Performance Measurement of Road Freight Transportation: A Case of Trucking Industry

Abstract:

The aim of this study is to measure the current state of the trucking business and its performance in existing literature and transportation management system. The research question is to what extent the performance measurement systems contribute in preference-based strategic decision-making in trucking industry and draws a path to their desired levels of success. This study integrates Balance Score Card (BSC) with Imprecise data envelopment analysis (IDEA). A systematic review of academic literature, trade journal, and the magazine has been conducted to develop the key performance measures based on four perspectives of the Balance Score Card (BSC): financial; customer; internal processes; learning, and growth. This study explored the different inputs and outputs to measure the performance and subsequently, data have been collected from the eighteen transporters, and the preference degree approach is used for comparison and ranking of the efficiency intervals of the transporters. The results show that the financial perspective requires special attention, which indicates that the operational cost due to the competitive market and underutilization of fleets contributes to the lower financial performance of the transporters. Furthermore, the study also reveals that there is considerable scope in customer service improvement. These findings will help practitioners to analyze their business from different perspectives and give suggestions for taking timely corrective action when necessary.

Keywords: *Trucking industry, Imprecise data, Balanced scorecard, Interval efficiency, Performance measurement.*

1. Introduction

Transportation of goods by road has grown exponentially over the years as compared to other modes of freight transport. In road freight transportation, trucks play an essential role due to their flexibility and ability to distribute goods to both urban and geographically remote locations (Pathak *et al*., 2021). Despite the huge dynamic demand and competitive market for road freight movement, achieving high performance has become a significant concern for truck operators (Parming, 2013; Zolfagharinia and Haughton, 2017). Operators seek to manage their performance, which is affected by several external factors such as globalization, fuel price fluctuation (Shams *et al*., 2017), increasing safety and social regulations (Rodrigues *et al.,* 2015), technological influence (Thornton *et al*., 2009; Shaik and Abdul-Kader, 2013), and consumer expectation (Raghuram, 2015). Transport companies need to evaluate their business performance and ensure that they fulfill their intended function in the growing competitive scenario (Chen *et al.,* 2019). Performance measurement helps practitioners in making decisions to establish new strategies; it also assists in the execution of new plans (Kumar and Anbanandam 2020). However, the previous studies related to performance evaluation of the trucking industry are often focused on a specific environment, such as financial performance (Francia *et al*., 2011), operational performance, and related important metrics as reliability, on-time delivery, and agility to customers' requirements (Saldanha *et al*., 2013), safety performance (Scott and Nyaga, 2019), and environmental performance (Thornton *et al*., 2009)

. Further, to achieve the optimum results and improve their overall performance, the practitioners in the trucking industry are suggested to consider all perspectives, namely, the economy, customers' perspective, business growth, and learning perspective (Webmaster, 2017). In addition, de Campos *et al.* (2019) pointed out that to compete and sustain in today's competitive market, the modern trucking business must focus on analyzing its performance considering different perspectives collectively. Therefore, to improve and manage performance, the practitioners must measure the current level of performance and identify the areas for improvement and management, which presents the motivation for this current study. For example, the National Association of Small Trucking Companies (NASTC), USA, reported that among the newly formed Indian trucking companies, only 15% are able to survive in their second year of operation. This statistic clearly shows the condition of the trucking business in India and motivates to analyze the importance of evaluating the performance to sustain in the competitive market.

Several methods are available in the extant literature that aims to assess the activities conducted by business organizations in their performance evaluation. Some of the ways are Balanced Scorecard (BSC), Data Envelopment Analysis (DEA), Ratio Analysis, and Multi-Criteria Decision Making (MCDM). Among these techniques, BSC is extensively used to align business activities with organizational strategies by strategic planning and management (Varmazyar *et al*., 2016). BSC system is a popular performance management technique that integrates key measurement indices regarding organizational goals and categorizes them into four perspectives, namely, financial, customer, internal business process, and learning and growth (Kaplan and Norton, 2001). In this study, the BSC has been adopted, which is able to take different aspects of trucking industry activities into consideration, with the objective of comparing the performance of the different transporters. Based on the existing literature and application of BSC, it is highlighted that the basic mechanism of the BSC model relies on the assumption that four perspectives of the model are connected by cause-effect relations, forming a system (Zahoor and Sahaf, 2018; Bento et al., 2013). A learning, growth, and innovation lie at the bottom of the system and affect the internal process perspective (service quality and processing timing). Further internal business process (ETO and waiting time) perspective, in turn, affects the customer perspective (customers satisfaction and reputation) and which further in turn, leads to the financial perspective, which is positioned at the top of the chain (Basso et al., 2018).

On the other hand, DEA is a mathematical approach for identifying and analyzing the best practice of peer decision-making units (DMUs) (Charnes *et al.*, 1978; Sarkis, 2016) used by works undertaken by Rashidi and Cullinane (2019); Chen *et al.,* (2019) and Xiong *et al*. (2019). Izadikhah and Saen (2019) proposed a context-dependent DEA approach considering economic, social, and environmental perspectives for a sustainable supplier selection process. Further, Sarraf and Nejad (2020) have emphasized that the development of integrated BSC-DEA can provide more insights and accuracy to assess the performance of an organization.

Despite the advantages of the integrated BSC-DEA model, only a few authors have explored their integration and therefore, in this paper, an integrated approach has been adopted for performance measurement of the trucking industry. Furthermore, the use of the BSC technique to consider imprecise data for enhanced performance assessment is absent in the literature, and this approach can complement each other to overcome their limitations (Amado *et al*., 2012; Tan *et al*., 2017; Basso *et al*., 2018; Dolasinski *et al*., 2019). The integrated BSC-DEA model helps managers in the decision-making process by providing a conceptual framework for the performance, as well as an efficiency evaluation of their operational process (Kádárová *et al*., 2015). These approaches assume that the data are precise, but due to the existence of uncertainty and the fragmented nature of the trucking industry (Francia *et al*., 2011), this assumption is not valid. To the best of our knowledge, this is the first study of its kind where integration of BSC and Imprecise Data Envelopment Analysis (IDEA) regarding exact, ordinal, interval, and fuzzy data for performance measurement of the trucking industry is considered to capture the most realistic scenario, thereby, contributes to the performance measurement literature of the trucking industry. Finally, the efficiency intervals are compared and ranked using preference degree approach is used for comparison and ranking of the efficiency intervals of the transporters and,. Hence, this study pursues the following research objectives to characterize issues related to performance measurement and management of Indian micro-truck owners:

RQ1: How many performance measures help with preference-based strategy adoption for micro-truck owners?

RQ2: What measures should be considered to analyze the performance of micro-truck owners?

