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ORIGINAL RESEARCH

Modeling drivers to big data analytics in supply chains

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Abstract

The recent emergence of data-driven business markets and the ineligibility of traditional data management systems to trace them have fostered the application of Big Data Analytics (BDA) in supply chains of the present decade. Literature reviews reveal that the successful implication of BDA in a supply chain mainly depends on some key drivers considering the size and operations of an organization. However, collective analysis of all these drivers is still neglected in the existing research field. Therefore, the purpose of this research is to identify and prioritize the most significant drivers of BDA in the supply chains. To this aim, a novel Best-worst method (BWM) based framework has been proposed, which has successfully identified and sequenced the twelve most significant drivers with the help of previous literature and experts' opinions. Theoretically, this study contributes to the BDA literature by offering some unique drivers to BDA in supply chains. The findings show that 'sophisticated structure of information technology' and 'group collaboration among business partners' are the top most significant drivers. 'Digitization of society' is identified as the least significant driver of BDA in this study. The outcome of this study is expected to assist the industry managers to find out the most and least preferable drivers in their supply chains and then take initiatives to improve the overall efficiency of their organizations accordingly.

Keywords: Big data analytics; Multi criteria decision making; Best-worst method; Drivers; Supply chain management.

1. Introduction

Rapid developments in information and communication technology (ICT), as well as the collaboration of different departments in the supply chain, have generated a massive amount of data that is difficult to handle traditionally (Zhong et al., 2016; Choi & Luo, 2019). The expansion of online business as well as the use of smart devices for effective market analysis are the primary sources of the bulk amount of data that necessitate appropriate data analytics and management system (Tan et al., 2015). Besides, data complexity and data uncertainty is rising sharply and thus lift up a requirement for maintaining the diversity of supply chain data (Amankwah-Amoah & Adomako, 2019; Serdarasan, 2013). Big data analytics (BDA) has often been valued as a key solver to mitigate risks when a supply chain is exposed to data-related problems

(Hung et al., 2020; Bag et al., 2020). Big data is paving new ways to analyze and enhance the overall process and performance of supply chains (Belaud et al., 2019).

Although the field of BDA is vast, consolidated definition and application of BDA in supply chains have been developed successfully by researchers and industry practitioners (Huang et al., 2015; Kacfah Emani et al., 2015; Tiwari et al., 2018). Deployment of BDA in supply chains and manufacturing industries has been found effective in handling the wide range of data generated by all operations on a daily basis (Lamba & Singh, 2017; Majiwala et al., 2019). Analysis of bullwhip effect (Hofmann, 2017), sustainability in process, and operational excellence (Bag et al., 2020) in supply chains have successfully been covered by BDA.

The dynamic behavior of a modern complex supply chain is required to be adequately investigated in order to ensure optimization of the business process and thus achieve a competitive advantage (Shamout, 2019). BDA drivers are often considered to be a significant role-player by providing an innovative solution for logistics and production firms (Witkowski, 2017; Elia et al., 2020). Nevertheless, the application of this technique to supply chains is still facing some primary challenges (Kache & Seuring, 2017; Moktadir et al., 2019). Properly analyzing and evaluating the driving factors of BDA can significantly improve the performance of the supply chains by both profitability and responsiveness.

Although data quality management, data analytics can significantly improve supply chain competency and consistency, there has been a significant lack in applying BDA tools to supply chains (Janssen et al., 2017). Gunasekaran et al., (2017) and Zhan & Tan, (2020) have mentioned some key drivers of BDA separately; however, an aggregated analysis of all the key drivers and their contributions are still missing in the existing literature. Thus, the main goal of this research is to include the most influential BDA drivers of the supply chains. Besides, this study will also assess the contribution level of each driver comparing others and then rank them accordingly by using the Best-Worst method (BWM). Understanding and prioritizing the most significant drivers according to their contribution will be of paramount importance for the industry managers. Hence, this study tries to enrich the existing literature with a view to assist supply chains managers by addressing the following specific objectives:

a) To identify the drivers of BDA in supply chains.

b) To analyze and evaluate the contribution level of these drivers by applying BWM.

c) To discuss the managerial implications of the research.

Amongst the different methods of multi-criteria decision-making techniques (Chowdhury & Paul, 2020), BWM is often considered as more robust optimization technique compared to others for clustering the available alternatives. BWM is a multi-criteria decision-making technique in which several different alternatives have been evaluated based on several different criteria and then rank all of them to find out the best and worst alternatives (Rezaei, 2015). BWM has been suggested in this paper due to its' ability to reduce the inconsistency between the alternatives, a prerequisite to analyze and categorize the available drivers more accurately whereas in Analytical Hierarchy Process it is difficult to get the consistent results and also needs greater efforts and time.

The remaining of the paper is organized as follows. Section 2 provides a brief theoretical background of big data analytics, its application in the supply chains, and the drivers of big data analytics. Section 3 discusses the research methodology proposed for this study. Section 4 addresses the application of the proposed research methodology with a real-world case problem and lists the result. Discussion on the results and sensitivity analysis are presented in section 5. Finally, conclusions, along with managerial implications and future research direction, are articulated in Section 6.

2. Theoretical background

2.1 Big data and big data analytics

BDA is considered as a revolutionary tool to perform massive-scale complicated computations by high-performance data processing and analysis (Zhou et al., 2016; Isik, 2018). It is mainly characterized by 5'V-Volume, variety, velocity, veracity, and value (Inmon & Linstedt, 2015; De Mauro et al., 2016). Volume refers to the exponentially increasing data (Philip Chen & Zhang, 2014). BDA can synthesize voluminous and complex amounts of data while maintaining the security and privacy of the data (Picciano, 2012; Kaur et al., 2018). Variety refers to the data generated from multiple sources by multiple types (Limaj & Bilali, 2018). BDA can store and analyze data in different formats like discrete, probabilistic, and multifactor. Velocity means the rate of data generation. BDA can ensure the quick processing of data and thus accelerate the decision-making process (Picciano, 2012). Veracity means the quality, reliability, and importance of data.

During dealing with the exploded amount of data, big data can sort out the bad data from the list (Ishwarappa & Anuradha, 2015). Thus, the accuracy and credibility of the data are also ensured by the analysis (Kaur et al., 2018). Finally, value refers to the added impact on the decision making strategy (Addo-Tenkorang & Helo, 2016). Value is often treated as the most significant feature of big data as the remaining 4 V'S will fail if the collected data can't be turned into the desired value (Ishwarappa & Anuradha, 2015).

