Exploring dynamic relationships between travel behaviour and attitudes using a psychometric network approach

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SHORT SUMMARY

Attitudes towards transport modes have gained increasing attention in terms of their role in explaining travel behaviour. They are often included as latent variables in unidirectional modelling approaches that frequently overlook the bidirectional relationships between attitudes and behaviour. This study aims to understand better the complex dynamic relationships between travel behaviour and attitudes by separating between-person and within-person associations. We use a psychometric network approach operationalised within a panel multilevel graphic autoregressive model, which allows us to disentangle three types of associations: temporal predictions over time, contemporaneous correlations and between-subjects relationships. Our analysis considers attitudinal variables from five waves of the Netherlands Mobility Panel Survey and a broader set of psychometric variables from three waves of a longitudinal behaviour change study in Denmark. Our findings provide insights into the bidirectional relationship between transport behavioural choices and attitudes regarding car, train, and bicycle, as well as electric vehicle adoption.

Keywords: temporal associations, correlations, longitudinal data, psychometrics, transport behaviour.

1. INTRODUCTION

Transport research explores relationships among individual attitudes and behaviour. These relationships are not static, and recent research has focused on how these dynamics could evolve over time. They have been explored in multiple contexts related to the individual's choices, implying the use of psychometric variables to capture unobserved factors. For example, attitudes towards transport modes influence their usage, and the experience of using them also influences new or reinforced attitudes (Kroesen et al., 2017). These attitudes are commonly included in models as latent variables, assessed by multiple items on Likert scales.

However, psychological research, especially in the psychopathology field, has raised some discussions about the treatment of latent variables in theoretical models. For example, from the epistemological and ontological definition, the understanding and operationalism of unobserved latent factors and their reflective causal relationships with selected psychometric indicators cannot be defended in within-subject analysis (Guyon et al., 2017). Consequently, new exploratory techniques, such as network psychometrics, have started to be used. Instead of measuring relations between latent variables, multiple pairwise relationships are analysed among the single psychometric variables (previously used as indicators in the definition of the latent variables). This methodology is an exploratory analysis where the patterns of pairwise conditional dependencies among the items present in the data are evaluated (Borsboom et al., 2021), and some variations allow the evaluation of interactions between attitudes conceptualised as reactions in a causal attitudinal network (Dalege et al., 2016).

In a cross-sectional analysis, a psychometric network allows the representation of a graphical model using a network with undirected edges that indicate a full conditional association between two nodes after conditioning on all other nodes, termed as a pairwise Markov random field (PMRF) (Epskamp, van Borkulo, et al., 2018). One of the most applied model structures for the estimation is the Gaussian graphical models (GGM), which are closely tied but not fully equivalent to SEM-directed structures (Epskamp, Waldorp et al., 2018). In a transport research application, cross-sectional networks have been explored to analyse between-person relationships in psychometrics and modal transport usage (Kroesen & Chorus, 2020).

However, when analysing panel data, a multilevel network model can analyse repeated measures that enable the disaggregation of within-person and between-person effects. This allows the study of individual variabilities, temporal dynamics and heterogeneity in responses, obtaining insights into the potential cause-effect mechanisms that could lead to the relationships among the variables. When the GGM model includes relationships of the variables over time, it takes the form of a graphical vector-autoregression model (GVAR) (Epskamp, 2020). The temporal dynamics explored in this methodology provide insights into Granger causality, where past values of a variable contain information that predicts future values of another (Jordan et al., 2020). The panel graphical vector-autoregressive model (Panel GVAR) is an application that allows separating within-person and between-person effects with the inclusion of at least three observations from the same individual (Epskamp, 2020). Panel GVAR is a multi-level GVAR, with only random intercepts that assume the same network structure for every person but allow people to differ on their averages and use the variance-covariance structure of these random means to model the between-person network (Epskamp, 2020).

Using Panel GVAR, the outcome analysis allows the separation of a 1) **within-person temporal** network with **temporal prediction** relationships between individual variables across any two-time points, as it is focused on differences from the mean of a person on a variable at a certain measured point and the same variable or a different variable one time step later; 2) **within-person contemporaneous** networks with the **correlations** relationships between variables at the same measurement point, focusing on individual differences removing time influences; and 3) **between-person** network, which provides insights for the variable's **associations**[1] between means across measurement points and individuals.