1.1 Background of the study

The role of growing industrialization plays a key role in the growing Indian economy, in which one of the main consequences is growing road freight movement through trucks (Prasanta et al., 2022). As, the Indian road network is the second largest (33 lakh km) in the world and stretches to about 96,000 kms (1.7% of the road network) of national highways, which constitute around 40 % of the total road (MORTH, outcome budget 2013-14). Road freight transport is the backbone of India's supply chain network, in which the trucking industry transports around 70% of India's total freight (Kumar Gangadhari and Kumar Tarei, 2021). This compares with 75% in Europe (Eurostat, 2020) and 63% in the USA (Bureau of Transportation Statistics, 2020). Further, a recent report by Mordor intelligence (2021) highlighted that the "India Road Freight Transport Market stood at 139.02 billion USD in 2022 and is projected to register a CAGR of 6.53% to reach 203.21 billion USD in 2028". Despite of these facts and the importance of the trucking industry in road freight transportation, the industry is still working very inefficiently (Prasanta et al., 2022).

One of the main reasons behind this is the fragmented nature of the Indian trucking industry because it is largely owned by the private sector and is dominated by small truck owners. Around 90% of this belongs to micro truck owners, having less than twenty trucks, making it totally fragmented and unorganized. This leads to operating cost, which might be one of the main reasons in its inefficient functioning (Parikh and Khedkar, 2013). Hence, the aim of this study is to suggest an appropriate way to measure the performance of the Indian trucking industry.

The aspects related to performance and consequences impair the efficiency of the trucking industry, such as inefficiency in operating costs (Deloitte, 2022; De Oliveira et al., 2019), fleet management (Parihar et al., 2021), and training to promote business actions (Kumar Gangadhari and Kumar Tarei, 2021), and absence systematic technological advancement for better customer service (Kant et al., 2022a). As such, operators focus on retaining the quality and performance under their jurisdiction at required operational levels (Karlaftis, and Kepaptsoglou, 2012). It has been critically observed that consideration of the financial side alone neglects to take into account other very important resources that are vital for performance improvement of the trucking business, such as the skills of the staff, customer satisfaction, equipment utilization, and the culture of innovation etc. (Webmaster, 2017).

Deploying an effective way of performance measurement in the Indian trucking industry has been on the rise over the last few years. As the Indian government focuses on Make in India, National Logistics Policy (NLP) considers the expected benefits on cost optimization and environmental concerns over the traditional way of managing performance (Raja Simhan, 2022; Conde and Twinn, 2019). This research has considered the Indian trucking industry; according to the findings and statistics, the majority of trucking business is owned by micro truck owners. Nevertheless, an improper data management system is mentioned in the literature and can thus be considered to have an impact on performance, which may need to be reviewed further. The integrated approach BSC-DEA allows transporters to consider the most relevant and contextual data they need to measure and manage the performance of their business (Izadikhah et al., 2017). Eventually, the purpose of this study is to enable reciprocity learning processes through self-analysis and systematic intervention by providing a foundation to find which perspectives the problem areas lie.

Hence, the finding of the study will not only help the Indian transporters to identify the relevant performance measures and efficiency but also helps in reciprocal learning considering their customer's perspective, business growth, and learning perspective (Webmaster, 2017). Also, it is observed that struggling with any one of these perspectives can affect a company's ability to fulfill the needs of another. This study supports the transport companies to perform their best with higher organizational efficiency.

The remainder of the paper is organized as follows: a literature review is presented in Section 2; Section 3 presents the model development; in Section 4, results, discussion, and managerial implications are discussed; in Section 5, the conclusion and future scope of the study are presented.

2. Literature review

Performance measurement is the initial step for managing the performance of any organization (Lebas, 1995; Stefaniec *et al*., 2020). Bititci *et al*. (1997) stated that performance measurement is an information system that allows management practices to function effectively. Therefore, in the modern and competitive market scenario, performance measurement must be the first step to managing the performance of the transport business, which links the operational, strategic, and tactical levels in the decision-making process (Frederico and Cavenaghi, 2008). The exponential growth in goods movement via roads shows that the road freight transport sector performs at its best to achieve the overall success of supply chain management (Mačiulis *et al*. 2009; Shaik and Abdul-Kader, 2013).

Conventional techniques to measure performance generally fail to account for uncertainty and ambiguity of the information, which may result from deviation in the efficiency of the DMUs of an organization (Kao, 2006). However, the recent approach to integrating BSC-DEA helps in performance measures by considering the vision and mission of the organization, which includes both outcome measures and the drivers of the measures. Nowadays, road freight transporters' concern is not only from the financial perspective but also from the customer's perspective, innovative learning and business growth perspective (Agbo and Zhang, 2017). Consequently, information accuracy is vital in the performance measurement of transporters to sustain their position in the market (Budak and Sarvari, 2021).

According to Emrouznejad and Yang (2017), the application of DEA has been ranked the fourth most popular technique in performance measurement of transportation systems in the last three years. Their study also reveals that in recent years, the use of DEA in the transportation sector has become more popular. DEA is one of the popular non-parametric approaches to assessing the performance of DMUs. This approach is proposed by Charnes *et al*. (1978) to estimate the DMU's efficiency by considering multiple inputs and multiple outputs. There are a few studies of the application of DEA in road freight transportation (Cruijssen *et al*., 2010; Álvarez and Blázquez, 2014; Ji *et al*., 2016; Liu *et al*., 2017; Wu *et al*., 2018; Pachar *et al*., 2021). However, due to uncertainty and complexity in the operational process of the industry, the accuracy of the data has become one of the main concerns for performance management. To improve accuracy in efficient calculation regarding such situations, we have considered imprecision and uncertainty in data availability.

Cooper *et al.* (1999) noted the way to deal with situations where information is known only within a prescribed format. To deal with such situations, Zhu (2003) presented the Chames, Cooper and Rhodes (CCR) model by considering unknown decision variables in the form of imprecise data. The authors demonstrated that their approach can be implemented for existing DEA methods for performance analysis by considering further efficiency information such as return to scale classifications, pathways to improve efficiency etc. Kao (2006) suggested that in a real situation, the performance measurement considering imprecise data provides better and more detailed information for efficiency calculation. Shokouhi *et al.* (2010) proposed a robust IDEA optimization approach regarding ambiguous, uncertain and imprecise data in the performance measurement using DEA. Azizi *et al.* (2015) emphasized IDEA as a more realistic approach concerning uncertainty and complexity in real-world decision making. Padhi and Mohapatra (2009) proposed a fuzzy multi-attribute scoring approach to measure the performance of the contractors, which enables consideration of the uncertainty and ambiguity in the performance measurement. Izadikhah *et al.* (2017) proposed an Enhanced Russell model determining the interval data from the imprecise data when only fuzzy data and ordinal data are present. According to Wei and Wang (2017), IDEA provides a more robust and comprehensive picture of the relative efficiency of DMUs when precise data information is unavailable. In Table 1, we have presented a comparison of earlier conducted studies with the proposed work and, accordingly, set the study to bridge the gap in the literature. It shows that our proposed approach is more complete than other published BSC-DEA models. In line with the recommendations proposed by other authors, we have developed an integrated BSC-DEA model for the trucking industry, considering various types of data input.

