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DOI

[10.1016/j.tra.2020.10.019](https://doi.org/10.1016/j.tra.2020.10.019)

Publication date

2020

Document Version

Final published version

Published in

Transportation Research Part A: Policy and Practice

Citation (APA)

Li, Q., Rezaei, J., Tavasszy, L., Wiegmans, B., Guo, J., Tang, Y., & Peng, Q. (2020). Customers' preferences for freight service attributes of China Railway Express. *Transportation Research Part A: Policy and Practice*, 142, 225-236. <https://doi.org/10.1016/j.tra.2020.10.019>

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Transportation Research Part A

journal homepage: www.elsevier.com/locate/tra

Customers' preferences for freight service attributes of China Railway Express

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ARTICLE INFO

Keywords:

Freight demand preferences
Rail freight services
Best-Worst Method (BWM)
Cluster analysis
China Railway Express (CRE)

ABSTRACT

China Railway Express (CRE) is one of the most important constituent parts of the Belt and Road Initiative. Freight demand analysis is fundamental as a basis for the operational strategy of CRE and the investment policy along the CRE-routes. Most of the existing relevant literature has focused on the organization of the train operations of CRE, with little research related to demand analysis. This paper contributes to filling this gap by estimating customers' demand preferences for rail freight service attributes, by using a novel multi-criteria decision-analysis (MCDA) method namely Best-Worst Method (BWM). To this end, a BWM survey was conducted in China to capture customers' preferences for the main attributes that define the transport service offered by CRE. Two variants of BWM, the linear and the Bayesian, are employed for the analysis. Reliability is suggested as the most important attribute for CRE to focus on, to gain customers. We also conduct a cluster analysis based on the results, which helps the CRE operator to identify homogeneous customer segments, and to optimize the use of CRE's resources with a differentiated pricing strategy.

1. Introduction

China Railway Express (CRE), the important carrier for the rail services of the Belt and Road Initiative (BRI), was initiated by the Chinese government in 2011 to increase economic exchange and trade between China and Europe. CRE represents a new important mode to transport goods between China and Europe, besides maritime and air services (Jiao et al., 2018). With the growth of trade between China and Europe and the promotion of CRE, the number of trains of CRE has been growing rapidly from 17 in 2011 to 8225 in 2019 (Yidaiyilu.gov.cn). Because of the imbalance in trade, there is more transport demand from China to Europe versus from Europe to China. The increasing freight transport demand has caused a shortage of capacity and other transport resources, which finally brings a negative impact to the freight service quality of CRE (Li et al., 2019). In order to better meet the freight transport demand, the Chinese government is investing in infrastructure along the completed and planned routes of CRE (see Fig. 1) to increase the capacity. In addition, operators try to improve the operational efficiency of CRE by optimizing freight transport organization (Zhao et al., 2018).

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<https://doi.org/10.1016/j.tra.2020.10.019>

Received 3 October 2019; Received in revised form 24 August 2020; Accepted 29 October 2020

Available online 20 November 2020

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Rail demand analysis is a crucial basis for the two types of measures mentioned above. However, most of the existing relevant literature is focused on the organization of train operation of CRE (Jiang et al., 2018; Wu et al., 2019), and little focus has been put on demand analysis. Therefore, this article aims to contribute to filling this research gap. Firstly, by reviewing the literature, we identify the most relevant attributes that play a role in customers' choice of purchasing the CRE freight transport service. Secondly, a multi-criteria decision-analysis (MCDA) method called Best Worst Method (BWM) is adopted to find the importance of those attributes. On the basis of customer survey results conducted in China, two variants of BWM are employed for the analysis from two different angles. From a macro perspective, the Bayesian BWM results amalgamate the preferences (we use the term "preferences" to indicate weights of attributes) of a sample of customers. The ranking scheme for attributes, called Credal Ranking, assigns a confidence level to measure the extent to which the sample of customers prefer one attribute over the other. From a micro perspective, the linear BWM is used to find how individual customers might have different freight service attributes priorities. The results of the linear BWM are then used for a cluster analysis. This provides a reference for the CRE operator to optimize the use of CRE's limited freight transport resources by implementing a differentiated pricing strategy based on demand preferences.

Although previous studies have used different methods to research freight service choice related issues (De Jong, 2015), this study is unique with respect to its focus on measuring customer's demand preference of CRE. Compared with most of existing freight demand research studies that focus on a domestic or regional scale, our context gives us a case to understand the demand characteristics of long-distance, intercontinental railway transport (Rodemann and Templar, 2014). Most of the current literature related to CRE is about the organization of train operation which contributes to CRE from the angle of optimizing supply. This article contributes to CRE from the angle of analyzing demand, which is a crucial foundation for optimizing supply.

The focus of the research is to understand the valuation of the CRE services by its current customer base – the primary use of these values being to assess the direct economic impacts of CRE service improvements. Using a within-mode approach, one can identify whether the values found here fall within the range of values reported in the literature for rail freight service valuation. This also allows us to assess the net impact of inter-modal competition on these valuations until the present day. One should note, however, that the approach presented here does not allow to predict changes in valuations due to the modal shift of CRE or non-CRE users; recommendations are provided in further research.

Compared to the existing literature that applies discrete choice models to find demand preferences related to freight mode choice, this article employs a novel MCDA method namely BWM, to study attribute rankings of CRE customers. While the linear BWM provides insight at individual level, the Bayesian BWM provides a comprehensive understanding of the entire sample of customers. The use of these two variants of BWM for one data set provides unique insights for decision-makers.

The rest of this paper is organized as follows. Section 2 reports the review of the relevant literature. Section 3 describes the model formulation. Section 4 presents the estimation results. Section 5 provides a discussion of the results and the policy implications of the study. The paper is concluded in Section 6 with a summary of the findings and with recommendations.

2. Literature review

In this review section, we identify the most relevant attributes that play a role in the freight mode choice process. Next, we discuss methods used in the literature to evaluate the importance of these attributes.