This paper uses a psychometric network approach to explore longitudinal relationships among psychometrics used in transport research. Specifically, we aim to 1) examine the pairwise conditional dependencies within panel observations using transport modes and attitudinal variables to identify patterns over time; 2) investigate the dynamic relationships in transport psychometrics by analysing single items directly without relying on the estimation of latent constructs; 3) differentiate the dynamic effects by considering both intra-individual (temporal and contemporaneous relations) and between-person effects within the analysis of the transport usage and attitudinal outcomes; 4) discuss the implications of psychometric network approaches on panel data within the context of travel behaviour research.

2. METHODOLOGY

Case study description

As the first application (case 1), we used information from the Netherlands Mobility Panel (MPN) to explore attitudes towards different transport modes. MPN has collected yearly travel behaviour information from a panel sample at the household level since 2013, and every second year, it has included a special questionnaire regarding attitudes and perceptions during the even-numbered years. A more extensive description of the MPN can be found in Hoogendoorn-Lanser et al. (2015). Thus, five complete waves of responses to the special questionnaire are currently available for a sample of n=**1473** respondents from 2014 to 2022. This sample comprises 46.8% men and 53.2% women, where 61.9%

[1] Literature also referred to this as a correlation in the between-person network, but here we are using the terminology 'association' only to differentiate them from the correlations obtained in the contemporaneous network.

are the main income earner in the household, 29.5% partner of the main income earner, and the rest 8.5% are other relatives (e.g., children, parents). To avoid bias in the sample composition, future work in this paper will explore including observations with at least three waves (n=4748) and using estimators for the modelling that allow handling missing observations, such as the full information maximum likelihood (FIML).

For three transport modes – i.e. car (C), train (T), and bicycle (B) - the items include a measure of behaviour, that is, how frequently individuals use each mode (USE) as presented in Figure 1. Among the sample, car usage is almost stable, and as Figure 1 shows, bike usage decreases over time, which is also expected considering the overrepresentation of older individuals in the sample. Attitudinal variables included an overall evaluation of a mode assessed, as the personal impression (PI), on a 5-point scale from very positive (1) to very negative (5), as well as more specific evaluations of to what extent respondents perceived travelling by each mode as comfortable (1), relaxing (2), saving time (3), safe (4), flexible (5), pleasant (6) and prestigious (7), each of them rated on a 5-point agreement scale.