Table 1: Comparison of the proposed approach with other studies

	Features		Data Type			
Authors	Multiple inputs and outputs	Implemented Area	Interval data	Ordinal Data	Fuzzy data	Exact data
Hsu (2005)	√	R & D project performance			√	
Eilat *et al.* (2008)	√	R & D project evaluation		√		√
Chiang and Lin (2009)	√	Commercial bank industries				√
Asosheh *et al.* (2010)	√	Information technology project	√	√		√
Amado *et al.* (2012)	√	Vertical transportation				√

Shafiee *et al*., (2014)	√	Food industry		√		
Haghighi *et al*. (2016)	√	Plastic recycling companies		√		√
Basso *et al*. (2018)	√	Museum				√
Raval *et al*. (2020)	√	Manufacturing organizations				√
Proposed Study	√	**Trucking Industry**	√	√	√	√

As observed from the review of literature, there is extensive literature on the integrated BSC-DEA approach. Nevertheless, to our knowledge, this is the first study that offers an integrated application of BSC and DEA regarding imprecise data for performance measurement of the trucking industry. This study, therefore, contributes to the literature in this area.

3. Development of BSC-IDEA model

The presence of uncertainty and complexity in the operation of the trucking industry makes it difficult to measure its performance. The performance evaluation must consider different levels of decision-making (strategic, tactical and operational) and, simultaneously, types of data used for the evaluation process. For the convenience of the reader and understanding of the conversion of data type, the preliminary definition, including the methodological property for conversion of data type and preference degree approach, has been discussed in **Appendix I**.

As the efficiency score of each DMU is determined as an interval, we need a practical, approach in order to rank and comparae the intervals.There are studies (Ishibuchi and Tanaka, 1990; Salo and Hämäläinen, 1995; Sengupta and Pal, 2000; Song et al., 2012) discussed a number of approaches proposed in order to rank the interval numbers, however these approaches fails when intervals have identical center but different width (Azizi *et al*., 2015). In order to overcome this limitation we have adopted peference-based approach developed by (Izadikhah et al., 2017; Azizi et al., 2015; Wang et al. 2005a,b).

As per the initial interaction and discussion with experts from the trucking industry, it is found that to improve efficiency, and it is necessary to focus on different areas of performance measures (financial, customer, internal business process, and learning and growth). Based on the outcome of the discussion, an integrated BSC-DEA model has been developed for performance measurement of the trucking industry. Presently, the trucking industry is categorized into three types, first large truck operators with more than 100 trucks. Second is medium truck operators with more than ten trucks and the third type is that of micro-truck operators with less than ten trucks (Chen *et al*., 2020).

This study proposed a mixed research framework to provide a better and complete understanding of the research questions. Pure qualitative or quantitative research may not be able to provide a better understanding of performance and strategic decision making for Indian micro-truck companies (transporters). Also, the implementation of the right strategy would help transporters in the long-term growth of their business. BSC has been proven as one of the most effective tools for assessing the performance and strategic development of an organization. However, in practice, the improper database management system of Indian micro-truck owners makes it more challenging in the performance evaluation of the transporters. Therefore, to measure the performance of the transporters, the availability and accuracy of the data cannot be ignored. Therefore, this study aims to consider the data from the transporters based on the availability and nature of the data type. This study collected imprecise data and aimed to calculate the efficiency of different transporters using the DEA approach.

Hence, integrating the BSC and DEA approaches may strengthen the weakness of each other as BSC helps in the selection of relevant criteria and choice of input and output data for DEA. Furthermore, BSC enables the cause-and-effect relationship between the input and outputs considering the four perspectives, which are useful for implementing DEA to measure the efficiency of transports. Therefore, this study integrated the BSC and DEA to measure the performance of Indian micro-truck companies.

To develop the model, data were collected from micro-truck owners of India since 90% of the industry is represented by these small-truck owners (truck owners with less than 20 trucks are called micro-truck owners) and belong to the unorganized sector without having a scientific data management system (Raghuram, 2015). Irrespective of poor database management, the manager can measure and identify the main reasons for the inefficiency of their organization and areas for improvement by conducting brainstorming sessions. An integrated approach that combined BSC with IDEA regarding imprecise data has been developed for performance evaluation of the trucking industry. This is the pioneer study to relate the inefficiency of the Indian micro-truck owners and suggest the area for improvement in the performance.

Turning to an example from the trucking industry, we specifically refer to the Indian micro-truck owners to show how the information and type of data (ordinal, interval, fuzzy as well as exact data) can be used to measure the performance of their business. The case of the Indian trucking industry is presented to validate and draw insights from the proposed approach. The development of the proposed BSC and DEA model is discussed in two phases as follows:

3.1. *Phase 1:* Development of BSC for the trucking industry

To improve and manage the performance of the trucking industry, the essential criteria of identification and measurement of performance have become very important to practitioners. The practitioners may have different managerial approaches to performance measurement, selection and control as this is an integral part of their business strategy. For example, Tubis and Werbińska-Wojciechowska (2017) and Frederico and Cavenaghi (2008) proposed a performance management model for the road freight transport sector using BSC. According to Staš *et al*. (2015), while developing the BSC for the transport industry, various perspectives needed to be taken into account to capture all aspects of the business. The importance of the proposed method is that it is a top-down approach that begins with the vision, mission and strategy of the business and then translates into actions. To understand this, several meetings were conducted during the period with truck owners and other senior managers of the industry.

A semi-structured questionnaire was used to capture the perceptions of micro-truck owners because they were key informants with the necessary knowledge of and experience in the Indian trucking industry and captured 90% of the industry. All the performance measurement criteria were included in the questionnaire to assess their opinion regarding different scales for each data type and discussed in the subsequent section. As the first step in this under-explored research area, the micro-truck owners were selected as the target of the study. Before starting the field survey, we collected the key performance measures from the research article, trade journal, and magazine. This helps to present our questionnaire in documented form for a better understanding of relevant terminology and the overall objective of the research. Hence, we solicited only one response from each expert; the questionnaire was prepared after discussions with transporters and subsequently, questions were presented to the different transporters from the eastern parts of the state of India through personal meetings and discussions.

In this phase, we conducted a semi-structured survey with the truck owners based on the BSC framework. The survey in this stage is limited to performance measures considering the four perspectives of BSC to identify the performance measures of the Indian micro-truck companies. The process of compiling the questionnaire and collection of the data was conducted from January 2020 to May 2020, and the specific information and data were collected during those five months. To identify the performance measures, 28 micro transporters with and experience of more than 5 years in the field were considered for the first stage. Based on the discussions and information collected**,** the strategy map and the BSC for the trucking industry are developed and presented in Fig. 1.