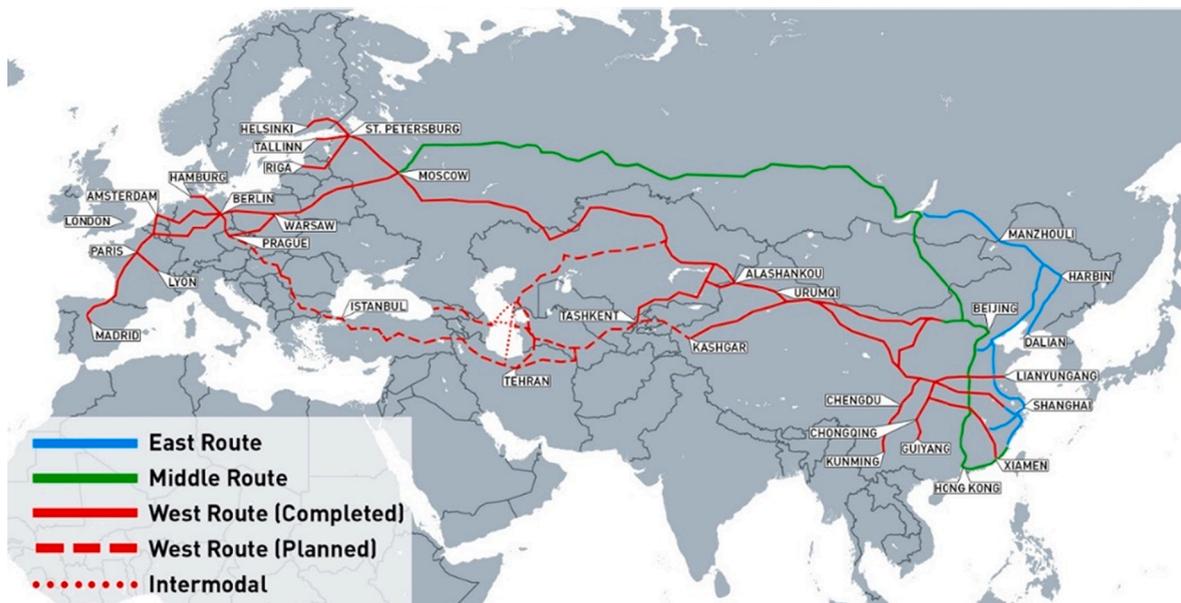


Fig. 1. The routes of CRE. (source: Ministry of Transport of the People's Republic of China).

2.1. Freight mode choice attributes

Identifying the relevant attributes is the first step before measuring their importance. As for freight mode choice, it is now 50 years ago since [Baumol and Vinod \(1970\)](#) first investigated shippers' choice of transport and developed a model to describe mode choice using the attributes cost, time, reliability and safety. Since then, many researchers have used different attributes to research freight mode choice from different perspectives. [Cullinane and Toy \(2000\)](#) used content analysis methodology to systematically analyze seventy-five freight route/mode choice articles published by 2000. They found that “cost”, “time” and “reliability” are the three most commonly used attributes for freight route/mode choice decision. [Shinghal and Fowkes \(2002\)](#) applied Stated Preference techniques to analyze freight mode choice in India. They found that there are obvious differences among the six different product sectors' (exporters, freight forwarders/transporters, chemicals, electrical/electronics, auto parts, and food) preference on the four attributes of “cost”, “time”, “reliability” and “frequency”. [Beuthe et al. \(2003\)](#) using the utility additive (UTA) multicriteria method researched the freight transport managers' stated preferences of the six attributes: “cost”, “time”, “reliability”, “frequency” “flexibility”, and “safety”, among freight transport alternatives. [Tuzkaya and Oenuet \(2008\)](#) proposed the fuzzy analytic network process (ANP) to evaluate the alternative modes of transport between Turkey and Germany using the attributes “cost”, “time”, “reliability”, “frequency” “flexibility”, and “traceability”. The main attributes related to the choice of transport mode were about service quality and cost ([Arencibia et al., 2015](#)). With the climate change resulting from the environmental impacts of industrial production, trade, and transport, issues such as environmental sustainability have started to gain greater attention. Comparing the published articles before and after 2010, there is more concern about “sustainability” in freight mode choice after 2010 ([Bask and Rajahonka, 2017](#)). Environmental sustainability is not only considered through greenhouse gases but also through air pollutants ([van Fan et al., 2018](#)). The above criteria are the ones used in the majority of mode choice studies ([Mardani et al., 2015a](#)) – we note that some attributes come under different names but have similar definitions ([Liu, 2016](#)).

Other attributes were found in the literature that were typical for bulk carriers, such as “capability” and “infrastructure & equipment availability” ([Meixell and Norbis, 2008](#); [Subhro Mitra, 2013](#)). As we deal with container transport, these are not considered.

Besides the performance attributes related to the mode itself, there are also user-side attributes that affect mode choice ([Gray, 1982](#)). Goods characteristics (value/weight ratio and goods category) are often considered ([Brooks et al., 2012](#)). [Fries et al. \(2008\)](#) and [Patterson et al. \(2010\)](#) claimed that shippers and Logistic Service Providers (LSP) have different preferences on mode choice. Also, the origin/destination type (e.g. factory, warehouse, or customer home) of goods may be of influence ([McDonald, 2016](#)).

As the main focus of this paper is to investigate the customers' preferences for freight service attributes related to the mode itself, we use the eight attributes shown in [Table 1](#) as the main target in the survey. In addition, we use other attributes such as goods characteristics as the ancillary target in the survey. A focus group consisting of freight transport experts and CRE consultants was used for validation and confirmed that these attributes are opportune in the survey. Although there was discussion about the expected practical relevance of “sustainability”, given its growing importance in freight policy and decision making, we decided to include it in this study.

In the next section, we discuss the methods reported in the literature to measure customers' preferences for freight mode choice attributes. Also we discuss our choice of method in this study.

