



5th International Conference on Ambient Systems, Networks and Technologies (ANT-2014)

A survey on the use of computational models for ex ante analysis of urban transport policy instruments

Banafsheh Hajinasab^{a*}, Paul Davidsson^a, Jan A. Persson^a

^a*Department of Computer Science, Malmö University, Malmö, Sweden*

Abstract

This paper provides an analysis of the use of computational models for predicting the effects of different policy instruments on urban transport systems. We define a framework for describing and comparing current approaches that takes into account (i) what policy instruments are studied, (ii) what type of effects are predicted, (iii) which factors are modeled, (iv) the type of model used, and (v) what data sources are used. The main conclusions of the analysis are: (i) despite the recognized potential of agent-based modeling to study behavioural change of a population, it rarely has been used for ex-ante analysis of policy instruments using real-world data, (ii) some factors that influence travellers' decisions, such as comfort and departure time, have not been considered much in the modeling, (iii) ex-ante analysis of economic instruments constitute the majority of studies, but informative instruments have been recently considered due to the increasing use of information technology in transportation.

© 2014 Published by Elsevier B.V. This is an open access article under the CC BY-NC-ND license (<http://creativecommons.org/licenses/by-nc-nd/3.0/>).

Selection and Peer-review under responsibility of the Program Chairs.

Keywords: survey; policy instruments; computational models; travel behaviour; ex ante analysis

1. Introduction

There is a wide set of policy instruments that can be used for designing transport strategies in order to achieve transport system objectives. Examples of such objectives are reduction of congestion, private vehicle use, emissions, or more generally, travel demand management. Policy instruments range from more conventional instruments such as land use regulation, vehicle regulation, infrastructure investment, and pricing schemes, to newer instruments such

* Corresponding author. Tel.: +0-000-000-0000 ; fax: +0-000-000-0000 .
E-mail address: author@institute.xxx

as application of information technology to improve resource allocation and service quality, as well as attitudinal changes [1]. The policy instruments are very different in nature and have different effects on different transport systems. Moreover, the combination of policy instruments might have a totally different effect on the transport system compared to applying each individual instrument alone [2]. It has been argued that the development of sustainable transport strategies often fails due to lack of integration of different policy instruments [3,4].

In order to know which policy instruments to choose in a particular situation, it is important not only to have knowledge about availability of policy instruments, but also their potential impact on the transport system. There are different methods to analyze the effects of policy instruments. Kremers et al. [5] have categorized methods for transport policy analysis into two main types: qualitative ad-hoc approaches that are solely based on expert judgment or interviews, and quantitative structured approaches, where a statistical or econometric model based on quantified data is used. Ad-hoc approaches are typically used in situations where there is no possibility for a structured approach due to time constraints, non-repetitive situations, or lack of data. We will here focus on structured, or quantitative approaches that have used computational models to estimate the effects of policy instruments.

In the project KonSULT, an international knowledge base on the impact of different urban transport policy instruments was developed [1,6]. It provides an online decision-support tool that can assist policy makers in developing urban transport strategies. While this work has some similarities with our research, there are also fundamental differences. We do not aim to develop a comprehensive encyclopedia of policy instruments, but rather focus on the use of computational models for impact assessment of policy instruments.

In the present work we have analyzed the applications of computational models to estimate the effects different policy instruments that we have found in the literature. The aim is to understand which policy instruments have been investigated, which kinds of models have been used to estimate the effects of policy instruments, and how these models have been applied. To do this in a systematic way, we have developed a framework for characterizing the applications. In order to develop this framework, we have extracted the common characteristics of different published studies in the area of ex ante analysis of urban transport policies. We have collected a set of papers through online databases of peer-reviewed articles. We first conducted an exploratory, opportunistic literature review in which the set of policy instruments have been studied was identified, followed by a more focused literature search where we gathered the relevant studies investigating each of the policy instruments.

1.1. Scope

In this survey, we have focused on policy instruments that aim to change the behaviour of travellers, rather than to change the behaviour of transport system planners. That is, we do not regard policy instruments, such as regulative requirements on regional planning or public transport tendering. In addition, our focus is on instruments that have direct effects on the travel behaviour. Thus, we exclude instruments such as vehicle tax, which affect long-term travel decisions e.g. concerning what type of car to buy.