3.2. Phase 2: Development of slack based measures (SBM) DEA model

CRS (CCR) model characteristic has some intriguing ramifications in terms of the features of the final DEA model. In fact, Lovell and Pastor (1999) demonstrated that a CRS model with a single constant input/output corresponds to a VRS (BCC) model with the same variables. In addition, Lovell et al. (1995) demonstrated that VRS is applicable if and only if the service slacks excluded from the radial efficiency measure, are modest and not systematic. In our study, incorporating slacks into the performance evaluation (SBM) is related to the extended additive DEA model proposed by Charnes et al. (1987), which is more aprropriate. As a result, this study has utilized the CRS model.

As is often the case, conventional DEA models (e.g., CRS models) contain multiple valid DMUs (with an efficiency value of 1) simultaneously. Hence, it is impossible to compare directly the efficacy of these legitimate DMUs, which must be further ranked. Managers can use the combined DEA-BSC model to analyze the competitive position of transporters by identifying each transporter's efficiency, benchmarking partners, and inefficient slacks. Each transporter should be aware of its relative position in terms of efficiency. The findings of this study are meant to give firms the competitive data and learning partners necessary for formulating their long-term goals and objectives (Wu et al., 2014).

Du et a., (2010) commented on the super-efficiency SBM model to rank the efficiency ratings of DMUs further. The relaxation variables are added directly to the objective function in the SBM model, in contrast to the conventional CRS and VRS models. Note that, as stated by Seiford and Zhu (1999), super-efficiency DEA models based on radial DEA models can be infeasible in non-CRS situations. Xue and Harker (2002) proved that SBM super-efficiency model seems to cause the inability to obtain full rank for all DMUs under the alternate return to scale model other than CRS.

Our choice of a CRS assumption is further reinforced by Fancello et al., (2014), who evaluated the performance of CRS and VRS using the DEA approach and compared the two. They found that the CRS approach is more suitable for analyzing the performance of road transportation and produces more realistic findings than the VRS method. The greatest benefit of applying the CCR model is that it permits authorities to consider multiple views, depending on the objectives (input- or output-oriented), while still achieving the same results.

Banker et al. (2004) introduced a BSC-DEA model that evaluates the performance of local transporters. Four BSC perspectives were regarded as the output variables of a BCC-DEA model, which is identical to a CRS model with a constant input. Utilizing the DEA-BSC model, an output-oriented constant returns to scale orientation was selected because it assesses relative efficiency and gives information in the form of slacks that enables inefficient DMUs to benchmark efficient ones (Dolasinski et al., 2019; Basso et al., 2018). The results of a non-radial slack-based measure of efficiency were independent of the units of measurement and the conversion of original data (Rezaee et al., 2021; Tone, 2001). Transporter efficiency was determined using a CRS model. Transporter efficiency equal to 1 indicates that the DMU has attained the best efficiency relative to other DMUs, whereas production efficiency below 1 indicates that the DMU is inefficient compared to other DMUs (Wu et al., 2014).

Based on the discussions and meetings, it is observed that the identification of strategic objectives and critical success factors are exhaustive from each perspective of their business. However, during the DEA modeling, measures were chosen subject to reliable data available from the transporters. The data for inputs and outputs were identified from the BSC model which are the source for measuring their relative efficiencies (Dolasinski *et al.*, 2019; Basso *et al.*, 2018). When using DEA, the group transporters (DMUs) is considered and investigated in this study included. Descriptions of Inputs and outputs for the study were presented in Table 4. Then based on the selected inputs and outputs, we prepared another questionnaire (Basso *et al.*, 2018; Wu *et al.,* 2014).

However, during the DEA modelling, measures were chosen subject to reliable data availability from the transporters. It should be noted that during the meeting with different transporters, there were ambiguity, uncertainty, and hesitancy on the part of the responders in revealing the required data, also many cases, data were of different types. Therefore, the responders were asked to provide the data in a different format, such as ordinal, interval, exact, or fuzzy with respect to our predefined criteria (Azizi, and Jahed 2021; Izadikhah et al. 2017; Azizi et al., 2015). The personnel interview survey was administered for 25 Indian micro-truck companies, experienced with more than 10 years. Seven experts expressed less interest; hence their responses have been omitted. Therefore, we considered 18 transporters for efficiency calculation.

Integration of BSC and DEA begins with the development of the BSC, which includes all the measures in respect of the different perspectives of BSC. This step is followed by identifying the inputs and outputs for the DEA approach to calculate the efficiency of the transporters. The data were collected using the linguistic scale related to ordinal data and triangular fuzzy numbers, as presented in Table 2 and Table 3.

Table 2: Rating related to ordinal data

Rating		Linguistic variable
1	Extremely infrequent deployment of safety standards	Strongly disagree (Str D)
2	Very infrequent deployment of safety standards	Disagree (D)
3	Infrequent deployment of safety standards	Slightly disagree (SD)
4	Low deployment of safety standards	Can't say (CS)
5	Frequent deployment of safety standards	Slightly agree (SA)
6	High frequent deployment of safety standards	Agree(A)
7	Extremely frequent deployment of safety standards	Strongly agree (Str A)

Table 3: Linguistic variables and their associated triangular fuzzy numbers

Linguistic variable	Fuzzy number	Associated intervals using weighting function f (α, α) = $4\alpha^3$
Very low (VL)	(0, 0.1, 0.2)	[0.08, 0.12]
Low (L)	(0.1, 0.2, 0.3)	[0.18, 0.22]
Medium Low (ML)	(0.2, 0.3, 0.4)	[0.28, 0.32]
Medium (M)	(0.4, 0.5, 0.6)	[0.48, 0.52]
Medium High (MH)	(0.6, 0.7, 0.8)	[0.66, 0.72]
High (H)	(0.7, 0.8, 0.9)	[0.78, 0.82]
Very High (VH)	(0.8, 0.9, 1.0)	[0.88, 0.92]

Thus, the performance assessment model has been developed for the types of data that were available. Each transporter provided input data in two different formats to produce one output for each perspective of BSC. For example, from the financial perspective, the two inputs of data provided by the transporter are in crisp and interval format, respectively, and the output is fuzzy for the financial perspective, as presented in Table 4, and the dataset is shown in Table 5.

Here, we assume that inputs and outputs are presented in imprecise data type, elicited from the experts using different scales and personnel interviews and discussions. Amado *et al.* (2012) suggested that, while integrating BSC- DEA, there is a greater potential in terms of radial input and output slacks to achieve more accurate results. To deal with such a situation, a slack-based DEA model is applied to obtain interval efficiency for each transporter. Recently, Izadikhah and Saen (2018) proposed a two-stage DEA model to calculate upper and lower efficiency using linear models to assess the sustainability of the supply chain. One benefit of this approach is that efficiency scores can be appropriately defined for weakly efficient DMUs; thus, SBM is suitable in many cases (Kao, 2018; Pournader *et al.*, 2019).

