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THE OPTIMUM STRATEGY FOR MODE CHOICE MODELLING OF INTERREGIONAL FISH TRANSPORT CONSIDERING SHIPPERS' HETEROGENEITY

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Abstract:

The determinants of mode choice of interregional transport of fish, which is highly perishable, vastly differ from that of other commodities. These determinants are to be identified to improve transport efficiency. A questionnaire survey of shippers is used to collect the data. Highly correlated observed variables are combined to form four latent factors by factor analysis to reduce the errors in modelling. Logical relations among the component variables of latent factors are perceived, and mathematical formulations are used to estimate new variables. It is found that transportation costs and shipment weight contributes to factor 1, while distance contributes to factor 2. However, transportation costs are associated with distance and shipment weight. Thus, the variable, transportation cost per q-km, is estimated. Survey respondents' attitudes are also incorporated into modelling by including qualitative factors obtained by the factor analysis of shippers' preference ratings. A latent class analysis confirmed the existence of heterogeneity among shippers. Misrepresentations of effects occur in modelling if the heterogeneity in the data is not considered. No studies have found the best combination of observed variables, latent factors, estimated variables, and qualitative factors, considering shippers' heterogeneity in freight mode choice. Hence, this study is done to find the optimum modelling strategy. Modelling revealed that models built with estimated variables outperformed those built with latent factors. Including qualitative factors along with observed variables and estimated variables showed further improvement. However, the model that includes observed variables, estimated variables, and qualitative factors considering shippers' heterogeneity is the best. It was found that the mode selection behaviour of different latent classes of shippers is distinct. A mode shift from road to rail could be achieved by lowering transportation costs and increasing speed, reliability, and safety for fish transport. Expanding roll on–roll off facilities, dedicated freight corridors, parcel trains, refrigerated containers, and piecemeal service by rail promote a mode shift from road to rail and reduce energy usage.

Keywords: *fish transport, mode choice modelling, binary logit model, heterogeneity, latent class analysis*

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1. Introduction

India is the world's second-biggest fish producer, accounting for 7.56 per cent of worldwide output. India's fish production was 14.5 million tonnes in 2020-21, contributing to 1.24% of the country's gross value added. This industry provides employment opportunities for 28 million underprivileged people. The fishing industry earned INR 466.6 billion in exports in 2019-20 (Department of Economic Affairs, 2022). Fish is a highly perishable product that must be transported quickly to avoid damage. Hence, the mode selection criteria for interregional fish transport differ entirely from those for other commodities. Sensible planning necessitates understanding the significant characteristics and their impact on mode choice (Transportation Research Board, 2019). So, this study aims to identify the determinants of fish transportation to improve its efficiency.

The most significant adverse effect of freight movement on the environment is greenhouse gas emissions (Agyapong & Ojo, 2018; Bauer et al., 2010; Hwang & Ouyang, 2014; Liedtke, 2009; Mishra et al., 2018; Tian, Y., Q. Zhu, K. Lai, 2014). India is responsible for 6.6 per cent of global total CO_2 emissions. In India, road and rail account for 61 per cent and 30 per cent of interregional freight transport, respectively, resulting in high energy consumption as road transport consumes more energy than rail (Planning Commission of India, 2014). As road transport significantly contributes to environmental pollution, efforts to improve the share of alternate modes of transport are required (Souza et al., 2021). Rail transport uses significantly less fuel than road transport (U.S. Energy Information Administration, 1999; Davis & Boundy, 2021). Even a small shift of freight from road to rail reduces energy consumption and emissions (Regmi & Hanaoka, 2015; Li & Zhang, 2020).

Shippers consider transportation costs the most crucial factor when selecting the mode of transport, disregarding CO_2 emissions (Chang & Thai, 2017; Tavasszy et al., 2020; Zeybek, 2019). If the government imposes a penalty on CO_2 emissions, shippers choose more environment-friendly means of transport (Chang & Thai, 2017; Jiang et al., 2020). Thus, government policy measures are required to increase the efficiency of freight transport and reduce its environmental impacts (Behrends, 2017). Tao et al. (2017) opined that while subsidies encourage mode shift from road to rail transport in the short-term, financial, technological, operational, and managerial measures are necessary as a long-term approach.

Different types of variables used in mode choice modelling affect the accuracy of the predictions. Researchers used factor analysis to form latent factors to overcome the problem of multicollinearity among the observed variables. However, logical relations among the observed variables are perceived and used to estimate new variables. McFadden (2001) asserts that a person's attitude influences their behaviour. Survey respondents' attitudes are deduced from factor analysis of their choice preferences as qualitative factors. Even though freight transport plays a vital role in the nation's development, studies on freight mode choice are limited (Figliozzi, 2006; Middela et al., 2018; Regan & Garrido, 2001).

Due to varying tastes, not all shippers behave similarly under similar conditions in freight mode choice (Arunotayanun & Polak, 2011; Bergantino et al., 2013; Chu, 2014; Duan et al., 2017; Kim et al., 2017; Marcucci et al., 2017; Piendl et al., 2017, 2019; Román et al., 2017). Modelling without considering heterogeneity produces incorrect results. Hence, it is better to identify latent groups of decision-makers (Astroza et al., 2019). Magidson & Vermunt (2002) established the superiority of latent class analysis over K-means clustering to identify heterogeneity. The latent class analysis incorporates categorical, count, continuous variables, and covariates, as well as probability-based categorisation. As a result, latent class analysis is employed in this study.

No studies have considered optimal combinations of observed variables, latent factors, estimated variables, and shippers' preferences, considering the heterogeneity of shippers to arrive at the best freight mode selection models. Hence, this study is done to find the optimal combination of different types of variables in modelling. The characteristics of mode selection can be enhanced to increase transportation efficiency and reduce energy consumption.

This study includes a literature survey, data collection, database development, preliminary data analysis, identification of latent factors, qualitative factors, heterogeneity in data, and development of mode choice models. Since road and rail account for 91 per cent of interregional freight, this study is limited to these two modes of transportation.