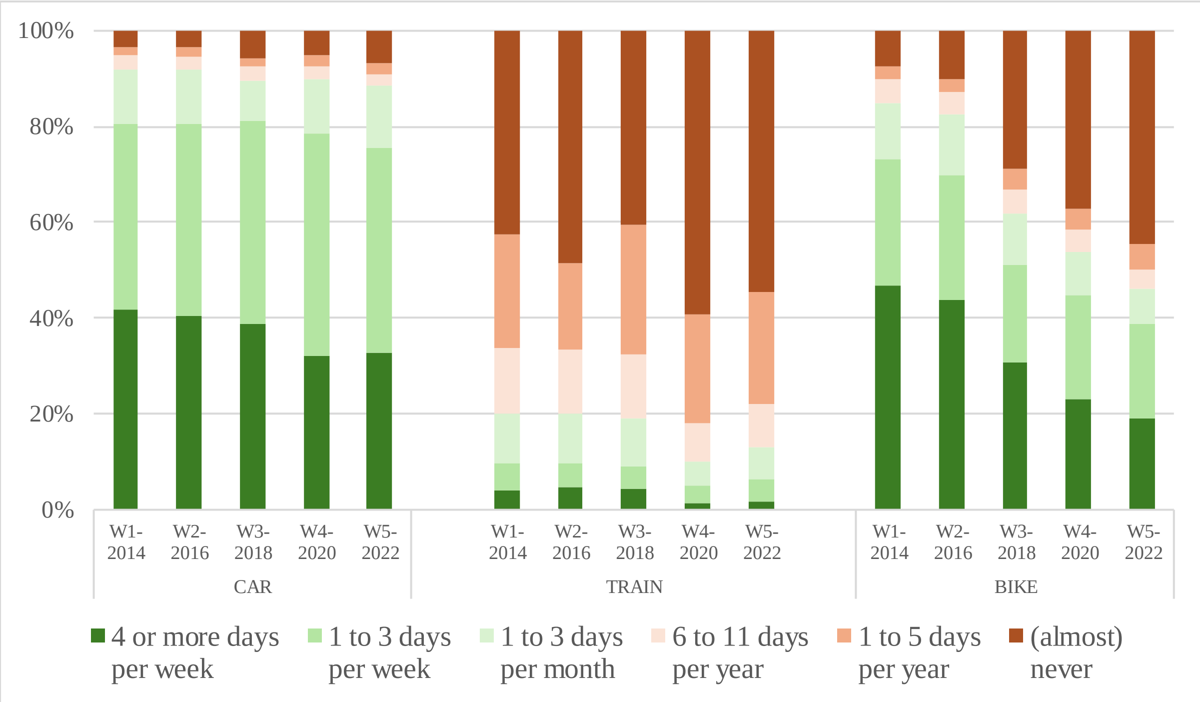

Figure 1 Distribution of the frequency of using different transport modes over the five waves of complete responders in the MPN dataset.

Analysing the selected variables using a longitudinal network model perspective as panel data implies the inclusion of nine variables per mode (this is 27 nodes) measured five times. However, this estimation would include a full-information network model with all covariances between the measured variables, which is computationally challenging for the number of nodes and many time points. When the panel data model uses GVAR models, some authors and software developers advise keeping the model specification as small as possible, e.g., around ten nodes (Burger et al., 2022). Thus, to analyse our selected attitudes and their influence on transport mode usage, we split the analysis into a general network model with the three transport modes' usages and overall evaluations (model 1). In addition, three more specific models, one for each transport mode, included the usage item and attitudinal variables related to the car (model 2), train (model 3), and bike (model 4).

Analytical approach

In the analysis of longitudinal panel observations, we adopted a Panel GVAR model, where the individual responses on a time step are modelled as an extended Gaussian graphical model (GMM) after conditioning their responses in the previous measure (Epskamp, 2020). This approach allows separating the within-person effects into 1) a causal network (predictive effect with the directed relationships, termed as ***temporal network***), and 2) a correlation network (the covariance structure that remains after controlling for the previous measurement occasion, termed as ***contemporaneous network***). Furthermore, 3) the associations from the between-person effects with an additional GGM (relationships between stable means, termed as ***between-person network***).

The model networks were estimated with the function panel-lvgvar from *psychonectrics* R-package version 0.13 (Epskamp, 2021). This function allowed the specification of latent structures, but as we considered the inclusion of only measured psychometrics, our models took a similar form as a cross-lagged panel model with a random intercept, where the first temporal structure implies the covariance structure (O'Driscoll et al., 2022). The within-person and between-person structures were defined as GGMs, and both within and between-residual variances were modelled using a covariance model.

We follow a model search strategy suggested by Epskamp (2020). First, using a maximum likelihood (ML) estimation, all the network edges were considered in a saturated model. Next, a pruned model with only significant edges ($p<0.01$) was estimated, considering a step-up function that stepwise added edges that increased the modification index until the Bayesian information criterion (BIC) of the pruned model no longer improved. The best-fitting network model between saturated and pruned was chosen based on BIC. Fit criteria, such as the normed fit index (NFI) and RMSEA, were considered in evaluating the final model.

Our reports for the final model include network visualisation using the *qgraph* package (Epskamp et al., 2012; version 1.6.5). Some of the networks are presented with a 'circle' structure where the proximity of the items does not imply any further insights. And just for illustration, in cases where perceptual psychometrics were involved, the network layout represents the average association among their nodes. Following previous applications, we calculate and report centrality measures (Epskamp, Borsboom, et al., 2018). We only presented the measure of node strength (also known as degree), which is equal to the sum of absolute partial correlation coefficients between the respective node and all other nodes (Kroesen & Chorus, 2020). In addition, for the contemporaneous and between networks, we report matrices with estimated partial correlation (lower triangle: estimated edges from the network, where the relation among pair of variables is isolated after controlling the temporal effects and other variables) and model-implied marginal correlations (upper triangle: correlations derived from the model's covariance structure, including the direct and indirect relationship between variables after regularisation). The comparison of both gives insights into whether there are mediator effects of other variables in the model, providing a generalisable picture of how the pairwise variables are correlated (Tamura et al., 2022).