The following SBM model is used to calculate the lower and upper efficiency of DMUs.

In interval DEA, input values $x_{ij}$and output values y_{rj} that they lie within the upper and lower bounds of the intervals [x_{ij}^L, x_{ij}^U] and $\left[y_{rj}^L, y_{rj}^U\right]$ and assume that there are *n* DMUs to be evaluated, each consisting of *m* inputs and *s* outputs. X_{ij}^U (*i*=1, 2…., *m*) and Y_{rj}^L (*r* =1, 2..., *s*) denote the input and output values of *j* DMU (*j* =1, 2..., *n*), all of which are known and non-negative. S_i^-(*i* =1, 2..., *m*) and S_r^+ (*r* =1, 2..., *s*) are called slacks. Also, λ_j is the intensity value of DMU*j*.

Table 4: Factors used in assessing the performance of transporters

Factors	Notation	Measurement	Definitions	Unit	Data type	Perspective
Inputs	X1	Reduce operating cost (ROC)	Actual operating expenses/Target operating expenses	%	Crisp (Exact)	F
	X2	Fleet Utilization	This is a KPI to measure how active the fleets have been, i.e., how actively they have been utilized	%	Interval	F
	X3	Call center customer satisfaction (CCS)	This indicates the customer satisfaction rate from the management by providing helpline support (call center). This measure helps to improve customer satisfaction.	%	Ordinal	C
	X4	Corporate image (CIM)	This measure signifies the present perceived image to the anticipated image to be set up for the successful execution of all activities associated with the objective. CIM is associated with the objective – improve the CIM	Number of customers	Interval	C
	X5	Employee turnover (ETO)	This indicates that the number of resigned employees for any reason during the year,	Number of employees	Interval	BP
	X6	Waiting time of trucks in transshipment (h)	Idle time loading and unloading	%	Ordinal	BP
	X7	Personnel training (PTR)	This measures the average training hour per employee in a year. The duration of training hours connects PTR and their corporate culture activities. It is measured in hours.	Hours or months	Exact	L & G
	X8	Expenditure on the development of systems supporting the company's management	The number of purchased software licenses. Number of implemented IT innovations in passenger service	INR	Ordinal	L & G
Outputs	Y1	Return on investment (ROI) (%)	This is a question that can be asked and answered every time you spend money on your business	%	Fuzzy	F
	Y2	Overall customer satisfaction (OCS)	Overall corporate customer satisfaction is related to improving customer satisfaction. It is the ratio of the total customers' complaints to the number of services provided.	%	Fuzzy	C

Y3	Safety and health standards	About working culture, social life, and working hour rule	Ordinal	L & G
Y4	Freight claim	Analysis of the number of claims filed, claims resolved and resolution time will enable you to monitor and improve customer service to build customer loyalty and command the best price for your service.	Ordinal	BP

Table 5: Data set

	Financial Perspective			**Customer Perspective**			**Learning and Growth perspective**			**Internal business process perspective**		
	Input		Output	Input		Output	Input		Output	Input		Output
	X1	X2	Y1	X3	X4	Y2	X5	X6	Y3	X7	X8	Y4
T1	6200.000	(0.4, 0.5)	M	SA	(0.666, 0.800)	H	(0.181, 0.4)	StrA	SD	5000	StrA	D
T2	7233.333	(0.4, 0.5)	H	A	(0.200, 0.500)	VH	(0.588, 0.750)	StrA	SA	10000	A	D
T3	8266.667	(0.666, 0.733)	H	A	(0.300, 0.500)	M	(0.461, 0.666)	StrA	A	60000	StrA	D
T4	10333.333	(0.733, 0.833)	H	A	(0.333, 0.666)	M	(0.476, 0.6)	A	SA	120000	SA	SA
T5	4650.000	(0.600, 0.733)	H	SA	(0.666, 0.800)	H	(0.600, 0.666)	StrA	A	60000	A	CS
T6	7233.333	(0.600, 0.733)	L	SA	(0.500, 0.800)	ML	(0.476, 0.600)	StrA	SA	120000	CS	D
T7	10333.333	(0.666, 0.733)	VH	A	(0.466, 0.666)	M	(0.295, 0.666)	A	SD	120000	SA	D
T8	4650.000	(0.733, 0.833)	M	SA	(0.266, 0.533)	ML	(0.461, 0.500)	A	CS	30000	A	SA
T9	9816.667	(0.733, 0.833)	H	1	(0.200, 0.500)	ML	(0.400, 0.666)	CS	CS	120000	A	D
T10	8886.667	(0.4, 0.5)	M	SA	(0.333, 0.583)	H	(0.666, 1)	CS	SD	60000	A	D
T11	7750.000	(0.600, 0.666)	M	A	(0.200, 0.500)	H	(0.645, 0.688)	CS	SD	20000	A	A
T12	7233.333	(0.4, 0.5)	M	A	(0.300, 0.600)	H	(0.222, 0.500)	A	A	20000	StrA	SA
T13	9300.000	(0.666, 0.733)	H	A	(0.400, 0.500)	M	(0.500, 0.666)	SA	A	60000	A	CS
T14	9300.000	(0.600, 0.666)	H	A	(0.400, 0.600)	ML	(0.666, 0.857)	SA	SD	120000	CS	CS
T15	12400.000	(0.733, 0.833)	VH	SA	(0.333, 0.666)	H	(0.857, 1)	CS	A	10000	SA	A
T16	4650.000	(0.666, 0.733)	M	CS	(0.266, 0.533)	H	(0.285, 0.666)	A	CS	30000	CS	D
T17	6716.667	(0.4, 0.5)	L	CS	(0.400, 0.666)	M	(0.500, 0.564)	CS	CS	60000	A	CS

T18	5166.667	(0.666, 0.733)	M	CS	(0.333, 0.666)	H	(0.900, 1)	A	SA	60000	A	CS

4. Computational Results and Investigations

The slack-based DEA model was coded and solved in MATLAB R2016a and implemented in Intel(R) Core (TM) i5, 3.20GH computer with 4 GB RAM. The lower and upper efficiencies for each perspective were calculated for 18 transporters. The dataset for each transporter from the performance score was calculated and is shown in Table 6. Following the analysis of our study, these results were discussed for their validation and usefulness with the transporters and compared with the recent literature, report, and trade journals. This can be regarded as a suitable representation of each transporter's performance.

Fig. 2. Performance scores obtained for the various transporters

According to the perceptions of the transporters, their business should perform at relatively high levels for financial, customer and learning, and growth perspectives. It is expected that the relative performance scores for different transporters in different perspectives may differ. Applying the SBM model, the efficiency scores and ranking that use the preference degree approach of transporters are presented in Table 6, which indicates that the highest number of efficient transporters for the customer, internal business process, and learning and growth are three (3 out of 18) while only two are for the financial perspective. This may be due to the fragmentation of the trucking industry, causing operation on a very thin profit margin (Magoci, 2016).