2. Literature review

Freight demand modelling is done in four stages. Mode choice modelling is the most policy-relevant among them (Brooks et al., 2012). It aids in determining the characteristics that affect mode selection (de Jong et al., 2004; Tavasszy & Jong, 2014). Modelling at a disaggregate level is theoretically sound, includes many causal variables, and is highly policy sensitive. Thus, developing freight mode choice models at a disaggregated level is needed (Regan & Garrido, 2001).

Mode choice is a discrete choice problem where the utility maximisation concept is used to model choice behaviour. Discrete choice models estimate the likelihood of choosing an alternative among many depending on a range of decision variables. The logit model, the nested logit model, the cross-nested logit model, the mixed logit model, the probit model, and the ordered generalised extreme value model are used for discrete choice modelling. Apart from these, there are models of non-random utility maximisation, such as prospect theory and regret minimisation (Tavasszy & Jong, 2014). Wang et al. (2013) established that the outcomes of probit and logit models for freight mode selection are indistinguishable. Moreover, logit models are commonly used to model mode selection in freight transport (Catalani, 2001; Golias & Yannis, 1998; Holguin-Veras, 2002; Siridhara et al., 2019). Hence, this study employs logit modelling.

Errors occur when highly correlated observed variables are included in a model (Jourquin, 2021). As a result, factor analysis combines highly correlated quantitative variables to construct a smaller number of orthogonal latent factors to eliminate these errors. Jeffs & Hills (1990) used factor analysis to identify significant freight mode choice determinants. Factor 1 included dependability, control over dispatch and delivery times, damage avoidance, security, transportation time, and easy transportation availability. In contrast, factor 2 includes two variables: haul length and consignment size. Grue & Ludvigsen (2006) used the principal component method to extract three latent factors influencing rail mode choice in international freight transport: service failures, intermodal expediency, and cargo intake and discharge efficiency. In comparison, the five latent factors influencing shippers' decisions regarding road-based freight supply are operational efficiency and sustainability, service availability, dealing with service failures, technical efficiency, and value for money.

Some studies have included qualitative attributes in freight mode choice. Danielis et al. (2005) found that logistics managers emphasise quality attributes like time, safety, and reliability above cost. McGinnis (1979) and Murphy, Daley & Dalenberg (1991) conducted a factor analysis on the importance ratings of freight mode choice variables to ascertain the mode choice determinants.

3. Data collection and data summary

Disaggregate models require large amounts of data, which is not publicly available in India. Hence, disaggregated data on fish shipments is collected for this study. Disaggregated data collection is challenging due to the high resource requirements and the proprietary nature of the data.

The freight mode selection depends on various characteristics of the commodity, shipment, the shipper, distance, and the mode of transport used. Identifying the determinants that affect freight mode selection is crucial (Jiang et al., 1999; Tavasszy & Jong, 2014). Content analysis of the previous related research articles was done to identify significant variables for questionnaire design. Characteristics of the mode of transport, such as transportation cost, speed, reliability, safety, frequency, flexibility, pickup and delivery time, and the availability of handling equipment, influence mode choice for freight transport (Arunotayanun & Polak, 2011; Bergantino et al., 2013; Firdausiyah & Chrisdiani, 2021; Jensen et al., 2019; Jourquin, 2021; Kalahasthi et al., 2022; Kim et al., 2017; Leleń & Wasiak, 2019; Moufad & Jawab, 2019; Pålsson & Sternberg, 2018; Piendl et al., 2019; Tavasszy et al., 2020; Tripathi et al., 2021; Wichitphongsa & Ponanan, 2022).

Commodity type, shelf-life/time sensitiveness, inventory cost, fragility, hazardousness, and type of handling equipment of commodities are the commodity characteristics that influence the selection of transport mode (Ahmed & Roorda, 2021; Holguin-Veras, 2002; Holguín-Veras et al., 2021; Murakami & Matsuse, 2014; Piendl et al., 2019). Major shipment characteristics affecting mode choice are weight, value, frequency, and packaging quality (Ansu & Anjaneyulu, 2020; Cantillo et al., 2018; Grue & Ludvigsen, 2006; Holguin-Veras, 2002;

Jeffs & Hills, 1990; Mitra & Leon, 2014; Moschovou & Giannopoulos, 2012; Piendl et al., 2019; Román et al., 2017; Shen & Wang, 2012; Uddin et al., 2021). Distance, accessibility, location, weather, and economic activity at origin and destination are significant spatial characteristics of mode choice (Chang & Thai, 2017; Marcucci & Scaccia, 2003; Moschovou & Giannopoulos, 2012; Olkhova et al., 2017; Park & Suh, 2011). The characteristics of shippers which affect the mode selection are employee count, truck ownership, rail sideline, and firm type (Jiang et al., 1999; Nuzzolo & Russo, 1998; Román et al., 2017; Wang et al., 2013). A stakeholder workshop was also organised to know shippers' concerns regarding freight transport.

Fig. 1 and 2 depict the questionnaire prepared based on the variables identified by content analysis and the stakeholders' workshop. The questionnaire included both quantitative and qualitative variables that influence mode selection. It is essential to comprehend the shippers' preferences on mode selection for fish. Hence, the shippers were requested to specify the importance of each variable for the mode selection. The variables were ranked according to their importance on a five-point Likert scale. Weights 1 to 5 are assigned to: not at all important, slightly important, moderately important, very important, and extremely important. Insignificant variables were eliminated from the questionnaire following the pilot survey.

Data was collected from the shippers of Kozhikode, Kannur, Palakkad, Thrissur, Malappuram, Thiruvananthapuram, and Ernakulam districts in Kerala and Mahe, who import and export fish to other regions of the country. Kerala is a state in south India. It covered an area of 38,863 km2 out of 3.287 million km2 of India. It is bounded on one side by the sea and the other sides by Tamil Nadu and Karnataka. According to the 2011 census, Kerala has a population of 33.4 million (National Informatics Centre, 2011) and is divided into 14 districts. The Mahé district is surrounded by Kerala but is part of the Puducherry Union Territory.

