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A stochastic logistics model for Indonesia's national freight transport model: Transport chain choice from the shipper perspective

Lydia Novitriana Nur Hidayati [a,b,*], Gerard De Jong [a,c], Anthony Whiteing [a]

[a] Institute for Transport Studies, University of Leeds, United Kingdom
[b] Civil Engineering Department, Universitas Sebelas Maret Surakarta, Indonesia
[c] Significance, the Netherlands

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ABSTRACT

This paper presents research towards the development of a stochastic approach for estimating the transport chain choice for domestic shipments in Indonesia. This stochastic model aims to improve the logistics choices within Indonesia's national freight transport model (INTRAMOD), which currently handles such choice deterministically. The INTRAMOD logistics model presents five distinct transport chain possibilities involving four main modes: truck, rail, ship, and plane. To acquire the necessary data, revealed preference (RP) and stated preference (SP) survey work has been undertaken. Using the obtained RP/SP data, multinomial logit (MNL) models have been used to estimate the transport choice model. The model with a single time coefficient was found to be superior to the other models. Additionally, this preferred MNL model was extended by segmenting according to shipment characteristics, particularly for high and low value of goods. The results indicate that shipments with a high value of goods are more sensitive to transport time.

1. Introduction

Improving model reliability is essential to the development of national freight transport models, and model outputs must be well-grounded to anticipate and predict actor behaviour (e.g., shipper and carriers). Incorporating logistics activities in the form of a logistics module within the freight modelling framework is a notable new direction within the field of freight transport modelling (Gerard et al., 2013). A logistics model is a simplification of the relationship between the choices of freight transport actors in logistics operations and the underlying decision-making criteria. Some notable logistics model directions study inventory choices and transport choices on a multimodal transport network (Davydenko, 2015; Halim, 2016; Huber, 2017).

According to Abate et al. (2016), freight transport models that contain logistics decisions often rely on optimization theory in which firms seek to minimise the annual total logistics cost. The version of the national freight model for Norway and Sweden that was established in the first decade of the twenty-first century contained such logistics models (De Jong et al., 2007; Ben-Akiva and De Jong, 2008). Developed within the framework of the aggregate-disaggregate-aggregate (ADA) model, the Norwegian and Swedish national freight models estimate the shipment size and transport chain choices of firms following the Economic Order Quantity (EOQ) concept by balancing inventory costs, order costs, and transport costs to achieve the lowest annual logistics cost. A similar approach is also being examined in the development of the National Freight Transport Model for Indonesia (INTRAMOD).

Three main modules are constructed within INTRAMOD: (1) Aggregate zone-to-zone demand model (i.e., to model the zonal trade flow distribution between production (P) zone and consumption (C) zone, i.e. PC flows), (2) Disaggregate logistics model (testing both deterministic and stochastic approaches), and (3) Aggregate network assignment. In the second stage, an initial subtask is performed to disaggregate the zone-to-zone flows into hypothetical firm-to-firm flows, a prerequisite for modelling the transport chain selection of individual firms. After the transport chain choice, aggregation to origin-to-destination (OD) flows will be carried out prior to network assignment. This paper focuses on the stochastic logistics model approach. The current logistics model in INTRAMOD is developed using a deterministic approach (i.e., it follows the EOQ theory) for both shipment size and transport chain selection. A deterministic model that assumes shippers will choose the transport chain and shipment size with the lowest cost is simple to construct and the necessary data is readily available, albeit

* Corresponding author. Institute for Transport Studies, University of Leeds, United Kingdom.
E-mail addresses: lydia.hidayati@staff.uns.ac.id, tslnnh@leeds.ac.uk (L.N.N. Hidayati), g.c.dejong@its.leeds.ac.uk (G. De Jong), a.e.whiteing@its.leeds.ac.uk (A. Whiteing).

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lacking an empirical foundation. In contrast, a stochastic model (e.g., a logit discrete choice model) is typically based on observed behavioural data, which may more accurately reflect the actual process of logistics option decision making (Abate et al., 2018). Nonetheless, for such a stochastic model comprehensive data collection is necessary. Consequently, this research tries to improve the prediction of the current INTRAMOD logistics model by incorporating the behaviour of shippers in relation to their transport chain selection in order to enable a more robust and realistic policy analysis. However, the shipment size choice has to remain deterministic in INTRAMOD as the disaggregate data collected does not allow estimation of a model for a choice combination of transport chain and shipment size (mainly because the sample size is too small for a model with so many alternatives).

Recent research has shifted away from the deterministic model and toward the stochastic model (Abate et al., 2014, 2016, 2018; De Jong et al., 2014). The stochastic method applies the random utility discrete choice model to determine the probability that a shipper will select a particular combination of transport chain (and shipment size). The stochastic approach is intended to circumvent an issue inherent to the deterministic approach. One implication of the all-or-nothing assumption is that the deterministic model may suffer from overshooting or sticky choices (Abate et al., 2014). Overshooting happens when the logistics cost function is relatively flat, so that small changes in logistics costs can result in drastically different decisions. Meanwhile, sticky choice occurs when one alternative is significantly less expensive than the others. Consequently, the enhancement of another alternative will have no effect on this alternative's mode share unless this alternative becomes the lowest cost option, resulting in a radically different model outcome. Whilst there are several examples of studies in developed countries (e.g., Abate et al. (2018)), studies of logistics models with regard to transport chains within developing countries are scarce. This research attempts to fill the gap and provides additional context of logistics model development specific for Indonesia including novel data collection at the level of shipper/manufacturer.