Big data analytics (BDA) is often mentioned as a business analytics tool to investigate high voluminous data and then incorporate it into organizational purposes (Lezoche et al., 2020). BDA consists of a wide range of data analysis and management tools such as artificial intelligence, machine learning algorithms, statistical tools like single and multiple regression analysis, database management, and so on. BDA revolves around reporting, filtering, and corelating all accessible datasets and then convert it to a scaled output to make it understandable in the organizational context (Hung et al., 2020).

2.2 Applications of BDA in supply chains

BDA has overshadowed the limitations of the conventional data handling system to analyze the complex data structure of today's business organization. It is a holistic approach to analyze the huge amount of data characterized by volume, variety, value, veracity, and velocity to get useful ideas for profit-making capability and competency of any organization (Wamba et al., 2017). The applicability of BDA is already shown in the fields where a massive amount of data is needed to deal with, such as cloud computing (Kchaou et al., 2015; Hussain & Roy, 2016), banking sectors (Srivastava & Gopalkrishnan, 2015), health care (Raghupathi & Raghupathi, 2014; Srivathsan & Yogesh, 2015), energy management (Rodríguez Fernández et al., 2016), and life science (Deus, 2019). BDA has already been implemented successfully in many supply chain operations like supplier selection, managing warehouse inventory, logistics, and transportation networking, production planning, and control. In recent times, BDA has been found useful to predict or forecast the supply and demand (Gunasekaran et al., 2017). Moreover, a mitigation strategy for supply chain disruption risk is also now suggested using BDA (Singh & Singh, 2019). A detailed literature review on the applications of BDA in different supply chain sectors has been summarized in Table 1.

Table 1: Application of BDA on different sections of the supply chain

Authors	Area	Objective of the study	Methodology
Singh & Singh, (2019)	Supply chain risk management	Developing a suitable recovery plan to mitigate the supply chain disruption risks	Structural equation modeling
Hofmann & Rutschmann, (2018)	Demand management	Demand can be forecasted based on Big Data Mining.	Qualitative and Quantitative forecasting method
Wu et al., (2017)	Sustainability in supply chain	Supply chain risks and uncertainties are investigated through exploring data attributes	Fuzzy, Grey Delphi
Wang et al., (2016)	Logistics and Transportation	Big data analytics significantly increase the decision-making capability of logistics.	Comprehensive literature review
Lee et al., (2015)	Manufacturing	Applying the BDA technique, Manufacturing system can be integrated.	Conceptual analysis
Huang & Mieghem, (2014)	Warehousing	Developing an inventory model and conduct empirical analysis using big data.	Statistical analysis using clickstream data
Sevkli et al., (2007)	Procurement	Discussed the application of BDA in supplier selection.	Data envelopment based AHP (DEAHP)

However, the handling of big data is not easy for firms because of its complexity, differentiability, and a lack of infrastructure of those firms (Wixom et al., 2014). As a result, only 17% of the total organization of the world adopts the BDA technique in at least one of its' supply chain branches (Tsai et al., 2015). Therefore, the application of BDA in supply chains can be viewed as a pinnacle once it has been applied successfully. Meanwhile, the successful implementation of BDA depends mostly on finding the drivers which control the supply chain characteristics (Lai et al., 2018). Then based on the identification of the effective drivers, firms' performance can be evaluated (Waller & Fawcett, 2013; Provost & Fawcett, 2013), and decisions can be taken properly. Nonetheless, it is still a challenge to identify the most suitable BDA drivers and incorporate them in such a way that the quality of data will remain convenient for further analysis, acquisition, and preservation.

The next section addresses the most significant drivers of BDA that can influence supply chains greatly. All these drivers are identified according to the thorough review of existing literature and then confirmed by expert opinions.

2.3 Proposed drivers of BDA

The BDA drivers are those factors that can accelerate the BDA implementation process in the supply chain. It is very crucial to assess the drivers supply chains of the current world are generating highly heterogeneous data, which creates a need to identify and prioritize the most suitable BDA drivers (Loebbecke & Picot, 2015). Different studies on BDA has discovered the strengths of these drivers for different kinds of firms and industries (Singh & Teng, 2016; Terrada et al., 2019). Some of these studies present these drivers just based on the synthesis of data (Rodriguez & Cunha, 2015; Spanaki et al., 2017), while others outline them from a view of cognitive and collaborative approach (Buchmann, 2016; Christofferson, 2018). From another point of view, some of the drivers are highlighted as internal to the supply chain (Turkulainen et al., 2017; Salamai et al., 2019), and the rest of the drivers are considered external (Gandhi et al., 2015; Asrawi et al., 2017). After an in-depth investigation of all these related literature reviews, we have finally identified twelve drivers of BDA. Then a brainstorming session has been conducted with the experts of relevant supply chain industries to achieve the cogency of the discovered drivers. A brief explanation of the identified drivers has been presented in Table 2

Table 2: Summary of BDA drivers related to supply chains

Drivers	Brief explanation	References
Data-driven innovation	Data-driven innovation can help to faster the implementation process. Machine learning (ML), Artificial intelligence (AI), etc. are the emerging innovations of BDA to apply and understand the dynamic environment of supply chains.	Proposed in this Article
Application of social media to manage data	Big data acts as a pioneer to connect not only the different groups of supply chains but also the customers from different ethnicism through social media. It is essential to observe the consumers' behaviors and choices for sustaining in the market. Therefore, social media data can help to observe the consumers' choices and behaviors for business decision making.	Proposed in this Article
Increase connectivity through cloud computing	Cloud computing in supply chains will lead to supervise a product throughout its' life cycle by making effective communication among the participants.	Proposed in this Article
Application of Internet of Things (IoT)	Enabling the use of IoT devices is proven successful in monitoring the movement of the product and ensure quality with the use of chips, sensors, etc.	Ahmed et al., (2017) and Amanullah et al., (2020)
Digitization of society	Digitization of society amalgams the use of technology and human beings in such a way that it ultimately results in a successful digital supply chain network.	Proposed in this Article
Group collaboration among business partners	Adopting the solution from big data analytics is seemed to be a successful approach to maintain increased collaboration due to the vast amount of distributive data.	Cao & Zhang, (2011) and van den Broek & van Veenstra, (2018)
Organizational commitment towards the application of BDA	Big data can enhance the transparency and credibility of supply chains by providing a benchmark for organizational commitment towards the application of BDA.	Fawcett et al., (2006) and Busse et al., (2011)
Availability of predictive analytics	Predictive analysis, which is mainly based on both sorted and unsorted data, has often been treated as the frontier to anticipate the uncertain business environment and then make decisions accordingly.	Hazen et al., (2016) and Gunasekaran et al., (2017)

