Improving efficiency and reducing waste for sustainable beef supply chain

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for degree of

Doctor of Philosophy

Norwich Business School

January, 2018

Abstract

In this thesis, novel methodologies were developed to improve the sustainability of beef supply chain by reducing their environmental and physical waste. These methodologies would assist stakeholders of beef supply chain viz. farmers, abattoir, processor, logistics and retailer in identification of the root causes of waste and hotspots of greenhouse emissions and their consequent mitigation. Numerous quantitative and qualitative research methods were used to develop these methodologies such as current reality tree method, big data analytics, interpretive structural modelling, toposis and cloud computing technology. Real data set from social media and interviews of stakeholders of Indian beef supply chain were used.

Numerous issues associated with waste minimisation and reducing carbon footprint of beef supply chain are addressed including: (a) Identification of root causes of waste generated in the beef supply chain using Current Reality Tree method and their consequent mitigation (b) Application of social media data for waste minimisation in beef supply chain. (c) Developing consumer centric beef supply chain by amalgamation of big data technique and interpretive structural modeling (c) Reducing carbon footprint of beef supply chain using Information and Communication Technology (ICT) (d) Developing cloud computing framework for sustainable supplier selection in beef supply chain (e) Updating the existing literature on improving sustainability of beef supply chain.

The efficacy of the proposed methodologies was demonstrated using case studies. These frameworks may play a crucial role to assist the decision makers of all stakeholders of beef supply chain in waste minimization and reducing carbon footprint thereby improving the sustainability of beef supply chain. The proposed methodologies are generic in nature and can be applied to other domains of red meat industry or to any other food supply chain.

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Acknowledgments

I am very grateful to my PhD supervisor, Prof. Nishikant Mishra for his kind guidance, motivation and support throughout my PhD research. His knowledge, experience amalgamated with approachability and trust shown in me really helped me to progress in my research. He was an inspiration for me throughout my studies.

I am thankful to Dr. Homagni Choudhary for his able guidance. I also acknowledge the kind support from my family who keep encouraging me despite the distances. I am also very grateful to my dear friends from SGI-UK.

Finally, I am grateful to my friends in Norwich Business School, University of East Anglia for their help over the years.

CHAPTER 1

Introduction

In this thesis, various methodologies are developed for making beef supply chain more sustainable by reducing their environmental and physical waste. The developed methodologies could be implemented by stakeholders of beef industry viz. farmers, abattoir, processor and retailer for waste minimization (physical and financial) and for mitigating their carbon footprint. The proposed methodology is generic in nature and can be applied to other domains of red meat industry or to any other food supply chain. In current chapter, background information, research motivation, objectives of conducting this research and structure of the thesis are mentioned.

1.1 Background and Motivation

The amount of food discarded worldwide is approximately 1.3 billion tonnes, which is around one third of the total food produced (Save Food, 2015). Food waste in developed nations is around 670 million tonnes and is worth approximately US $ 680 billion (Save Food, 2015). The developing nations are generating roughly 630 million tonnes of food waste whose monetary value is US $ 310 billion (Save Food, 2015). It accounts for exploitation of various resources such as land, water, energy, finance and human workforce. Waste in food supply chain affects all the segments of supply chain from farmer to consumer. Food and Agriculture Organisation of United Nations predicts that even if a quarter of food waste could be saved, it would feed 870 million people globally (Save Food, 2015). It was revealed that one third of the food is lost along the supply chain (Save Food, 2015), which has a direct impact on some of the serious global challenges. The foremost of them is the food scarcity. It is estimated that 795 million people or one in nine people globally are facing the misery of chronic undernourishment (FAO, 2015). The food lost in the supply chain could be avoided to address the issue of global hunger. Food waste also has a monetary impact on all the stakeholders of the supply chain. Global food industries and national economies can remarkably strengthen their financial fortunes by addressing food waste generated in the supply chains. Food waste is usually being overlooked as its financial aspect is often under rated. Multinational firms of food industry generally do not reveal their waste figures pertaining to data sensitivity. There is need to raise awareness among food industry about the alarming consequences of food waste. Minimising waste would raise the financial return to all the segments of food supply chain especially for farmers, who receives the least profit. Food waste also has severe implications on the environment as numerous resources (land, energy and water) are consumed for food production. In most of the nations, it is rendered to landfill, which releases methane, a very strong greenhouse gas thereby contributing to global warming. It was estimated that approximately 4.4 Gt CO_2 equivalent per annum is generated by the food waste (FAO, 2015). These emissions account for 8% of aggregate anthropogenic greenhouse gas emissions (FAO, 2015). If food waste be categorised as a nation, it would be the third largest carbon footprint generating nation on the planet (FAO, 2015). Moreover, emissions generated by food waste are equivalent to that of emissions from road transport globally (FAO, 2015).

