No. 121/22, 7–19
ISSN 2657-6988 (online)
ISSN 2657-5841 (printed)
DOI: 10.26408/121.01

Submitted: 06.10.2021
Accepted: 09.01.2022
Published: 31.03.2022

CLIMATE-FRIENDLY TRANSPORT – ANALYSING STRUCTURAL RELATIONSHIPS

Ines Kolanović*[1], Dragan Čišić[2], Alen Jugović[3], Željko Smojver[4]

[1] Faculty of Maritime Studies, University of Rijeka, Studentska 2, 51 000 Rijeka, Croatia, e-mail: ines.kolanovic@pfri.uniri.hr, ORCID 0000-0001-9545-8601

[2] Faculty of Maritime Studies, University of Rijeka, Studentska 2, 51 000 Rijeka, Croatia, ORCID 0000-0001-6235-0987

[3] Faculty of Maritime Studies, University of Rijeka, Studentska 2, 51 000 Rijeka, Croatia, ORCID 0000-0001-5031-4655

[4] Rijeka Plus d.o.o, Blaža Polića 2

* Corresponding author

Abstract: The objective of this study is to assess the impacts of technology, and social, economic, and legal effects on climate-friendly transport. A model is created to identify the relationships between important factors that are creating the concept of climate-friendly transport. Structural equation modelling was used to identify the relationships between 21 measured influencing factors and four latent constructs: technology, legislative, and socioeconomic factors, and green transportation as abstract concepts used to group them. The relationships between all of the measured factors and constructs are calculated indicating the correlations, regression, and covariance between all elements of the study. The relationships between the abstract concepts and factors are calculated. The results of this research will improve insight into all environmentally friendly transport-influencing factors and concepts.

Keywords: climate-friendly transport, influencing factors, structural equation modeling.

1. INTRODUCTION

Climate change is one of humanity's most demanding challenges. Due to the growth in international trade and mobility, transportation is one of the main sources of greenhouse gas (GHG) emissions. As of 2018, transportation has produced the largest share of GHG with 28% [Agency 2020] of all emissions, surpassing electricity production, and industry. In fact, an ITF model predicts [OECD 2015] that freight transport emissions will rise by a factor 3.9 by 2050.

Until now, the primary focus of transportation has been to minimise costs and maximise profit, neglecting the social and environmental costs. The social and environmental issues have only been reinforced in recent years, and due to climate problems, ecology has been promoted as the main functional problem. Transport is an exceedingly complex system, and small changes can have very big effects on other areas, making a single transport measure is exceedingly difficult to explore alone, without considering its impacts on other measures. When a measure for CO_2 reduction is considered, there are constant side effects that impact the outcome of this measure.

This impact can be aimed in the same direction as the original measure's impact, creating a multiplier effect, but sometimes its impact decreases the original effect and is known as a rebound effect.

This research uses a specific structured methodology to outline high-level measures that can be used for the reduction of GHG in transport services. The research uses results from the FP7 REACT project[1] open consultation procedures, which are part of the strategic research agenda. The project analysis, comprised of expert consultation, questionnaires, and the Delphi method, identified 14 different measures (influential factors) for GHG reduction [Čišić et al. 2011]: transport fuels, improving vehicle efficiency, vehicle technology, transport efficiency, traffic infrastructure management, integration of transport systems, safety and security, economic aspects of change, broader environmental impacts, equity and accessibility, information and awareness, infrastructure, pricing and taxation, and regulation.

Assessing the effect of the individual influential factors, irrespective of the multiple effects of several influential factors, may result in undervaluing the overall effects on green transport. The influential factors have been grouped into three separate constructs that present high-level categories that have rarely been used as influential factors: technology, socioeconomic impacts, and legislation.

All of these factors influence climate-friendly (green) transport which further impacts: competitiveness, possibility to overcome social and/or political obstacles, other ecological impacts, social equity, quality of life, and job creation.