2.2. Freight mode choice appraisal method

To elicit respondents' preferences, discrete choice models and multi-criteria decision-analysis (MCDA) methods are the two main approaches that are usually considered in scientific research ([Meixell and Norbis, 2008](#)). Discrete choice models, based on random utility theory, are beneficial to describe how shippers choose a freight service, often in a between-mode choice situation ([Revelt and Train, 1999](#)). MCDA is more widely used to rank service quality for within-mode situations ([Mardani et al., 2015b](#)). As we aim to

Table 1
The chosen freight service attributes and their definition based on previous literature.

No.	Attribute	Definition	Author (year)
1	Cost	Total transport cost from origin to destination	Cullinane and Toy (2000) ; Shinghal and Fowkes (2002) ; Beuthe et al. (2003) ;
2	Time	Total transport time from origin to destination	Grue and Ludvigsen (2006) ; Reis (2014) ; Tavasszy and de Jong (2014) ; Arencibia et al (2015) ; Duan et al. (2016) ; Feo-Valero et al. (2016) ; Kim et al. (2017) ;
3	Reliability	Unexpected deviation from the expected duration of freight travel	Larranaga et al.(2017) ; Román et al. (2017) ; Shams et al. (2017) ; Pham and Yeo (2018) ; Zhang and Zhu (2018)
4	Frequency	Frequency of the freight services, number of departures per week	Shinghal and Fowkes (2002) ; Grue and Ludvigsen (2006) ; Feo et al. (2011) ; Arencibia et al (2015) ; Duan et al. (2016) ; Feo-Valero et al. (2016) ; Kim et al. (2017) ; Román et al. (2017)
5	Safety	Commercial value lost from damages, stealing and accidents	Grue and Ludvigsen (2006) ; Duan et al. (2016) ; Kim et al. (2017)
6	Flexibility	Capacity of the transport mode to adapt to unexpected changes in the requirements of the demand	Grue and Ludvigsen (2006) ; Sun et al. (2006) ; Tuzkaya and Önüt (2008) ; Mason and Nair (2013) ; Reis (2014) ; Tosun and Uysal (2015) ; Yu et al. (2017)
7	Traceability	Capability for tracking & tracing of the shipment	Tuzkaya and Önüt (2008) ; Moschovou and Giannopoulos (2010)
8	Sustainability	Emission of greenhouse gas and air pollutants during the transport journey	Bask and Rajahonka (2017) ; Fan and Perry (2018)

research rail freight service customer preferences, especially about the importance of the attributes, MCDA is preferred (Zavadskas and Turskis, 2011). We only found four studies that employed MCDA to measure the weights of decision-makers/users' preference to freight service attributes. Beuthe et al. adopt the UTASTAR (a variant of UTA (UTILites Additives)) to identify weights, for six mode attributes and eight segments based on the stated preference (SP) survey dataset from about one hundred firms (Beuthe, 2005). Tuzkaya and Önüt (2008) used a fuzzy analytical network process (ANP) model to measure the weights for 32 attributes (of 8 clusters of attributes), from interviews among managers of a LSP in Turkey. Pham and Yeo (2018) employed the Delphi method and the Consistent Fuzzy Preference Relations method to study the adequate transport choice of electronic components from China to Vietnam using 14 attributes. Tavasszy et al. (2020) report on the use of linear BWM for freight mode choice in 4 industries, considering 5 choice attributes. We can see that using MCDA to empirically determine weights of freight service attributes is still an unexplored research area. Thus, employing MCDA in our research is also a contribution to fill this research gap.

MCDA is a sub-discipline of Operations Research that explicitly evaluates multiple (conflicting) criteria in decision-making in cases with more than one decision attribute (Camargo Pérez et al., 2014). Many different MCDA approaches are employed in the literature. Chai et al. (2013) summarized 123 articles published between 2008 and 2012. Besides Analytic Hierarchy Process (AHP), there are some other classical methods such as Analytic Network Process (ANP), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), ELimination Et Choix Traduisant la REalité (also known as ELimination and Choice Expressing REality) (ELECTRE), VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR), Preference Ranking Organization METHod for Enrichment Evaluations (PROMETHEE), and Best-Worst Method (Rezaei, 2015). From the existing MCDA methods, we prefer Best Worst Method (BWM) which is characterized by some salient features. For example, (i) By identifying the best and the worst attributes before conducting the pairwise comparisons, the decision-maker (DM) has a clear understanding of the range of evaluation which could lead to more reliable pairwise comparisons; (ii) The use of two pairwise comparisons vectors formed based on two opposite references (best and worst) in a single optimization model could mitigate possible anchoring bias that the DM might have during the process of conducting pairwise comparisons; (iii) BWM is one of the most data-efficient methods which could at the same time allow a consistency check. Other pairwise comparison-based methods (e.g. SMART and Swing family) that use one vector for input data (which are more data efficient) do not allow a consistency check of the provided pairwise comparisons; (iv) checking and finding the reasons behind potential low inconsistencies, and revising the vectors to increase the consistency ratio is relatively easy; and (v) the method can be easily integrated with other multi-criteria decision-making methods, even those that use more complete pairwise comparison matrices (Rezaei, 2020).

3. Methodology and data

In this section, we introduce the method employed in this study in more detail. We introduce the two variants of BWM named linear BWM and Bayesian BWM. Then we present the questionnaire and respondents in the case at hand of CRE.

3.1. Original Best Worst method (BWM)

The Best Worst Method (BWM) is a pairwise-based MCDA method that was developed in 2015 (Rezaei, 2015). It is suitable to evaluate the importance of attributes (or alternatives) based on the input provided by the decision-maker/expert (Rezaei et al., 2016). The original BWM (Rezaei, 2015) involves a non-linear optimization which might result in multiple optimal solutions, while the linear BWM (Rezaei, 2016), provides a unique solution which is a very good approximation of the weights. Below we present the main steps of the linear BWM (Brunelli and Rezaei, 2019).

Step 1: Determine a set of evaluation attributes.

In the first step, a set of evaluation attributes $\{C_1, C_2, \dots, C_n\}$ is considered to evaluate the alternatives. In our study, these attributes are the eight attributes that have been discussed in Table 1.

Step 2: Determine the best (the most important) attribute, B , and worst (the least important) attribute, W .