Beef is regarded as one of the richest source of protein and is extensively consumed worldwide. Beef products accounts for around 24% of meat production globally (Boucher et al., 2012). It is one of the most resource intensive food product. Livestock production corresponds to 40% of total agricultural GDP and employs 1.3 billion people across the globe (Steinfeld et al., 2006). Almost 70% of total agriculture land worldwide is devoted to livestock production, which is approximately 26% of ice free terrestrial land of earth (Steinfeld et al., 2006). All the stakeholders of beef supply chain viz. farmers, abattoir, processor, logistics, retailers and consumers are responsible for generating waste. It was estimated that 14,572 tonnes of waste is generated in production and distribution stage of the supply chain from farm to retailer (Whitehead et al., 2011). Usually, waste generated at one segment of the supply chain has their root cause in the other segment of the supply chain. For instance, if the beef loses its fresh red colour prior to end of its shelf life, it could be due to deficiency of vitamin E in the diet of cattle in the beef farms (Liu et al, 1995). The distinct segments of beef supply chain are generating numerous kinds of waste. Food retailers have to cope with lots of pressure for waste minimisation in their supply chain in the form of government legislation, sustainable production, market competition from rival brands, etc. In literature, numerous methodologies have been implemented for waste minimisation in the domain of food supply chain such as six sigma (Nabhani & Shokri, 2009), lean principles (Cox, A & Chicksand, 2005), value chain analysis (Taylor, 2006), etc. The maximum amount of waste is being generated at the consumer households. In the UK, 34000 tonnes of beef products are discarded annually by the households, which are worth approximately £260 million and is equivalent of 300 million beef burgers (Smithere, 2016). Retailers are making an attempt for waste minimisation by utilising the consumer complaints made in the retail stores. Most of the consumers doesn't make complaints in the retailer store because of multiple reasons such as inconvenience, time constraint, long distances, ignorance, etc. Hence, retailer stores receive limited information about the issues faced by consumers, which are leading to food waste. Retailers have also made an attempt to get the insight into consumer's issues leading to food waste by various mechanisms like consumer surveys, interviews, etc. However, the amount of information received is very limited. Social media have now become the intrinsic part of people's life to express their opinion. Most of the unhappy consumers post their complaints on social media regularly. It was observed that on an average 45000 tweets regarding beef products were made on daily basis. It comprises of numerous quality attributes and issues associated with beef products such as flavour, tenderness, discoloration, presence of foreign body, etc. There is enormous amount of information freely available on social media, which reflects the true opinion of consumers about the issues resulting to food waste at consumer end. The retailer could use this information to find out the root causes of waste within their supply chain and thereby frame a waste minimisation strategy.