This paper attempts to bypass the body of previous research that measured influential factors separately, and proposes a structural model that describes the relationships between the categories and influential factors. Structural equation modelling can facilitate measuring multiple effects of the various influential factors and identify influential paths rather than individual influential factors to better simulate green transport research.

Objectives of the paper are as follows:

(1) identify the factors affecting green transport;
(2) categorise the factors into categories; and
(3) develop a structural model to describe the relationships between categories and influencing factors.

[1] https://cordis.europa.eu/project/id/233984.

2. CONCEPTUAL FRAMEWORK

Raw data from [Čišić et al. 2011] was used for this analysis, which was created using a questionnaire as a part of the open consultation procedure. The questionnaire had 92 questions with 233 participants answering. The research priorities were analysed and presented in [Radmilović and Čišić 2011], and the influencing factors were classified in previous studies.

The identified influencing factors from the findings of [Čišić et al. 2011] are shown in Figure 1.

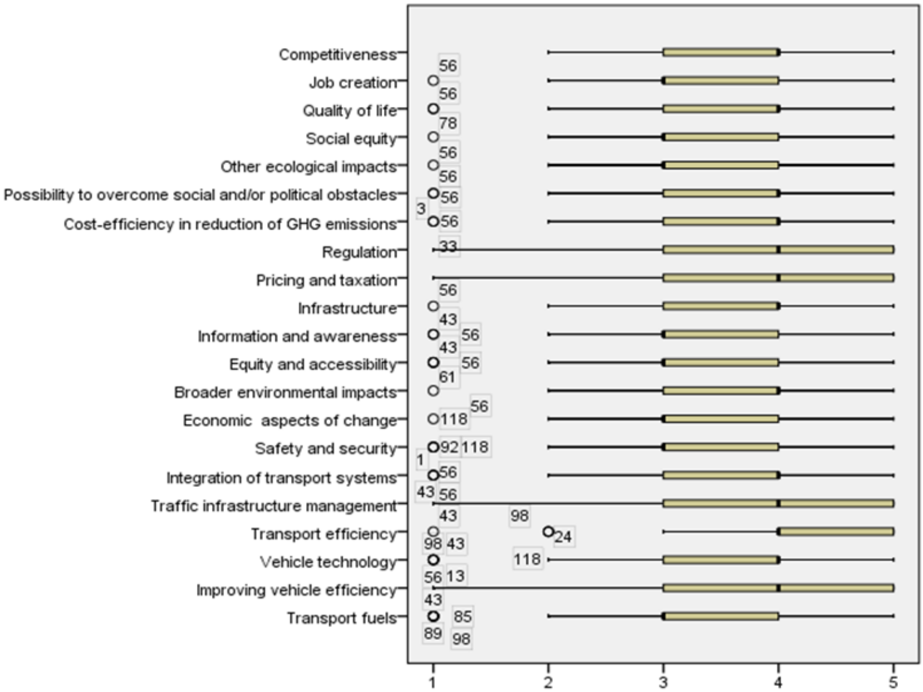

Fig. 1. Box plot for green transport influencing factors

Source: own compilation based on Čišić et al. [2011].

The analysis shows significant correlations between influential factors, and therefore analysing them is a very complex task. The authors propose an efficient and effective model that describes the relationships between influencing factors and environmentally friendly transport. To analyse both the influential factors and their grouping into categories, this research used structural equation modelling.