The remainder of the paper is organised as follows. In the second section, a review of existing research of transport actors' decisions regarding transport chain is provided. The third section outlines the stated choice experiment designed to collect data on manufacturers transport chain selection. Section 4 discusses the multinomial logit (MNL) model utilising the RP/SP survey data and the extensions of the best MNL model by segmenting the shipment characteristics are then discussed in Section 5. Finally, section 6 concludes with conclusions and suggestions for future research.

2. Transport chain choice

A transport chain is the sequence of modes used to carry commodities from the point of production P to the place of consumption C (PC flows), during which the goods may pass via logistics hubs such as warehouses, distribution centres, and transport terminals (Gerard et al., 2013; Huber et al., 2015; Huber, 2017). Huber (2017) contends that many goods movements incorporate multiple modes. It is often impossible to move goods straight from the location of production to the area of consumption. In addition, direct shipping may induce high cost due to lack of consolidation. These factors have prompted academics to place greater emphasis on the significant issue of transport chain selection and investigate its potential to improve the performance of goods transport models (Abate et al., 2018; Jensen et al., 2019).

Huber (2017); De Tremerie (2018); Tuğdemir Kök and Deveci (2019) offer exhaustive literature reviews on the topic of transport chain (i.e., transport mode) selections. The transport chain, according to these authors, is a complicated subject. Consequently, it is essential to identify several significant criteria that influence the selection of transport chain options. There are generally three key factors to consider. First, we need to consider the actors and their complicated relationships, as the organisation of the transport chain could involve a variety of players with distinct functions. Second, we need to consider shipment characteristics, such as shipment size, weight, and value, as well as shipment frequency and delivery time, etc. Finally, we need to consider the transportation system characteristics (e.g., transportation network and transport terminals).

Huber (2017) examines logistics models in existing freight transport models and discovers that comparatively few national freights transport models include logistics. Among the 126 freight transport models available on a global scale, only 14 featured multimodal transport changes, and almost all of these 14 were established in developed nations. Tuğdemir Kök and Deveci (2019) examine freight transport choice models using the stated preference (SP) method. De Tremerie (2018) provides a more in-depth analysis of a comparable topic, examining several elements such as the mode type being forecasted, the most-used explanatory variables, the most examined players, and the most applied techniques (models). Both De Tremerie (2018) and Tuğdemir Kök and Deveci (2019) find that transport cost, transport time, reliability, and transport frequency are the most often utilised and influential variables in explaining transport mode selection. Consequently, the variables and methodology used in this research have been chosen based on these reviews.

In this research, shipper transport chain choice covers five distinct transport chain possibilities involving four main modes: truck, rail, ship, and plane. Some may argue that the selection of chain seems closely related to the mode choice. In some respects, this assumption is correct, but as this research is designated to estimate the transport chain choice of shippers which will later on be utilised to generate freight origin destination (OD) flows at the level of national domestic shipping, this selection of transport chains is comprehensive enough. However, we do neglect possible chains involving consolidation within the same type of mode (i.e., chains involving from small truck to bigger truck or small vessel to bigger vessel (at a hub port) are not modelled). More detailed chains would require more extensive data collection and increase computer run time. Our focus on the main transport chains provides sufficient insight into how road, rail and sea transport may compete.

This paper refers to all Indonesian domestic freight transport. As far as the authors are aware, such research into transport chain choice in the context of developing countries has received very little attention in the freight mode choice literature. Most previous research studies utilising disaggregate mode choice data in the developing countries context have their main objective as the enhancement of the logistics performance of the specific respondents, as in Filla (2022), or their scope is limited to applications at the level of urban or regional freight mode choice, rather than national Nugroho (2015).

3. Setup of the stated choice experiment

3.1. Joint RP/SP research

RP surveys aim to gather respondents' actual choice behaviour, whereas SP surveys present respondents with a variety of scenarios and record their choices under varied conditions (Lavasani et al., 2017). SP can be used to test consumer responses to unimplemented new choices. Another advantage of the SP survey collinearity between attributes can be reduced. However, the primary problems with SP are the dependence of the results on the experimental design (i.e., a bad design may lead to a misleading or less accurate model) and the fact that "in reality, what individuals say they will do is often not the same as what they really do' (Train, 2009). RP studies, on the other hand, will not have these issues because they focus on the actual decisions made by participants in actual settings. A major problem of RP in the context of freight transport chain choice is the difficulty in gathering data, often resulting in a very limited number of observations. Another issue is the lack of information on how shippers make their selection. Using RP data, the researcher has insufficient understanding of the shipper's trade-off behaviour due to a lack of information on the shipper's unselected alternatives and the alternatives' availability. In the case of SP, the possible alternatives of transport chain choices along with their attributes are presented by the researcher to the shippers. Furthermore, RP data can suffer from the problem of heavy correlation between attributes, whereas in SP the researcher can control for such correlation.

Even though RP data provides a foundation in reality, its drawbacks might cause difficulties in estimating a significant coefficient with the right sign for an attribute when the available alternatives have only a very limited variation in this attribute. As an example, loss and damage is an important factor for all stakeholders. Knowing this, all the available transport providers will also devote considerable attention to this factor and the result could be minimal variation in damage between the available alternatives. Therefore, despite the importance of this factor in shipping freight, damage to the goods is rarely found as one of the main attributes in an RP study. As another example, transport cost is an essential factor in determining mode choice for shipper. Consequently, many carriers using the same mode (e.g., truck) will offer more or less the same price to the shipper and this lack of variation due to market equilibrium could make the estimated coefficient of a cost variable insignificant. In an extreme case, the researchers may conclude that the cost variable is not important due to this insignificance. Consequently, combining SP and RP data will be advantageous because one dataset can complement the other. The SP data provides variety in characteristics, whereas "the revealed-preference data root the expected shares in reality' (Train, 2009). Combined RP/SP data is utilised in this study to estimate the transport chain choice made by the shipper in respect of their domestic shipments.