Drivers	Brief explanation	References
Sophisticated infrastructure of information technology	BDA has been applied successfully to information clustering, classification, and resolve mismatch of shared information among different constituents of supply chains.	Ghosh, (2016) and Kache & Seuring, (2017)
Skilled management team	The expansion of BDA in an organization is mainly dependent on the appropriate skills of the manpower to leverage data. Skilled manpower can help business managers to gain strategic advantages over others.	Berk & van Binsbergen, (2015) and Mauro et al., (2018)
Dynamic analytical capabilities of firms	The analytical thinking ability of a firm is often considered as one of the major significant differences between big data analytics and traditional data management system. For some industries, it is valued as equally important as the technical skillsets.	Popovič et al., (2012) and Debortoli et al., (2014)
Strategic alignment towards BDA application	Successful implementation of BDA is enabled by the well-established alignment between the supply chain objectives and the overall goal of the organization.	Hult et al., (2007) and Watson, (2014)

3. Methodology

3.1 Proposed operational framework

The purpose of this research work is to find out the drivers of BDA in supply chains. The operational framework for this study is presented in Figure 1. The proposed research mainly consists of four steps, as mentioned below:

Step 1: Identification of drivers

In this step, a comprehensive list of BDA drivers is generated based on previous literature reviews and from the opinions of the experts who have comprehensible knowledge on the supply chains and the use of data for creating value.

Step 2: Compare the drivers within themselves

This step is conducted through a questionnaire where the experts reflect their insight to compare different drivers within themselves. In this phase, the experts were mainly asked to express their preferences of the top most significant driver over the other drivers using a 1-9-point importance rating scale.

Step 3: Evaluation of weightage of the driver based on BWM

In this stage, the importance of each driver is calculated for every expert opinion by BWM. Then the average of all the weight is taken for analysis. The working mechanism of BWM is discussed in detail in section 3.2.

Step 4: Result analysis and explanation

Finally, the best and the worst driver has been identified according to the BWM analysis and the significance of each driver and how they help to build a reliable, resilient, competitive supply chains is discussed.

3.2 Best worst method

In this research, the BWM is used for finding the weightage of the drivers. The BWM is a multi-criteria decision-making (MCDM) method developed by Prof. Jafar Rezaei in 2015 (Rezaei, 2015). Since then, BWM has been implemented successfully in several relevant fields of MCDM techniques such as health sectors, software industries, aerospace engineering, and agricultural firms (Beemsterboer et al., 2018; Pinto et al., 2019). The main principle of BWM is to identify the available alternatives and then rank from best to worst criteria. Also, it provides some relaxation about the required number of decision-makers to perform the method, and even a single decision-maker can conduct it (Guo & Zhao, 2017).

BWM has outperformed other popular MCDM methods in some aspects, such as:

(i) It does not require to process all data for pairwise comparison;

(ii) It provides identical comparisons, so the final results will also be more consistent and reliable.

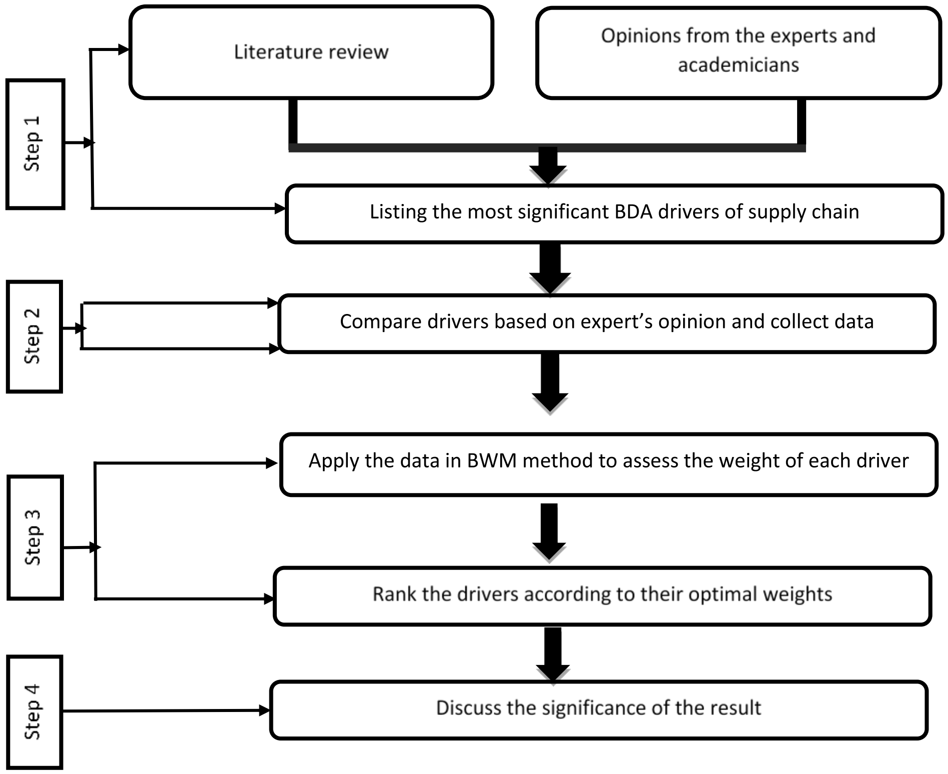

Fig. 1: Steps of the proposed operational framework

An MCDM problem having *m* number of different alternatives $(A_1, A_2, \ldots \ldots \ldots . A_m)$ which will be determined by *n* number of different attributes $(C_1, C_2, C_3 \ldots \ldots \ldots . C_n)$ formulates an $m \times n$ decision matrix, as shown in Eq. (1). Individual element x_{ij} of the matrix is the performance rating indicator of the i^{th} alternative, A_i, corresponding to the j^{th} attribute, C_j,

$$D = \begin{array}{c} \\ A_1 \\ A_2 \\ A_3 \\ . \\ . \\ A_m \end{array} \begin{array}{c} \begin{array}{cccccccc} C_1 & C_2 & C_3 & . & . & . & C_n \end{array} \\ \left[\begin{array}{cccccccc} X_{11} & X_{12} & X_{13} & . & . & . & X_{1n} \\ X_{21} & X_{22} & X_{23} & . & . & . & X_{2n} \\ X_{31} & X_{32} & X_{33} & . & . & . & X_{3n} \\ . & . & . & . & . & . & . \\ . & . & . & . & . & . & . \\ X_{m1} & X_{m2} & X_{m3} & . & . & . & X_{mn} \end{array}\right] \end{array} \quad (1)$$

The steps regarding the Best-Worst method (BWM):

Step 1: Determine the decision criteria.

The decision maker addresses the criteria that have to be evaluated and used to make a decision. If the decision maker identifies *n* criteria, it will be symbolized as $\{C_1, C_2,, \ldots, C_n\}$.

Step 2: Determine the best and the worst criteria.

The most preferable criterion and least preferable criterion are identified by the decision maker.