Structural equation modelling (SEM) is a statistical methodology for studying relationships among multivariate data [Bowen and Guo 2012; Heck and Thomas 2020]. It derives from hypothesis testing and the confirmatory analysis methodology to investigate the impact of the structural theory on the research phenomenon. The SEM statistical model is a generalisation of both multiple regression and factor analysis. SEM has a substantial advantage over many statistical techniques including factor analysis, multiple regression, and principal component analysis because it allows for interactions between the data and theory [Chin 1998]. SEM allows the creation of latent or unobserved variables that are indirectly deduced from experimental data and then their interaction with observed variables. It can demonstrate relationships between multiple experimentally created variables and then construct unobservable latent variables. SEM also utilises the modelling of errors in the measurement of observed variables and the statistically confirmatory analysis tests [Asparouhov and Muthén 2009; Bowen and Guo 2012]. For structural equation analysis, a smaller sample size is needed and there are fewer requirements on the sampling distribution in comparison to other statistical tests [Allison 2003], and it can be used to model relationships between influencing factors obtained from questionnaires or experiments and other constructs [Byrne 2013]. Moreover, the SEM methodology makes it easy to replicate the results, providing a covariance matrix of entries used in the model, allowing further studies and reanalyses with alternative models. Besides all of this, structural equation modelling can help to measure multiple effects of the various influential factors on latent variables.

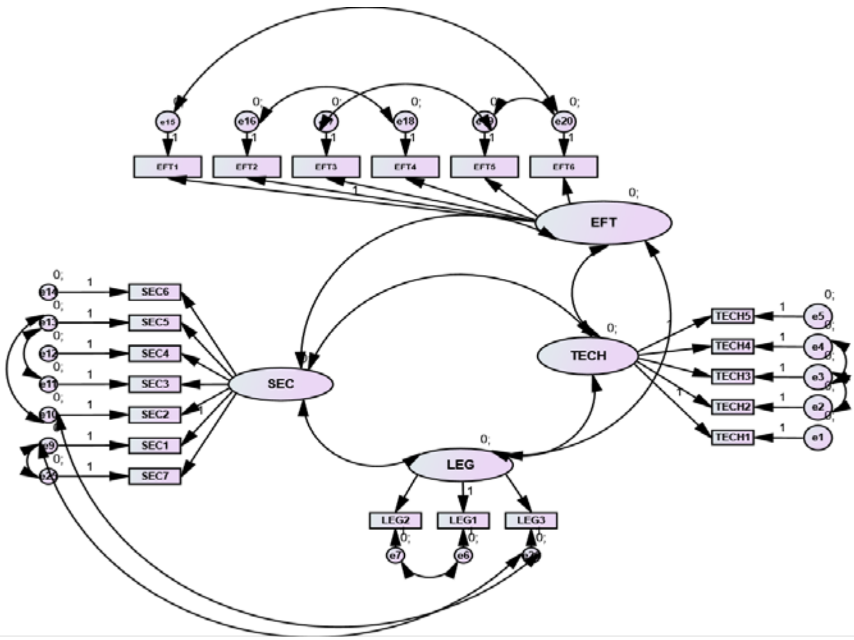

Fig. 2. Proposed SEM model

Source: own study.

SEM also builds the relationship between the measured and latent variables [Molenaar, Washington and Diekmann 2000]. Latent variables are abstract and cannot be directly measured. In this research, the measured variables are obtained from the questionnaire (transport fuels, improving vehicle efficiency, vehicle technology, transport efficiency, traffic infrastructure management, integration of transport systems, safety and security, economic aspects of change, broader environmental impacts, equity and accessibility, information and awareness, infrastructure, pricing and taxation, and regulation). The latent variables are technology, socioeconomic impacts, and legislation. An SEM model is divided into two parts: the first is used to determine the relationships between the measured and latent constructs [Anderson and Gerbing 1988], and the second is used to determine the relationships between the latent variables.

Using the presented framework and influential factors as well as the influential factors that are presented as consequences of climate-friendly (green) transport, a hypothetical structural model of climate-friendly transport is presented in Figure 2.

Table 1. Variables and abbreviations (those in grey are latent variables)

Variable	Abbrev.	Variable	Abbrev
Legislation	LEG	Technology	TECH
Pricing and taxation	LEG1	Transport efficiency	TECH1
Regulation	LEG2	Vehicle technology	TECH2
Infrastructure	LEG3	Improving vehicle efficiency	TECH3
Socioeconomic	SEC	Transport fuels	TECH4
Traffic infrastructure management	SEC1	Safety and security	TECH5
Integration of transport systems	SEC2	Green Transport	EFT
Economic aspects of change	SEC3	Competitiveness	EFT1
Broader environmental impacts	SEC4	Possibility to overcome social and/or political obstacles	EFT2
Equity and accessibility	SEC5	Other ecological impacts	EFT3
Information and awareness	SEC6	Social equity	EFT4
Cost efficiency in reduction of GHG emissions	SEC7	Quality of life	EFT5
		Job creation	EFT6

Source: own study.