3.2. Efficient survey design

An experimental design is a process to produce a set combination of attributes and attribute levels to be presented to the respondent. In this study, the principles of "efficient experimental design" are employed. Such efficient design is intended to produce more accurate parameter estimation with the same or a smaller sample size (Rose and Bliemer, 2009). With the goal of minimising the expected asymptotic variance-covariance (AVC) matrix and with previous knowledge of alternative parameter values, the NGene software was used to build such an efficient experimental design. Pilot survey priors were sourced from Nugroho (2015) for attribute parameter priors and Kim (2014) and Valeri (2013) for mode alternative specific constant priors (ASC).

The alternatives for the SP scenarios are the available transport chain options between production (P) and consumption (C) zones (alternatives vary between PC pair). The zone represents a group of regions (i.e., categorized as city or "kabupaten' i.e., Indonesian administrative area). There are 509 regions in Indonesia; however, to make the calculations manageable, these regions are aggregated into 91 Transport Analysis Zones (TaZ). Therefore, around 8281 PC pairs will be generated. Each PC pair has at most five possible transport chains: Truck (alternative 1), truck-train-truck (alternative 2), truck-vessel-truck (alternative 3), truck-plane-truck (alternative 4), and truck-train-vessel-truck/truck-vessel-train-truck (alternative 5). These alternatives reflect single mode used (one leg), two modes used (three legs) or three modes used (four legs). Among these possible alternatives, the SP scenario will only show a maximum of four alternatives to each respondent. The four cheapest alternatives and the base values of the attributes time and cost for each alternative are determined using a multimodal chain builder called transport chain builder (TC builder), which will be explained in the next section. Meanwhile, the attributes employed are transport cost, transport time, and reliability.

The Multinomial logit (MNL) model, which is commonly used for such estimation, was then employed as a starting point for executing the NGene software in order to obtain an effective experimental design for estimating such a model. Using the MNL utility function with a single parameter for each of the attributes and a unique prior for each alternative, the utility of alternative will be described in detail in the next section. The base values for the transport cost and transit time attributes supplied to respondents vary depending on the origin and destination locations of the goods. As no data existed to support these core characteristics, the 'transport chain builder' was created to calculate 'base value' data on transport cost and transport time between all zones for each type of transport chain option. In the following section, the TC builder is described in depth. The final characteristic is reliability, which is defined as the percentage of shipments that are delivered on time. For instance, if a shipper makes five shipments per month and a shipment is delayed once per month (without considering the duration of the delay), the shipper's reliability is 80%. The attribute values for reliability are not specific for each firm's relation, they are postulated by the researcher.

The survey's attribute levels and expected attribute indicators are as follows: The transport cost characteristic has four distinct levels: 40%, −20%, 15%, and 30% of the initial ('base') value. In addition to the initial number, the transport time has four levels: 15%, −7%, +15%, and +30%. The levels for the reliability characteristics are 70%, 75%, 90%, and 98%. These choices of attribute levels are based on previous research, the variety of situations that respondents may encounter, and the results of the pilot survey.

The online survey consists of three sections, the first of which enquires about the respondent's company. There are three subsections relating to the shipment in the second section: 1. The type of commodity, 2. The present options for shipment transport chain and shipment size in detail, and 3. The SP scenarios. The third section is a question about the impact of pandemic on their shipping decisions. The number of SP scenarios presented to the respondent varies based on the number of potential transport chain possibilities for the shipment. If the number of possibilities is more than three, eight SP scenarios are provided; otherwise, twelve SP scenarios are displayed. Fig. 1 demonstrates how an SP situation may appear in an online survey.

3.3. Determination of base values

This section describes the general design of the transport chain (TC) builder, a tool that estimates the transport cost and transport duration of each transport chain option for each zone relationship. This programme was used to establish the base levels in the SP, and it is required because there are no available statistics for transport cost and transport time between every zone pair. As noted above, there are 91 TaZ in Indonesia known as TC zones. The TC zones are divided into three categories: zones with a strategic port (Zone A), zones with additional transport terminals besides ports (such as an airport or train station) (Zone B), and zones without any transport terminals (Zone C).

In Indonesia, a multimodal transport network comprising the road, rail, sea, and air transport networks was established and became the foundation of the TC builder. This study utilised this network to identify all viable transport chain alternatives and their characteristics: transport cost and transport time. As previously mentioned, there are three sorts of zones based on the availability of transport terminals (port, airport, train station); in the network model, transport terminals will be considered as nodes alongside TC zones and road intersections. In the meantime, the links symbolise the national highway, railroads, sea lines, and air routes.