Step 3: Determine the preference of the best criteria over all other criteria

The preference of the best criteria over others is done by using scale 1-9 and formulated as a Best-to-Others (BO) vector of criteria expressed as follows:

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

Where a_{Bj} indicates the preference of *B-best* criteria over *j* criteria and it is simply $a_{BB} = 1$.

Step 4: Determine the preference of all other criteria's preference over the worst criterion

The preference of all criteria over the worst is done by using scale 1-9 and formulated as an Others-to-Worst (OW) vector of criteria expressed as follows:

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

Where a_{jW} indicates the preference of *j* criteria over the *W-worst* criteria and it is simply $a_{WW} = 1$.

Step 5: Find out the optimal weight of the criteria $(w_1^*, w_2^*, \dots, w_n^*)$

The optimal solution can be obtained from the following equation as expressed in Eq. (2):

$$\text{Min}\, max_j \left\{ \left| \frac{w_B}{w_j} - a_{Bj} \right|, \left| \frac{w_j}{w_w} - a_{jw} \right| \right\}$$

Subject to,

$$\sum_j w_j = 1 \qquad (2)$$

$$w_j \geq 0 \quad \text{for all } j$$

The optimal weights $(w_1^*, w_2^*, \dots, w_n^*)$ and the value of the objective function will be obtained after transforming Eq. (2) into a linear programming model, as shown in Eq. (3) and then solve it by using a suitable mathematical solver.

$$\text{Min}\, \xi$$

Subject to:

$$\left| \frac{w_B}{w_j} - a_{Bj} \right| \leq \xi \text{, for all } j$$

$$\left| \frac{w_j}{w_w} - a_{jw} \right| \leq \xi \text{, for all } j \qquad (3)$$

$$\sum_j w_j = 1$$

$$w_j \geq 0 \text{, for all } j$$

When the value of the comparison matrix, ξ equals or tends to zero, it indicates a consistent as well as a reliable comparison system.

4. Application of the proposed framework

This section demonstrates the proposed methodology, as suggested in the previous section, with a real-world case application. The whole process involved a team of experts from both the academic field and different industrial sectors to enhance the credibility of the overall framework.

4.1 Identification and comparison of BDA drivers

A google form was used to obtain the responses from the academicians and industry experts. It is a structured communication technique or method through which the expert's opinions are collected systematically and interactively. Although there is hardly any hard and fast rule about the target number of participants required to validate the process, 10-15 experts of different industrial sectors are recommended (Somsuk & Laosirihongthong, 2017). In this study, ten responses have been received from 10 experts, including researchers of the supply chain field. A brief profile of the participating respondents has been presented in Table 3.

The participants expressed their opinions based on their knowledge and experience that reflect the present position of Bangladeshi organizations. For this study, the identity of the corresponding participant is kept anonymous. This anonymity encourages the participants to feel free while making their decisions irrespective of their hierarchical positions in the organization. Moreover, this form of confidentiality also prevents dominating characteristics to make every opinion equally important. Consequently, the responses from the participants are free from bias and reflect the true expression of opinions for a particular industry.

Initially, the primary questionnaires were sent to 20 industrial managers and academicians via Google form. The questionnaire is set in a structured way, and there is freedom of the participants to express their opinions (see Appendix A). Next, a 1-9-point importance rating scale is provided with an explanation to the respondents for evaluating the importance of the drivers (see Appendix B). Experts are suggested to go through the subsequent questionnaire and then answer the questions Q.1, Q.2, and Q.3 as shown in Appendix C with the help of the importance rating scale.

Table 3: Profile of the selected respondents

Respondents	Type of Industry/ organization	Position of the Participant	Experience in Years	Area of Specialization
R-1	Educational Institute	Associate Professor	>10	Supply chain management
R-2	Sewing Thread Manufacturer	Head of Manufacturing	10+	Production and control
R-3	Apparel and textile manufacturer	Chief Operating Officer	15+	Production and Maintenance
R-4	Apparel manufacturer	Head of IE and Planning	10+	Production planning and quality control
R-5	Automobiles	Sr. Executive	>10	Supply chain management
R-6	Software industry	Software Engineer	12	Software development
R-7	Pharmaceuticals (FMCG)	Officer, Quality Assurance	10+	Quality Assurance
R-8	Pharmaceuticals (FMCG)	Executive, Quality Assurance	>15	Quality Assurance
R-9	Footwear	Manager	>20	Supply chain and logistics
R-10	Leather Goods	Production manager	>16	Production

4.2 Implication of Best-worst method

The responses from the experts and academics are listed and have been applied through BWM to find out the rank of the drivers. It mainly comprises of four stages as follows:

Stage 1: Determination of best and worst drivers

In this stage, the individual response was collected, and then the best and worst significant drivers have been identified. Resulting best and worst drivers, according to the ten experts, have been shown in Table 4.

Table 4: Best and Worst driver identified by R1-R10 respondents

Drivers	Best (most significant) drivers mentioned by respondent	Worst (least significant) drivers mentioned by respondent
Data-driven innovation (d1)		
Application of social media to manage data (d2)	R2	
Increase connectivity through cloud computing (d3)		R6, R9
Application of Internet of Things (IoT) (d4)		R1, R4, R8
Digitization of society (d5)		R2, R3, R5, R7, R10

Drivers	Best (most significant) drivers mentioned by respondent	Worst (least significant) drivers mentioned by respondent
Group collaboration among business partners (d6)	R1, R4, R8	
Organizational commitment towards the application of BDA (d7)		
Availability of predictive analytics (d8)		
Sophisticated infrastructure of information technology (d9)	R3, R5, R7, R9, R10	
Skilled management team (d10)		
Dynamic analytical capabilities of firms (d11)		
Strategic alignment towards BDA application (d12)	R6	

Note: 'R' denoted respondent

Stage 2: Determination of the best driver over the other drivers

In this stage, a preference vector has been formed to indicate the preference of individual experts using the 1-9 importance scale. Table 5 presents the best preference driver of expert 1 over the other drivers.

Table 5: Best driver preference over other drivers by Expert 1

Best to Others	d1	d2	d3	d4	d5	d6	d7	d8	d9	d10	d11	d12
Best driver-d6	7	4	5	9	8	1	2	6	6	7	5	3

Stage 3: Determination of the other drivers over the worst driver

The preference of other drivers over the worst driver for expert 1 is listed in Table 6.