This study did not consider freight shipments shorter than 77 kilometres, urban shipments, shipments to the islands, full trainloads of goods, and international shipments due to the limited scope of mode choice. Origin and destinations should be reasonably accessible by the transport modes considered to facilitate mode choice. Hilly districts that do not have rail connectivity are also not considered.

A revealed preference survey was carried out to collect responses from shippers through direct interviews. The number of cases in the data should be at least twenty times the number of significant variables in the model or 200, whichever is the maximum (Hair et al., 2009). Outliers were eliminated from the analysis. Nine hundred ninety four cases were available for use in modelling after data cleaning. Rail shipments require road transport at both ends of the transport. However, for simplicity, the combination of road-rail-road is stated as rail in this study. There were 210 shipments by rail and 784 by road in the data.

A preliminary analysis of data was done by performing statistical analysis. Table 1 summarises the continuous variables. According to the analysis of nonmetric variables, 97% of shippers choosing the road and 49% of shippers choosing rail believe their mode of transportation is safe. Sixty-four per cent of rail shippers and 76 per cent of road shippers believe their respective transport modes have good overall service quality. Sixty-three per cent of road shippers believe that road is highly reliable, while 73 per cent of rail shippers believe that rail reliability is normal.

4. Identification of latent factors

Uncorrelated variables were found and eliminated from the factor analysis. The principal component analysis extraction was used. The Bartlett test of sphericity was used to determine the statistical significance of correlations between variables. The central limit theorem implies that each variable is normally distributed if the sample size is large enough. The Kaiser-Meyer-Olkin measure of sampling adequacy value indicates how well the factors are predicted. A value of 0.8 or greater is deemed meritorious. Values between 0.7 and 0.8 are considered middling, values between 0.6 and 0.7 are considered mediocre, values between 0.5 and 0.6 are considered miserable, and values below 0.5 are considered unacceptable. If the sampling adequacy measure is less than 0.5, the variables with the lowest sampling adequacy are eliminated sequentially.

The degree to which a factor structure explains a variable's variance is known as its communality.

Variables with communality greater than the minimum requirement of 0.5 forming meaningful costructs were considered. Variables with a high degree of correlation with multiple factors are omitted.

Freight Transport Survey of Shippers

CENTRE FOR TRANSPORTATION RESEARCH

DEPARTMENT OF CIVIL ENGINEERING

NATIONAL INSTITUTE OF TECHNOLOGY CALICUT

Freight transportation plays a critical role in the economic and social development of the nation. Efficient freight transportation minimises negative effects such as traffic congestion, environmental pollution, accidents, etc. Efficiency of freight transportation can be achieved by increasing the mode share of fuel-efficient modes of transportation. An understanding of the preferences of shippers will enable the planners and decision makers to improve the characteristics fuel efficient modes so that they will be the preferred modes of shippers. This survey is organised to find out the significant factors that influence the shippers' choice mode of transportation. We request your whole hearted cooperation and provide the necessary details. The data collected will be used solely for academic purpose.

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Name of the shipper	
Address	
Phone Number	

Shipper characteristics (Please check mark ✓ to indicate your choice in the appropriate boxes ☐)

Age of shipping firm (Years)			
Number of employees in the firm			
Number of road vehicles owned	Truck - LCV:	Truck - MCV:	Truck - HCV:
Do you have rail side-line?	Yes ☐	No ☐	
What industry you are in?	Agriculture ☐	Construction☐	Manufacturing ☐
	Mining ☐	Trade ☐	Others (Please specify)
Structure of the firm	Domestic ☐	International ☐	

Shipment details of single consignment

Spatial characteristics

Name of origin of shipment and district	
Distance from origin to the nearby railway station (km)	
Name of destination of shipment and district	
Distance from destination to nearby railway station (km)	
Distance from origin to destination (km)	

Commodity characteristics

Name of the commodity				
Type of handling of commodity	Bulk liquid ☐	Bulk solid ☐	Unitised ☐	Containerised ☐
Shelf life of commodity (days)				
Weight of shipment (tonnes)				
Value of shipment (Rs.)				
Quality of packaging	Good ☐	Average ☐	Poor ☐	
Is the commodity fragile?	Yes ☐	No ☐		
Shipment frequency per month				
Is the commodity seasonal?	Yes ☐	No ☐		

Fig. 1. Page 1 of the questionnaire

Modal characteristics

Mode of Transportation	Truck: LCV □	Truck: MCV □	Truck: HCV □
	Rail alone □	Road-Rail-Road □	Others(Please specify)

Whether this shipment transported in own truck	Yes □	No □		
Transportation cost (Rs.)				
Handling charges (RS.)				
Door to door transportation time (hours)				
Pickup time (hours)				
Delivery time (hours)				
Reliability of mode (Degree of on time delivery)	High□	Normal □	Low□	
Is the handling equipment like cranes available?	Yes □	No □		
Capacity of primary mode (tonnes)				
Is the mode Safe from damage and theft?	Yes□		No□	
Cost of loss, damage or theft				
Availability of Tracking facility, etc.	Yes □		No □	
Whether there is transhipments	Yes □		No □	
Flexibility of the mode in terms of ability to handle short term requests, convenient schedule, pickup, delivery etc.	Yes □		No □	
Please rate the overall service quality of transport firm	Excellent □	Good □	Average □	Poor □

Please rate the importance of the reason for selecting the mode of transportation (Put tick✓)

	Characteristic	Not at all important	Slightly important	Moderately Important	Very Important	Extremely important
Spatial	Distance of shipment					
	Accessibility of the origin and destination to transportation terminal					
Commodity	Type of commodity					
	Shelf life (perishability)					
	Volume of Shipment					
	Frequency of shipment					
	Weight of shipment					
	Value of Shipment (Rs / t)					
	Packaging quality					
Transport Mode	Transportation cost including handling, damages etc.					
	Availability of the mode of transportation at required time					
	Transportation time					
	Reliability (On time delivery)					
	Safety from damage and theft					
	Capacity of mode					
	Availability of handling equipment					
	Facility for tracking, tracing etc.					
	Flexibility of the mode in terms of ability to handle short term requests, convenient schedule, pickup and delivery etc.					
	Ownership of rail side line by the shipper					

Are there any other factors, which affect your choice of transport mode, which is not mentioned in this questionnaire? If yes, please give below:

Please give, below, your suggestions for improving freight transport:

Thank you for your cooperation

Name of Enumerator: Date of Survey:

Fig. 2. Page 2 of the questionnaire

Rotation generates factors that are orthogonal or oblique. While the oblique factors reveal the underlying structure, they introduce modelling errors due to factor correlations. Alternatively, orthogonal rotated factors are uncorrelated and ideal for further use in modelling. Hence, this study employs orthogonal rotation using the varimax method. The correlation analysis of continuous variables is presented in Table 2. Many variables are found to be highly correlated. Hence factor analysis is done.