Furthermore, we will not include instruments that concern infrastructure development and network expansion. The motivation for this is that in the recent years, the focus of urban transport system planning has shifted from building new infrastructure to more efficient use of the existing infrastructure [7]. In particular, investments on road infrastructure are usually very expensive and time consuming, and above all, it is often impossible to find the space needed due to the high density of cities and land-use regulations.

As mentioned earlier in this paper, we limit our search to those papers that have used computational models to estimate the effects of policy instruments.

2. Survey framework

In this section we describe the framework that has been used to characterize the applications of computational models to estimate the effects of policy instruments.

2.1. Policy instruments

Below we describe the policy instruments investigated in the studies we have reviewed.

- **Road user charging (RUC)** is a common name for different methods to collect money from road users [8]. The motivation for introducing RUC is often either to make the road users compensate for the costs caused by their transports such as road wear and accidents, i.e., internalization of external costs, or to change the behaviour of the road users to be consistent with the objectives of the transport policies, e.g. to reduce congestion [9], and/or emission [10]. There are different approaches to implement RUC such as *road link-based*, *cordon/area-based*, *time-based*, and *distance-based* charging. The distance-based approach computes the charges based on the distance traveled in a specified area, while the road link approach computes the charge based on the number of times a vehicle crosses a specific link. Cordon-based charges are calculated in a similar way as road link charges, but in this case based on the number of times the vehicle enters an area, referred to as the cordon. In case of time-based charging, the time spent in a specified area provides the basis for calculating charges. In addition, the specific time period in which the travel is happening can determine the level of charges.
 - **Road User Rewarding (RUW)** is closely related to RUC, but in this case the travellers will be awarded by money or other kinds of incentives instead of punishment. Charging and rewarding can alternatively be called as push and pull strategies [11]. Rewarding is claimed to be more acceptable and effective as it makes people happier, thus increasing the effectiveness of people. However, there are at least two disadvantages to be considered which might affect the effectiveness of rewarding. First and foremost, charging provides revenues, which can be used to enhance the transportation services in order to increase social welfare, whereas rewarding does not. Secondly, it is argued that losses have more emotional impact than gains, which makes them more effective [11].
 - **Parking fees** refer to the charges related to on-street or off-street parking of a vehicle. Parking fees either can be sensitive to the time of the day, or not. In general, parking fees seem to be more acceptable for drivers than other kinds of policies since they have been used for a long time [12].
 - **Public transport fares** concern the cost that travellers need to pay in order to use public transport services. Public transport here refers to the passenger transport services provided by a 'third party' and available for use by all members of the community [13] including buses, metro, ferries, light rail, subways, commuter rail, and regional or inter-urban rail [14].
 - **Fuel price** comprises the actual cost of the fuel and the fuel tax determined by the government. Governments can either pursue fuel subsidization policies or increase fuel taxes to control people's transportation behaviour [15,16].
 - **Private car restrictions** correspond to the rules and regulations that the government may impose in order to decrease attractiveness and possibility of private car usage. It can be in the form of some restrictions on the car use such as time, zone and distance restrictions, or speed limits, as well as rules for car ownership [17,18].
 - **Road capacity allocation** often concerns introduction of bus priority policies such as Bus Rapid Transit (BRT) systems. BRT operates on exclusive lanes of existing roads and provides flexible and high performance service, which is comparable to light rail transit or metro systems but to a much lower cost [19]. Compared to the traditional busses, BRT systems reduce travel time and hence increase the attractiveness of public transport [20].
 - **Pre-trip planning support** is an information-provisioning instrument in which the traveller can obtain useful information before the actual travel. The purpose is to make the travellers more informed before deciding on mode, route, and departure time, or even whether to travel or not. Examples of pre-trip information are public transport schedules and travel time estimations. The pre-trip information can be obtained via smartphones, radio channels, television, and online services [21]. Advanced Traveller Information Systems (ATISs) are an example of information source for travellers that provide travellers with pre-trip, as well as real-time information [22].
 - **Real-time traffic information** is the provision of information about the current traffic situation to the travellers, which can be used to adapt the travel behaviour, e.g. route choice or departure time [23,24,25]. The real-time information can be provided through en-route guidance on the road, e.g. variable message signs, or ATISs [26].
- According to [27] the policy instruments fall into three main categories: Economic, Administrative, and Informative. Using this classification, we can summarize the above-mentioned policy instruments as illustrated in Figure 1.