Table 6: Preference of other drivers over the worst driver by Expert 1

Others to the Worst	Worst driver- d4
d1	3
d2	7
d3	6
d4	1
d5	2
d6	9
d7	8
d8	5
d9	6
d10	3
d11	6
d12	7

Stage 4: Determination of the optimal weights of drivers

In this stage, the optimal weights of each driver are calculated from the objective functions and constraints mentioned in Eq. (3) for all ten experts. As an example, the mathematical model for expert 1 is shown below:

Min, ξ^L

Subject to,

$$
\begin{array}{llll}
|w_{d6} - 7w_{d1}| & \leq \xi^L; & |w_{d1} - 3w_{d7}| & \leq \xi^L; \\
|w_{d6} - 4w_{d2}| & \leq \xi^L; & |w_{d2} - 7w_{d7}| & \leq \xi^L; \\
|w_{d6} - 5w_{d3}| & \leq \xi^L; & |w_{d3} - 6w_{d7}| & \leq \xi^L; \\
|w_{d6} - 9w_{d4}| & \leq \xi^L; & |w_{d4} - 1w_{d7}| & \leq \xi^L; \\
|w_{d6} - 8w_{d5}| & \leq \xi^L; & |w_{d5} - 2w_{d7}| & \leq \xi^L; \\
|w_{d6} - 1w_{d6}| & \leq \xi^L; & |w_{d6} - 9w_{d7}| & \leq \xi^L \\
|w_{d6} - 2w_{d7}| & \leq \xi^L; & |w_{d7} - 8w_{d7}| & \leq \xi^L; \\
|w_{d6} - 6w_{d8}| & \leq \xi^L; & |w_{d8} - 5w_{d7}| & \leq \xi^L; \\
|w_{d6} - 6w_{d9}| & \leq \xi^L; & |w_{d9} - 6w_{d7}| & \leq \xi^L; \\
|w_{d6} - 7w_{d10}| & \leq \xi^L; & |w_{d10} - 3w_{d7}| & \leq \xi^L; \\
|w_{d6} - 5w_{d11}| & \leq \xi^L; & |w_{d11} - 6w_{d7}| & \leq \xi^L; \\
|w_{d6} - 3w_{d12}| & \leq \xi^L; & |w_{d12} - 7w_{d7}| & \leq \xi^L
\end{array}
$$

$$w_{d1} + w_{d2} + w_{d3} + w_{d4} + w_{d5} + w_{d6} + w_{d7} + w_{d8} + w_{d9} + w_{d10} + w_{d11} + w_{d12} = 1$$

$$w_{d1}, w_{d2}, w_{d3}, w_{d4}, w_{d5}, w_{d6}, w_{d7}, w_{d8}, w_{d9}, w_{d10}, w_{d11}, w_{d12} \geq 0$$

The optimal values of weights for the drivers and corresponding values of the objective function for expert 1 are calculated using Excel Solver and shown in Table 7.

Table 7: Optimum weight of the drivers from the opinion of expert 1

Driver	d1	d2	d3	d4	d5	d6	d7	d8	d9	d10	d11	d12	ξ^L
Weight	0.0464	0.0813	0.065	0.0206	0.0406	0.2554	0.1625	0.0542	0.0542	0.0464	0.0650	0.1083	0.0697

For a comprehensive analysis, the optimal weights of the objective function and other drivers for the remaining nine experts have been calculated similarly and presented in Appendix-D in Tables D1, D2, and D3, respectively. Finally, Simple averages of the optimal weights for all the ten experts have been calculated for each driver and tabulated in Table 8.

5. Results and discussion, and Sensitivity analysis

5.1 Results and discussion

The final result of this study is tabulated in Table 8. The value of ξ^L is the objective function of the constructed LP model. The low value of ξ^L equals 0.0656 indicates that the consistency of the comparison system is relatively high, and the obtained results are reliable.

Based on the opinion of experts and then analyzing them through BWM, it has been evident that 'sophisticated infrastructure of information technology' is the leading driver of BDA in the supply chains with the maximum weight of 0.1836. Industries that have incorporated and ensured appropriate use of information technology have been significantly benefited in their organizational activities (Colin et al., 2015). Besides, the adaptation of information technology requires the integration of some other key drivers as well (Bresnahan et al., 2002; Ngai et al., 2011). Thus, the company should distribute high voluminous data among its' stakeholder in a synchronous way to maintain a balanced interlinked information flow throughout the supply chains. However, reliable data processing platforms are also needed to be developed in parallel to analyze structured, semi-structured, and unstructured data of the supply chain database.

Table 8: Optimal Average weightage according to expert's opinion for the BDA drivers

Name of the drivers	Average Weight	Averageξ^L	Final Rank
Data driven innovation (d1)	0.0489		10
Application of social media to manage data (d2)	0.1019		4
Increase connectivity through cloud computing (d3)	0.0548		8
Application of Internet of Things (IoT) (d4)	0.0349		11
Digitization of society (d5)	0.0308		12
Group collaboration among business partners (d6)	0.1392	0.0656	2
Organizational commitment towards the application of BDA (d7)	0.1184		3
Availability of predictive analytics (d8)	0.0598		7
Sophisticated infrastructure of information technology (d9)	0.1836		1
Skilled management team (d10)	0.0502		9
Dynamic analytical capabilities of firms (d11)	0.0787		6
Strategic alignment towards BDA application (d12)	0.0988		5

The second most significant driver is the group 'collaboration among the business partners' of the supply chains with an optimal weight of 0.1392. Higher optimal weight indicates that large data volume alone cannot be solved with technological advancement. Authority, accountability, and above all, mutual trust and respect among the group collaborators are also fastening the process of BDA implementation in the supply chains. Many researchers have already found that the success of group collaboration is interlinked with the accurate and efficient data processing system (Braunscheidel & Suresh, 2009; Cao et al., 2010). Especially, the supply chains of the ongoing decade are so versatile that the top management independently can't analyze the future market pattern and foresee the demands of upcoming products precisely. However, if there is strong coordination prevalent among the members of the supply chain, data integration in the overall supply chain becomes convenient and trustworthy. Consequently, top management can rely on the final database to make the right decision at the right time. So, extending relationships among the group partners is still a good strategic tool for accurate data inspection and effective decision making to improve operational performance. Nevertheless, top management also needs to ensure that the individual stage does not seek its profit maximization rather than creating new opportunities as a whole and adding new values.