Table 1. Summary statistics

Variable	Min.	Max.	Mean	Standard Deviation
Firm's age, years	2	45	18.5	9.4
Employee count	1	40	11.3	9.5
Truck count	0	8	1.8	2.0
Distance, km	77.0	2,608.0	551.1	450.0
Shelf life, days	1.0	10	5	3
Shipment weight, t	0.02	16	4.41	4.94
Shipment value, INR	800	88,00,000	11,72,082	18,00,382
Shipment frequency, per month	1	30	10.9	10.3
Transportation cost, INR	30	65,000	7,399	9,565
Handling charges, INR	20	9,600	2,480	2,852
Transportation time, h	2	240	26	35.4
Pickup time, h	1	12	1.9	1.4
Delivery time, h	1	12	1.5	0.9
The capacity of mode, t	1.5	40	14.7	13.7
Cost of loss, INR	0	25,000	250	1,380
Transportation cost per q-km, INR	3.1	308	60.9	45
Distance of road shipments, km	80	2133	479.4	384
Distance of rail shipments, km	77	2608	818.6	564.5

Table 2. Correlation matrix of mode choice variables

Variable	Firm's age	Employee count	Truck count	Distance	Shelf life	Shipment weight	Shipment value	Handling charges	Transportation cost	Transportation time	Pickup time
Firm's age	1.00										
Employee count	0.67	1.00									
Truck count	0.41	0.69	1.00								
Distance	0.11	-0.11	-0.16	1.00							
Shelf life	0.19	-0.32	-0.51	0.39	1.00						
Shipment weight	-0.25	0.04	-0.11	-0.30	-0.47	1.00					
Shipment value	-0.18	0.03	-0.08	-0.21	-0.32	0.82	1.00				
Handling charges	-0.34	-0.05	-0.17	-0.30	-0.47	0.98	0.81	1.00			
Transport cost	0.00	0.24	0.09	0.16	-0.34	0.58	0.47	0.50	1.00		
Transport time	0.16	-0.21	-0.32	0.65	0.64	-0.32	-0.23	-0.32	-0.05	1.00	
Pickup time	0.03	-0.16	-0.15	0.23	0.42	-0.37	-0.30	-0.36	-0.26	0.36	1.00
Delivery time	-0.03	-0.04	0.05	0.03	0.17	-0.21	-0.16	-0.20	-0.12	0.18	0.76

Factor analysis revealed that Kaiser-Meyer-Olkin sampling adequacy was mediocre, at 0.68. The Bartlett test of sphericity was significant. The scree plot criterion revealed six factors. On the other hand, the Kaiser stopping criterion was adopted as it identified four factors that explained 81.62 per cent of the variability in the data. Factors 1, 2, 3, and 4 accounts for 35.1, 20.95, 13.63, and 11.94 per cent of variability, respectively. Table 3 illustrates the rotated component matrix. Factor 1 includes shipment weight, handling charges, shipment value, and transportation cost. This factor is referred to as the 'shipment size' factor. Factor 2 is referred to as the 'spatial proximity' factor, which considers the transportation time, the distance travelled, and the shelf life. Factor 3 includes the employee count, the truck count, and the firm's age. This factor is referred to as the 'firm size' factor. Factor 4 is named the 'access time' factor because it includes delivery time and pickup time.

5. Analysis of shippers' preferences

The variables influencing mode selection were ranked according to their importance in analysing shippers' preferences. The weighted average score is used to determine the importance of the attribute. The number of cases with various importance ratings and the weighted average score for the variables are depicted in Table 4. The most critical variables in mode selection are reliability and safety. These variables are followed by accessibility, availability of transport mode, transportation time, flexibility, commodity type, mode capacity, shelf life, shipment weight, shipment frequency, shipment volume, transportation cost, and distance.

6. Qualitative factors of preference ratings

Table 5 depicts the correlation analysis of these preference ratings. Many preference ratings on the importance of variables are highly correlated. The ratings were factor analysed to form the qualitative factors, which enable us to incorporate qualitative measurements of respondents' behaviour into the modelling process.

The Kaiser-Meyer-Olkin sample adequacy measure was 0.622, which is mediocre. Bartlett's sphericity test was found to be significant. The scree plot criterion yielded four components. In contrast, the Kaiser stopping criterion revealed three factors which are adopted. These three factors explained 74.26 per cent of the variance in the data. Factors 1, 2, and 3 accounts for 30.09, 27.07, and 17.10 per cent of the variance, respectively. Table 6 displays the rotated component matrix. Factor 1 includes ratings for mode flexibility, accessibility, and availability of transport modes. This factor is defined as the 'flexibility' rating factor. Factor 2 consists of time, safety, and shipment value ratings. As a result, this factor is known as the 'safety' rating factor. Factor 3 consists of commodity type and reliability ratings. As a result, this is defined as the 'reliability' rating factor.