The road transport network in the TC builder is restricted to national roads, as only these types of roads can carry trucks with a maximum payload greater than 10 T. The model includes only one toll road, the Jakarta Outer Ring Road (JORR), as truck drivers in Indonesia typically choose arterial roads over toll roads to save money. Still within the road network, the ferry route between Sumatera Island and Java Island, as well as the ferry link between Java Island and Bali Island, are charged roads. These connections represent ferry transportation, which plays a key role in facilitating road connection between Java and its neighbouring islands. These ferry lines connect Sumatera with Java: Bakauheni – Merak and Ketapang – Gilimanuk (i.e., connecting Java – Bali). Meanwhile, Indonesia's rail network is limited to the islands of Java and

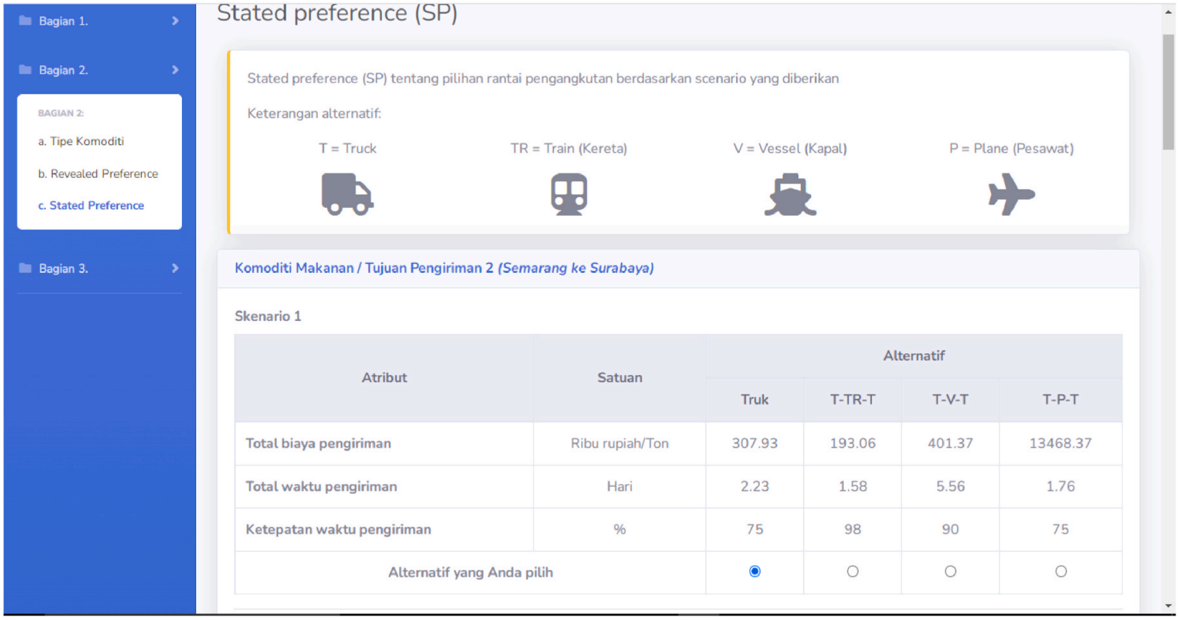

Fig. 1. The SP scenario part of the online survey.

Sumatera and is administered primarily by the Indonesia Railway Company (PT KAI). In total, there are 21 train stations connected by 4816 km of rail track, of which 3464 km are on Java Island and 1352 km are in the north, west, and south of Sumatera Island (as part of a non-continuous railway network).

This chain builder examines 32 ports, including various ports in the new sea routes network designed by the Ministry of Transport (MoT) and 24 strategic ports recommended in the blueprint for the national logistics system. In Indonesia, liner shipping companies are permitted to determine their own routes, however these routes must be registered with the MoT for permission. Private operators primarily provide liner service between well-established locations, whereas the state-owned shipping firm mostly operates between less developed or rural regions and well-developed regions (Halim, 2016). The TC builder has around 246 linkages across 193 marine routes connecting the 32 ports. The maritime mileage and air mileage are derived from the following websites: https://www.airmilescalculator.com/, https://sea-distances.org/, and http://ports.com/sea-route. The rail distance is based on the data from the railway operator (i.e., PT KAI). With the exception of the distance between the ferry terminals, the driving distance was calculated using ArcGIS software. The information on ferry was acquired from the ferry port administration.

Based on the road development plan in the directorate general of highways strategic plan 2015–2019, the average travel time for road transport in 2014 was around 2.7 h per 100 km, or approximately 37 km per hour. In this chain builder, only three-axle trucks with a 15 T capacity are considered for road transport in the current study. According to (Nugroho, 2015), Java's rail service is superior to Sumatera's in terms of train speed. Java and Sumatera have average train speeds of 36.24 and 27.13 km per hour, respectively.

In the TC builder, we employ sea vessels between 5000 and 10,000 DWT, the second-highest volume in terms of the number of boats operated. This is believed to be the only type of vessel in the network. The assumed sailing speed is 18.52 km per hour (10 knots). As there are just a handful of specialist cargo planes in Indonesia, the vast majority of air freight is transported on a planes that also transport passengers (Susanto, 2005). According to the historical operating statistics of the airline Garuda Indonesia, a freight capacity of around 3 tonnes (or 25% of payload) each flight is anticipated for air freight transport using a shared aircraft. Connections between smaller economic regions in Indonesia are typically supplied by small aircraft (Yuliana et al., 2019), however due to a lack of data, we assume that shared aircraft are the only type of plane providing interregional freight trips in Indonesia. The plane's speed is assumed to be 635 km per hour (343 knots).

The mode characteristics described above have an effect on the unit cost applied to a certain mode of transportation, which in turn has an effect on the five potential alternatives that may be generated by the TC builder. In the TC builder, the level of service of the links corresponds to the mode unit charges mentioned previously. The transport cost function employed here is taken from a cost function applied to truck, train, and vessel in Frazila et al. (2018). Consideration is given to the cycle time, daily operation cost, and cargo capacity when calculating the transport cost. The cycle time is a function of round-trip travel time, waiting time, loading and unloading time. The daily operation cost is then derived from the mode purchasing cost, the depreciation cost, the regular cost for operating the mode and the maintenance cost. Table 1 displays the base value for each mode. The unit cost of air freight is taken as 1.02 USD per tonne km. This figure is determined via trial and error within the TC building computation in order to balance with a World Bank (2009) assumption that air freight is 12–16 times more expensive than sea freight.

