>Cycling is fun</td>
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<td>-0.92</td>
</tr>
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<td>B4</td>
<td>Cycling is healthy</td>
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<td>B5</td>
<td>Cycling is safe</td>
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</tr>
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<td>B6</td>
<td>Cycling is environmental friendly</td>
<td>0.77</td>
<td>0.81</td>
</tr>
</tbody>
</table>
5. Discussion

This study is the first to estimate psychological network models using data related to travel-related attitudinal and behavioral measures. The models have yielded outcomes that could not have been revealed by applying models that are typically applied in travel behavior research, in particular, the finding that the convenience of the car takes a central position in the (between-person) network and the observed clustering of the 6 items in two sub-clusters (for each of the three modes) in both the between-person and within-person network.

The first finding is interesting from a policy perspective, as influencing this attitudinal position presumably will have more impact on the other positions in the network (and thus travel behavior) than influencing attitudinal positions in the periphery of the network. Hence, this result suggests that policies aimed at lowering the convenience of using the car will be more effective than those focused on increasing the beliefs that cycling or PT use are healthy or environmentally friendly. Of course, the validity of this conclusion is conditional on the validity of the assumption that the attitudes causally precede the behavior, which we did not test explicitly in this research.

The identification of the two sub-clusters, a result which is found in both the between-person and within-person network, is interesting and relevant from a theoretical perspective. In contrast to previous studies, it is found that the convenience of using a mode as an instrumental motivation actually clusters together with the two affective motivations (use of the mode is relaxing / fun), and not with the other instrumental motivations of health, safety and environment. While this pattern of clustering seems counterintuitive at first, it can be well understood when explained as a way to maintain belief accuracy while reducing cognitive dissonance. Hence, the network approach, as an explorative method, can be used to identify new mechanisms and hypotheses on how attitudes are interrelated with one another and with behavior.

While the network approach may yield new insights, it also leads to new questions. In particular, the inconsistency revealed between the within-person and between-person network regarding the links between the attitudes and the behaviors warrants further discussion and empirical research. It should be noted here that the fact that no associations are revealed in the within-person network does not automatically mean that such relationships are absent at this level. Since the estimated within-person network is based on deviation scores from the means, the model only captures contemporaneous relationships between (in this case) attitudes and behavior and not lagged ones. It may be possible, however, that a change in an attitude may (at the within-person level) not directly manifest itself in a change in behavior (i.e. a contemporaneous effect), but affect behavior after a period of time (i.e. a lagged effect).

Such lagged (within-person) effects may be explored using other models such as the multi-level VAR model or the random intercept cross-lagged panel model, but these require more than two waves of data. To this end, an experience sampling procedure could be set up, in which on a regular (e.g. daily) basis, respondents would be required to report their travel behavior by various modes, as well as their experiences, cognitions and feelings associated with the use of these modes. This would then allow the researcher to assess at the level of individuals, which experiences, cognitions or feelings are indeed instrumental in making people switch between modes over time, yielding scientifically relevant (and policy relevant) insights. Indeed, such an approach may be instrumental in developing new dynamic and intra-individual theories of travel behavior, which would provide a much more solid foundation for transport policy than is provided by the currently employed inter-individual / cross-sectional frameworks of analysis.

In addition to this extension, other research directions may also be explored. One relates to the inclusion of structural variables, like socio-demographic variables. In principle, the direct inclusion of structural variables in the network is possible, but only if they have the same measurement levels as the attitudinal/behavioral items (i.e. ordinal). Another interesting way to deal with structural variables is by estimating separate networks for different groups. For example, separate networks may be estimated for groups that
are (very) familiar with the use of a certain mode and those that are not. Such an analysis would allow the researcher to explore whether the items in the psychological networks become more strongly interconnected with increasing familiarity with a mode, which one can hypothesize would be the result of the large number of experiences with the particular mode.

Another interesting research direction relates to the distinction between utilitarian and leisure travel. As shown by the research of Anable & Gatersleben (2005) instrumental and affective motivations play a different role in relation to these travel purposes. Related to the network models it may, for example, be hypothesized that leisure travel is more strongly connected with the affective motivations (and to a lesser extent with the instrumental ones) while utilitarian (e.g. work-related) travel is more strongly connected with the instrumental motivations (and to a lesser extent with the affective ones). Hence, an interesting and relevant research direction is to measure the travel behavior variables separately for mode and purpose and include these in the network model.

6. Conclusion

In this paper we introduced the field of network psychometrics to the field of travel behavior. We explain how the psychological network approach is able to address three conceptual and empirical problems associated with latent variables, while also providing a way (when panel data are available) to empirically explore the assumption of unidirectional causation and the assumed equivalence of between-person and within-person relationships. We illustrate the approach using the so-called Causal Attitude Network (CAN) model to analyze two-wave travel behavior data containing attitude-measures and travel behavior outcomes. Our analyses suggest that the CAN-model provides an intuitive and credible account of between-person and within-person relations between attitude- and belief-related items and choice outcomes. Our finding that there is hardly any empirical evidence for within-person relations between attitudes and behaviors runs counter to the assumptions embedded in models (such as hybrid choice models) and associated policy recommendations (aimed at inducing a change in a person’s behavior by means of a change in that person’s attitudes or beliefs) that have recently achieved prominence in the field of travel behavior research.