The proposed model is composed of four latent variables with three of them (legislation, technology, and socioeconomic influences) representing the aggregation of the measured input variables, and one (green transport) grouping the outcome variables. The legislation group consists of pricing and taxation, regulation, and infrastructure, as all are within the competence of the government. Technological variables are transport efficiency, vehicle technology, improvement of vehicle efficiency, transport fuels, and safety and security. Socioeconomic variables are environmental impacts, information and awareness, traffic infrastructure management, integration of transport systems, economic aspects of change, and cost efficiency in the reduction of GHG emissions. The output variables are grouped using the latent variable green transport, which consists of competitiveness, job creation, possibility to overcome social and/or political obstacles, social equity, quality of life, and other ecological impacts.

As mentioned above, the project is divided into two parts. The first is the measurement model to establish associations between the measured and the latent variables that are used to group them, indicating the relations between the latent variables and their indicators. The second, the structural model, is used to determine the relations between the latent variables: legislation, technology, socioeconomic, and green transport, showing potential causal dependencies between endogenous and exogenous variables. There is a covariance connection between the technology, legislation, socioeconomic, and green transport latent variables, indicating the impact that each has over the others.

Using this structure of factors and variables, a hypothetical diagram is presented in Figure 2. Arrows represent hypothesised influences in the model and double-headed arrows represent causal impacts between connecting structures. In the model, there are also causal impacts between infrastructure, and traffic infrastructure management, and between transport fuels, vehicle technology, and improving vehicle efficiency, due to the very strong correlations between them. Similarly, there is a causal impact between pricing and taxation, and regulation, then between infrastructure, and traffic infrastructure management and integration of transport systems, then between cost efficiency in reduction of GHG emissions and traffic infrastructure management, followed by a causal impact between integration of transport systems and equity and accessibility, and then the connection of the latter with economic aspects of change. For green transport there is a significant correlation between competitiveness and job creation, then between the possibility to overcome social and/or political obstacles and social equity, followed by a causal impact between other ecological impacts and quality of life. Finally, there is a causal impact between quality of life and job creation.

The corresponding hypotheses are as follows:

- Hypothesis 1: Presented model is suitable.
- Hypothesis 2: There is a significant correlation between technology, legislation, socioeconomic factors, and green transport.
- Hypothesis 3: All measured factors in the model significantly describe latent variables.

The above hypotheses embrace a conceptual structural model as they are part of the structural components of the SEM. As the factors that influence the latent variables are considered to be vastly subjective, it is a difficult matter to refine the measurement variables to accurately represent the latent factors. The first hypothesis is that the presented model is statistically correct, and the third hypothesis is created to verify that the input data accurately define the latent variables. The principal result of this model is to calculate correlations between the latent variables technology, legislation, socioeconomic factors, and green transport, as defined in hypothesis 2. The results should be calculated with acceptable significance.

3. DATA ANALYSIS

Cronbach's alpha coefficient was used to confirm the used measured variables and their consistency when grouped [Cho and Kim 2015]. This test allows us to determine if multiple-question Likert scale surveys are reliable.

The results of the Cronbach's alpha calculations are presented in Table 2.

Table 2. Consistency check of measured and latent variables

Variable	Cronbach's alpha
Legislation	0.777
Technology	0.738
Socioeconomic	0.776
Green transport	0.803

Source: own study.