According to the results of the TC builder, there are 18 conceivable alternative combinations between the TC zone pairs. In addition, the experimental design was created solely for 14 of these classes (i.e., an SP scenario is only applied for the situations which have 2 or more options since this is required for an SP choice experiment).

3.4. Utility function

Random utility functions are used in decision-making problems under uncertainty. They provide a way to quantify preferences and make rational choices based on expected utility. The multinomial logit (MNL)

Table 1
Transport cost functions for each mode.

Mode	Cost function (USD/ton.km)
Truck (capacity 15 T)	0.058
Rail mode (20 wagon @ 20 T)	0.047
Vessel (self-propelled barge 8000 T)	0.031
Plane (Boeing 737–300, capacity 3 T)	1.02

model, which is commonly employed for estimation purposes, was subsequently utilised as a foundation for conducting the efficient experimental design of a stated preference (SP) experiment. The error terms in such multinomial logit (MNL) models exhibit independent and identical distribution across alternatives and respondents, following the type I extreme value distribution. This characteristic yields the logit formula, as described by Train (2009). The identical model, MNL, is also employed for analysis subsequent to the collection of stated preference (SP) data, in conjunction with revealed preference (RP) data.

According to Guzman et al. (2021), the data enrichment paradigm posits that in a mixed model (combining RP and SP data), it is assumed that all utility functions should possess identical parameters. However, it is important to note that this assumption may not always hold true. Partial data enrichment refers to a situation when data from multiple sources is combined using a single common parameter, while the other coefficients are unique to each individual data source. The lack of common parameters in a given dataset can be attributed to factors such as measurement mistakes, correlations between features, or low variability. In order to determine the shared characteristics across the two domains, it is necessary to construct models utilising each dataset separately and derive the parameters of their respective utility functions. Further, the ASC in the combined model was tailored to each option and dataset due to the distinct market shares of the options represented by both settings. The utility of each alternative for their respective dataset may be described by the following equation (1) and equation (2) for RP and SP datasets respectively:

Category (i) is a choice using a specific transport chain type (i.e., alternative).[1]

$$U_{qmni_{RP}} = \mu_{RP}(ASC_{i_{RP}} + \beta_{cost}TC_{mni_{RP}} + \beta_{\text{time}}TT_{mni_{RP}} + \varepsilon_{i_{RP}}) \quad (1)$$

$$U_{qmni_{SP}} = \mu_{SP}(ASC_{i_{SP}} + \beta_{cost}TC_{mni_{SP}} + \beta_{\text{time}}TT_{mni_{SP}} + \beta_{\text{rel}}R_{mni_{SP}} + \varepsilon_{i_{SP}}) \quad (2)$$

where.

U_{qmni} = Utility of choosing alternative i by shipper q for shipment from m (origin) zone to n (destination) zone
ASC_i = Alternative specific constant of alternative i
β_{cost} = Parameter of transport cost
TC_{mni} = Transport cost of the transport chain alternative i for shipment from m to n
β_{time} = Parameter of transport time
TT_{mni} = Transport time of the transport chain alternative i for shipment from m to n
β_{rel} = Parameter of reliability
R_{mni} = Reliability of the transport chain alternative i for shipment from m to n
ε_i = error term
μ = scale parameter
$_{RP}$ = estimated parameter and data using RP dataset
$_{SP}$ = estimated parameter and data using SP dataset

4. Survey results and multinomial logit model

This research develops a disaggregated logistics model in order to understand the behaviour of individual shippers with regard to their selection of the transport chain choice. The survey respondents are manufacturers with domestic trade in Indonesia that are included in a directory of the manufacturing industry published by Indonesian Statistics in 2019.

The SP experiment was undertaken in two phases. From August to October 2021, a pilot survey was conducted, followed by the main survey between February and October 2022. The pilot survey results served as the empirical basis for updating the main survey scenario. The pilot survey was intended to validate the experiment's qualities, levels, and design, as well as to confirm the questionnaire and survey techniques. Following this, the estimated parameters arising from the pilot survey were accepted as the new priors for the main survey's efficient design. The survey collected the shipper's current selections of transport chain and shipment size as RP data, followed by collection of SP data on transport chain selection alone. The RP/SP data will serve here as the primary data source to estimate only the transport chain choice.

Inviting a total of 3374 possible respondents for these surveys resulted in 178 respondents who either partially or completely filled out the questionnaire, an average response rate of 5.5%. 236 responses were acquired from these respondents regarding the commodity type and origin-destination pair of the shipment, and 179 responses were obtained regarding the revealed preference of transport chain and shipment size (i.e., RP shipment). The response is greater than the number of respondents since each respondent had the option of providing information for more than one shipment. In the meantime, 624 valid SP choice observations were collected from 69 respondents for input into the stochastic method. The breakdown of respondents according to Indonesia's five largest islands is as follows: Java 116 respondents (65%), Sumatra 28 (16%), and Sulawesi 15 (8%), with Bali and Kalimantan having the lowest share of about 5% each with 10 and 9 respondents respectively.

This section will cover the key estimation results of the multinomial logit (MNL) model on the RP/SP data. In contrast to the deterministic model, the discrete choice in the stochastic approach only simulates the transport chain decision and not the shipment size choice, as the shipment size category from the RP data does not provide enough data records for analysis of so many choice alternatives. Here we provide a comparison between the base MNL model with all alternative-specific constants and another MNL model with joint coefficients across alternatives for certain variables (e.g. cost or time) in an attempt to improve the significance of various variable coefficients. Table 2 displays this comparison of MNL models based on the RP/SP data, with the statistical performance of each MNL model being provided in Table 3. Table 4 then displays the likelihood ratio test (LRT) and the chi-square critical value (the value in brackets) for each degree of freedom (difference in the number of parameters) respectively at a level of confidence of 95% (α = 0.05).