At this point it is worthwhile emphasizing that while the psychological network approach provides an innovative perspective compared to traditional modelling approaches in travel behavior research (as well as other fields), it is still in its early stages of development. This means that many important questions remain (largely) unanswered, for now. For example, an important question relates to the reproducibility of the networks across different contexts and populations; will application of the models presented in this paper to other datasets (with similar indicators) indeed reveal similar networks? A related issue concerns the selection of indicators. In the common factor model it is assumed that the items are interchangeable, making the issue of indicator selection less salient. However, within the psychological network approach it is assumed that the items ‘make up’ or constitute the construct. Hence, in models it is important that indeed all relevant aspects of the construct are sampled. Apart from substantive/conceptual omissions, the consequences of not sampling all relevant items may also have statistical/empirical repercussions, since the edges in the network are estimated by partial correlation coefficients controlling for all other nodes in the network. If relevant nodes would be missing one may thus falsely conclude that there is a potential causal link between two items. Alternatively, there may be large semantic overlap between two items, which could erroneously render any true relationships with other items spurious. Finally, psychological network models, because they capitalize on all associations between indicators, may also be more prone to context and/or question order effects (Tourangeau and Rasinski, 1988) than common factor models, which only capitalize on the shared variance across items. To conclude, important substantive and methodological issues surrounding psychological network models still need to be addressed.

Given the considerations above we would like to emphasize that we do not necessarily view the “network approach” as a substitution of existing methods/models applied to the travel behavior domain; it should be viewed as a complementarity method with its own particular strengths (e.g. the ability to visualise the network of relations between attitudes and behaviour) but also its own particular weaknesses (e.g. not being able to deal effectively with items that overlap strongly semantically). In general, we believe the continued use of traditional models is not problematic per se as long as researchers are aware that particular assumptions underlie their models that are not necessarily empirically valid. This may actually be viewed as the most important contribution of the network approach in that it helps making these assumptions explicit.

In line with this, we believe that the general practical implication of the present study is that we should be more cautious in translating the results of existing travel behavior models, including Hybrid Choice Models, to concrete policy recommendations. Note that this claim of ours should not be read as if we believe that attitudes (or psychological constructs in general) do not matter in the prediction of behavior; rather, given the problematic assumptions embedded in current conceptual/statistical models, we believe that we as a research community simply do not know enough about how they function and are interrelated with behavior in a dynamic and intra-individual context, to provide a foundation for policy recommendations.

Acknowledgement

The LISS panel data were collected by CentERdata (Tilburg University, The Netherlands) through its MESS project funded by the Netherlands Organization for Scientific Research. We thank the two anonymous reviewers for their careful reading of our manuscript and their insightful comments and suggestions.

Appendix A

See Tables 3 and 4.
Table 3
Weight matrix of between-person network (lower left triangle) and within-person network (upper right triangle).

<table>
<thead>
<tr>
<th>Label</th>
<th>Description</th>
<th>CU</th>
<th>C1</th>
<th>C2</th>
<th>C3</th>
<th>C4</th>
<th>C5</th>
<th>C6</th>
<th>PTU</th>
<th>PT1</th>
<th>PT2</th>
</tr>
</thead>
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<tr>
<td>CU</td>
<td>Car use</td>
<td>0.009</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
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<td>C1</td>
<td>Driving by car is convenient</td>
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<td>0.165</td>
<td>0.000</td>
<td>0.035</td>
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<td>0.016</td>
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<td>0.000</td>
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<tr>
<td>C2</td>
<td>Driving by car is relaxing</td>
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<td>0.432</td>
<td>0.093</td>
<td>0.090</td>
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<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
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<tr>
<td>C3</td>
<td>Driving by car is fun</td>
<td>0.015</td>
<td>0.213</td>
<td>0.642</td>
<td>0.061</td>
<td>0.108</td>
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<td>0.000</td>
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<tr>
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<td>0.118</td>
<td>0.111</td>
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<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
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<tr>
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<td>Driving by car is environmental friendly</td>
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<td>0.000</td>
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<td>0.000</td>
<td>−0.012</td>
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<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
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<td>Using PT is fun</td>
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<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
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<td>0.000</td>
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<td>0.000</td>
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<tr>
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<td>Using PT is healthy</td>
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<td>−0.010</td>
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<td>−0.058</td>
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<td>−0.023</td>
<td>−0.016</td>
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<td>0.000</td>
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<td>0.000</td>
<td>0.000</td>
<td>0.187</td>
</tr>
<tr>
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<td>0.023</td>
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</tr>
<tr>
<td>B4</td>
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<td>0.032</td>
<td>−0.026</td>
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<tr>
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Table 4
The centrality of each node in the between-person and within-person network in terms of strength, closeness and betweenness (raw scores).

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>Between-person network</th>
<th>Within-person network</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Strength</td>
<td>Between-ness</td>
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<td>Car use</td>
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</tr>
<tr>
<td>CI</td>
<td>Driving by car is convenient</td>
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<tr>
<td>C2</td>
<td>Driving by car is relaxing</td>
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<tr>
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<td>Using PT is convenient</td>
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<td>BI6</td>
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</tr>
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</table>

Strength the sum of absolute partial correlation coefficients between the respective node and all other nodes. Betweenness the number of the shortest paths between two nodes that go through the node in question. Closeness the inverse of the sum of all the shortest paths between one node and all other nodes.

Appendix B. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.tra.2020.01.014.

References