The next two significant drivers are 'organizational commitment towards the application of BDA' and 'application of social media' with optimal weights of 0.1184 and 0.1019, respectively. The readiness of the employees to accept the wide use of big data applications is a key indicator of the success of an organization (Shah et al., 2017), and social media or social networking helps the top management to gain insight about the most recent requirements of a product by the customer (Veeramani et al., 2019). These two drivers are followed by 'strategic alignment towards BDA application' and 'dynamic analytical capabilities of firms' having an optimal weight of 0.0988 and 0.0787 each. Although big data has already been established as a paradigm by serving complex data-related solutions in different fields, industry managers should decide its' applicability in a relevant way that reflects the business strategy to fulfill the organization's purpose. On the other hand, continuously changing market patterns of the present era demand the critical thinking ability of the employees to discover new and innovative business ideas. Giving adequate attention to developing analytical ability will result in a quick analogy of a situation, bring a simple solution to complex data problems, and effective decision making. Next, 'availability of predictive analytics' is ranked seventh with an optimal weight of 0.0598. The predictive analysis serves the most when an unprecedented critical event has occurred, and available solutions cannot meet the requirements. The markets of the 20th century are highly unpredictable that often create undiscovered and unexplored data and eventually require sophisticated knowledge to trace them with precision and accuracy. Thus, top management should nurture this skill among its' employees to interpret the novel data and find out the possible outcomes and findings.

'Connectivity through cloud computing' is in the eighth position with an optimal weight of 0.0548. Cloud technology contributes to making the supply chain processes more efficient by minimizing the cost of risks and failures

(Vemula & Zsifkovits, 2016). Cloud computing can be considered a game-changing opportunity for any type of business organization. Industries and firms can make a significant shift by facilitating internet and web-based applications in their operational activities and reduce the costs related to data maintenance. 'Skilled management team' having the optimal weight of 0.204 is in the ninth position amongst the identified drivers. Employers are struggling to maintain labor costs while ensuring an adequate number of skilled employees (Henao et al., 2019). So, achieving skilled manpower is a good opportunity to ensure competitive advantage, especially in uncertain market scenarios (Braunscheidel et al., 2010). The next two significant drivers are 'data-driven innovation' and 'application of internet of things' with optimal weights of 0.0489 and 0.0349, respectively. These two drivers are often found correlated as the internet of things often builds up new pathways for open innovation (Santoro et al., 2018). Therefore, top management should guide IoT to bring product and service-related innovation as an indicator of digital transformation. It is somewhat surprising from the point of view that the digitization of society has been rated as the least important driver on the survey with the optimal weight of 0.0308. However, it also plays a very significant role in optimizing business processes and achieves operational excellence throughout the supply chains Bronson, 2018).

5.2 Sensitivity analysis

Any technique of MCDM often involves data that is not accurate and reliable (Simanaviciene & Ustinovichius, 2010). Therefore, performing sensitivity analysis is often suggested by many researchers while implementing any MCDM technique (Tanino, 1999; Mukhametzyanov & Pamučar, 2018). Sensitivity analysis is a popular assessment tool to determine the variation in the targeted output values based on the change in input parameters and variables of a mathematical model. It can define the rate of change of other variables with the change of one. To perform the sensitivity analysis, we have changed the weights of the top-ranked driver from 0.1 to 0.9, as suggested by some researchers (Yu & Hu, 2010; Somsuk, 2014). The corresponding response of the remaining drivers with the change of weight for the "sophisticated infrastructure of information technology (d9)" is presented in Table 9. It is clearly observed from Fig. 2 that the weights of the other drivers are also changed with the alteration of the weightage of the selected driver. Table 10 and Fig. 3 display the ranking of the selected drivers with the help of sensitivity analysis. It has been found that 'Sophisticated infrastructure of information technology' loses the top spot when it weights equal to 0.1. However, the "digitization of society" always holds the last position irrespective of the variation of weights.

Table 9: Weight of other drivers by changing the value of 'Sophisticated infrastructure of information technology (d9)'

Selected Drivers	Values of preference weights for listed drivers									
	Normal (0.1836)	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
d1	0.0489	0.0539	0.0479	0.0419	0.0360	0.0300	0.0240	0.0180	0.0120	0.0060
d2	0.1019	0.1123	0.0998	0.0874	0.0749	0.0624	0.0499	0.0374	0.0250	0.0125
d3	0.0548	0.0604	0.0537	0.0470	0.0403	0.0335	0.0268	0.0201	0.0134	0.0067
d4	0.0349	0.0385	0.0342	0.0299	0.0257	0.0214	0.0171	0.0128	0.0086	0.0043
d5	0.0308	0.0340	0.0302	0.0264	0.0226	0.0189	0.0151	0.0113	0.0075	0.0038
d6	0.1392	0.1534	0.1364	0.1193	0.1023	0.0852	0.0682	0.0511	0.0341	0.0170
d7	0.1184	0.1306	0.1161	0.1015	0.0870	0.0725	0.0580	0.0435	0.0290	0.0145
d8	0.0598	0.0659	0.0586	0.0512	0.0439	0.0366	0.0293	0.0220	0.0146	0.0073
d9	0.1836	0.1000	0.2000	0.3000	0.4000	0.5000	0.6000	0.7000	0.8000	0.9000
d10	0.0502	0.0553	0.0492	0.0430	0.0369	0.0307	0.0246	0.0184	0.0123	0.0061
d11	0.0787	0.0867	0.0771	0.0675	0.0578	0.0482	0.0386	0.0289	0.0193	0.0096
d12	0.0988	0.1090	0.0969	0.0847	0.0726	0.0605	0.0484	0.0363	0.0242	0.0121
Total	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000

