The impact of covid-19 on modal shift in long-distance travel

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SHORT SUMMARY

This research aims to analyse the perception of covid-19 infection risk in long-distance travel in Europe and how it impacts mode choice and travel behaviour. We make use of an HII variant type experiment and model it by means of a latent class choice model, where we uncover four distinct user groups. For infection risk perception, we apply a novel approach in the field, utilising a weighted least squares regression, to obtain segment-specific regression functions, based on their respective probabilistic segment allocations. Some segments exhibit risk-aversion behaviour that is time-based (longer journeys perceived as more risky), whereas others see it as time-independent. With respect to modal preferences, the four segments either show a strong preference or aversion to one of the two land-based modes: car-loving, car-averse (using train or air), train-loving and train-averse (using car and air).

Keywords: COVID-19, Discrete choice modelling, Hierarchical information integration, Long-distance travel, Risk perception, Travel behaviour

1. INTRODUCTION

In recent years, long-distance travel has become an increasingly prolific topic of both scientific literature and political discussion. With many new proposals, projects and service launches, a fair amount of research has been carried out in order to evaluate their impacts. Sun et al. (2017), provide an extensive literature review on research concerning long-distance travel, with a focus on high-speed rail (HSR). Perhaps their most relevant finding is that many papers within this domain report conflicting conclusions with regard to the consequences of introducing HSR. These differences can presumably be attributed to varying implementations, service patterns, policies and regulation of the air, rail and road markets in different contexts.

With respect to long-distance travel behaviour, most studies analysed passengers' perception of in-vehicle time, access/egress time, frequency/headway/waiting time, reliability and comfort. In-vehicle time was found to be valued at 10-30 €/h, with travellers being 1-2 times as sensitive to access/egress time as opposed to in-vehicle time (Bergantino & Madio, 2018; Ortúzar & Simonetti, 2008; Román et al., 2014; Román & Martín, 2010). The perception of other attributes differed even more, due to the different survey contexts.

There are many other potential trip characteristics that travellers may consider (transfer characteristics, luggage, reliability,…), making it challenging to capture everything. An approach that can help alleviate this is Hierarchical Information Integration (HII), first proposed by Louviere (1984). In it, respondents firstly evaluate groups of attributes (safety, reliability, comfort,…) one at a time. Secondly, a bridging experiment includes all attribute groups in a single discrete choice task, requiring respondents to trade-off the values of the different groups. Since its introduction, different versions of HII have been proposed, summarised by Molin & Timmermans (2009) as Conventional HII (Louviere, 1984), HII variant (Bos et al., 2004) and Integrated Choice experiment (Oppewal et al., 1994). Recently, the HII variant approach was applied onto two topics relating to long-distance travel, namely to the perception of airline safety (Molin et al., 2017) and the perception of night trains (Heufke Kantelaar et al., 2022).

Another aspect impacting long-distance travel behaviour, which has been at the forefront of travel behaviour research in recent years, is the COVID-19 pandemic and the associated (travel) behaviour changes. While many studies look into the impact of the pandemic on everyday life and the perception of risk on commuters' behaviour (Currie et al., 2021; de Haas et al., 2020; Shamshiripour et al., 2020; Shelat et al., 2022; Shortall et al., 2022; Tirachini & Cats, 2020), its impact on long-distance travel behaviour has, to the best of our knowledge, not been studied.

Molin et al. (2017) and Heufke Kantelaar et al. (2022) both utilised a Panel Mixed Logit (ML) model for the bridging experiment to capture respondent heterogeneity. Another common approach for capturing heterogeneity is the Latent Class Choice Model (LCCM). While ML allows parameters to vary within the sample, LCCM probabilistically allocates respondents to a discrete number of Multinomial Logit (MNL) models, each with its own set of taste parameters. LCCMs allow for a more straightforward interpretation, as the market segments can be clearly distinguished based on their different trade-offs. Additionally, attitudinal and socio-demographic information can be used to predict an individual's probability of belonging to a specific segment.