The small number of measured variables that are part of the latent variable's sensitivity of Cronbach's alpha to the number of items in the test have no influence. When Cronbach's alpha is bigger than 0.7, the data is acceptable [Mohsen Tavakol 2011]. Since the data were found to be consistent, they were entered into the SEM software. Today, there is a significant number of programs available for representing and analysing SEM models, namely LISREL (the first widely used program), CALIS (a module of SAS), SEPATH (a module of Statistica), Mplus (fully integrated general latent variable framework), AMOS (an add-on for SPSS), and two R packages: Lavaan and piecewiseSEM. For this research, AMOS was used.

After coding the model in the software, the model had 46 variables (21 endogenous and 25 exogenous), and a total of 131 parameters. Additionally, 80 distinct parameters had to be estimated, creating 172 degrees of freedom.

First, we needed to test the hypothesis that the model is correct. This was tested by the conventional chi-square test of fit in maximum likelihood, resulting in a chi-square value for the current data of 319,337 with a probability level of 0.00, proving that the model is significant at the level of 0.05. Once the model estimation was complete the next step was to assess the goodness of fit and determine whether to accept or reject the hypothesised model.

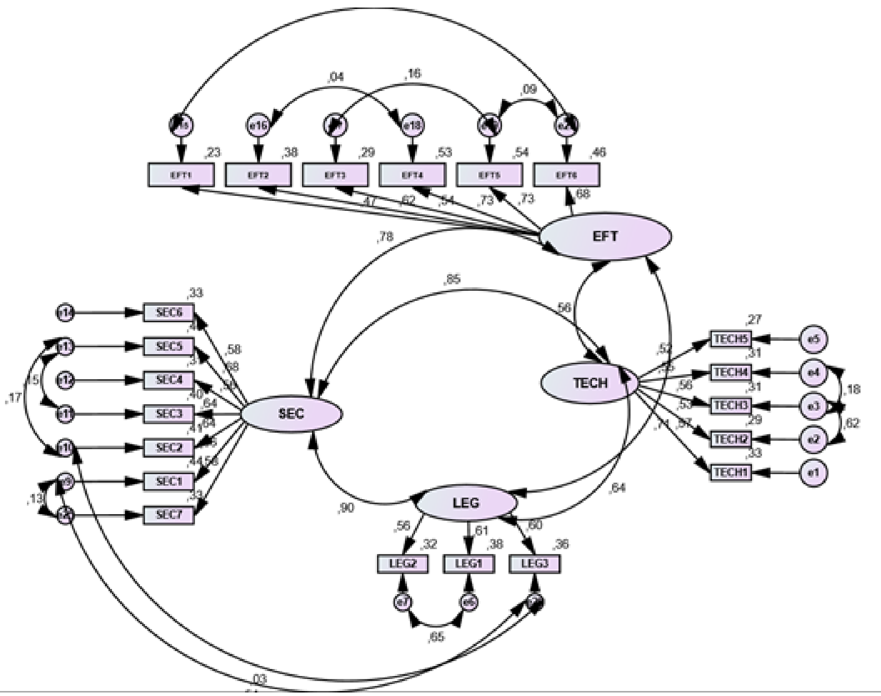

Fig. 3. Output path diagrams for calculated model

Source: own study.

Various statistical techniques are used based on the data to evaluate models [Wolf et al. 2013]. The appropriate statistical test has to be selected to fit the data model. Generally, a combination of statistic tests is used to evaluate the model [Viswesvaran and Ones 1995]. Minimum sample discrepancy tests are used with parsimony-adjusted measures to define the correctness of the model. The relative chi-square ($\chi2$/df) test, and the CMIN/DF test were used as the primary tests to validate the model fit. In this case, the $\chi2$ value was the same as the value of minimal discrepancy, and dividing them by the degrees of freedom produced a value of 1.857. Different researchers have proposed a CMIN/DF as low as 2 and as high as 5 as an acceptable fit [Marsh, Hau and Wen 2004].

In [Byrne 2013], the suggested range of $\chi2$/df is diminished to values less than 2 for the appropriate fit. The presented model has $\chi2$/df and CMIN/DF less than 2 (1.857), indicating that the model is appropriate.