In this step, the evaluator (expert, decision-maker) has to identify the best attribute B (e.g. the most important attribute to evaluate the alternatives) and the worst attribute W (e.g. the least important attribute to evaluate the alternatives) in general.

Step 3: Determine the preference of the best attribute B over the other attributes.

The evaluator then has to indicate the preference of the most important attribute over the other attributes, using a number between 1 and 9, where 1 indicates 'equal importance', and 9 means 'extremely more important', resulting in a Best-to-Others vector, A_B :

$$A_B = (a_{B1}, a_{B2}, \dots, a_{Bn}) \quad (1)$$

Step 4: Determine the preference of all the attributes over the worst attribute W .

The evaluator has to indicate the preference of all the other attributes over the attribute selected as being the least important, using a number between 1 and 9, where 1 indicates 'equal importance', and 9 means 'extremely more important', resulting in an Others-to-Worst vector, A_W :

$$A_W = (a_{1W}, a_{2W}, \dots, a_{nW})^T \quad (2)$$

Step 5: Find the optimal weights.

In this step, the optimal weights $(w_1^*, w_2^*, \dots, w_n^*)$ are identified. The set of optimal weights for the linear model is the one where the maximum value of the set $\{|w_B - a_{Bj}w_j|, |w_j - a_{jW}w_W|\}$ is minimized. The sum of the weights has to be equal to 1 and none of the weights can be negative, leading to model (3) to find the optimal weights.

$$\begin{aligned} & \min \max_j \{ |w_B - a_{Bj}w_j|, |w_j - a_{jw}w_w| \} \tag{3} \\ & \text{s.t. } \sum_{j=1}^n w_j = 1, \\ & w_j \geq 0, \text{ for all } j \end{aligned}$$

This problem can be transferred to the following linear programming problem (4):

$$\begin{aligned} & \min \xi^L \tag{4} \\ & \text{s.t. } |w_B - a_{Bj}w_j| \leq \xi^L, \text{ for all } j \\ & |w_j - a_{jw}w_w| \leq \xi^L, \text{ for all } j \\ & \sum_{j=1}^n w_j = 1 \\ & w_j \geq 0, \text{ for all } j \end{aligned}$$

Solving this linear programming problem (4) we find the optimal weights $(w_1^*, w_2^*, \dots, w_n^*)$ and ξ^{L^*} . ξ^{L^*} is considered as an indicator of the consistency of the pairwise comparisons. A value close to zero indicates a high consistency and therefore high reliability.

3.2. Bayesian BWM

The Bayesian BWM was developed in 2019 to find the optimal aggregated final weights reflecting the total preferences of all decision-makers/experts in a sample along with the confidence level for ranking the attributes from a probabilistic perspective (Mohammadi and Rezaei, 2019).

The first four steps of Bayesian BWM are the same as the linear BWM. Step 5, however, which aims to identify the optimal weights of the attributes is different in the Bayesian BWM, and is explained here.

We assume that the k^{th} ($k = 1, \dots, K$) DM, evaluates the attributes c_1, \dots, c_n by giving the vectors A_B^k and A_W^k . Then we get the set of all vectors of K DMs by $A_B^{1:K}$ and $A_W^{1:K}$. The superscript $1:K$ indicates the total of all vectors in the base. We consider the overall optimal weight as w^{agg} , and according to Bayesian BWM, we will get the following equation (5).

$$P(w^{\text{agg}}, w^{1:K} | A_B^{1:K}, A_W^{1:K}) \propto P(A_B^{1:K}, A_W^{1:K} | w^{\text{agg}}, w^{1:K}) P(w^{\text{agg}}, w^{1:K}) = P(w^{\text{agg}}) \prod_{k=1}^K P(A_B^k | w^k) P(A_W^k | w^k) P(w^k | w^{\text{agg}}) \tag{5}$$

The distributions of each and every element in equation (5) is specified. A_B^k and A_W^k can be modeled by using the multinomial distribution preserving the underlying idea of the original BWM.

$$A_B^k | w^k \text{ multinomial}(1/w^k) \tag{6}$$

$$A_W^k | w^k \text{ multinomial}(w^k) \tag{7}$$

Given w^{agg} , Dirichlet distribution is reparametrized with respect to its mean and a concentration parameter.

$$w^k | w^{\text{agg}} \text{ Dir}(\gamma \times w^{\text{agg}}) \tag{8}$$

Where w^{agg} is the mean of the distribution and γ is the concentration parameter.

A reliable option is the gamma distribution which satisfies the non-negativity constraints, i.e.,

$$\gamma \text{ gamma}(a, b) \tag{9}$$

Where a and b are the shape parameters of the gamma distribution.

The prior distribution over w^{agg} is supplied by using an uninformative Dirichlet distribution with the parameter $\alpha = 1$ as

$$w^{\text{agg}} \text{ Dir}(\alpha) \tag{10}$$

Markov-chain Monte Carlo (MCMC) techniques are used to compute the posterior distribution as the specified model does not have a closed-form solution. As for the MCMC sampling, the Just Another Gibbs Sampler (JAGS) is employed. The outcome of the model is the posterior distribution of weights and the aggregated w^{agg} .

The notion of credal ranking is introduced to calibrate the degree to which one attribute is superior to another. The Credal Ordering, which is the foundation of credal ranking, is defined as follows: For a pair of attributes c_i and c_j , the credal ordering O is defined as

$$O = (c_i, c_j, R, d) \tag{11}$$

Where R is the relation between the attributes c_i and c_j , i.e., $<$, $>$, or $=$; $d \in [0, 1]$ represents the confidences of the relation.

The Credal Ranking is predicted on a set of attributes $C = (c_1, c_2, \dots, c_n)$, the credal ranking is a set of credal orderings which includes all pairs (c_i, c_j) , for all $c_i, c_j \in C$.