Applying LCCMs to HII data is challenging, as the perception of the subjective ratings in the bridging experiment will result in different parameters for each market segment. If the rating experiment is modelled with a regression function (as is common practice), it results in an equal perception of factors across segments. Intuitively, this subjective perception should differ between segments, yet to the best of our knowledge, latent class segmentation has not been attempted in HII.

One possible way of capturing segments' different perceptions of rating factors is by estimating separate regression models for each segment. However, since the class allocation of individuals in LCCM is probabilistic, this would have to be translated into the regression models as well. One approach that could utilise the allocation probabilities is Weighted Least Squares (WLS), which associates a weight with each data point, indicating the accuracy/importance of said data point for the regression model.

The contributions of this paper are twofold. Firstly, we evaluate the perception of various COVID-19 measures aimed at limiting the spread of the COVID-19 virus, through an HII variant type SP survey. The rating experiment includes eight attributes associated with the perception of infection risk. This is then carried into the bridging experiment, along with travel cost, travel time and travel class, where respondents choose their preferred travel mode for a long-distance trip of approximately 500km and 1000km. Secondly, upon modelling the bridging experiment by means of an LCCM, we estimate several WLS regression models to uncover different perceptions of infection risk as experienced by different population segments obtained from the LCCM.

2. METHODOLOGY

We design an HII variant type experiment, comprised of two sections: the rating experiment and the bridging experiment. Both experiments have their own design and modelling approach, all of which is presented in this section. We first present both survey designs, followed by both modelling approaches.

Survey design

In the rating experiment, respondents are presented with a variety of factors pertaining to COVID-19 and their perceived risk of infection. Shelat et al. (2022) performed an HII experiment for COVID-19 risk perception for train route choice in the Netherlands. In the rating experiment, they analysed on-board crowding, number of transfers, mask policy, sanitisation, infection rate and lockdown status. Crowding has also been recognised as a major influencing factor on mode choice by Currie et al. (2021). We consider most of the listed factors as relevant for long-distance travel. We do not consider the number of transfers, as in long-distance travel, these can vary substantially and would be very difficult to present to respondents in a consistent and understandable way. We expand the lockdown status into two categories, one considering the originating country (travel advice) and the other considering the destination country (entry requirements). Finally, we add vaccination rate to the design, as vaccination had become widespread and the concept of herd immunity may make travellers feel more at ease.

As we do not have priors for all factors, we design an orthogonal (fractional factorial) design in Ngene (ChoiceMetrics, 2018). The design has 20 rows, divided into four blocks, resulting in five choice tasks per respondent. Based on the levels of the following eight factors, respondents had to indicate their perceived level of risk on a 5-point Likert-scale :

- Mask policy (type of mask required)
- Air circulation (ventilation, air-conditioning)
- Cleaning policy
- Government travel advice (in the origin country for the destination country)
- Visiting country entry requirements (proof of vaccination/recovery/negative test)
- Infection rate at the destination
- Vaccination rate at the destination

Next, respondents are confronted with the bridging experiment, where the perceived risk of infection is presented alongside travel time, travel cost and travel class (first/business or second/economy class). Each attribute is associated with three travel modes: car, train, aircraft. Based on past research, these seem to be the most frequently used modes and the most relevant attributes in long-distance travel (Bergantino & Madio, 2018; Ortúzar & Simonetti, 2008; Román et al., 2014; Román & Martín, 2010). For both travel time and cost, we consider them to be door-to-door, meaning they include the access and egress time to the airport/train station and the time spent there.

We employ a Bayesian D-efficient design, using priors from literature. A value-of-time of 10 €/h is used, based on a detailed study carried out for the Dutch government (Kouwenhoven et al., 2014). For first/business class, we assume an additional willingness-to-pay (WtP) of 50€ (Ortúzar & Simonetti, 2008). For perceived risk, we take the value of 5€ per risk level (Shelat et al., 2022). We make no assumptions on mode-specific constants and leave them at 0. A Bayesian efficient design includes standard errors of all priors, indicating the level of certainty. We set these standard errors at half the value of the prior. Given the assumed normal distribution, this results in a 0.975

certainty that the prior has the correct sign (negative for travel time, cost and perceived infection risk, positive for comfort).