3. RESULTS

Figure 2 presents the network results for Model 1, where the overall evaluations and transport modes usage are included. We infer causal (temporal) relationships from the temporal network (2a). Each one of the variables tends to reinforce its value in the next wave. As expected, for the three modes, we found that when individuals use a mode more frequently, their evaluation becomes more positive over time. Besides, the car variables (C_PI and C_USE) showed a vice-versa effect, in which positive evaluations are reflected in more car usage for the subsequent waves. On a lower but significant scale, car use (C_USE) is a negative predictor of train usage (T_USE), which suggests that in the sample, those who start to use the car are less likely to increase their train usage afterwards. Furthermore, we identify a double causal effect on using trains (T_USE) and bikes (B_USE), suggesting that changes in one could lead to changes in the other, which gives insights into the usage of both modes in multimodal trips. According to the centrality measures, the use of the bike (B_USE) is the variable that generates more influence over the other included variables.

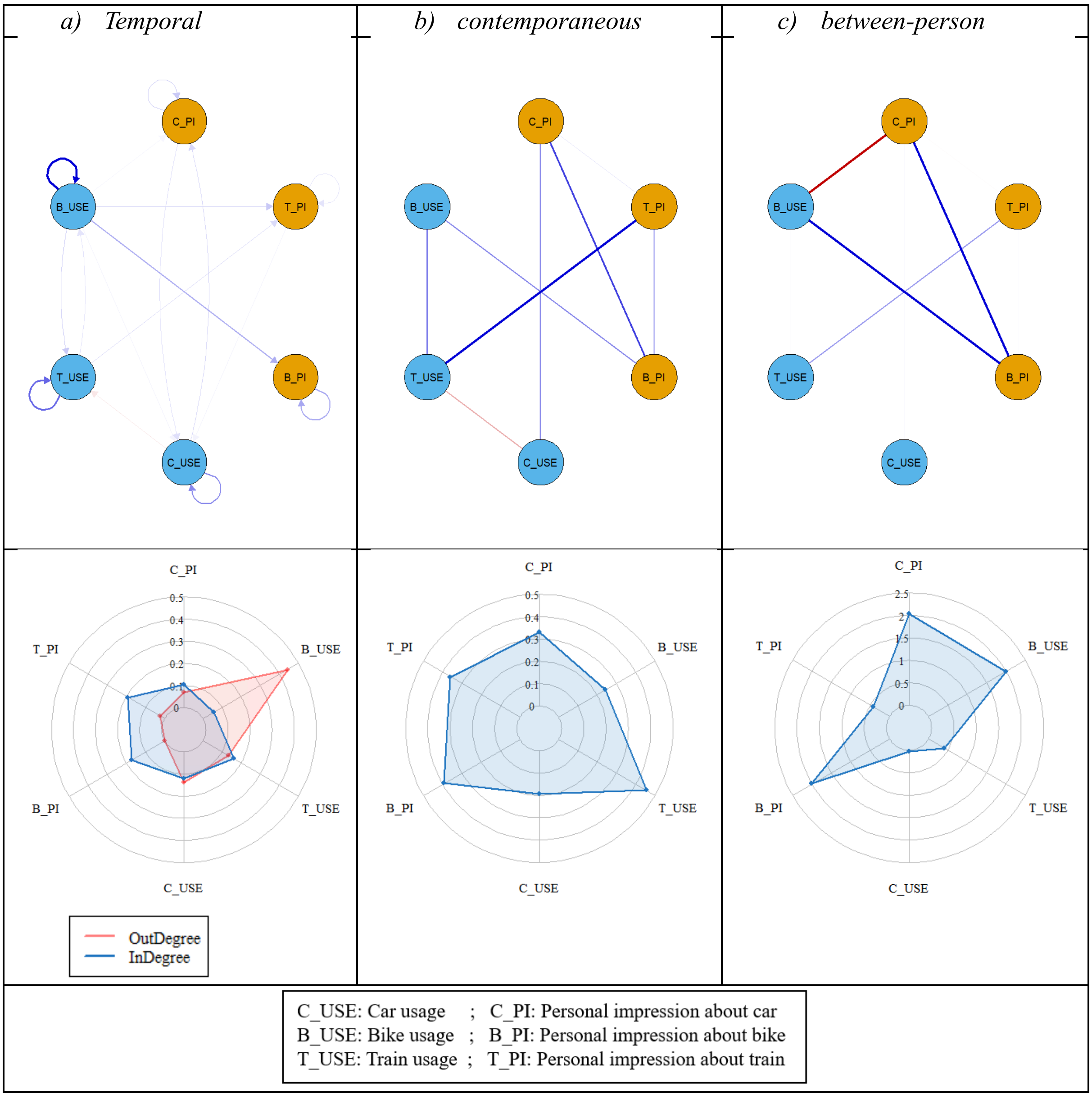

Figure 2. Estimated networks for model 1: general evaluation and usage of three transport modes. Centralities measures (strength) are included for each network.