Table 3. Regression weight and standardised regression estimates (*** – significant at 0.001)

			Regression weight estimate	Std error.	P	Stan-dardised regres-sion estimate
Transport_efficiency	←	Technology	1			0.56
Vehicle_Technology	←	Technology	1.073	0.392	0.006	0.543
Improving_vehicle_efficiency	←	Technology	1.149	0.398	0.004	0.564
Transport_fuels	←	Technology	1.125	0.37	0.002	0.558
Safety_and_security	←	Technology	1.063	0.379	0.005	0.533
Pricing_and_taxation	←	Legislative	1			0.613
Regulation	←	Legislative	0.841	0.131	***	0.563
Infrastructure	←	Legislative	0.814	0.194	***	0.596
Traffic_infrastructure_management	←	Socioeconomic	1			0.661
Integration_of_transport_systems	←	Socioeconomic	0.946	0.169	***	0.64
Economic_aspects_of_change	←	Socioeconomic	0.964	0.187	***	0.637
Broader_environmental_impacts	←	Socioeconomic	0.789	0.17	***	0.559
Equity_and_accessibility	←	Socioeconomic	0.946	0.177	***	0.681
Information_and_awareness	←	Socioeconomic	0.786	0.167	***	0.576
Cost_efficiency_in_reduction_of_GHG_emissions	←	Socioeconomic	0.774	0.159	***	0.576
Competitiveness	←	Green_transport	1			0.476
Possibility_to_overcome_social_and_or_political_obstacles	←	Green_transport	1.276	0.365	***	0.619
Other_ecological_impacts	←	Green_transport	0.935	0.267	***	0.536
Social_equity	←	Green_transport	1.27	0.333	***	0.73
Quality_of_life	←	Green_transport	1.443	0.358	***	0.734
Job_creation	←	Green_transport	1.309	0.3	***	0.676

Source: own study.

Another measure of model adequacy is based on the comparative fit index CFI [Bentler 1990]. CFI is an index that has values between 0 and 1. Values close to 1 indicate a very good fit of the model. In this case, the CFI is equal to 0.872, representing a good model fit. Finally, the model complexity is taken into account using the root mean square error of approximation RMSEA [Browne and Cudeck 1992]. The applied knowledge shows that a RMSEA of approx. 0.05 denotes a close fit of the model [Browne and Cudeck 1992], which suggests that a value of 0.09 or less for the RMSEA indicates a tolerable error of approximation, and RMSEA >0.1 indicates that the model is not applicable. The model used for this research has a RMSEA of 0.9, meaning that the model has a satisfactory fit.

All of these measures verify hypothesis H1: the model is appropriate as all presented model fit measures indicate that the model is suitable and acceptable.

Data presenting the regression weights and correlations are presented in Figure 3, and the regression weights between the measured variables and their corresponding latent variables are depicted in Table 3.

Hypothesis 3 is supported by the data presented in Table 3. All regression weight estimates are significant at 0.001, except for the measured factors that describe Technology, where the p-values are 0.006, 0.004, 0.002, and 0.005, respectively. This similarly shows that all data are significant within the significance level of 0.01 (1%) and therefore hypothesis 3 is accepted.

Table 4 presents covariance estimates and correlation estimates between the latent variables: technology, legislation, socioeconomic factors, and green transport.

Table 4. Covariance and correlation estimates between latent variables (*** – significant at 0.001)

			Covariance estimate	S. E.	P	Correlation estimate
Legislative	↔	Socioeconomic	0.468	0.126	***	0.904
Technology	↔	Socioeconomic	0.348	0.091	***	0.852
Technology	↔	Legislative	0.254	0.084	0.002	0.645
Green_transport	↔	Socioeconomic	0.265	0.084	0.002	0.78
Green_transport	↔	Technology	0.144	0.055	0.009	0.556
Green_transport	↔	Legislative	0.232	0.08	0.003	0.707

Source: own study.