Beef products accounts for 18% of global greenhouse emission, which is higher than that of transport (Steinfeld et al., 2006). The majority of these emissions are caused by deforestation for expansion of pastures and farming of cattle feed crops. The enteric fermentation (occurs in digestive system of cattle, where food is broken down and methane is released) in cattle accounts for 37% of global anthropogenic methane (23 times more global warming potential than CO_2) (Steinfeld et al., 2006). The manure of cattle is responsible for 65% of anthropogenic nitrous dioxide (296 times more global warming potential than CO_2) worldwide (Steinfeld et al., 2006). 64% of ammonia emissions across the world is attributed to livestock production, which is leading to acid rain and making ecosystem more acidic (Steinfeld et al., 2006). Livestock production involves 8% of global water use, primarily for irrigation of feed crops of cattle (Steinfeld et al., 2006). Beef products have the highest carbon footprint among all the agro-products (Food and Agriculture Organization of United Nations, 2013). Usually, the priority of beef industry is to align their products as per the priorities of the consumer, which are high quality (colour, tenderness and flavour), reasonable price, animal welfare and traceability in the supply chain. However, there is rising awareness among the consumers regarding the carbon footprint of all the products they are consuming especially edible products. There is also legislative pressure from government authorities on beef industries to limit emissions in their supply chains. The slaughterhouses and processors are implementing numerous procedures to curb their carbon footprint such as utilising renewable sources of energy for their butchering and boning operations. Nevertheless, 90% of emissions of beef supply chain are occurring at beef farms. There is an obligation to reduce these emissions and integrate it with the supplier selection process of beef cattle by abattoir and processor. There are several methods mentioned in literature to measure carbon footprint generated at farms. It is a sophisticated process for beef farmers to make selection of appropriate carbon emission measuring mechanism and implement it. Carbon calculators are usually very costly. Therefore, it is a challenging procedure for beef farmers to perform record keeping of emissions of their farm. There is need for abattoir and processors to raise the awareness among their beef cattle suppliers and select the most eco-friendly cattle supplier for their business. Apart from beef farmers, other stakeholders of beef supply chain viz. abattoir, processor, logistics and retailer are also generating significant carbon footprint. The major root cause of these emissions is the energy utilised in their premises such as electricity, diesel and the use of fuel in logistics. In the past, measurement of emission at beef industry is being performed at segment level i.e. farmer, abattoir, processor and retailer doing it independently in a segregated way. There is lack of an integrated model for calculating the carbon footprint of the whole beef supply chain and to give feedback to mitigate it.

Keeping the aforementioned issues in mind, the research work performed in this PhD is focused on addressing the lack of work done by academia and beef industry in improving the sustainability of beef supply chain. During this PhD, various issues inhibiting the sustainability of beef supply chain were investigated. The following issues were specifically addressed in this research:

(a) How to use social media data for waste minimisation in beef supply chain.
(b) How to identify root causes of waste in beef supply chain using Current Reality Tree.
(c) How to reduce carbon footprint of beef supply chain using ICT.
(d) How to develop consumer centric beef supply chain.

1.2 Research Objectives

In this research, various methodologies were developed to address the waste and carbon footprint generated in the beef supply chain. During the development of these methodologies, the issues of physical, financial waste and the greenhouse gas emissions generated by beef supply chain and existing techniques to resolve them were systematically examined. The main aim of this thesis is to address research objectives, which are mentioned as following:

(a) To explore the numerous existing methods in improving the sustainability of red meat supply chain.
(b) To develop a methodology for identifying the root causes of waste in the beef supply chain.
(c) To use social media data for identifying root causes of waste at consumer end in beef supply chain and to develop a waste minimisation strategy.
(d) To develop an integrated mechanism to minimise the carbon footprint of whole beef supply chain.
(e) To develop a cloud computing framework for sustainable supplier selection in beef supply chain.
(f) To develop consumer centric beef supply chain by using big data technique and interpretive structural modeling.

1.3 Structure of the Thesis

This thesis consists of seven chapters including the current introduction chapter. The thesis is classified into three broad segments as depicted in figure 1.1. In first segment, physical waste and carbon footprint generated in beef supply chain is described along with methods available in literature to mitigate them. The second segment is composed of various chapters based on improving the sustainability of beef supply chain. These chapters illustrate the application of various state of the art methodologies in waste minimisation and reducing carbon footprint of beef supply chain such as Cloud Computing Technology, Current Reality Tree, Social media data, Interpretive Structural Modeling and Toposis. The third segment of the thesis comprises of conclusions and future work. Grey colour is used to depict the contribution of each chapter. A summary of each chapter of the thesis is described as following:

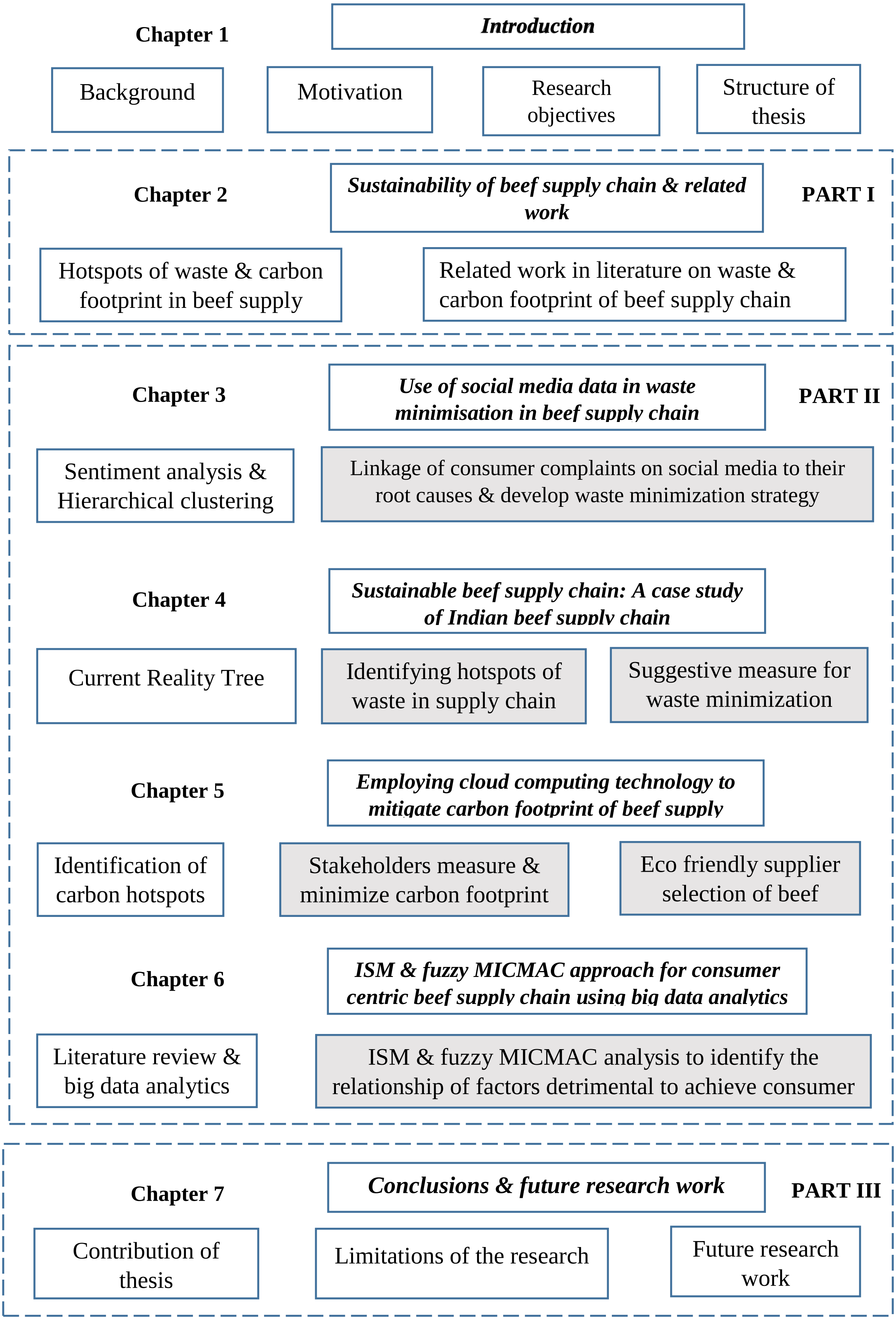

Figure 1.1 Showing structure of PhD thesis

Chapter 2: 'Sustainability of beef supply chain and related work': In this chapter, product flow in beef supply chain, the physical waste and carbon footprint generated in beef supply chain is described. The methods available in literature to improve sustainability of beef supply chain are discussed.

Chapter 3: 'Use of social media data in waste minimisation in beef supply chain': This chapter presents a novel methodology in which Twitter data in the form of consumer complaints is extracted and linked to the root causes of waste at consumer end in the supply chain. Firstly, more than a million tweets associated with beef products have been extracted by utilising various keywords. The positive and negative sentiments of the consumers have been examined by application of text mining using support vector machine and hierarchical clustering with multiscale bootstrap resampling. The major issues raising disappointment among consumers were identified such as discoloration, food safety, bad smell, poor flavour and presence of foreign body. This waste generating issues found at consumer's end was then linked to their respective root causes in the beef supply chain. The methodology described in this chapter would help beef retailers to develop waste minimisation strategy to reduce waste in their supply chain, improve customer satisfaction and hence their financial revenue.