Without considering the lagged effect, the contemporaneous network (Figure 2b) shows how these pairwise variables correlate over the same time step. We identified positive correlations between usage and general evaluations for each transport mode. Table 1 also shows the estimated partial correlations and model-implied marginal correlations for the contemporaneous network, and their results are consistent among each pair of variables. This suggests that the pairwise relationships are not heavily mediated or influenced by other variables in the model; they are straightforward, and the overall structure of the data is consistent with the direct pairwise correlations, which means that the between and with-person network structures are similar.

Table 1. Estimated partial correlations (lower triangle) and model-implied marginal correlations (upper triangle) for the contemporaneous network

	C_PI	T_PI	B_PI	C_USE	T_USE	B_USE
C_PI	·	0.04	0.19	0.12	0.00	0.02
T_PI	0.03	·	0.10	-0.02	0.25	0.04
B_PI	0.19	0.09	·	0.02	0.04	0.12
C_USE	0.12	·	·	·	-0.08	-0.01
T_USE	·	0.25	·	-0.08	·	0.13
B_USE	·	·	0.12	·	0.13	·

Furthermore, the between-person network (Figure 2c) presents the associations among the averages over time, focusing on individual differences and examining across-person relationships. These results show edges where the between-person correlations reach unrealistic estimate values, a challenge previously identified in the estimation of between-person networks using panel GVAR (Freichel & Epskamp, 2024). The results show a perfect correlation between the personal evaluations of cars and bikes and a perfect negative correlation between the car's personal evaluation and bike usage. This implies that those with a more negative opinion of the car (C_PI) also ride bikes more frequently (B_USE).

Table 2. Estimated partial between-person correlations (lower triangle) and model-implied marginal between-person correlations (upper triangle).

	C_PI	T_PI	B_PI	C_USE	T_USE	B_USE
C_PI	·	-0.39	-0.14	0.65	-0.41	-0.89
T_PI	-0.01	·	0.26	-0.25	0.52	0.44
B_PI	1.00	0.01	·	-0.09	0.27	0.57
C_USE	0.04	·	·	·	-0.27	-0.58
T_USE	·	0.39	·	·	·	0.47
B_USE	-1.00	·	1.00	·	0.01	·

Figure 3 presents the results for the model focused on specific car attitudes. In addition, a model for train and bike attitudes was estimated, but due to word limitation, they are not deeply discussed in the scope of this extended abstract. They will be presented in the final paper and during the conference.

Some main takeaways from these models are the identification of causal (temporal) associations between items from the temporal network models (e.g., C2 as a predictor of C6, C1 and C4 and T6 as a predictor of T2). This means that the relation as the individual perception of travelling by car is relaxing (C2) influences dynamics of the perception of pleasant (C6), comfort (C1) and safety (C4). This result reflects the gain of using single items in studying temporal dynamics instead of defining a common cause (latent factor) model with no direct temporal causal relationship between single items.