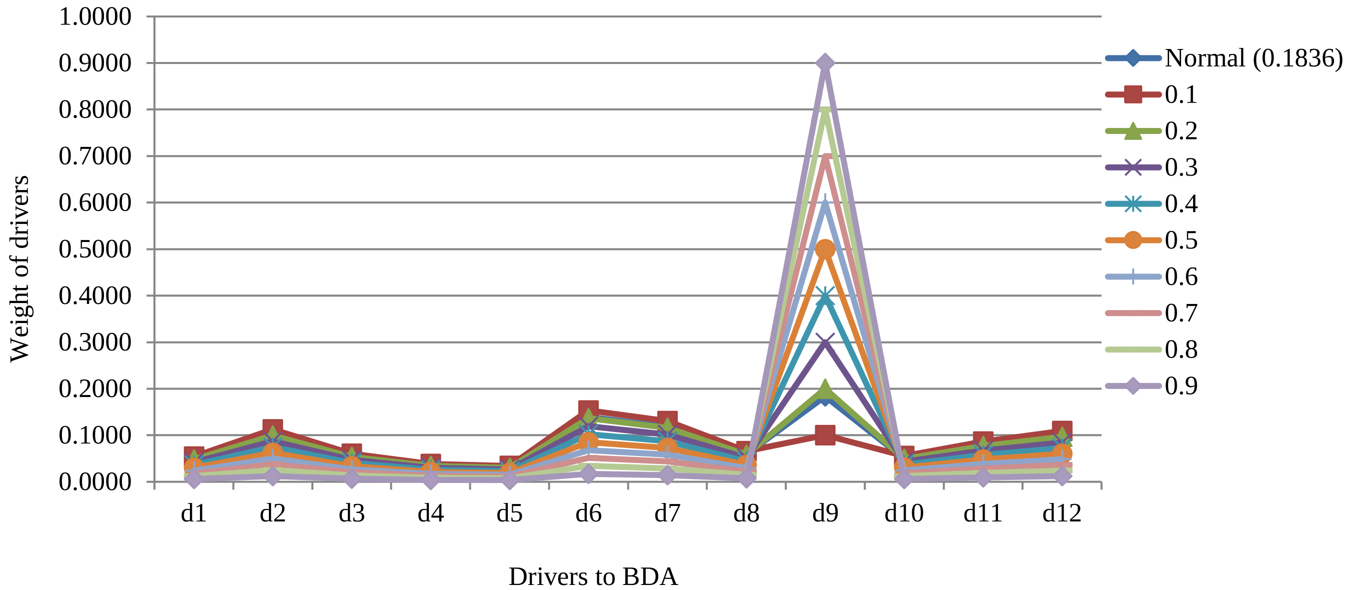

Fig. 2: Weights of different BDA drivers during sensitivity analysis

Table 10: The ranking of the drivers with a change of weights of 'Sophisticated infrastructure of information technology (d9)'

Selected Drivers	Values of preference weights for listed BDA drivers									
	Normal (0.1836)	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
d1	10	10	10	10	10	10	10	10	10	10
d2	4	3	4	4	4	4	4	4	4	4
d3	8	8	8	8	8	8	8	8	8	8
d4	11	11	11	11	11	11	11	11	11	11
d5	12	12	12	12	12	12	12	12	12	12
d6	2	1	2	2	2	2	2	2	2	2
d7	3	2	3	3	3	3	3	3	3	3
d8	7	7	7	7	7	7	7	7	7	7
d9	1	5	1	1	1	1	1	1	1	1
d10	9	9	9	9	9	9	9	9	9	9
d11	6	6	6	6	6	6	6	6	6	6
d12	5	4	5	5	5	5	5	5	5	5

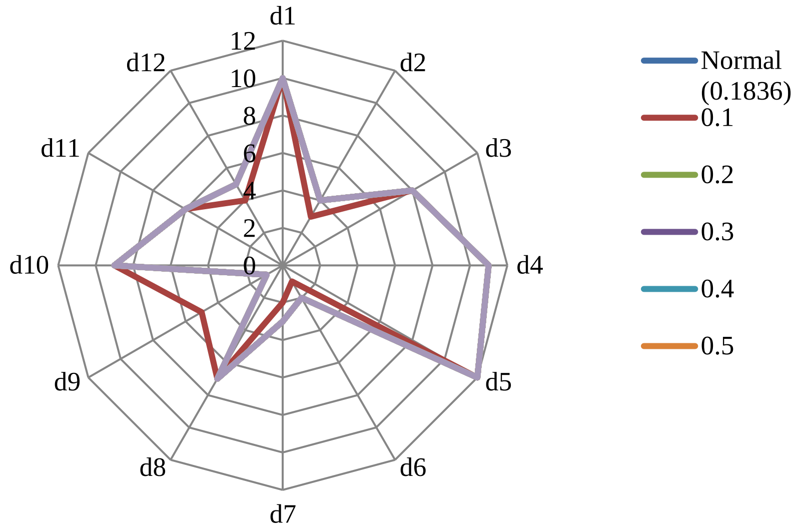

Fig. 3: Ranking of the BDA drivers based on sensitivity analysis

6. Conclusions, managerial implications, and recommendation for future research

6.1 Conclusions

Traditional data management system is found obsolete in most of the cases to address the complex data-related issues of today's supply chains management system (Chehbi-Gamoura et al., 2020). In addition, communication media is improving day by day; lots of data is generating in the form of texts, emotions, and numerical digits, which cannot be processed easily as before. BDA is now supporting the organizations to get rid of data related problems that cannot be dealt with through conventional methods and systems. However, the proper implication of BDA relies on the successful determination of the BDA drivers in the supply chains. This study has proposed an operational framework that successfully identified the most significant BDA drivers of supply chains after a comprehensive literature review and consultation of the experts from different industrial sectors, including academic researchers in the supply chains field. BWM, a recently developed MCDM technique, has been applied to prioritize the drivers according to their optimal weights. This priority-based ranking will assist the industrial managers in choosing and focusing on the most significant driver of big data in their supply chains.

The outcome of this study shows that amongst all the identified drivers, the 'sophisticated infrastructure of information technology' is the most significant driver of BDA with the highest optimal weight. This finding stresses the necessity of building a sophisticated information structure to support the organizational efforts for extracting meaningful information from a massive amount of supply chain data. However, it is also found from this study that the 'group collaboration among the business partners' is also needed along with the 'sophisticated infrastructure of information technology' to gain strategic as well as a tactical advantage from big data. The output also reveals that digitization of society is the least significant BDA driver compared to the other identified drivers in this study.

6.2 Managerial implications

The final framework developed in this study has numerous implications for industrial firms, production factories, and other industries that deal with a massive amount of structured and unstructured data in their regular activities. One key feature of this study is that all the aforementioned steps are simple and straightforward to follow, and it is hoped that top management can easily find out the most and least significant drivers of BDA in their supply chains. Successful identification and then focus the most significant driver of BDA may bring strategical and tactical advantages to achieve competitive advantages in the supply chain field. Some managerial implications of this research are discussed as follows.

- **To build up a sophisticated information technology structure:** It has been found from this study that sophisticated infrastructure of information technology is now providing a leading edge of today's highly clustered data environment. So, managers should ensure energetic information technology building blocks to establish transparent and cross-functional communication among its' constituents.

- **To enhance team-work practices in the supply chains:** Although the success of big data implementation relies on the processing capacity of the enormous volume of data, a cooperative mindset is also found crucial in this study. So, Collaborative culture should be cultivated in a supply chain to overcome the lack of decision-making strategies in the supply chains.
- **To achieve the overall goals of business organizations:** Any industry can utilize the BDA drivers identified in this paper as their tactical weapons to fulfill their future mission and vision. However, long term commitment, as well as alignment of decisions in every stage of the supply chains, is the prerequisite for achieving this. Top management should conduct a survey on a regular basis, including the middle and frontline managers, to justify the credibility of the obtained drivers to ensure continuous improvement in supply chain operations.

6.3 Recommendations for future research

In the future, this study can be extended to find the interdependencies among the identified drivers by applying the Decision Making Trial and Evaluation Laboratory, another popular MCDM technique. Also, the extension of BWM like the multiplicative BWM, Bayesian BWM can be used to assess the drivers for BDA in future studies. Moreover, cross country analysis can be carried out to understand the current practices among different countries. Furthermore, the model can be robust if more drivers can be added for the analysis. Besides, the drivers observed in this paper are considered at a macro level. However, if it has been observed from the micro-level, every driver can be composed of several sub-drivers. Some key drivers, for example, the sophisticated infrastructure of information technology has sub-drivers like complexity, compatibility, and relative advantage over others, which can be added in the model. A detailed analysis of these sub-drivers will provide better insight into the effectiveness of each driver.