From Table 2, we can infer that the parameters of attributes usually yield the expected sign, though in some cases with an insignificant coefficient value. The number indexed into the attributes shows the alternative where the coefficient belongs. As an example, b_cost1 represents the cost coefficient for alternative 1, whereas b_cost35 and b_rel35 represent coefficients for both alternative 3 and alternative 5 for cost and reliability attributes respectively. All of these models were estimated to provide clear explanation of how the authors determined the preferred MNL model that will be utilised in INTRAMOD.

The alternative specific constants (ASC) were estimated separately for each data set (SP or RP) because the shares of the alternatives (which are being matched by the ASCs) are different in SP and RP. Furthermore, in the SP dataset we have additional soft variables affecting transport chain choice (such as reliability).

Still in Table 2, the final coefficient to be estimated is the mu_SP, for which the value is relative to mu_RP. These coefficients show the scale parameter between the RP and SP data. This is related to the variance of the unobserved component which is likely to differ between the different datasets. According to (Guzman et al., 2021), best practice to deal with this problem is to set the scale factor of the RP data to one and the scale of the SP interpreted as being relative to that of the RP.

According to the results shown in Tables 2–4, despite being supported by economic theory, grouping the cost coefficients for all alternatives does not lead to a better model, rather this model performs the worst compared to the other models. In selecting the best model, we rely on several criteria, such as significance of coefficients and their signs,

[1] Reliability variables only applied to SP data set.

Table 2
Comparison of MNL models for RP/SP data.

Base model			Single cost coefficient			Single time coefficient			Single reliability coefficient			Preferred final model		
	Estimate	*t*-test		Estimate	*t*-test		Estimate	*t*-test		Estimate	*t*-test		Estimate	*t*-test
asc_alt1	0	NA	asc_alt1	0.000	NA	asc_alt1	0.000	NA	asc_alt1	0.000	NA	asc_alt1	0.000	NA
asc_alt2	−2.808	−4.961*	asc_alt2	−1.431	−1.228	asc_alt2	−2.837	−5.751*	asc_alt2	−2.714	−4.519*	asc_alt2	−2.791	−5.645*
asc_alt3	−1.813	−3.660*	asc_alt3	−0.510	−0.412	asc_alt3	−1.912	−3.994*	asc_alt3	−1.649	−3.050*	asc_alt3	−1.838	−3.871*
asc_alt4	−3.580	−3.724*	asc_alt4	−5.676	−3.108*	asc_alt4	−4.296	−6.156*	asc_alt4	−4.202	−4.071*	asc_alt4	−4.312	−6.122*
asc_alt5	−4.324	−3.157*	asc_alt5	−1.354	−0.478	asc_alt5	−4.194	−3.226*	asc_alt5	−4.169	−2.883*	asc_alt5	−4.260	−3.735*
asc_alt1_SP	0.000	NA	asc_alt1_SP	0.000	NA	asc_alt1_SP	0.000	NA	asc_alt1_SP	0.000	NA	asc_alt1_SP	0.000	NA
asc_alt2_SP	2.916	1.494	asc_alt2_SP	9.520	1.386	asc_alt2_SP	3.213	1.588	asc_alt2_SP	−0.019	−0.035	asc_alt2_SP	−0.302	−1.454
asc_alt3_SP	1.307	0.898	asc_alt3_SP	3.235	0.584	asc_alt3_SP	1.228	0.819	asc_alt3_SP	−0.437	−0.801	asc_alt3_SP	−0.547	−0.537
asc_alt4_SP	2.450	1.181	asc_alt4_SP	2.403	0.346	asc_alt4_SP	1.367	0.772	asc_alt4_SP	−2.257	−1.675	asc_alt4_SP	−2.556	−2.415*
asc_alt5_SP	1.293	0.629	asc_alt5_SP	1.582	0.185	asc_alt5_SP	1.458	0.635	asc_alt5_SP	−0.826	−0.722	asc_alt5_SP	−0.819	−0.763
b_cost1	−0.003	−2.103*	b_cost	0.000	−2.282*	b_cost1	−0.003	−2.521*	b_cost1	−0.003	−2.372*	b_time	−0.263	−2.045*
b_time1	−0.105	−0.595	b_time1	−2.358	−3.065*	b_time	−0.266	−2.054*	b_time1	−0.094	−0.477	b_cost1	−0.003	−2.536*
b_rel1	0.058	1.973**	b_rel1	0.241	2.456*	b_rel1	0.067	2.256*	b_rel	0.043	2.226*	b_rel124	0.044	2.330*
b_cost2	−0.002	−1.901**	b_time2	−1.937	−2.544*	b_cost2	−0.002	−2.374*	b_cost2	−0.002	−2.097*	b_cost2	−0.002	−2.407*
b_time2	−0.222	−0.952	b_rel2	0.109	1.843**	b_rel2	0.025	1.674	b_time2	−0.276	−1.023	b_cost35	−0.001	−2.036*
b_rel2	0.022	1.555	b_time3	−1.004	−2.475*	b_cost3	−0.001	−1.855**	b_cost3	−0.001	−1.637	b_rel35	0.040	2.077*
b_cost3	−0.001	−1.491	b_rel3	0.158	2.144*	b_rel3	0.042	1.983*	b_time3	−0.322	−1.907**	b_cost4	−0.0001	−2.149*
b_time3	−0.263	−1.712	b_time4	0.046	0.056	b_cost4	−0.0001	−2.140*	b_cost4	−0.0001	−1.960*	mu_RP	1.000	NA
b_rel3	0.037	1.801**	b_rel4	0.088	1.266	b_rel4	0.022	1.237	b_time4	−0.264	−0.675	mu_SP	0.980	2.401*
b_cost4	−0.0001	−1.700	b_time5	−1.405	−2.253*	b_cost5	−0.001	−1.670	b_cost5	−0.001	−1.505			
b_time4	−0.551	−1.351	b_rel5	0.198	1.707	b_rel5	0.038	1.350	b_time5	−0.274	−1.387			
b_rel4	0.013	0.709	mu_RP	1.000	NA	mu_RP	1.000	NA	mu_RP	1.000	NA			
b_cost5	−0.001	−1.392	mu_SP	0.253	2.634*	mu_SP	1.015	2.382*	mu_SP	0.983	2.293*			
b_time5	−0.225	−1.245												
b_rel5	0.033	1.211												
mu_RP	1.000	NA												
mu_SP	1.161	2.049*												