The Bayesian test based on which we can find the confidence of each credal ordering is predicated on the posterior distribution of w^{agg} . The confidence that c_i being superior to c_j is computed as

$$P(c_i > c_j) = \int I_{(w_i^{agg} > w_j^{agg})} P(w^{agg}) \tag{12}$$

where $P(w^{agg})$ is the posterior distribution of w^{agg} and I is one if the condition in the subscript holds, or zero otherwise. This integration can be approximated by the samples obtained from the MCMC. Having Q samples from the posterior distribution, we can compute the confidence as

$$P(c_i > c_j) = \frac{1}{Q} \sum_{q=1}^Q I(w_i^{agg_q} > w_j^{agg_q}) \tag{13}$$

$$P(c_j > c_i) = \frac{1}{Q} \sum_{q=1}^Q I(w_j^{agg_q} > w_i^{agg_q}) \tag{14}$$

Where w^{agg_q} is the q^{th} sample of w^{agg} from the MCMC samples. It's obvious that $(c_i > c_j) + P(c_j > c_i) = 1$. c_i is more important than c_j if $P(c_i > c_j) > 0.5$. Thus, the traditional ranking of attributes is obtainable by applying a threshold of 0.5 to the credal ranking.

3.3. Questionnaire and respondents

In addition to the questions needed for the BWM, two questions were added to identify possible different user groups. The first extra question involved characteristics of the goods (value, weight, goods category and origin/destination type (factory, warehouse, wholesaler, retail outlet (shop), consumer home)). Secondly, the interviewed persons were asked to answer a question on customer type (e.g. shipper or freight forwarder/logistics service provider) and company size (employee number). These questions allowed us to analyze the preference difference between different groups. The details of the questionnaire are shown in Annex 1.

We conducted the survey from March 29th, 2019 to April 18th, 2019 via face-to-face personal interviews at Chengdu International Railways Service Co., LTD in China. This company is the platform where the frequent CRE customers gather. We asked 200 customers (including shippers and freight forwarders) with the simple random sampling method to fill out the questionnaire. 85 respondents agreed to be interviewed and fill the questionnaire. Of the 85 respondent questionnaires, 22 had to be excluded because of some obvious mistakes such as low consistency of BWM results or some essential information absence. This left 63 useful responses. A response rate of 85/200 for a survey request can be considered good. In most cases, surveys based on interviews do not present response rates or discuss and analyze the responses only. The ultimate share of useful responses based on those initially approached is 63/200 which can still be considered good (Larson and Poist, 2004). We note that the total customer base lies around 3500 (<https://www.cdirs.com/>); Therefore we regard this sample as reasonable (Starnes et al., 2010). We note that this is the largest sample of rail freight clients amongst all the reviewed survey studies (Wiegmanns et al., 2007). Although some other studies have had larger samples of firms in total, only a small fraction of these used the rail freight service (Li, S et al., 2019). The results of the survey are presented and discussed in the following.

4. Results and discussion

In this section, first we describe the results of the study, including the sample demographics. Secondly, we describe the Bayesian BWM results of all DMs along with visualized Credal Ranking from a macro perspective. Finally, we present the results obtained from the linear BWM in a form of cluster analysis from a micro perspective.

Table 2
Sample demographics.

Item	Detail and percentage	
Goods category	Machine part & automobile parts (16%)	
	Cloth & textile (14%)	Food & drink (11%)
	Chemical products (13%)	Cars (9%)
	E-commerce products (13%)	Electronic products (8%)
	Electronics products (11%)	Artware & handiwork (5%)
Origin type	Warehouse (44%)	Retail outlet (22%)
	Factory (33%)	
Destination type	Warehouse (51%)	Retail outlet (14%)
	Factory (25%)	Consumer home (9%)
Customer type	Freight forwarder (59%)	Shipper (41%)

4.1. Sample demographics

The transported goods are specified as the current flows of the respondents. The survey results show that the value/weight ratio (€/kg) ranges from the lowest 4.4 to the highest 283, with the mean value of 61.4 and the standard deviation of 71.7. This very high standard deviation means that the value/weight ratio of goods is quite widely distributed. The other information about goods category, origin type, destination type, and customer type are as shown in Table 2.

As can be seen from Table 2, the goods categorization contains 9 types. It is worth noting that e-commerce products (13%) are a special category as they contain a variety of goods overlapping with the other categories. As it was not possible to control for this in the survey, we consider e-commerce products as a mixed category. The composition of the commodity mix shipped by the sampled companies is largely in line with existing descriptions of the commodity mix of the CRE, with a dominant share of manufactured products, and a small share of chemical products (Wu et al., 2017). As for the origin type and destination type, we can see that most of the goods originate from the warehouse (44%) and factory (33%), and more than half of the goods is destined to the warehouse (51%) compared to only a small percentage of goods destined to consumer homes (9%). Combined with the result that customers type is freight forwarder (59%), and the shipper (41%) are all from manufacturers' logistics departments, we can expect that most of these goods from China to Europe have a business-to-business (B2B) motive. This is meaningful for the rail operators because they can do the precise marketing focusing more on the companies or organizations that have trade or business between China and Europe, especially on the manufacturing goods such as the nine kinds mentioned above. From the 63 valid responses, most respondents consider "Cost" as the most important variable, while only three consider "Reliability" as the most important. Every respondent considers "Sustainability" as the least important. A further analysis is done in the following subsections.

4.2. Bayesian BWM results

By solving the Bayesian BWM model, the aggregated weights of different attributes were obtained as shown in Table 3, and the visualized weighted directed graph is as shown in Fig. 2. The MATLAB implementation of the Bayesian BWM model can be found at <http://bestworstmethod.com/software/>.

According to the aggregated values obtained, it can be seen that "cost" is the most important attribute in the customers' preference, followed by "reliability", which seems slightly more important than in most other studies. "Time" is third followed by "safety" and then "frequency". "Traceability", which is not often considered in previous similar studies but included in this paper, is the sixth, closely followed by "flexibility" and lastly "sustainability".