Table 3. Component matrix

Variable	**Factor**			
	1	**2**	**3**	**4**
Shipment weight	0.921			
Handling charges	0.888			
Shipment value	0.851			
Transportation cost	0.776			
Transportation time		0.870		
Distance		0.841		
Shelf life		0.683		
Employee count			0.916	
Truck count			0.809	
Firm's age			0.780	
Delivery time				0.958
Pickup time				0.873

Table 4. Ranking of mode selection variables

Variable	Number of shipments with ratings as: Extremely important	Very important	Moderately important	Slightly important	Not at all important	Weighted average score
Reliability	501	286	151	36	20	4.22
Safety	192	484	180	76	62	3.67
Accessibility	321	228	168	158	119	3.48
Availability of mode	149	338	276	173	58	3.35
Transportation time	121	370	309	71	123	3.30
Flexibility	207	363	31	196	197	3.19
Type of commodity	217	132	365	86	194	3.09
Capacity of mode	206	252	140	173	223	3.05
Shelf life	119	297	219	169	190	2.99
Shipment weight	78	381	148	189	198	2.95
Shipment frequency	130	252	230	181	201	2.93
Shipment volume	209	66	302	224	192	2.88
Transportation cost	65	150	264	401	114	2.65
Distance	102	26	154	610	102	2.41
Shipment value	1	136	358	254	245	2.39
Packaging quality	58	136	55	47	698	1.80
Handling equipment	0	4	67	159	764	1.31
Tracking facility	0	8	71	134	781	1.30

Table 5. Correlation matrix of preference ratings

Qualitative variable	Accessibility	Shipment value	Time	Reliability	Safety	Flexibility	Mode availability	Commodity type
Accessibility	1.00							
Shipment value	0.13	1.00						
Transportation time	-0.09	0.52	1.00					
Reliability	0.45	0.10	0.08	1.00				
Safety	0.15	0.42	0.57	0.32	1.00			
Flexibility of mode	0.73	-0.13	-0.26	0.33	-0.09	1.00		
Availability of mode	0.52	0.03	-0.06	0.28	0.01	0.60	1.00	
Commodity type	-0.02	-0.08	-0.23	0.39	-0.21	0.05	0.04	1.00

Table 6. Component matrix

Variables	Factor 1	2	3
Flexibility of mode	0.90		
Accessibility	0.88		
Availability of mode	0.79		
Transportation time		0.84	
Safety		0.84	
Shipment value		0.75	
Commodity type			0.90
Reliability			0.73

7. Identification of heterogeneity among shippers

Latent class analysis deduces subgroups from multivariate data and classifies cases based on their maximum likelihood of belonging to a specific group. The heterogeneity in data is examined based on the observed variables. A latent class model is a mathematical relationship between a collection of observed variables and a set of latent variables. A class is defined by a sequence of conditional probabilities indicating the likelihood that latent variables take on particular values.

Equation 1 illustrates the general formula for the latent class model with observed dichotomous or polytomous variables, *A* and *B*, and one unobserved (or latent) dichotomous or polytomous variable, *X* (Hagenaars & Mccutcheon, 2002). Variable *A* has *I* classes, *B* has *J* classes, and variable *X* has *T* classes. The model shows that variables *A* and *B* are conditionally independent of each other, given the class level on variable *X*. The latent class model with more variables and the application of latent class analysis with numerical examples are illustrated by Hagenaars & Mccutcheon (2002).

$$\pi_{ijt}^{ABX} = \pi_t^X \pi_{it}^{\bar{A}X} \pi_{jt}^{\bar{B}X} \quad (1)$$

for $i = 1,..., I$; $j = 1,..., J$; $t = 1,..., T$,

where: π_{ijt}^{ABX} is the joint probability that a case is in class *i* on variable *A*, in class *j* on variable *B*, and in class *t* on variable *X*; π_t^X denote the probability that a case is in class *t* on variable *X*; $\pi_{it}^{\bar{A}X}$ denote the conditional probability that an observation is in class *i* on variable *A*, given that the case is in class *t* on variable *X*; $\pi_{jt}^{\bar{B}X}$ denote the conditional probability that an observation is in class *j* on variable *B*, given that the case is in class *t* on variable *X*.

The Bayesian information criterion (BIC) based on log-likelihood statistics indicates the parsimony of the model. The BIC value decreases as the cluster size increases, and at some point, it increases. The optimal number of clusters for a particular variable combination is determined as the one with the lowest BIC value.

In this study, the characteristics of the shipping firms considered to ascertain the heterogeneity are their age, employee count, number of trucks possessed, and whether their trucks are used for shipments. Table 1 presents the summary statistics of the variables. A value of one is assigned if the owner's trucks are used for shipment; otherwise, zero.

The latent class analysis was performed for clusters 1 through 15 for all possible combinations of the four variables. The first set of trials took into account all four variables. The subsequent trials considered four possible combinations of three variables. The last trials included six possible combinations of two variables. The best combination of variables for latent class analysis is one that is significant, has the lowest classification error, and has a small number of classes.

The latent class analysis discovered that there exists heterogeneity among the shippers. Table 7 summarises the significant latent class models. These models are ranked in the order of increasing classification error. The model with the lowest classification error was selected for classifying shippers. The BIC value based on the log-likelihood statistics of the best model was 2868.19, and the L^2 statistic was 14.99. The optimal class size, obtained from the latent class, is two, with a classification error of 0.0005. The model includes two variables: the truck count and their use for shipments.

Shipping firms of fish were divided into two latent classes. Class 1 contains 512 shipments in the data, while Class 2 contains 482 shipments. Only 3.5% of the shipments in Class 1 are sent by shippers' trucks, and 96.5% are sent by hired trucks or trains. In contrast, all the shipments in Class 2 are sent by trucks owned by the shipper. All the Class 2 shippers own and use trucks for shipments. The profile plot of latent classes of shippers of fish is illustrated in Figure 3.