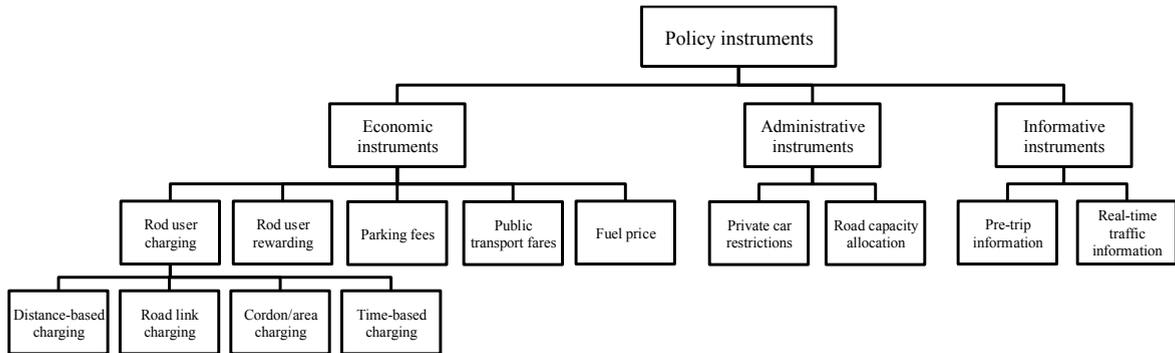


Figure 1. Categorization of policy instruments in this study.

2.2. Travel behaviour effects

This aspect concerns how the policy instruments influence traveller behaviour. More specifically, it deals with how policy instruments play a part in people's travel-related choices. The following effects have been studied in the articles reviewed:

- *Mode choice*: changes in the selection of transportation mode, e.g. bus, train, car, bicycle, etc.
- *Route choice*: changes in which route is taken.
- *Travel time*: changes to the time duration of the travel, from origin to destination.
- *Departure time*: changes to the time when the traveller leaves the origin and starts traveling.
- *Destination choice*: changes in the travellers' choice of destination.
- *Parking choice*: changes to where the travellers park their cars.

2.3. Factors

This aspect is referring to the factors that are considered in modeling of travellers' decision making. The factors we have identified in the studied literature fall into the following categories:

- *Time*: covers all the time-related factors which have been included in the models such as expected travel time, departure time, and time of the year in which travel happening (e.g. season), etc.
- *Cost*: all the cost-related factors fall into this category, e.g. in-vehicle cost, cordon cost, parking fee, congestion charge, emission charge, fuel cost, tolls, public transport cost, etc.
- *Socio-demographic characteristics*: includes characteristics of the travellers such as age, gender, income, education level, household structure, vehicle type, car availability, driving license ownership, public transport pass ownership, personality characteristics (e.g. strong habits or environmental awareness), etc.
- *Trip purpose*: the motive for the travel such as work, education, leisure, shopping, or even mix of them.
- *Comfort*: includes characteristics related to the traveller's comfort during a travel such as number of transfers, number of stops, availability of seats, in-vehicle crowding, out of vehicle facilities, personal security, safety, cleanness and temperature inside vehicle, etc.

2.4. Model

As was mentioned in the introduction, our focus in this paper is quantitative methods of impact assessment of policy instruments. We have different types of models in the literature. A majority of the studies have applied different kinds of discrete choice models such as multinomial logit model (MNL), mixed logit model (MXL), binary logit model (BIL), nested logit model (NLM), probit model, alternative-specific discrete choice model, multiple regression analysis, and logistic regression. Some studies have applied agent-based simulation models in which the travellers' interaction are taken into account, while others are based on conventional simulation methods [28]. There

are some studies that have combined different models, such as [35] in which an integrated model of MNL and agent based simulation have been used.

2.5. Data sources

This aspect deals with the origin of the data that is fed into the models. Data can be acquired by several ways, including national surveys and censuses, stated preferences surveys, and revealed preferences. In a stated preference survey, the travellers are asked to provide their preferences and choices in different situations, whereas in revealed preference experiments, the empirical observation of travellers' choices is considered as source of information [29]. Data from national surveys may be less valid for the particular area and situation studied.