* Significance at the level of 5%.
**Significance at the level of 10%.

Table 3
Statistical significance of the MNL model and the modification.

	A0	A1	A2	A3	A4
	Base model	Single cost coefficient	Single time coefficient	Single reliability coefficient	Preferred final model
No observation	803	803	803	803	803
RP	179	179	179	179	179
SP	624	624	624	624	624
No of parameter	24	20	20	20	16
LL (start)	−888.94	−888.94	−888.94	−888.94	−888.94
LL (final)	−630.78	−661.29	−631.45	−634.34	−634.88
Rho-squared (0)	0.1528	0.1118	0.1519	0.148	0.1473
Adj Rho-squared (0)	0.1206	0.085	0.125	0.1212	0.1258

Table 4
Result of likelihood ratio test.

LRT	A0	A1	A2	A3	A4
A0		61.02 (9.488)	1.34 (9.488)	7.12 (9.488)	1.44 (15.507)
A4	1.44 (15.507)		0.1 (9.488)		

the likelihood ratio test, as well as reasonable values of time (VOTs). With regard to the significance of coefficients, we can see from Table 2 that the coefficients in the base model give the expected signs, which are that transport time and transport cost should have a negative impact on transport chain choice, while reliability should have a positive effect. However, the number of significant parameters is quite low.

In order to reduce the number of insignificant parameters, we develop further models. In these, we grouped some parameters into a single coefficient: a single cost coefficient (model A1), a single time coefficient (model A2), a single reliability coefficient (model A3), and finally the preferred model (modification of the single time coefficient model with some adjustment for cost and reliability variables - model A4).

Grouping to a single cost coefficient does serve to reduce the number of insignificant coefficients, but it also leads to an unexpected sign for the time variable in alt 4 (plane), which later on results in an unreasonable VOT. Developing separate models grouping into a single time variable and a single reliability variable reduces the number of insignificant parameters, with the single time variable model giving slightly better results. Finally, in the preferred final model, apart from grouping time coefficients for all alternatives, we also group the cost and reliability variables for some alternatives. The cost coefficient for alt 5 (train-vessel) was grouped together with alt 3 (vessel) as it has the same main mode. This was also done for their reliability variables. The reliability coefficients for alt 1 (truck), alt 2 (train), and alt 4 (plane) were grouped into one coefficient resulting in alt 4 having a higher and significant reliability coefficient.

In principle, grouping parameters relative to a base model in the manner described above will always result in lower value in the Likelihood Test. The test can only be applied to case where nested hypotheses can be formulated in which the derived model (the one with fewer coefficients) is essentially setting coefficients in the larger model to zero. For example, model A1 is basically model A0 in which the cost parameters of all alternatives are grouped (nested) into one coefficient. The MNL model outcomes in terms of statistical significance are shown in Table 3. For example, the base model (A0) with 24 parameters has a higher LL (final) in comparison to the preferred model (A4) with 16 parameters, but the difference is only small. Model (A4) has more significant variables and a higher adjusted Rho-squared value. Using the Likelihood Ratio Test (LRT) in Table 4 for comparison between the preferred model (A4) and base model (A0), we find that, by having a smaller LRT value than the chi square critical value (values in parentheses), the null hypothesis is accepted, in which the large model (A0) is not significantly better than the preferred smaller model (A4).

The final factor in determining the preferred MNL model for transport chain choice within INTRAMOD is the value of time (VOT). VOT values derived from the various models are shown in Table 5, whereas can be seen the single cost coefficient model has an implausible negative VOT value for plane. VOTs from the final model (A4) are more consistent with previous VOT studies for freight mode in Indonesia as reported by Binsuwadan et al. (2021) and Tao and Zhu (2020). Both previous studies provide meta-analysis of VOT for freight transport for various countries. Estimating the VOT for Indonesia based on the meta-model, Binsuwadan et al. (2021) predicted the VOT for several freight modes from the point of view of both shippers and carriers. As our research assumes the decision maker of the transport chain choice to be a shipper, then we only compare our findings to the VOT for shippers in Binsuwadan et al. (2021). Meanwhile, Tao and Zhu (2020) also provide VOT values for freight but only for road transport, these being derived from a study by Arunotayanun and Polak (2011). Focusing on the truck mode, the VOT for alt1 (truck) from our research is 0.255 USD per ton hour from the preferred model A4, compared to VOT values from the previous studies of 1.602, 2.151 and 0.22 (USD per ton hour) according to Arunotayanun and Polak (2011), Tao and Zhu (2020), and Binsuwadan et al. (2021) respectively. For the other modes, we only compare our VOT values with Binsuwadan et al. (2021), as the other sources do not provide these values. Based on our stochastic model, the highest VOT is for air transport, as also found by Binsuwadan et al. (2021). Binsuwadan et al. (2021) however suggested that VOT for sea transport is lower to that for rail transport, in contrast to our findings.