Model estimation

The bridging experiment in HII is a regular discrete choice experiment (DCE) and can thus be analysed using choice modelling techniques. We assume that respondents make decisions by maximising their expected utility (Random Utility Maximisation) (McFadden, 1974). As outlined in the Introduction, we apply a Latent Class Choice Model (Greene & Hensher, 2003) on the bridging experiment. We also include socio-demographic information in the class allocation function and iteratively exclude them one-by-one, until only significant predicting socio-demographics remain (significant for at least one of the classes).

Based on the parameter estimates of the LCCM, each respondent is assigned a probability of belonging to each of the market segments. These probabilities are included in the modelling of the rating experiment by means of a WLS regression. WLS is very similar to regular Ordinary Least Squares (OLS) regression, with the weighted sum of squares (WSS) assigned an extra variable – weight (π) –determining the importance of each data point. As a higher probability of belonging to a certain class is analogous to the importance of a data point, we adopt this approach. Equation 1 presents the calculation of WSS, where x represents the attribute level, y the observed perceived risk value and β the estimated parameter, determining the impact of an attribute on the level of perceived infection risk.

$$WSS_s = \sum_{n=1}^{N} \left(\pi_{n,s} \cdot \left(y_n - \sum_{k=1}^{K} x_{n,k} \cdot \beta_{s,k} \right)^2 \right) \tag{1}$$

3. RESULTS AND DISCUSSION

Preliminary results, based on 705 valid responses collected through the Dutch railways' panel (NS, 2020), indicate that our sample can be segmented into four distinct groups with respect to long-distance international trips in Europe. Based on their travel preferences, we denominate the four segments as follows:

1. Time-sensitive travellers
2. Prudent travellers
3. Frequent train-loving travellers
4. Cautious car travellers

Time sensitive travellers are, as the name implies, highly time sensitive (WtP > 70 €/h, compared to 40€/h for the full sample). They prefer the train for shorter trips and flying for longer ones, avoiding the use of car, indicating they may also value the time they have while travelling (not having to drive themselves). With respect to infection risk, they perceive it as a function of time, not as a fixed penalty irrespective of travel time. **Prudent travellers** exercise the most trading-off behaviour, showing the highest variation in mode choice, switching modes quickly when circumstances change. Unlike the previous segment, they see risk as a fixed penalty, irrespective of travel time (but different per mode). **Frequent train-loving travellers** strongly prefer the train, even for very long trips. For them, risk is also seen as a fixed penalty, not based on the duration of travel. Finally, the **Cautious car travellers** will often choose to travel by car. They have the lowest WtP (< 20 €/h) and see infection risk as both a function of time and a fixed penalty. To better highlight the modal share of each segment for different risk levels and trip distances, we simulate trips varying between 100km and 1500km. The results are presented in a ternary graph in Figure 1.