2.6. Size of the modelled area

We have characterized the study areas according to their population as follows: Very small city (less than 100,000), Small city (100,000–1 million), Medium-sized city (1–5 million), Large city (5–10 million), and Megacity (more than 10 million) inhabitants.

3. Discussion

The results of the survey are summarized in Table 1. In this section, we will analyze the results in terms of the different aspects of the survey framework, starting with the type of policy instrument studied.

It can be observed that it is the effects of economic policy instruments that have been analyzed the most in the literature. One explanation for this finding can be the fact that the cost-related instruments have been the most widely used in the past and they are still very common in travel demand management. Therefore, it is natural that the policy makers wish to focus on ex-ante analysis of the economic instruments. Another reason could be that travellers' decisions based on cost are easier to model than those based on information availability etc. Looking into the year of publication reveals that the economic instruments have been evenly considered in the literature from the past till nowadays. However, the type of instrument has changed over the time and new ways of road-user charging or public transport fare regulations have been studied. Moreover, we can see that the administrative instruments have only recently been considered. Another interesting observation is that the informative instruments have been mostly investigated in the period of 2001-2002 and then after 2011. The introduction of new information systems and the growing trend towards application of new ITS services in the beginning of 2000 may account for this result.

We observe that changes in mode choice and route choice are the most commonly studied effects of policy instruments on people's travel behaviour. Also change in departure time has been studied rather frequently, but slightly less than route choice. We note that the changes in travel time are seldom regarded, as well as changes in where to travel and park.

Concerning the factors considered in modeling, socio-demographic characteristics, travel time and cost are the most frequently considered, whereas factors such as trip purpose, time of the year, departure time and comfort are seldom considered. In particular, we found that in almost all cases some socio-demographic characteristics of the study population have been considered. Among socio-demographic characteristics, age, gender, income, work schedule flexibility and car availability are the most used factors, while vehicle type and residential location are the least used. Although it has been argued that comfort and convenience of travellers during a journey can have significant effects on travellers' choices (especially mode choice) [30], they are typically not considered. This may be due to the difficulty of gathering data about comfort and travellers attitudes because these factors have subjective constructs [31].

The majority of studies have used some kind of discrete choice model, in particular logit models have been the most frequently used. We notice that the use of agent-based simulation models has increased in recent years. Due to high computational power requirement of these kinds of models and difficulty of collecting disaggregated data, these models have been considered difficult to implement and therefore were not very commonly used in the past.

However, the conventional discrete choice models have been criticized for neglecting the interaction effects and oversimplification which can introduce significant biases in output [43].

The data required for the models is mainly acquired through stated preferences surveys, whereas revealed preferences surveys were used only in two cases. There are also some studies that have used artificial data. It can be seen from the table that all the studies that have used artificial data, use agent-based simulation for impact analysis. It can be due to the fact that agent-based simulation method requires a lot of detailed data about the network and population that might not be easy to acquire.

Medium-sized cities (1-5 million inhabitants) are dominant in the studied models, just as many as large and mega cities taken together, whereas cities smaller than 1 million have been less studied.

4. Conclusions and future work

Based on the review, we conclude that mathematical-based and discrete choice models have been considered as the main method for ex-ante analysis of policy instruments for many years. However, due to oversimplification of discrete choice models in considering interaction effects, the results from these models are often inaccurate especially in real-world problems where the interactions of policies/people are high [43]. Therefore, we argue that there is a need to develop agent-based models that use real-world data. In particular, such models may be useful for smaller cities, which to date often have not been the target for policy instrument studies although they often have major traffic problems. Moreover, there are some policy instruments used in reality that to the best of our knowledge have not been studied using computational models for ex-ante analysis, e.g. travel awareness campaigns, and ITS-based travel ticketing systems. We think that it is worth investigating whether also these instruments could be analyzed using computational models.