The aggregated weight above shows that an attribute is more important than another if its weight is higher; it is a deterministic representation. We can also compare all pairs of attributes with each other using the Credal Ranking and visualize its outcome using a weight directed graph as shown in Fig. 2 (the most important is on top, and the least important is at the bottom). The nodes in this figure are the attributes and each edge $A \xrightarrow{d} B$ indicates that the attribute A is more important than B with the confidence d . As mentioned before, the credal ranking visualized in Fig. 2 can be changed into the conventional ranking merely by applying the threshold of 0.5 to the obtained confidences. Further, the degree of certainty about the relation of attributes is evident. For instance, "reliability" is certainly more important than "safety", but it is more desirable than "time" with the confidence of 0.83. "Frequency" is certainly more important than "flexibility", but it is more desirable than "traceability" with the confidence of 0.86. "Time" is not 100 percent certainly more important than "safety" with the confidence of 0.99, and so is the relationship between "traceability" and "flexibility". In general, all d values are larger than 0.8, which represents a high confidence on the ranking of the attributes.

The Bayesian BWM finds the aggregated final weights of attributes for a sample of DMs at once, from a probabilistic angle. But as for the individual level, the original BWM is more suitable, because it can measure the individual's preference from a micro perspective. To explore the characteristics of DMs' preference from a micro perspective, we perform a cluster analysis based on the linear BWM results. We describe this analysis in the next section.

4.3. Cluster analysis

After following the steps in 3.1 to get the linear BWM results, we explore further the heterogeneity of the sample given the weights attached to the eight attributes, performing a two-step cluster analysis (Chiu et al., 2001). This analysis helps us to identify natural classes in the sample of respondents with homogeneous preferences. Two-step cluster analysis has been shown to perform well in the case of quantitative indicators (Bacher et al., 2004). An additional benefit of this method, compared to K-means cluster analysis, is that it provides statistical attributes to select the optimal number of clusters through BIC (Bayes Information Criterion) and AIC (Akaike Information Criterion) values (Rezaei et al., 2018). The software package SPSS version 22 was used to perform the analysis. Table 4 presents the results cluster analysis. The low standard deviation (<0.1) of every attribute under each cluster shows that there is a good clustering effect using this approach.

Table 3
Aggregated weights of the attributes.

Cost	Reliability	Time	Safety	Frequency	Traceability	Flexibility	Sustainability
0.204	0.160	0.151	0.131	0.111	0.103	0.090	0.050

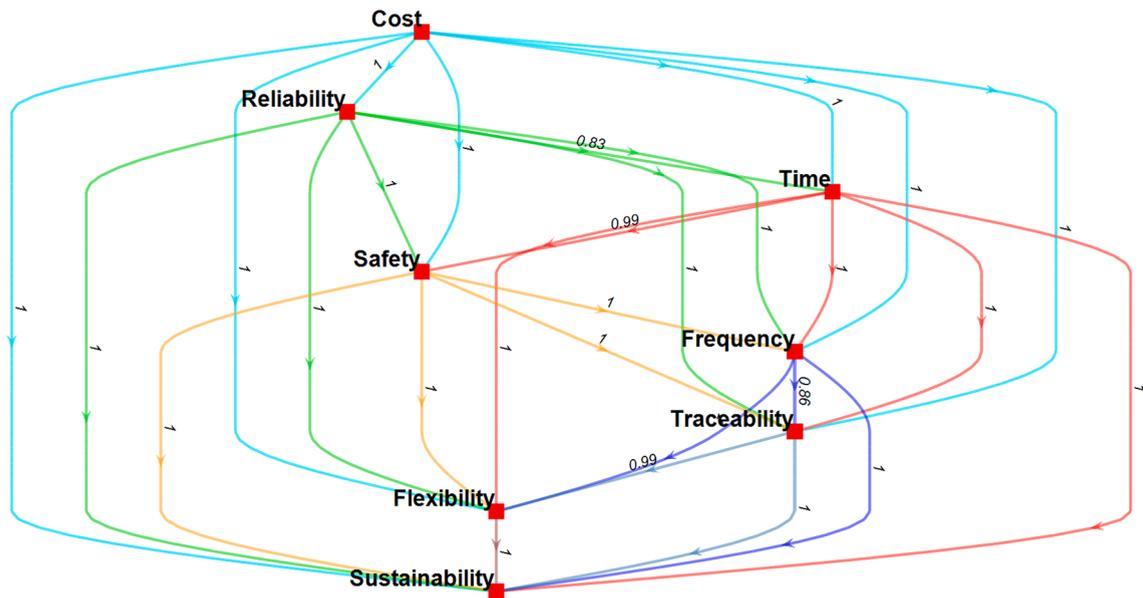


Fig. 2. Visualization of attribute relations using the credal ranking.

It can be interpreted clearly:

Cluster 1, representing the majority (63.5%) of the sample, is more strongly focused on “cost” (mean weight of 0.330) which is obviously higher than other attributes with every other attribute is weighted under the range of 0.18.

In cluster 2, representing 36.5% of the sample, the valuation of “reliability” is similar as the value of “cost”, with comparable means. Customers in Cluster 2 pay more attention to reliability, compared to customers in Cluster 1. We can also see that “safety” (mean weight of 0.168) and “traceability” (mean weight of 0.097) are also obviously more important compared with those in cluster 1.

The histogram as Fig. 3 shows significant differences in “cost” compared to the other attributes.

To assess whether the clusters could be profiled on directly observable characteristics, relationships were explored between cluster membership and several background variables of respondents. For this, the following variables were considered: goods value/weight ratio, goods category, origin/destination type, customer (DM) type. Correlation is hard to find between demand preference and value/weight ratio, goods category, and origin type. But we find that destination type and customer type can be associated with cluster membership. In cluster 1, ‘Destination type’ is the warehouse in 62.5%, compared with 30.4% in cluster 2. In cluster 1, ‘Customer type’ is freight forwarder in 72.5%, compared with 39.1% in cluster 2. Our sample may be small, but we can still infer that the need for “reliability”, “safety”, and “traceability” may be lower when the destination type is “warehouse” everything else remaining constant (ceteris paribus). Also, the freight forwarder may care more about “costs” than the shipper. An interesting topic for new research would be the formation and testing of different hypotheses concerning cluster membership of customers based on other observable characteristics than those recorded here (e.g. business profit benefit from goods). In any case, this classification will already help to predict responses to freight service improvement programs more accurately than when only using the aggregate valuations.