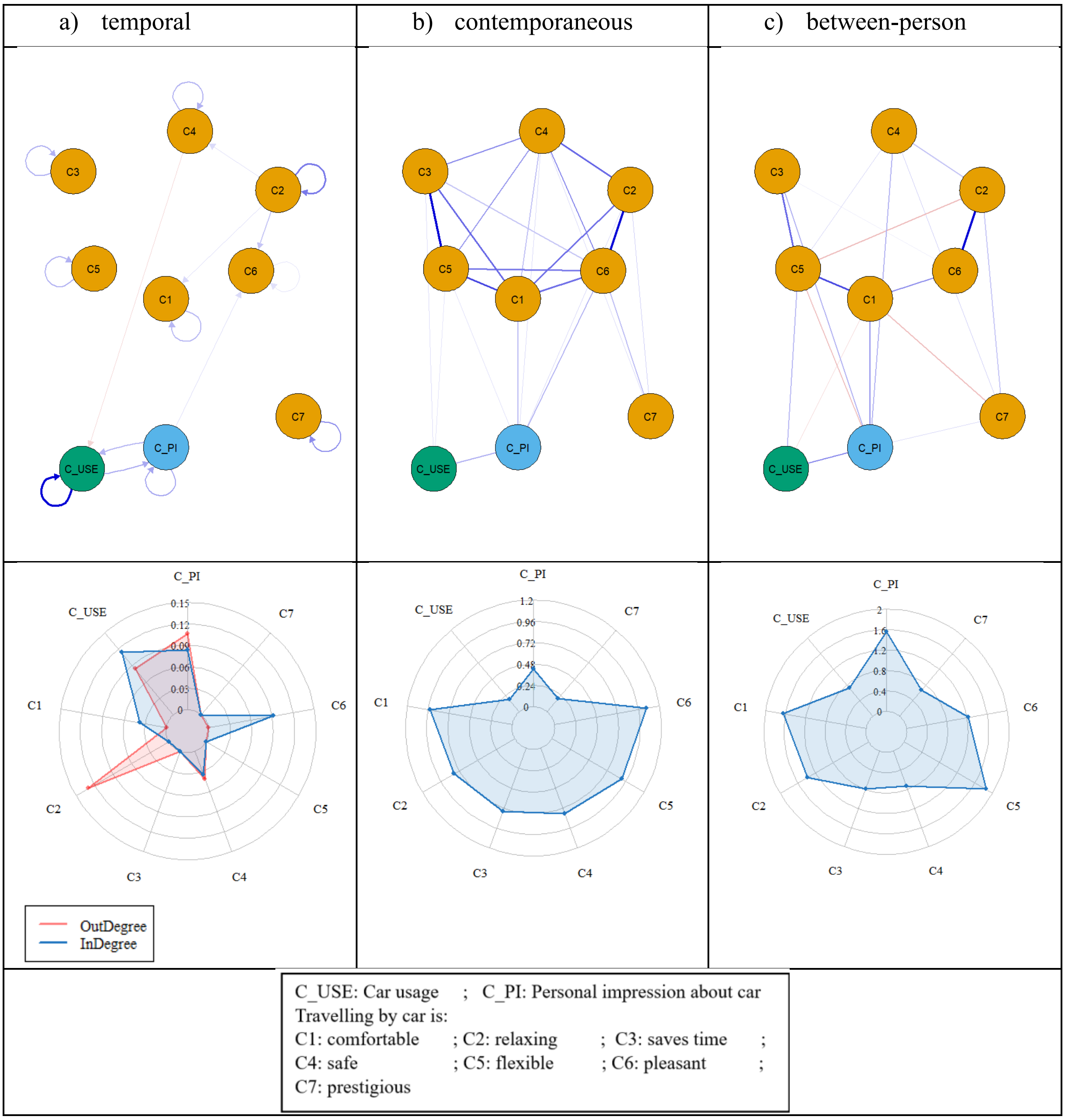

Figure 3. Estimated networks for model 2: personal impression, car use, and the seven items for perceptions about car attributes. Centralities measures (strength) are included for each network.

4. DISCUSSION AND FUTURE WORK

Panel data provides the opportunity to explore the temporal relations of transport attitudes and behaviour. This paper explored these relationships using a psychometric network approach, a methodology mainly used in psychopathology. This methodology allowed us to disentangle the dynamics of these relationships in different psychometric variables without using latent variables and identify how different attitudinal variables are related to the individual usage of transport modes. In the case of the MPN dataset, we explore how general impressions and attitudes towards transport modes (e.g., comfort, flexibility, safety, etc.) could influence their usage or vice versa. We identify that in the case of general evaluations and the three transport modes usages, the between-person and within-person associations from the network structures are similar. In addition, this methodology allowed us to identify how single items have temporal prediction relationships, which would not be possible with a longitudinal latent variable methodological approach. In the next stage and for the conference timing, this work will explore these relationships using a wider set of psychological variables, such as attitudes, norms and self-identity, in the context of environmental behaviours, such as electric vehicle adoption in Denmark's case study. We expect to identify to what extent we find similar results on the specific role of transport modes with the usage and other psychosocial variables.

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