It can be seen that the correlation estimates are significant, and that the covariance is significant at the level of 0.001 for the Legislative ↔ Socioeconomic, and Technology ↔ Socioeconomic pairs. For Technology ↔ Legislative, and Green transport ↔ Socioeconomic, the significance is 0.002, and for Green transport ↔ Legislative, it is equal to 0.003, while the Green transport ↔ Technology pair is equal to 0.009. This shows that all data is significant within the significance level of 0.01 and therefore hypothesis 2 is supported.

4. FINDINGS AND DISCUSSION

The created research model was accepted as suitable for analysing the relationships between the high-level constructs: technology, legislative, socioeconomic, and green transport. The model implies that there is a significant and very strong correlation between the legislative and socioeconomic factors (correlation = 0.904), followed by technology and socioeconomic factors (correlation = 0.852). This means that there is a strong relationship between the listed latent variables. The correlation between technology and legislative is moderate and is equal to 0.64.

The correlation between green transport and the other latent variables slightly weaker. The correlation between green transport and socioeconomic factors is strong and has a value of 0.78, while the correlation with legislative is weaker, with a value of 0.707, but still preserving a strong relationship. The correlation between technology and green transport is moderate (correlation = 0.556).

This means that socioeconomic factors have the most influence over other factors as the average cumulative correlation for socioeconomic is equal to 0.845, indicating very strong relationships with the other factors.

From the socioeconomic factors, economic aspects of change has the biggest regression estimate, with a regression weight of 0.946, meaning that when socioeconomic factors change by a value of 1, economic aspects of change rise by 0.946. Conversely, this means that when economic aspects of change grow by 1, socioeconomic factors will grow by 1.04. For technology and transport efficiency, the regression estimate is equal to 1, as it is fixed. This is because the measurement scale of the unobserved variable is unspecified, and therefore fixing the value to 1 sets the restriction on the latent variable which is appropriate for identifying the model. This is why there is also a standardised regression weight. Standardised regression estimates are calculated using standard deviation and therefore the meaning is a little different. For the previously defined group, it is equal to 0.56, signifying that when Technology goes up by 1 standard deviation, transport efficiency will go up by 0.56 standard deviations.

One of the interesting results is that when green transport goes up by a value of 1, quality of life is augmented by 1.44, job creation by 1.308 and social equity by 1.274, and possibility to overcome social and/or political obstacles rises by 1.278. This means that if there is significant growth in green transport, job creation will rise by 130% of the green transport growth, and quality of life will rise by 144%.

5. CONCLUSIONS

A model was created and presented to explain the influencing factors of climate-friendly transport. It presents a comprehensive view of factors affecting climate-friendly transport, grouped into 4 groups represented by unobserved, latent variables that are expressed as influencing factors: technology, socioeconomic factors, legislative, and by the suggested output, green transport. The study has exhibited how factors of different categories can be merged in a model and how structural equation modelling can be used to analyse the principal relationships between the influencing factors themselves.

The results show that the measured elements can be grouped into four categories and presented as interrelationships between the latent factors themselves, and the latent factors and measured factors. Before the model was created, the measured factors were integrated into categories. The results show that the distribution of the factors in the groups is meaningful. The presented model improves the understanding of the influence of all factors in the model on each other.

This study contributes to the body of knowledge in several ways. First of all, the study created a general, integrated structural model of climate-friendly transport, and validated the associations between observed factors and their corresponding grouping structures that are latent and unobservable. Secondly, the study used structural equation modelling as a method and showed that this innovative method can be used to describe and explain facts better than classical statistical models and data analytics. Third, relationships between observed and latent factors are recognised and calculated. Finally, this study can improve the overview and understanding of factors that influence climate-friendly transport.

On the other hand, there are some limitations to the study. Primarily, the data used are from a survey with 233 responses. Although this is suitable for structural equation modelling, more data would certainly improve the model and enhance its validity. Further research, and more detailed and enriched models should be developed to further investigate the relationships between the influencing factors for climate-friendly transport.