Table 4
Cluster analysis results.

Cluster size	Cluster 1 63.5%		Cluster 2 36.5%	
	Mean	SD	Mean	SD
Cost	0.330	0.041	0.202	0.035
Time	0.150	0.051	0.149	0.041
Reliability	0.180	0.045	0.208	0.068
Frequency	0.083	0.023	0.076	0.033
Safety	0.098	0.017	0.168	0.048
Flexibility	0.060	0.010	0.075	0.082
Traceability	0.069	0.007	0.097	0.041
Sustainability	0.030	0.010	0.025	0.013

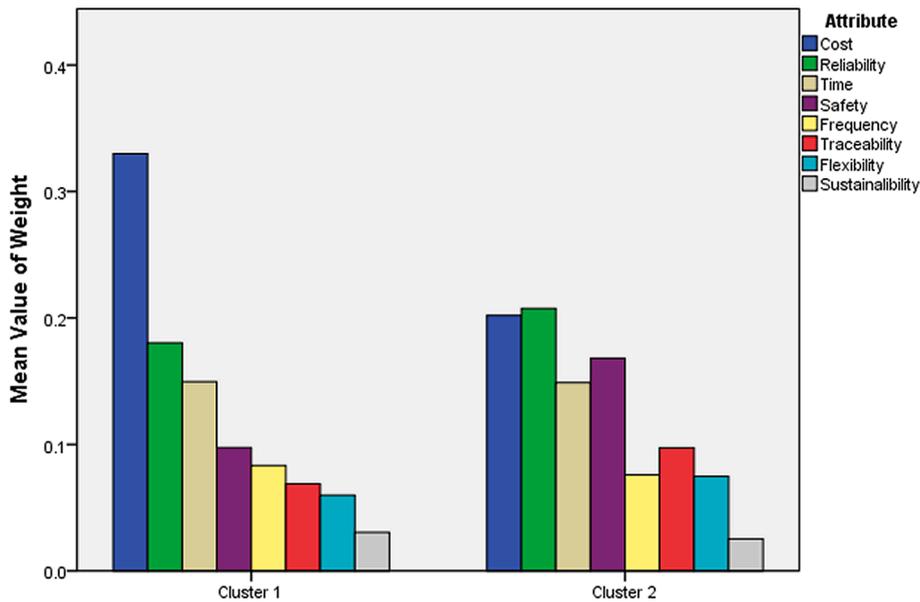


Fig. 3. Comparison of the two clusters.

5. Discussion and policy suggestions

5.1. Macro perspective

As this is the first study that evaluates the preference of international long-distance rail freight services, we cannot directly compare our results with other studies. Nonetheless, we can show how our findings compare to the findings of other relevant freight mode choice studies.

In line with the conclusion drawn from the review of seventy-five freight choice related articles, “cost”, “time”, and “reliability” are the three most important attributes in freight choice decision (Cullinane and Toy, 2000). The three most important attributes based on our analysis of the sample are “cost” (weight: 0.204), “reliability” (weight: 0.160), and “time” (weight: 0.151).

Pham and Yeo (2018) measure 16 experts’ preferences for 14 attributes to find adequate electronic component transport routes from China to Vietnam. The comparable part is that we both study freight choice behavior from China to another country or region, and their attributes cover the same part as ours except “traceability” and “sustainability”. The largest difference between their result and ours is about “reliability”. The customers transporting goods from China to Europe put “reliability” (weight: 0.160) in the second place, but the experts in Pham and Yeo’s research put “reliability” (0.073) at a much less important place. We speculate that one of the reasons for this significant difference might be the different roles of China, Europe, and Vietnam in the global value chains. Many of the electronics goods from China to Vietnam are for manufacturing while most of the goods from China to Europe is for consumption (Malesky and London, 2014).

Duan et al. (2016) measure the importance of five Chinese domestic rail service attributes based on choice-based conjoint analysis, with the outcome not showing the weight but showing the order. The most important attribute is “safety”, followed by “cost”, “reliability”, “time”, and “frequency”. In our research, also these five attributes are the top five, but the position of “safety” is fourth. A possible explanation is that goods are generally better conditioned in container transport and hence are found less important. Tuzkaya and Önüt (2008) found “traceability” as the least important attribute (weight: 0.043) in the study of transportation-mode choice between Turkey and Germany, while in our study it is worth noting that “traceability” weight is 0.103, and is more important than “flexibility” (weight: 0.090) which is often used in freight transport studies. In the short run, this means that a good “traceability” might give CRE an advantage. “Sustainability” is the least important attribute in our study, although CRE is a relatively friendly mode to the environment. Different from Lammgard (2007) and López-Navarro (2014), our findings about “sustainability” are relatively close to the study of Konings and Kreutzberger (2001) who concluded that practitioners rarely worry about “sustainability” aspects of freight performance.

Our results may be useful for the public investment policy along CRE routes. For example, the planned west route of CRE (as mentioned in Fig. 1) crossing the Middle East is the shortest route to Western-Europe among all the existing routes (ydl.china.com.cn). When completed, this route may lead to the lowest transport time. But, the complex geopolitics in some areas of the Middle East (Ehteshami, 2007) may have a negative impact on “safety” and “reliability” for this route and therefore might make this route less attractive. The precise strategy to be implemented here might be an interesting subject for further research. According to our results, these two service attributes are important for customer choice behavior, and their decrease will have a negative impact on customers’ satisfaction with CRE. Thus, it will be advisable for the Chinese government to invest more prudently along this route.