References

-
- [1] May, A. D., & Taylor, M. A. (2002). KonSULT-Developing an International Knowledgebase on Urban Transport Policy Instruments (Doctoral dissertation, Bureau of Transport and Regional Economics).
 - [2] May, A. D., Kelly, C., Shepherd, S. (2006). The principles of integration in urban transport strategies. *Transport Policy*, 13(4), 319-327.
 - [3] Schöller-Schwedes, O. (2010). The failure of integrated transport policy in Germany: a historical perspective. *Journal of Transport Geography*, 18(1), 85-96.
 - [4] Santos, G., Behrendt, H., & Teytelboym, A. (2010). Part II: Policy instruments for sustainable road transport. *Research in Transportation Economics*, 28(1), 46-91.
 - [5] Kremers, H., Nijkamp, P., & Rietveld, P. (2002). The scope of meta-analysis for transport policy impact analysis in environmental economics. *Comparative Environmental Economic Assessment*, Edward Elgar, Cheltenham, UK, 47-73.
 - [6] KonSULT, the Knowledgebase on Sustainable Urban Land use and Transport. (2013). Retrieved December 27, 2013, from <http://www.konsult.leeds.ac.uk/public/level1/sec09/>
 - [7] Illenberger, J., Flotterod, G., & Nagel, K. (2007). Enhancing matsim with capabilities of within-day re-planning. In *proceedings of 10th International IEEE Conference on Intelligent Transportation Systems (ITSC 2007)*, IEEE (94-99).
 - [8] Johansson, B., & Mattsson, L. G. (1995). Principles of road pricing. *Road pricing: Theory, empirical assessment and policy*. Springer Netherlands, 7-33.
 - [9] Eliasson, J., Börjesson, M., van Amelsfort, D., Brundell-Freij, K., & Engelson, L. (2013). Accuracy of congestion pricing forecasts. *Transportation Research Part A: Policy and Practice*, 52, 34-46.
 - [10] Mishra, S., & Welch, T. F. (2012). Joint Travel Demand and Environmental Model to Incorporate Emission Pricing for Large Transportation Networks. *Transportation Research Record: Journal of the Transportation Research Board*, 2302(1), 29-41.
 - [11] Bliemer, M. C., & van Amelsfort, D. H. (2010). Rewarding instead of charging road users: a model case study investigating effects on traffic conditions. *European Transport*, 44, 23-40.
 - [12] Albert, G., & Mahalel, D. (2006). Congestion tolls and parking fees: A comparison of the potential effect on travel behavior. *Transport Policy*, 13(6), 496-502.
 - [13] D'Este, G., Taylor, M. A. P., & Radbone, I. G. (1994). Demand responsive public transport for Australia: 1. The trade-offs. In *Papers of the Australian Transport Research Forum*, 1994, Vol 19.