8. Identification of optimum mode choice modelling strategy

Factor analysis found that the transportation cost and shipment weight contribute to factor 1 and the shipment distance to factor 2. However, logically, transportation cost is associated with the weight of the shipment and distance. Hence, the variable transportation cost per q-km is estimated by dividing the transportation cost by the shipment weight and the distance. Similarly, transportation time is proportional to the distance travelled. Hence speed is estimated. These estimated variables were used in the

modelling. However, it must be found if latent factors or estimated variables work well in modelling.
This section describes the various conceptual models of mode choice developed using various types of variables. Conceptual model 1 includes the estimated and observed variables, as depicted in Figure 4. Conceptual model 2 includes the qualitative factors of importance ratings, observed variables, and estimated variables, as shown in Figure 5. Conceptual model 3 includes latent factors, observed variables not included in the latent factors, and qualitative factors, as depicted in Figure 6. As latent factors are obtained from observed variables, this model excludes estimated variables, which are also obtained from the same observed variables.
Models 4 were formulated to account for shipper heterogeneity by incorporating observed variables, estimated variables, and qualitative factors for the latent classes 1 and 2. These models are named models 4-1 and 4-2. Figure 7 depicts conceptual model 4 for the latent classes of shippers.
In the mode selection modelling, the rail is considered the dependent variable with the road as the reference category. A stepwise modelling approach was used to obtain the best model. A ninety-five per cent confidence interval is used. The significance of Wald statistics indicates that an independent variable significantly influences the dependent variable. Significant variables have a significance value of less than 0.05. The following models include only significant variables. A significant Chi-square value indicates a strong association between the dependent and the independent variables. The four conceptual models are presented below.

Table 7. Selection of variables for latent class analysis

Rank	Firm's age	Employee count	Truck count	Use of own trucks	Optimum number of classes	Classification error	Number of variables
1			Yes	Yes	2	0.0005	2
2		Yes	Yes	Yes	4	0.0041	3
3	Yes	Yes	Yes	Yes	7	0.0051	4
4		Yes	Yes		4	0.0092	2
5	Yes		Yes	Yes	6	0.0235	3
6		Yes		Yes	3	0.0254	2
7	Yes	Yes			4	0.0276	2
8	Yes	Yes	Yes		7	0.0341	3
9	Yes	Yes		Yes	6	0.0453	3
10	Yes		Yes		6	0.0512	2
11	Yes			Yes	4	0.1118	2