Table 6: Interval performance score, rank and degree of preference

	Financial Perspective		**Preference Degree**	**Ranking**	**Customer Perspective**		**Preference Degree**	**Ranking**	**Business process**		**Preference Degree**	**Ranking**	**Learning and growth**		**Preference Degree**	**Ranking**
	φ_L	φ_U			φ_L	φ_U			φ_L	φ_U			φ_L	φ_U		
T1	0.636	0.691	$\rho_1 \overset{0.628}{>} \rho_{13}$	6	0.864	0.909	$\rho_1 \overset{0.500}{>} \rho_{15}$	4	0.492	0.811	$\rho_1 \overset{0.512}{>} \rho_5$	5	0.606	1.000	$\rho_1 \overset{0.500}{>} \rho_6$	1
T2	0.951	1.000	$\rho_2 \overset{1}{>} \rho_7$	2	0.956	1.000	$\rho_2 \overset{0.528}{>} \rho_{16}$	**1**	0.558	0.921	$\rho_2 \overset{0.629}{>} \rho_1$	4	0.542	0.893	$\rho_2 \overset{1}{>} \rho_{18}$	8
T3	0.701	0.735	$\rho_3 \overset{1}{>} \rho_1$	5	0.490	0.531	$\rho_3 \overset{0.582}{>} \rho_4$	11	0.317	0.523	-	18	0.501	0.826	$\rho_3 \overset{0.500}{>} \rho_{12}$	10
T4	0.601	0.626	$\rho_4 \overset{0.553}{>} \rho_{12}$	10	0.483	0.524	$\rho_4 \overset{0.500}{>} \rho_{13}$	12	0.347	0.573	$\rho_4 \overset{0.986}{>} \rho_7$	16	0.551	0.909	$\rho_4 \overset{0.500}{>} \rho_5$	6
T5	0.951	1.000	$\rho_5 \overset{0.500}{>} \rho_2$	**1**	0.864	0.909	$\rho_5 \overset{0.697}{>} \rho_{11}$	6	0.486	0.802	$\rho_5 \overset{0.566}{>} \rho_{14}$	6	0.551	0.909	$\rho_5 \overset{0.517}{>} \rho_2$	7
T6	0.182	0.222	-	18	0.310	0.354	$\rho_6 \overset{0.857}{>} \rho_{14}$	17	0.381	0.628	$\rho_6 \overset{0.594}{>} \rho_4$	15	0.606	1.000	$\rho_6 \overset{0.500}{>} \rho_{15}$	2
T7	0.742	0.764	$\rho_7 \overset{1}{>} \rho_{14}$	3	0.483	0.524	$\rho_7 \overset{0.661}{>} \rho_9$	14	0.343	0.566	$\rho_7 \overset{0.580}{>} \rho_3$	17	0.376	0.620	$\rho_7 \overset{0.597}{>} \rho_{10}$	16
T8	0.585	0.634	$\rho_8 \overset{0.500}{>} \rho_{10}$	12	0.315	0.361	$\rho_8 \overset{0.566}{>} \rho_6$	16	0.425	0.701	$\rho_8 \overset{0.527}{>} \rho_{10}$	11	0.455	0.751	$\rho_8 \overset{0.500}{>} \rho_{17}$	13
T9	0.637	0.643	$\rho_9 \overset{1}{>} \rho_{15}$	8	0.454	0.519	$\rho_9 \overset{1}{>} \rho_8$	15	0.439	0.724	$\rho_9 \overset{0.366}{>} \rho_{17}$	9	0.455	0.751	$\rho_9 \overset{0.500}{>} \rho_8$	12
T10	0.585	0.634	$\rho_{10} \overset{0.500}{>} \rho_{16}$	13	0.864	0.909	$\rho_{10} \overset{1}{>} \rho_{12}$	8	0.414	0.683	$\rho_{10} \overset{0.500}{>} \rho_{18}$	12	0.342	0.564	$\rho_{10} \overset{0.500}{>} \rho_{11}$	17
T11	0.494	0.507	$\rho_{10} \overset{0.500}{>} \rho_{16}$	16	0.847	0.891	$\rho_{11} \overset{0.302}{>} \rho_{10}$	7	0.606	1.000	$\rho_{11} \overset{0.500}{>} \rho_{15}$	2	0.342	0.564	-	18
T12	0.585	0.634	$\rho_{12} \overset{0.500}{>} \rho_8$	11	0.796	0.837	$\rho_{12} \overset{0}{>} \rho_{17}$	9	0.606	1.000	$\rho_{12} \overset{0.500}{>} \rho_{11}$	1	0.501	0.826	$\rho_{12} \overset{0.597}{>} \rho_9$	11
T13	0.597	0.692	$\rho_{13} \overset{0.545}{>} \rho_9$	7	0.483	0.524	$\rho_{13} \overset{0.500}{>} \rho_7$	13	0.459	0.758	$\rho_{13} \overset{0.546}{>} \rho_9$	8	0.551	0.909	$\rho_{13} \overset{0.500}{>} \rho_4$	5
T14	0.708	0.727	$\rho_{14} \overset{0.490}{>} \rho_3$	4	0.282	0.322	-	18	0.455	0.751	$\rho_{14} \overset{0.490}{>} \rho_{13}$	7	0.414	0.683	$\rho_{14} \overset{0.591}{>} \rho_7$	15
T15	0.604	0.636	$\rho_{15} \overset{0.614}{>} \rho_4$	9	0.864	0.909	$\rho_{15} \overset{0.500}{>} \rho_5$	5	0.606	1.000	$\rho_{15} \overset{0.583}{>} \rho_2$	3	0.606	1.000	$\rho_{15} \overset{0.596}{>} \rho_{16}$	3
T16	0.585	0.634	$\rho_{16} \overset{1}{>} \rho_{18}$	14	0.95	1.000	$\rho_{16} \overset{0.500}{>} \rho_{18}$	2	0.429	0.708	$\rho_8 \overset{0.620}{>} \rho_6$	14	0.551	0.909	$\rho_{16} \overset{0.500}{>} \rho_{13}$	4
T17	0.228	0.280	$\rho_{17} \overset{1}{>} \rho_6$	17	0.585	0.634	$\rho_{17} \overset{1}{>} \rho_3$	10	0.501	0.826	$\rho_{17} \overset{0.325}{>} \rho_8$	10	0.455	0.751	$\rho_{17} \overset{0.597}{>} \rho_{14}$	14
T18	0.562	0.571	$\rho_{18} \overset{1}{>} \rho_{11}$	15	0.951	1.000	$\rho_{18} \overset{1}{>} \rho_1$	3	0.414	0.683	$\rho_{18} \overset{0.547}{>} \rho_{16}$	13	0.501	0.826	$\rho_{18} \overset{0.500}{>} \rho_3$	9

Dadsena *et al.* (2019) identified the difficulties in the survival of micro-truck owners regarding financial, learning and growth, and internal business process perspectives and the effect on budget allocation. It is also interesting to note that no transporter is efficient in respect of all the perspectives, i.e., no single one is perfect. The result shows that transporter number two (T2) is efficient with respect to the financial and customer perspectives; however, for the internal process and learning and growth perspectives, this transporter is inefficient. Similarly, T15 is efficient with respect to the internal process and learning and growth perspectives, but for the financial and customer perspectives, it is inefficient.