- [14] Glover, L. (2011). Public Transport as a Common Pool Resource. In *proceedings of the 34th Australasian Transport Research Forum (ATRF)*, 28 - 30 September 2011, Adelaide, Australia.
- [15] Khoo, H. L., Ong, G. P., & Khoo, W. C. (2012). Short-term impact analysis of fuel price policy change on travel demand in Malaysian cities. *Transportation Planning and Technology*, 35(7), 715-736.
- [16] Vrtic, M., Schuessler, N., Erath, A., & Axhausen, K. W. (2007). Route, Mode, and Departure Time Choice Behaviour in the Presence of Mobility Pricing. In *proceedings of Transportation Research Board 86th Annual Meeting* (No. 07-1618).
- [17] de Grange, L., Troncoso, R., & González, F. (2012). An empirical evaluation of the impact of three urban transportation policies on transit use. *Transport Policy*, 22, 11-19.
- [18] Massot, M. H., & Armoogum, J. (2003). Speed and car traffic regulation in urban areas. *IATSS research*, 27(2), 46-55.
- [19] ITDP, Bus rapid transit planning guide. (2007). Retrieved December 28, 2013, from <http://www.itdp.org/microsites/bus-rapid-transit-planning-guide/>
- [20] McDonnell, S., & Zellner, M. (2011). Exploring the effectiveness of bus rapid transit a prototype agent-based model of commuting behaviour. *Transport Policy*, 18(6), 825-835.
- [21] Jou, R. C. (2001). Modeling the impact of pre-trip information on commuter departure time and route choice. *Transportation Research Part B: Methodological*, 35(10), 887-902.
- [22] Zito, P., Amato, G., Amoroso, S., & Berritella, M. (2011). The effect of Advanced Traveller Information Systems on public transport demand and its uncertainty. *Transportmetrica*, 7(1), 31-43.
- [23] Ben-Elia, E., & Shiftan, Y. (2010). Which road do I take? A learning-based model of route-choice behaviour with real-time information. *Transportation Research Part A: Policy and Practice*, 44(4), 249-264.
- [24] Jou, R. C., Kitamura, R., Weng, M. C., & Chen, C. C. (2008). Dynamic commuter departure time choice under uncertainty. *Transportation Research Part A: Policy and Practice*, 42(5), 774-783.
- [25] Jou, R. C., Hensher, D. A., & Chen, K. H. (2007). Route Choice Behaviour of Freeway Travellers Under Real-time Traffic Information Provision—Application of the Best Route and the Habitual Route Choice Mechanisms. *Transportation Planning and Technology*, 30(6), 545-570.
- [26] Bonsall, P. (1992). The influence of route guidance advice on route choice in urban networks. *Transportation*, 19(1), 1-23.
- [27] Trafikverket. (2012). Styrmedel för ett effektivare transportsystem , *Trafikverket*, 2012:106.
- [28] Tsekeris, T., & Voß, S. (2010). Public transport and road pricing: a survey and simulation experiments. *Public Transport*, 2(1-2), 87-109.
- [29] Wardman, M. (1988). A comparison of revealed preference and stated preference models of travel behaviour. *Journal of Transport Economics and Policy*, 71-91.
- [30] Stet, M., & Rosu, A. (2012). PSPC (Personal, Social, Psychological, Cultural) factors and effects on travel consumer behaviour. *Economics and Management*, 17(4), 1491-1496.
- [31] Diana, M. (2010). From mode choice to modal diversion: A new behavioural paradigm and an application to the study of the demand for innovative transport services. *Technological Forecasting and Social Change*, 77(3), 429-441.
- [32] Ahmadi Azari, K., Arintono, S., Hamid, H., & Rahmat, R. A. O. (2013). Modelling demand under parking and cordon pricing policy. *Transport Policy*, 25, 1-9.
- [33] An, S., Cui, J. X., & Li, L. Y. (2011). Agent-based approach to model commuter behaviour's day-to-day dynamics under pre-trip information. *IET Intelligent Transport Systems*, 5(1), 70-79.
- [34] Ben-Elia, E., & Ettema, D. (2011). Rewarding rush-hour avoidance: A study of commuters' travel behaviour. *Transportation Research Part A: Policy and Practice*, 45(7), 567-582.
- [35] Dia, H. (2002). An agent-based approach to modelling driver route choice behaviour under the influence of real-time information. *Transportation Research Part C: Emerging Technologies*, 10(5), 331-349.
- [36] Eluru, N., Paleti, R., & Bhat, C. R. (2010). Examining the Influence of Tolls on Commute Departure and Route Choice Behaviour in the Chicago Region. *Southwest Regional University Transportation Center, Center for Transportation Research*, the University of Texas at Austin, (No. SWUTC/10/169200-1).
- [37] Fabbro, Y. (2013). Free public transport: a socio-cognitive analysis. (Master's thesis, Hasselt University, Hasselt, Belgium). Retrieved from <http://hdl.handle.net/1942/15542>
- [38] Feng, S. W., & Ye, J. J. (2008). A Comparative Study of Parking and Congestion Charge Policies based on Transport Mode Choice Estimation. ITSC 2008. In *proceedings of 11th International IEEE Conference on Intelligent Transportation Systems (ITSC 2008)*, IEEE (506-510).
- [39] Grether, D., Chen, Y., Rieser, M., Beuck, U., & Nagel, K. (2008). Emergent effects in multi-agent simulations of road pricing. In *proceedings of Annual meeting of the European Regional Science Association ERSA*, 8.
- [40] Wahle, J., Bazzan, A. L. C., Klügl, F., & Schreckenberg, M. (2002). The impact of real-time information in a two-route scenario using agent-based simulation. *Transportation Research Part C: Emerging Technologies*, 10(5), 399-417.
- [41] Washbrook, K., Haider, W., & Jaccard, M. (2006). Estimating commuter mode choice: A discrete choice analysis of the impact of road pricing and parking charges. *Transportation*, 33(6), 621-639.
- [42] De Palma, A., & Lindsey, R. (2006). Modelling and evaluation of road pricing in Paris. *Transport Policy*, 13(2), 115-126.
- [43] Takama, T., & Preston, J. (2008). Forecasting the effects of road user charge by stochastic agent-based modelling. *Transportation Research Part A: Policy and Practice*, 42(4), 738-749.