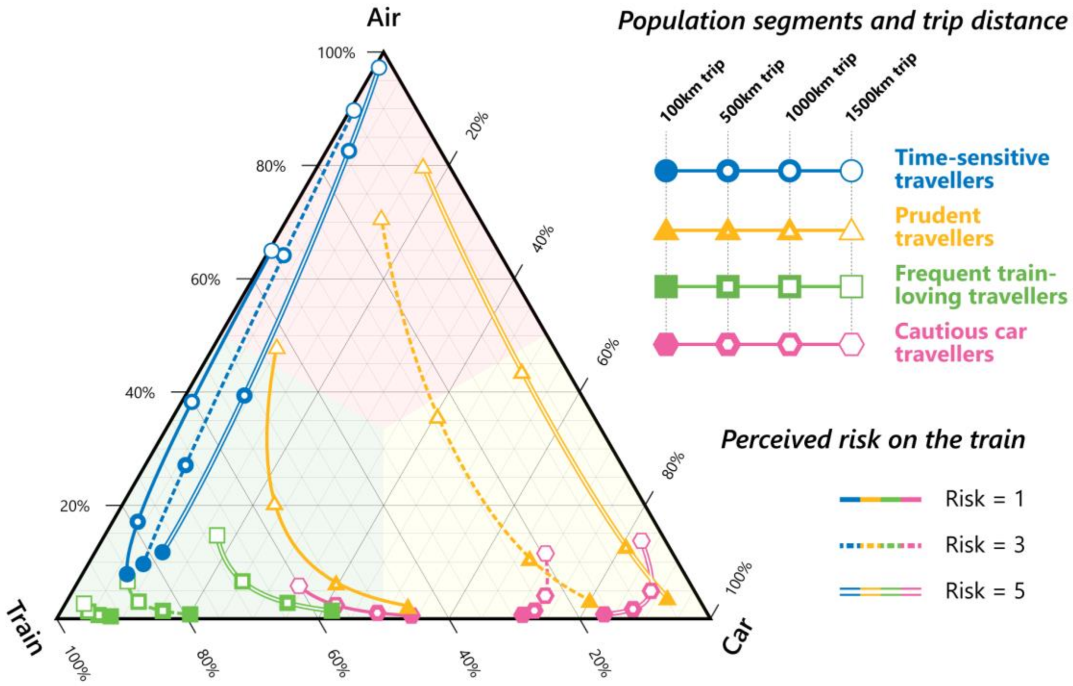

Figure 1. Ternary graph, indicating the modal split between car, train and air, for distances of 100km to 1,500km, for risk levels of 1, 3 and 5 for all four market segments

4. CONCLUSIONS

In this study we present a novel approach of capturing sample heterogeneity in an HII experiment through a latent class choice model, by utilising a weighted least squares regression approach, as opposed to the conventionally used ordinary least squares, when the full sample is analysed as a whole. We apply the model on survey data investigating the impact of COVID-19 infection risk on long-distance travel in Europe.

We identify four distinct user groups. Overall, risk for air travel is rarely seen as time-dependent due to the short flight time and small differences in flight time when travelling in Europe. For trains, some segments see risk as fixed, whereas others as time-dependent (increasingly risky with a longer travel time).

Through the rating experiment, we are also able to uncover which policy measures make travellers more at ease and reduce their perceived risk. This will be investigated further but preliminary outcomes show that some groups prefer to evaluate the data on their own (rate of infections, vaccination rate), whereas others rely on government policies and advice and trust those.

This gives operators and policymakers important knowledge on how to react in situations of increased risk of respiratory and other diseases. It enables them to make informed decisions on which measures to take, how to adjust their policies on masks, cleaning, pricing etc.

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REFERENCES

Bergantino, A. S., & Madio, L. (2018). High-Speed Rail, Inter-Modal Substitution and Willingness-to-Pay. A Stated Preference Analysis for the "Bari-Rome." *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3091537

Bos, I. D. M., Van der Heijden, R. E. C. M., Molin, E. J. E., & Timmermans, H. J. P. (2004). The choice of park and ride facilities: An analysis using a context-dependent hierarchical choice experiment. *Environment and Planning A*, *36*(9), 1673–1686. https://doi.org/10.1068/a36138

ChoiceMetrics. (2018). *Ngene1.2 User Manual & Reference Guide*. Retrieved from www.choice-metrics.com

Currie, G., Jain, T., & Aston, L. (2021). Evidence of a post-COVID change in travel behaviour – Self-reported expectations of commuting in Melbourne. *Transportation Research Part A: Policy and Practice*, *153*, 218–234. https://doi.org/10.1016/j.tra.2021.09.009

de Haas, M., Faber, R., & Hamersma, M. (2020). How COVID-19 and the Dutch 'intelligent lockdown' change activities, work and travel behaviour: Evidence from longitudinal data in the Netherlands. *Transportation Research Interdisciplinary Perspectives*, *6*, 100150. https://doi.org/10.1016/j.trip.2020.100150

Greene, W. H., & Hensher, D. A. (2003). A latent class model for discrete choice analysis: Contrasts with mixed logit. *Transportation Research Part B: Methodological*, *37*(8), 681–698. https://doi.org/10.1016/S0191-2615(02)00046-2