The results can be conveniently displayed in a radar chart illustrating the interval performance scores obtained for the four perspectives for all the transporters, as shown in Fig. 2. The visualization of the ranking obtained for each transporter, based on each of the perspectives of the BSC, is displayed in Fig. 3. This graph indicates the scope for improvement for the transporters because even the best performing transporters in some perspectives present relatively weak performances in other perspectives. For example, T14 needs to check their customer perspective and learning and growth as these are placed at the lower efficiency on that specific perspective.

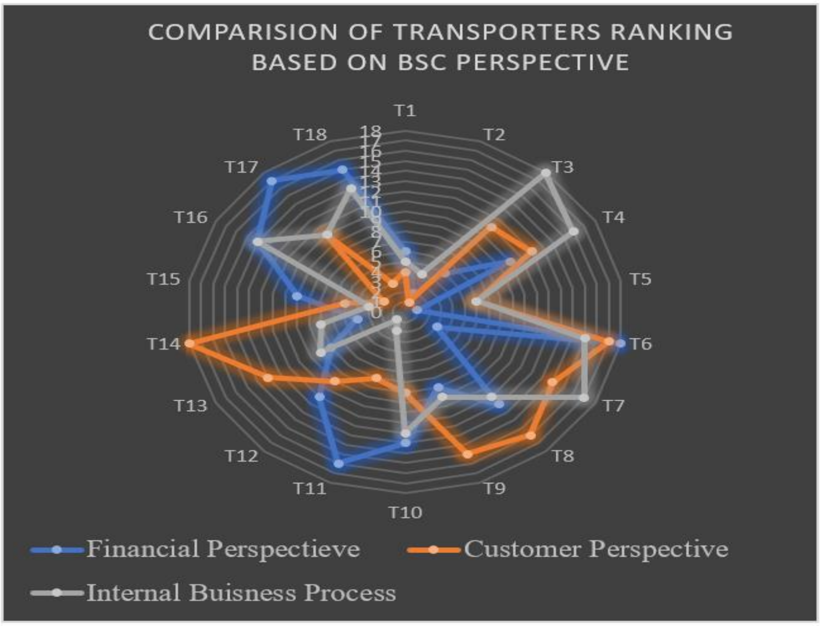

Fig. 3. Comparison of transporters ranking from the perspectives of BSC

Finally, we use the preference degree approach for comparison and ranking of the efficiency intervals of the 18 DMUs, as presented in Table 6. Table 6 shows that transporter number five (T5) is ranked first with a preference degree of 50% on T2, i.e., the performance of T5 is 50% better than T2 when considering the financial perspective. However, if we focus on the customer perspective for the performance of T5, it is 69.7% better than T11. Similarly, it can also be observed from Table 6 that for IBP and the learning and growth perspective, T5 performance is 56.6% better than T14 and 51.7% better than T2, respectively. Furthermore, it is clear from the result that the financial perspective, particularly for some transporters (T6 and T17) and for the customer perspective (T4 and T6), would require specific attention. This result shows that the transporters who scored the lowest scores for their respective perspectives should focus more on that specific perspective to manage and improve their performance.

5. Discussion of the findings

The main objective of this study is to systematically review and measure the performance of the trucking industry. With respect to performance measurement, we distinguish two main issues. The first one relates to the conceptualizing the key factors in performance measurement. The second one relates to the efficiency based on the important factors. The findings of the study cover these issues by considering BSC model, which helps in identifying the inputs and outputs for the efficiency calculation. With respect to trucking industry, we found that combining the BSC-DEA helps to identifying the most suitable performance measures that helps in calculating the and efficiency of the business process. As most of the transporters' started focusing not only on the financial perspective but also take in to account the other perspective as customer's perspective, innovative learning and business growth perspective (Agbo and Zhang, 2017).

This study also helps in distinguishing the specific perspectives which requires more attention for improving the performance for specific transporter. As the finding of the study reveals that, no transporter is efficient from all the perspectives, which indicates the reciprocal learning helps in overall performance improvement of the trucking industry.

At the same time this study provides a comprehensive view on how these perspectives may help in finding what and how these measures can be considered in the performance management process. Hence, the modern trucking business needs to also give priority to the business process improvement and learning and growth perspective, such as the implementation of information technology to improve the communication and service management in trucking business, capability development, improvement in truck drivers' efficiency (Kant et al., 2022b; Loske, and Klumpp, 2022). The present study is essential in analyzing the areas that need special attention in the overall performance improvement of the trucking industry.

5.1 Theoretical contribution

From a theoretical perspective, this study offers a few important contributions. Shi et al., (2019) highlighted that traditional trucking companies primarily consider financial and customer satisfaction as a performance measure for their business. In response to this, our study contributes to logistics literature by showing the way the trucking companies can monitor the effect of learning and growth and business process perspective in operational performance management.

Similarly, Sanchez-Rodrigues et al., (2015), pointed out that the use of estimated-based statistics for trucking industry performance assessment is one of the major issues due to the lack of empirical data. This indicates the importance of data availability in the unorganized nature of the trucking industry, which made performance measurement and management very difficult for practitioners. It is also observed that the micro-truck owner's database management system is not very strong, resulting in poor performance. In response to this call, our study uses a hybrid approach considering the imprecise data to study the performance of trucking industry. Further, while discussing the performance management of the trucking industry, it is important to consider different parameters (Saldanha *et al.,* 2013). Therefore. This research considers four perspectives of BSC and combines these with DEA considering imprecise data in performance evaluation for the first time in the trucking industry.