REFERENCES

Agency, U. E. P., 2020, S*ources of Greenhouse Gas Emissions*, 20.10.2020, https://www.epa.gov/-ghgemissions/sources-greenhouse-gas-emissions.

Allison, P.D., 2003, *Missing Data Techniques for Structural Equation Modeling*, Journal of Abnormal Psychology, vol. 112, no. 4, pp. 545–557.

Anderson, J.C., Gerbing, D.W., 1988, *Structural Equation Modeling in Practice: A Review and Recommended Two-Step Approach*, Psychological Bulletin, vol. 103, no. 3, pp. 411–423.

Asparouhov, T., Muthén, B., 2009, *Exploratory Structural Equation Modeling*, Structural Equation Modeling, vol. 16, no. 3, pp. 397–438.

Bentler, P.M., 1990, *Comparative Fit Indexes in Structural Models*, Psychological Bulletin, vol. 107, no. 2, pp. 238–246.

Bowen, N.K., Guo, S., 2012, *Structural Equation Modeling. Pocket Guides to Social Work Research Methods*, Oxford University Press (Copyrighted Material).

Browne, M.W., Cudeck, R., 1992, *Alternative Ways of Assessing Model Fit*, Sociological Methods & Research, vol. 21, no. 2, pp. 230–258.

Byrne, B.M., 2013, *Structural Equation Modeling with AMOS: Basic Concepts, Applications, and Programming*.

Chin, W.W., 1998, *Issues and Opinion on Structural Equation Modeling*, MIS Quarterly: Management Information Systems, vol. 22, no. 1, pp. vii–xvi.

Cho, E., Kim, S., 2015, *Cronbach's Coefficient Alpha: Well Known but Poorly Understood*, Organizational Research Methods, vol. 18, no. 2, pp. 207–230.

Čišić, D., Perić-Hadžić, A., Tijan, E., Ogrizović, D., 2011, *Methods of Defining and Evaluating Future Research Priorities in Climate Friendly Transport*: *Preliminary Results from the REACT Open Consultation*, pp. 346–349.

Heck, R.H., Thomas, S.L., 2020, *An Introduction to Multilevel Modeling Techniques*, Routledge.

Marsh, H.W., Hau, K.T., Wen, Z., 2004, *In Search of Golden Rules: Comment on Hypothesis-Testing Approaches to Setting Cutoff Values for Fit Indexes and Dangers in Overgeneralizing Hu and Bentler's (1999) Findings*, Structural Equation Modeling, vol. 11, no. 3, pp. 320–341.

Mohsen Tavakol, R.D., 2011, *Making Sense of Cronbach's Alpha*, International Journal of Medical Education, vol. 2, pp. 53–55.

Molenaar, K., Washington, S., Diekmann, J., 2000, *Structural Equation Model of Construction Contract Dispute Potential*, Journal of Construction Engineering and Management, vol. 126, no. 4, pp. 268–276.

OECD, 2015, *The Carbon Footprint of Global Trade*.

Radmilović, Z. Čišić, D., 2011, *Shaping Climate Friendly Transport in Europe: Key Findings & Future Directions*, REACT 2011, Proceedings. Belgrade: University of Belgrade – The Faculty of Transport and Traffic Engineering.

Viswesvaran, C., Ones, D.S., 1995, *Theory Testing: Combining Psychometric Meta-analysis and Structural Equations Modeling*, Personnel Psychology, vol. 48, no. 4, pp. 865–885.

Wayne, S.W., Sandoval, J.A., Clark, N.N., 2009, *Emissions Benefits from Alternative Fuels and Advanced Technology in the U.S. Transit Bus Fleet*, Energy and Environment, vol. 20, no. 4, pp. 497–515.

Wolf, E.J., Harrington, K.M., Clark, S.L., Miller, M.W., 2013, *Sample Size Requirements for Structural Equation Models: An Evaluation of Power, Bias, and Solution Propriety*, Educational and Psychological Measurement, vol. 73, no. 6, pp. 913–934.