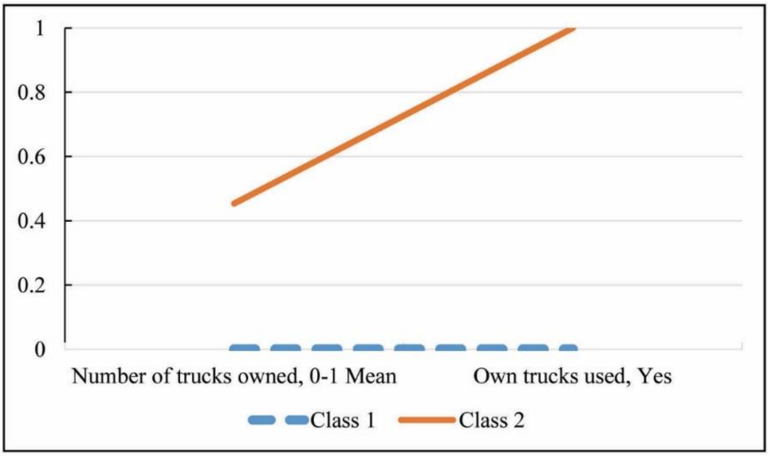

Fig. 3. Profile plot

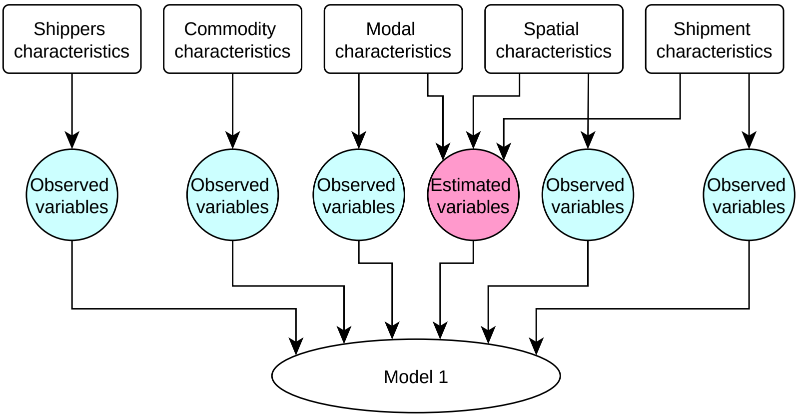

Fig. 4. Conceptual model 1

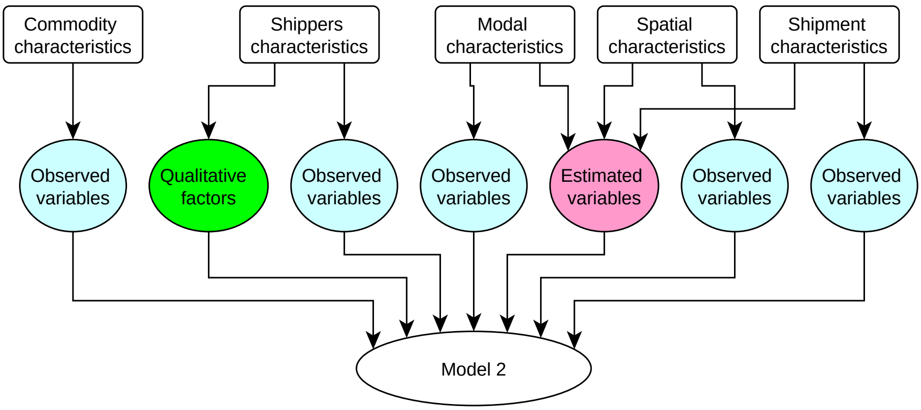

Fig. 5. Conceptual model 2

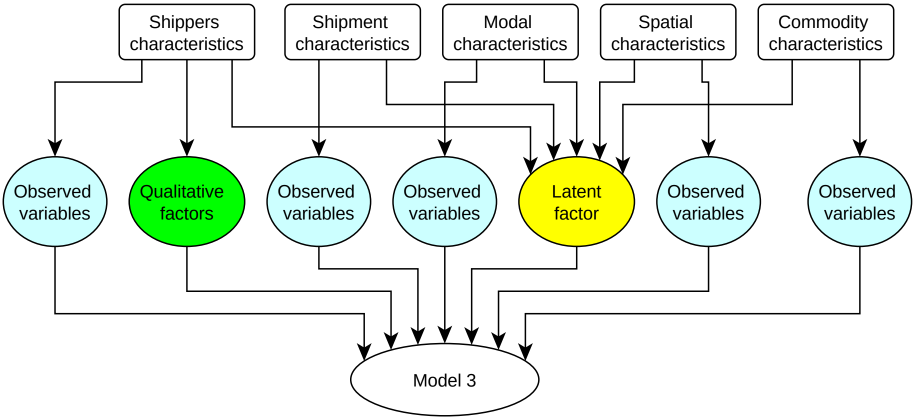

Fig. 6. Conceptual model 3

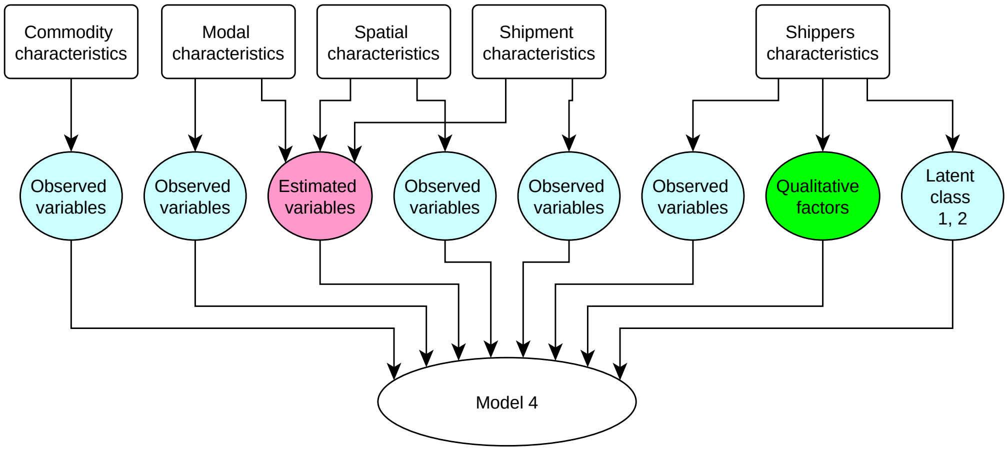

Fig. 7. Conceptual model 4

8.1. Model 1

The mode selection model 1 for rail, with the road as the reference category, is depicted in Table 8 with observed and estimated variables. The model has a significant Chi-square value of 793.36. The Nagelkerke R squared value is 0.855. The exponent of coefficient B is known as the odds ratio.

The significant variables in model 1 are speed, transportation cost per q-km, and shipment frequency. If a variable's coefficient is positive, its odds ratio will be greater than 1. So, as the variable's value increases, the modelled event (rail) becomes more likely to occur in comparison to the referent event (road). If a variable's coefficient is negative, its odds ratio will be less than one, which means that as the variable's value increases, the chances that shippers will choose rail over road fall.

Among the variables with a positive coefficient, the coefficient of speed is 0.216, which has less influence on rail mode choice than shipment frequency, which has a coefficient of 0.363. As the speed and shipment frequency increase, the probability of respondents choosing rail over road increases. The coefficient of the transportation cost per q-km has a negative effect on rail mode choice. Hence, as transportation costs rise, shippers' choice of rail over road decreases.

8.2. Model 2

Table 9 depicts model 2 for selecting the mode of transportation, including observed variables, estimated variables, and qualitative factors. The model's Chi-square value is 944.34, which is significant. The Nagelkerke R squared value is 0.955. As the distance to the railway station increases, the probability of respondents selecting rail over road decreases, which is logical. Shippers believe that the flexibility of rail is lower than the road. The effect of other variables on mode choice is discussed earlier.

8.3. Model 3

The mode selection model 3, which includes observed variables, qualitative factors, and latent factors, is shown in Table 10. The Nagelkerke R squared value is 0.721. The Chi-square value is 618.18, which is significant. As the shipment size factor increases, the rail choice decreases, which is attributed to the fact that the full trainload is not considered in this study due to a lack of mode choice.

8.4. Model 4

Model 4 for latent class 1:

Latent class analysis classified shippers into two latent classes. Only 3.5% of Class 1 shipments are delivered by the shipper's trucks, while the remaining 96.5% are delivered by hired trucks or trains. Table 11 shows the mode choice model 4-1, including observed variables, estimated variables, and qualitative factors, for latent class 1 of shippers. The model has a Chi-square value of 536.01. The Nagelkerke R squared value is 0.976. The significant variables are speed, transportation cost per q-km, flexibility rating factor, shelf life and employee count. Shippers prefer the road as the commodity's shelf life increases.

The rail share decreases with employee count. The effect of other variables is as mentioned earlier.

Model 4 for latent class 2:
All Class 2 shippers own and operate trucks for shipments. Table 12 illustrates the mode choice model 4-2. The Nagelkerke R squared value of the model is 0.932. The model's Chi-square value is 409.04, which is significant. The modelling revealed that, in addition to speed and cost considered by Class 1 shippers, Class 2 shippers value reliability and safety. Hence, the shippers who value reliability and safety for transporting fish were found to own trucks.

Table 8. Mode selection model 1

	B	Std. Error	Wald statistic	Sig.	Odds Ratio
Intercept	-7.597	0.993	58.488	0.000	
Speed	0.216	0.024	78.876	0.000	1.241
Cost of transportation per q-km	-0.126	0.014	85.406	0.000	0.881
Shipment frequency	0.363	0.036	101.842	0.000	1.437

Table 9. Mode selection model 2

	B	Std. Error	Wald statistic	Sig.	Odds Ratio
Intercept	-3.957	1.642	5.811	0.016	
Speed	0.144	0.033	19.395	0.000	1.155
Cost of transportation per q-km	-0.119	0.019	40.989	0.000	0.888
Distance to the railway station	-0.171	0.063	7.310	0.007	0.843
Rating factor of flexibility	-5.401	1.045	26.688	0.000	0.005
Shipment frequency	0.192	0.046	17.353	0.000	1.212