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Appendix

Appendix A

Primary Questionnaires

1. Please answer the following queries:

a) Name:

b) Name of the company/institution:

c) Role:

d) Years of experience:

e) Area of specialization:

2. Selection of BDA drivers: Please make a priority list of BDA drivers from the following

No.	BDA driver	Is it important? (Yes/No)	Priority serial
1	Data-driven innovation		
2	Application of social media to manage data		
3	Increase connectivity through cloud computing		
4	Application of Internet of Things (IoT)		
5	Digitization of society		
6	Group collaboration among business partners		
7	Organizational commitment towards the application of BDA		
8	Availability of predictive analytics		
9	Sophisticated infrastructure of information technology		
10	Skilled management team		
11	Dynamic analytical capabilities of firms		
12	Strategic alignment towards BDA application		

Appendix B

Table B1: Scores for the comparative importance between two drivers

Importance Scale	Definition	Explanation
1	Equal importance	Two drivers contribute equally to the objective
2	Somewhat between equal and moderate	Experts slightly favor one driver over another
3	Moderately more important than	
4	Somewhat between moderate and strong	Experts strongly prefer one driver over another based on their experience
5	Strongly more important than	
6	Somewhat between strong and very strong	

Importance Scale	Definition	Explanation
7	Very strongly important than	Strongly favored, the dominance of one driver over another is prevalent in daily practice
8	Somewhat between very strong and important	Experts have strong evidence to prefer one driver over another, a strong degree of affirmation
9	Absolutely more important than	

Appendix C

Secondary Questionnaire

Q.1: Finding the Best and Worst driver from the identified list

Drivers	Best (most significant) drivers	Worst (least significant) drivers
Data-driven innovation (d1)		
Application of social media to manage data (d2)		
Increase connectivity through cloud computing (d3)		
Application of Internet of Things (IoT) (d4)		
Digitization of society (d5)		
Group collaboration among business partners (d6)		
Organizational commitment towards the application of BDA (d7)		
Availability of predictive analytics (d8)		
Sophisticated infrastructure of information technology (d9)		
Skilled management team (d10)		
Dynamic analytical capabilities of firms (d11)		
Strategic alignment towards BDA application (d12)		

Table C1: Best driver preference over other drivers

Please provide your opinion based on Q.1

Q.2 Best driver preference over other drivers

Best to Others	d1	d2	d3	d4	d5	d6	d7	d8	d9	d10	d11	d12
Best driver-												

Table C2: Determination of the other drivers over the worst driver

Q.3: Determination of the other drivers over the worst driver

Others to the Worst	Worst driver-
d1	
d2	
d3	
d4	
d5	
d6	
d7	
d8	
d9	
d10	
d11	
d12	

Appendix D

Table D1: Best driver over the other drivers determined by respondents R2-R10

Respondents	Drivers	d1	d2	d3	d4	d5	d6	d7	d8	d9	d10	d11	d12
R2	Best (d2)	7	1	6	8	9	3	4	6	2	6	5	5
R3	Best (d9)	7	3	6	7	9	2	2	6	1	8	5	4
R4	Best (d6)	6	4	5	9	7	1	3	6	2	8	3	5
R5	Best (d9)	7	4	6	8	9	3	2	7	1	8	5	4
R6	Best (d12)	4	6	9	7	8	4	3	8	2	6	5	1
R7	Best (d9)	6	3	6	8	9	4	2	7	1	5	4	3
R8	Best (d6)	8	2	4	9	7	1	6	2	4	7	5	3
R9	Best (d9)	7	5	9	7	8	3	2	5	1	6	4	6
R10	Best (d9)	7	5	3	8	9	7	5	6	1	4	2	3

Table D2: Other drivers to worst driver determined by respondents R2-R10

Drivers	Respondents								
	R2	R3	R4	R5	R6	R7	R8	R9	R10
	Worst (d5)	Worst (d5)	Worst (d4)	Worst (d5)	Worst (d3)	Worst (d5)	Worst (d4)	Worst (d3)	Worst (d5)
d1	3	4	5	3	7	4	2	5	4
d2	9	7	6	5	7	5	8	4	5
d3	4	5	7	4	1	5	7	1	7
d4	2	3	1	2	4	7	1	3	2
d5	1	1	3	1	2	1	4	2	1
d6	7	6	9	7	6	7	9	7	3
d7	6	8	7	8	7	8	4	8	4
d8	4	5	5	4	3	6	6	5	5
d9	8	9	8	9	8	9	6	9	9
d10	4	2	2	2	3	5	3	4	6
d11	5	6	6	5	5	6	5	6	8
d12	6	7	4	6	9	7	7	3	7

Table D3: Optimal weights of identified drivers for respondents R2-R10

Respondents	Drivers	d1	d2	d3	d4	d5	d6	d7	d8	d9	d10	d11	d12	ξ^L
R2	Weights	0.0458	0.2566	0.0535	0.0401	0.0214	0.1069	0.0802	0.0535	0.1604	0.0535	0.0641	0.0641	0.0641
R3		0.0422	0.0984	0.0492	0.0422	0.0193	0.1477	0.1477	0.0492	0.2343	0.0369	0.0591	0.0738	0.0610
R4		0.0512	0.0769	0.0615	0.0187	0.0439	0.2379	0.1025	0.0512	0.1537	0.0384	0.1025	0.0615	0.0695
R5		0.0457	0.0799	0.0533	0.0400	0.0228	0.1065	0.1598	0.0457	0.2626	0.0400	0.0639	0.0799	0.0571
R6		0.0812	0.0541	0.0188	0.0464	0.0406	0.0812	0.1083	0.0406	0.1624	0.0541	0.0650	0.2472	0.0777
R7		0.0510	0.1020	0.0510	0.0383	0.0166	0.0765	0.1531	0.0437	0.2279	0.0612	0.0765	0.1020	0.0782
R8		0.0360	0.1441	0.0721	0.0188	0.0412	0.2287	0.0480	0.1441	0.0721	0.0412	0.0576	0.0961	0.0595
R9		0.0461	0.0645	0.0218	0.0461	0.0403	0.1075	0.1613	0.0645	0.2596	0.0538	0.0807	0.0538	0.0631
R10		0.0436	0.0610	0.1016	0.0381	0.0214	0.0436	0.0610	0.0508	0.2487	0.0762	0.1524	0.1016	0.0562

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