5. Segmenting the best MNL model

This subsequent section will give the estimation results based on the segmentation of the goods value (IDR/ton). We also performed the segmentation based on the shipment size and shipment frequency, but their additional coefficients emerged as insignificant and are not presented here. The selected segmentation applies a distinction between two groups based on the value of the commodities, with the distinguishing groups being (1) low value (less than or equal to 15 million IDR per tonne) and (2) high value (more than 15 million IDR per tonne). The dummy variable for product's value equals 1 for high value product and 0 for low value product. The utility function is as follows:

$$U_{qmni} = ASC + \beta_{cost} TC_{mni} + \beta_{time\_value} TTmn_i + \beta_{\mathrm{rel}} R_{mni} + \mathrm{I}$$

Table 5
Value of time (VOT) obtained from the various MNL models A0-A4.

VOT	A0	A1	A2	A3	A4
	USD per ton hour				
alt1	0.104	28.079	0.255	0.081	0.255
alt2	0.301	23.064	0.318	0.318	0.318
alt3	0.710	11.960	0.546	0.737	0.529
alt4	19.110	−0.548	7.593	7.079	7.573
alt5	0.496	16.736	0.487	0.504	0.529

$$where\ \beta_{time\_value} = \beta_{\mathrm{time}} + \beta_{\mathrm{timeHIGH}} * dummy\ (High\ value\ product = 1) \quad (3)$$

The estimation from the preferred MNL model with segmentation according to value of goods is given in Table 6. From this we can infer that high value goods are more sensitive to time than the low value goods, as shown by the negative value of b-time-value-high which is significant at the 90% confidence level. Calculated VOT values for each segment are shown in Table 7, in which high value products have higher VOT than the low value products across all modes. These results are consistent with findings by Nugroho (2015) who concluded that high value products within container shipping in Indonesia have higher values of time and reliability compared to low value products.

Table 6
Segmentation model based on the value of goods.

	Estimate	*t*-test
asc_alt1	0.000	NA
asc_alt2	−2.838	−5.677
asc_alt3	−1.834	−3.755
asc_alt4	−4.525	−6.060
asc_alt5	−4.300	−3.749
asc_alt1_SP	0.000	NA
asc_alt2_SP	3.593	1.810
asc_alt3_SP	1.614	1.096
asc_alt4_SP	1.242	0.751
asc_alt5_SP	1.320	0.901
b_time	−0.233	−2.058
b_time_value_high	−0.153	−1.778
b_cost1	−0.003	−2.938
b_rel1	0.074	2.586
b_cost2	−0.002	−2.701
b_rel24	0.027	1.975
b_cost35	−0.001	−2.196
b_rel35	0.044	2.344
b_cost4	−0.0001	−2.253
mu_RP	1.000	NA
mu_SP	0.917	2.779
No observation	803	
RP	179	
SP	624	
No of parameter	18	
LL (start)	−888.94	
LL (final)	−629.03	
Rho-squared	0.1551	
Adjusted Rho-squared	0.131	

Table 7
Values of time based on the value of goods.

	HIGH	LOW
b_time	−0.386	−0.233
VOT (USD per ton hour)		
alt1	0.343	0.207
alt2	0.515	0.311
alt3/alt5	1.029	0.621
alt4	10.293	6.213

6. Conclusion

This paper presents research towards the development of a stochastic logistics model for the national freight transport model of Indonesia (INTRAMOD). It describes in detail how the SP scenarios were designed, and how the pilot and main surveys were conducted. The RP/SP data were then analysed using MNL models to estimate the transport chain choice of Indonesia's domestic transport.

The SP scenario for the pilot survey was created using the so-called efficient experimental design and estimated priors from previous research. The result of the pilot survey was then employed to update the main survey. As with many other surveys on the selection of freight transport chains, the survey had a low response rate around 5.5%. Attaining a response of 178 respondents, a total of 179 R P data and 624 S P data were valid for analysis using the multinomial logit model. A total of five specifications of the MNL model were used for parameter estimation: (0) distinct coefficients for all SP attributes across all alternatives as the base model; (1) a single cost parameter across all alternatives; (2) a single time parameter across all alternatives; (3) a single reliability parameter across all alternatives; and (4) a single time parameter with single cost and reliability parameters for some alternative types. Despite being favoured in economic theory, the specification with one cost parameter for all alternatives (model 1) performed the worst compared to the other models. Models with single time and single reliability variables respectively produce better results than the base model, yet still have some insignificant variables. The final MNL specification is regarded as the preferred model when considering the significance and expected signs of the coefficients, the likelihood ratio test, and the plausibility of the VOT values obtained. Further, we modified the preferred model by segmenting into high and low value products, results indicating that shippers of high value products are more sensitive to transport time and hence more likely to opt for faster modes.

This stochastic approach allows for enhancement of the logistics model for INTRAMOD, which previously applied a deterministic model for its transport chain choice. Our stochastic approach has only been applied to the estimation of the transport chain choice, whilst the deterministic model estimates both the transport chain and shipment size choices of shipper. A consequence of this is that the next modelling stage - the ADA model - for INTRAMOD will still need to handle shipment size selection deterministically. Further research is planned to address this issue.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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