Table 10. Mode selection model 3

	B	Std. Error	Wald statistic	Sig.	Odds Ratio
Intercept	-3.051	0.440	48.017	0.000	
Shipment size factor	-1.063	0.401	7.026	0.008	0.345
Spatial proximity factor	-0.644	0.130	24.744	0.000	0.525
Rating factor of flexibility	-3.513	0.331	112.785	0.000	0.030
Distance to the rail station	-0.096	0.022	18.578	0.000	0.909

Table 11. Mode selection model 4-1

	B	Std. Error	Wald statistic	Sig.	Odds Ratio
Intercept	7.545	3.687	4.188	0.041	
Speed	0.301	0.098	9.360	0.002	1.351
Cost of transportation per q-km	-0.093	0.026	12.574	0.000	0.911
Rating factor of flexibility	-13.082	3.685	12.600	0.000	0.000
Shelf life	-1.802	0.625	8.322	0.004	0.165
Employee count	-0.857	0.306	7.839	0.005	0.424

Table 12. Mode choice model 4-2

	B	Std. Error	Wald statistic	Sig.	Odds Ratio
Intercept	4.607	2.316	3.957	0.047	
Speed	0.104	0.041	6.582	0.010	1.110
Cost of transportation per q-km	-0.333	0.065	26.197	0.000	0.717
Rating factor of reliability	-0.901	0.413	4.752	0.029	0.406
Rating factor of safety	-3.007	0.788	14.573	0.000	0.049

8.5. Discussion

All the conceptual models' goodness of fit measures is compared to establish the best modelling strategy. The Nagelkerke R squared values of the models are presented in Table 13. It was found that models built with logically estimated variables outperformed models built with latent factors. Furthermore, mode choice modelling could be improved by including qualitative factors derived from preference ratings in the mix of observed and estimated variables. However, models considering heterogeneity by incorporating observed variables, estimated variables, and qualitative factors outperformed all the other models.

Table 13. Comparison of various models

Model	Nagelkerke R squared value
1	0.855
2	0.955
3	0.721
4-1	0.976
4-2	0.932

The significant characteristics of mode selection are identified from Model 4-1 and Model 4-2, which consider heterogeneity among shippers. When policy variables are considered, it is discovered that as speed increases, the probability of shippers choosing rail increases. Whereas as transportation cost increases, the probability of respondents choosing rail decreases. Moreover, shippers believe that the reliability and safety of rail are lower than that of the road. Thus, rail's share can be increased by improving its speed, reliability, and safety, as well as by lowering the cost of transportation.

In India, the average truck speed is between 20 and 40 kilometres per hour, compared to 60 to 80 kilometres per hour in developed countries (Ernst & Young and Retailers Association of India, 2013). Trucks travel at a slower speed on highways causing delays for other fast-moving vehicles. All highways in India do not have four or more lanes. Hence, some truck traffic can be shifted to Roll on-roll off trains. Roll on-roll off trains haul trucks without unloading the freight on railway rakes and reduce highway traffic. Expanding roll on-roll off facilities throughout the country reduces transportation costs, highway congestion, and energy consumption.

Railways should also expand dedicated freight corridors to increase transport speed, reliability, and frequency. Kumar and Anbanandam (2020) recommended establishing a dedicated freight corridor and utilising multimodal services for long-haul freight transportation to improve the sustainability of freight transportation.

Furthermore, rail freight tariffs should be reduced by discontinuing sharing freight transport profits to offset passenger transport losses in India (Niti Aayog, 2017). Presently goods train transport only one commodity except for container trains. Most fish shippers cannot transport an entire trainload of freight. Hence, allowing for piecemeal service by transporting different commodities in different wagons on goods trains and increasing the number of parcel trains increase the freight speed and frequency and reduce transportation costs. Refrigerated container transportation by trains should be increased. All these policy measures increase train mode share for fish transport, reducing energy consumption and emissions.

9. Conclusions

Factor analysis of observed variables identified four latent factors for fish transport. The shipment size factor included shipment weight, handling charges, shipment value, and transportation costs. Time, distance, and shelf life form the spatial proximity factor. The firm size factor included employee count, truck count, and the firm's age. The access time factor included delivery time and pickup time. It was found that transportation costs and shipment weight contributes to factor 1, while distance contributes to factor 2. However, transportation costs were associated with distance and weight. Thus, the transportation cost per q-km was estimated for modelling.

A factor analysis of preference ratings for variables revealed three qualitative factors. The flexibility rating factor included ratings for flexibility, accessibility, and mode availability. In comparison, the safety rating factor included ratings of time, safety, and shipment value. Ratings of commodity type and reliability formed the reliability rating factor. The latent class analysis revealed significant taste heterogeneity in shippers' mode selection behaviour. Only 3.5% of Class 1 shippers own trucks, whereas all the shippers of Class 2 own and use trucks.

Mode selection modelling revealed that models with estimated variables outperformed those with latent factors. Models including observed variables, estimated variables, and qualitative factors showed further improvement. However, the models that included observed variables, estimated variables, and qualitative factors, which considered heterogeneity, are the best. Class 1 shippers consider the speed, cost of transportation per q-km, rating factor of flexibility, and shelf life as significant in freight mode choice. Class 2 shippers value reliability and safety in addition to speed and cost; hence, they own trucks. The rail share could be increased by improving speed, reliability, and safety and lowering transportation costs.

Railways should provide dedicated freight corridors across the country to improve transportation speed, reliability, and safety. Expanding rail roll on – roll off truck facilities reduce transportation costs and highway traffic congestion. Rail freight fares can be decreased further by discontinuing sharing the rail freight profits to offset passenger transport losses. Allowing for piecemeal service on goods trains by conveying different commodities in distinct waggons reduces transportation expenses by shifting more road freight to rail. Increasing the number of parcel trains will increase freight transportation speed and frequency. Improving intermodal refrigerated container transportation increase the safety of fish transport. These policy measures aid in the shift from road to rail, thereby reducing energy usage.

Since the study was restricted to interregional fish transportation by road and rail, this methodology can be extended to international shipments by all transport modes to improve efficiency. The future implementation of the electric or hybrid fleet for fish transportation can also be analysed in further studies.

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