There are several methods such as determining importance-performance analysis (IPA), key performance indicators (KPI), SERVQUAL, data envelopment analysis (DEA) and multiple criteria decision-making (MCDM) used for performance evaluation (Rezaee et al., 2021; Beheshtinia and Omidi, 2017). Existing literatures shows that approximately 30% of all BSC research has used BSC with MCDM methods (Analytic Hierarchy Process (AHP), Analytic Network Process (ANP) and Technique for an Order of Preference by Similarity to Ideal Solution (TOPSIS) methods) to analyze BSC results (Rezaee et al., 2021). However, these MCDM based methods may lead to the unreliability of results as it strongly dependent qualitative (experts judgment) data (Rezaee et al., 2021; Ishizaka and Labib, 2009). To solve this problem, Eilat, Golany, and Shtub (2008) used an integrated DEA and BSC for R&D project assessment. Hence this study adopted integration of BSC-DEA approach. Further, authors, Bray et al., (2014) and Bray et al., (2015) considered the fuzzy data in efficiency evaluation of transportation sector. Smirlis et al., (2012) highlighted the importance of ordinal data in efficiency evaluation of transport sector. In addition to this, Brian Aoaeh, (2020).

recommendation echoes that unreliable and imperfect data leads to imperfect decision-making in trucking industry. Hence, this study expands and enriches the role of imprecise data in a highly fragmented environment of the operating condition of trucking business. Hence this study adopted Imprecise Data Envelopment Analysis (IDEA) regarding exact, ordinal, interval, and fuzzy data for performance measurement of the trucking industry is considered to capture the realistic scenario. Thereby, contributes to the performance measurement literature of the trucking industry, by reference setting for each of inefficient DMUs.

Hassan, and Helo, (2021) argue for the need to have best practices with regard to developing a more nuanced understanding effectiveness of transportation plans and the need for improvement in trucking industry performance and thereby enriching strategic decision-making skills and providing meaningful guidance to the transporters. This study supplements the empirical application of the hybrid approach of BSC-IDEA in developing an effective plan by developing a performance matrix.

5.1.Managerial implications

Measuring the performance of trucking business considering the perspectives is a core tenet in modern transportation management systems (Jovanovic et al., 2020). In this regard, this study offers guidance to managers regarding how the different perspectives are expected to impact the overall performance of their business. The findings of this study have the potential to analyze their business from different perspectives and suggest timely corrective action when necessary.

Lyons, and Bandura, (2021) emphasize that reciprocal learning is important for a manager to use the right knowledge and skills for future attempts at learning and improvement reflective of various needs or conditions of their business. These findings reinforce the idea that managers may benefit from some perspectives, whereas other transporters might excel in that same perspective. For example, transporter (T3) may improve their business process and transporter (T12) may improve their financial performance through reciprocal learning. This shows that among the micro-truck owners, learning and growth can occur in both directions.
Further, this study provides the practical implication from the perspective of the supply chain analyst to conduct brainstorming sessions with the transporters who are regularly part of the supply chain. In doing so, the experts could manage the performance of their industry scientifically. However, the obstacles in traditional decision-making for transporters are mostly related to insufficient information and data (Shi et al., 2019). Our study also provides a strategic map for transporters by integrating BSC with imprecise data in performance management.

Also, inferences can be drawn relating to the types of methectic and their analysis in a systematic manner that would help transporters to improve the performance of their industry. Amado *et al.* (2012) suggested that revised data collection systems (considering different types of data) can improve the performance measurement process. The data on performance measures are very difficult to collect with a single type of data for each DMU. Thus, deliberation of different types of data can provide more accurate and effective results by eliminating all the weaknesses of the traditional approach (Ebrahimi and Toloo, 2019). Therefore, we conducted personal interviews and discussions regarding imprecise data for information collected from the transporters.

6. Conclusion

6.1. Conclusion and summary

In this study, we propose a BSC-IDEA approach to measure performance by evaluating the interval efficiency of a set of micro-truck owners. The BSC offers a managerial framework in decision-making, while the imprecise DEA provides the real scenario in detail and with greater accuracy. To the best of our knowledge, this is the first kind of study where integration of the BSC-IDEA approach has been developed for micro-truck owners. This approach enables consideration of uncertainty and competency in performance assessment by identifying the different performance measures that require attention. The results of this study indicate that most micro-truck owners describe their strategy in the form of general assumptions. This study assists transporters by providing flexibility in the decision-making process on strategy selection based on the desired preference and business success

Our study is an integrated concept considering BSC-IDEA, which is proven to be a useful approach for performance measurement in many practical applications. Thus, the aim of this study is to presents the BSC model to show transporters the specific areas of improvement in their business and operating strategies. This study will convince transporters to understand and guide them in practicing various healthy strategies. For example, the study strengthens the concept of collaboration to increase profit margin and meet customer requirements, as this affects their financial and customer perspective (Chen *et al*., 2013; Rajapakshe *et al*., 2014); similarly, the timely innovation by the use of advanced technology (ICT) to improve operational efficiency through smart and connected transport networks will improve their learning and growth as well as IBP perspective (Zhou and Wan, 2021; Perego *et al*., 2011); development of a database to improve response time; service and inter-functional incentives for continuous improvements (Scott, 2015). This study helps transport managers identify the areas that need attention through reciprocity learning processes using self-analysis and influential evaluation perspectives. It also helps in suggesting implementation and investment of time take necessary strategic actions that improve the performance of their business about their weak areas.

Based on the interviews conducted with the transporters, it is reasonable to link the DEA with the BSC to help decision-making by understanding the performance score for their business from different perspectives. The results of this study help the transporters in defining and implementing the strategies based on the attention required by each perspective. This study enables transport managers to make changes in process, culture, and advanced techniques to compete with growing competitive market demand.

6.2. Future scope

Potential future research opportunities arise from this study.

- **Employing budget with performance measures:** The micro-truck owners could evaluate their strengths and weaknesses according to their requirements and determine their investment policies. Therefore, it is essential to investigate how performance measurement would provide the correct direction in strategy selection under budget constraints.
- **Digital challenges of the trucking industry:** It would be interesting to explore the role of digitization in the performance of micro-truck owners. It is thus important to ensure how digital challenges affect the efficiency of micro-truck owners.
- **Fragmentation of the trucking industry**: The fragmented nature of the trucking business affects the efficiency of the micro-truck owners. Thus, it will be critically vital to explore how the fragmented nature of the industry affects the driver shortage, freight rate, and service quality of the micro-trucking industry
- **Study based on other models:** Furthermore, in the future, it would be recommended to link and explore the other possible DEA models, such as dynamic and network models.

The applicability of the model proposed has been shown through an empirical investigation that has involved the Indian micro truck owners, the model can be further validated through performing the analysis for other country. Further two stage DEA employing Tobit or Truncated regression can be used to evaluate the performance by considering factors such as maintenance of the transportation infrastructure, the development of the infrastructure of neighbor countries, the scale economies due to the country size, etc. (lo Storto et al., 2022). In future it would be interesting to analyse the role of link and carryover variables and explore the possibility dynamic models and network DEA models (Melo et al., 2017). Also, implementing hybrid and novel multiple criteria decision making (MCDM) approaches (Analytic Hierarchy Process (AHP), Analytic Network Process (ANP) and Technique for an Order of Preference by Similarity to Ideal Solution (TOPSIS) methods) to analyze BSC results in the research could be a scope for future research (Kaya et al., 2023; Rezaee et al., 2021; Peykani et al., 2018; Beheshtinia et al., 2017).

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