Heufke Kantelaar, M., Molin, E. J. E., Cats, O., Donners, B., & Wee, B. van. (2022). Willingness to use night trains for long-distance travel. *Travel Behaviour and Society*, *29*, 339–349. https://doi.org/10.1016/j.tbs.2022.08.002

Kouwenhoven, M., de Jong, G. C., Koster, P., van den Berg, V. A. C., Verhoef, E. T., Bates, J., & Warffemius, P. M. J. (2014). New values of time and reliability in passenger transport in The Netherlands. *Research in Transportation Economics*, *47*(1), 37–49. https://doi.org/10.1016/j.retrec.2014.09.017

Louviere, J. J. (1984). Hierarchical Information Integration: A new Method for the Design and Analysis of Complex Multiattribute Judgment Problems. *Advances in Consumer Research*, *11*, 148–155. Retrieved from https://www.acrwebsite.org/volumes/6233/volumes/v11/NA-11/full

McFadden, D. (1974). The measurement of urban travel demand. *Journal of Public Economics*, *3*(4), 303–328. https://doi.org/10.1016/0047-2727(74)90003-6

Molin, E. J. E., Blangé, J., Cats, O., & Chorus, C. (2017). Willingness to pay for safety improvements in passenger air travel. *Journal of Air Transport Management*, *62*, 165–175. https://doi.org/10.1016/j.jairtraman.2017.04.002

Molin, E. J. E., & Timmermans, H. J. P. (2009). Hierarchical information integration experiments and integrated choice experiments. *Transport Reviews*, *29*(5), 635–655. https://doi.org/10.1080/01441640902829470

NS. (2020). NS Panel. Retrieved December 6, 2022, from https://nspanel.nl/

Oppewal, H., Louviere, J. J., & Timmermans, H. J. P. (1994). Modeling Hierarchical Conjoint Processes with Integrated Choice Experiments. *Journal of Marketing Research*, *31*(1), 92–105. https://doi.org/10.1177/002224379403100108

Ortúzar, J. de D., & Simonetti, C. (2008). Modelling the demand for medium distance air travel with the mixed data estimation method. *Journal of Air Transport Management*, *14*(6), 297–303. https://doi.org/10.1016/j.jairtraman.2008.08.002

Román, C., & Martín, J. C. (2010). Potential demand for new high speed rail services in high dense air transport corridors. *International Journal of Sustainable Development and Planning*, *5*(2), 114–129. https://doi.org/10.2495/SDP-V5-N2-114-129

Román, C., Martín, J. C., Espino, R., Cherchi, E., Ortúzar, J. de D., Rizzi, L. I., … Amador, F. J. (2014). Valuation of travel time savings for intercity travel: The Madrid-Barcelona corridor. *Transport Policy*, *36*, 105–117. https://doi.org/10.1016/j.tranpol.2014.07.007

Shamshiripour, A., Rahimi, E., Shabanpour, R., & Mohammadian, A. (Kouros). (2020). How is COVID-19 reshaping activity-travel behavior? Evidence from a comprehensive survey in Chicago. *Transportation Research Interdisciplinary Perspectives*, *7*, 100216. https://doi.org/10.1016/j.trip.2020.100216

Shelat, S., Van De Wiel, T., Molin, E., van Lint, J. W. C., & Cats, O. (2022). Analysing the impact of COVID-19 risk perceptions on route choice behaviour in train networks. *PLoS ONE*, *17*(3 March), e0264805. https://doi.org/10.1371/journal.pone.0264805

Shortall, R., Mouter, N., & Van Wee, B. (2022). COVID-19 passenger transport measures and their impacts. *Transport Reviews*, *42*(4), 441–466. https://doi.org/10.1080/01441647.2021.1976307

Sun, X., Zhang, Y., & Wandelt, S. (2017, May 25). Air transport versus high-speed rail: An overview and research agenda. *Journal of Advanced Transportation*. Hindawi Limited. https://doi.org/10.1155/2017/8426926

Tirachini, A., & Cats, O. (2020). COVID-19 and public transportation: Current assessment, prospects, and research needs. *Journal of Public Transportation*, *22*(1), 1–34. https://doi.org/10.5038/2375-0901.22.1.1