5.2. Market segments

The cluster analysis reveals that “cost” rests mainly on a contrasting prioritization by the two distinct customer groups. Compared with Cluster1, Cluster 2 cares more about freight service quality, especially about “reliability”, “safety”, and “traceability”. This is meaningful for CRE because the operators can design or optimize the freight service based on the differences between these two demand types. The lack of traffic capacity along the routes caused by the rapid development of CRE in recent years has affected the holistic CRE’s freight service quality (Zhao et al., 2018). On the one hand, it is a long-term strategy that the Chinese government can invest in the infrastructure along the route to improve traffic capacity (Wiegman and Janic, 2018). This will fundamentally alleviate the problem of tight transportation capacity. On the other hand, considering that the current CRE’s pricing strategy is relatively simple (Wang et al., 2018), as a short-term strategy, we suggest that freight service quality can be combined with pricing strategy based on different demand preferences. In other words, considering the transport capacity and other limited resources, freight services provided with high reliability, safety, and traceability can be highly charged, and vice versa. According to *Yelkur and Herbig’s research (1997)*, different pricing based on different services will be good for enterprises to gain a competitive advantage (Resor et al., 2004). Also, network design becomes more effective when based on knowledge of heterogeneous preferences (Duan et al., 2019). But what needs attention is that, overall, “cost” remains the most important attribute for choice behavior, and customers may change to other freight transport alternatives if the price of CRE is too high. Thus when setting the price based on the two clusters, the competition from other alternatives such as maritime transport and air transport should be considered. As freight pricing is not the focus of this article, we only give the overall pricing- and other strategies here, and recommend further research to explore such policies.

6. Conclusions and recommendations

In this study, we operationalized and evaluated customers’ preferences for freight service attributes of CRE. Based on a literature review and focus group feedback, we obtained a comprehensive list of attributes. The application of Best-Worst Method (BWM) allowed a reliable measurement of the weights of these attributes.

A survey was held among customers from different areas of China through the CRE operating company, distributed by goods value/weight ratio, goods category, origin and destination type, and decision-maker type. The calculations were based on 63 valid full survey responses. From a macro perspective, the Bayesian BWM along with the Credal Ranking, regarding the overall preference of all DMs, confidently shows that “cost”, “reliability”, and “time” are the top three concerned attributes for CRE customers. This means reducing cost and time, and improving reliability is expected to significantly improve customer satisfaction. Besides that CRE is faster than maritime transport and cheaper than air transport, “reliability” appears to be a good third distinctive attribute for CRE to develop its competitive advantage. It is advisable for the Chinese government to consider reliability more explicitly in its investment policy. “Traceability”, which has seldom been considered in the previous demand related scientific research, is identified as an important new additional attribute in our research. Also improving “traceability” will give CRE another distinctive competitive advantage. From a micro perspective, a secondary cluster analysis based on BWM clearly shows 2 clusters of freight demand. In addition, we found that the clusters have different weight sets, focusing more on “cost” and, respectively, on service quality, related to “reliability”, “safety”, and “traceability”. This gives us a reference on how to optimize the use of CRE’s freight transport capacity and other limited resources by setting different pricing strategies based on different demand profiles of “costs” and service quality combinations. The details of these strategies are outside the scope of this research but are certainly interesting for future research. Under the premise of the competition from maritime transport and air, CRE services with higher quality can be higher charged than at present, and vice versa. The differences between attributes are more pronounced and even structured differently than the aggregated weights. This strongly suggests that price designs targeting the underlying clusters of customers may be more effective than designs targeting the aggregate. Besides CRE, the cluster analysis results can also inspire other freight transport systems. For example, most of China’s domestic rail freight transport is using a simple pricing mechanism without considering the demand heterogeneity. Identifying homogeneous customer segments and optimizing the use of transport resources with a differentiated pricing strategy, will help to improve the yield management. What’s more, our results could be useful for a larger audience although the profiles of costumers may be case-specific. We demonstrate the usefulness of the method to identify preference clusters, this is useful for other cases than CRE. Future research could compare these clusters with other cases.

Although yield management has been applied in several sectors (e.g. aviation, passenger trains) which usually goes much further than identifying two clusters as is done here, the seemingly less complex results in this article are very valuable because it begins to fill the research gap in yield management of rail freight transport and is an important starting point for further detailed research into rail freight yield management, hopefully based on price data. And also, this is the first paper that systematically researches the demand preferences of a very long distance, intercontinental rail service, the CRE, part of the Eurasian Belt and Road Initiative. Nevertheless, after comparing with some other studies about rail freight transport, we find that besides the intercontinental and long-distance nature of the CRE service; the most important factors for customers are somewhat similar for those freight transport systems that do not meet CRE characteristics. However, reliability is valued more important in our study (time is less important) and also traceability is identified as a new characteristic. In addition, the new method (BWM) that we introduced in this paper, requires much less intensive surveying than discrete choice studies and therefore is easier to repeat. This makes it amenable for frequent updates, with the changing market conditions in China and the fast development of the BRI (Belt and Road Initiative). Our findings are relevant for all stakeholders of CRE who have an interest in the customer-centric design of CRE freight services. These include government, shippers, freight forwarders, CRE designers and operators. The results can be used to aid decisions in the (re-) design of CRE freight service systems, with an aim to improve service quality and increase clientele.

We recommend future studies gathering more data from not only more regions in China but also more countries along the CRE route in order to make the findings more generalizable. In doing so, it is suggested to use proportional sampling considering the volume of freight traffic of those regions or countries. We also suggest the researchers design the survey by considering randomize the order of the columns and vary the example as well to see whether there will be any difference with our research results. Or, compare with our results by using a different method. In addition, the sample could be extended to include non-users of the CRE, to anticipate on the effects of competition with maritime (and possibly, air freight) services. Now we have been primarily interested in the existing user base of the rail services of the CRE and have therefore opted for a within-mode MCDA approach, in line with the many within-mode valuation studies that use choice models. As the valuations lie within the range of other rail values reported in the literature, we conclude that the net effect of the competition on valuation, if present at all, so far has been minor. In the future, however, these values might change with intensifying competition. A mode-abstract MCDA or a between-mode choice study could complement our research by focusing on the client base that may be regarded as footloose or prone to shift.

Acknowledgements

The research was performed at the Delft University of Technology and financially supported by the National Natural Science Foundation of China (No. 61803147) as well as the State Scholarship Fund from the China Scholarship Council (No. 201807000090).

Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.tra.2020.10.019>.

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