Chapter 4: 'Sustainable food supply chain: A case study on Indian beef industry': In this chapter, the waste related information generated at all segments of beef supply chain viz. farmers, abattoir and processor and retailer end is collected. Thirty interviews were conducted across the whole supply chain. It includes twenty beef farmers, four managers of abattoir and processor, three managers of logistic firm and three managers of the Vietnam based retailer who were working in India. Current Reality Tree method is used to analyse this data and find out the root causes of waste occurring in the whole beef supply chain. The good operation and management practices for waste minimisation in Indian beef supply chain were suggested. These practices will also improve the information exchanged among different stakeholders and enhance the vertical coordination in beef supply chain.

Chapter 5: 'Employing cloud computing technology to address carbon footprint of beef supply chain': In this chapter, Cloud Computing Technology (CCT) based integrated, collaborative and centric system is proposed, where all stakeholders of beef supply chain: farmer, abattoir, processor, logistics and retailer are brought to a single platform. This framework will assist each of them to measure and minimize carbon emissions at their end within minimum expenses and infrastructure. Firstly, carbon hotspots are identified for all segments of beef supply chain. Then, the private cloud developed by retailer maps the whole supply chain. This methodology will help in measuring and minimising the carbon footprint associated with the product flow of beef from farm to retailer. Thereafter, a cloud computing technology based framework is introduced to measure the carbon footprint of beef farms and incorporate it in the supplier selection process by abattoir and processor. It shows how carbon footprint generated in beef farms can be considered along with breed, age, diet, average weight of cattle, conformation, fatness score, traceability and price. TOPSIS method is used to make an optimum trade-off between conventional quality attributes and carbon footprint generated in farms, to select the most appropriate supplier.

Chapter 6: 'Interpretive structural modelling & fuzzy MICMAC approach for customer centric beef supply chain: Application of big data technique': This chapter is focused on making beef supply chain consumer centric by using amalgamation of big data analytics and Interpretive Structural Modelling (ISM). Initially, the variables influencing the consumer's beef products purchasing decisions are identified by using systematic literature review. Then, cluster analysis was performed on the consumer information in the form of big data extracted from Twitter. It helps in determining how the variables determining consumer's purchasing decisions are influenced. Expert's opinions and ISM are used to categorise these variables into: dependent, drivers, independent and linkage variables and to examine their interrelationship. This methodology assists to enforce decree on intricacy of the factors. Recommendations are given to achieve consumer centric beef supply chain.

Chapter 7: 'Conclusions and future research': This chapter consists of discussion and conclusion on the efficacy of the methodologies developed for improving sustainability of beef supply chain. The first segment investigates how the research objectives described in Introduction chapter were accomplished. The second segment presents certain recommendations for extension of the research work described in this thesis.

1.4 Dissemination of Results

The dissemination of the research work mentioned in this thesis has been done via journal and conference publications in the domain of operation and supply chain management. The details of these publications and conferences attended are described as following:

1.4.1 Journal articles

1. Mishra, N., & Singh, A. (2016). Use of twitter data for waste minimisation in beef supply chain. *Annals of Operations Research, 1-23.*

This article introduces a novel methodology in which Twitter data in the form of consumer complaints is extracted and linked to the root causes of waste at consumer end in the supply chain. Further, based on extracted information, waste minimisation strategy is developed. The execution process of proposed framework is demonstrated for beef supply chain.

2. Singh, A., Mishra, N., Ali, S. I., Shukla, N., & Shankar, R. (2015). Cloud computing technology: Reducing carbon footprint in beef supply chain. *International Journal of Production Economics*, *164*, 462-471.

In this article, Cloud Computing Technology (CCT) based integrated, collaborative and centric system is proposed, where all stakeholders of beef supply chain: farmer, abattoir, processor, logistics and retailer are brought to a single platform. This framework will assist them to measure and minimize carbon emissions at their end within minimum expenses and infrastructure.

3. Mishra, N., Singh, A., Rana, N. P., & Dwivedi, Y. K. (2017). Interpretive structural modelling and fuzzy MICMAC approaches for customer centric beef supply chain: application of a big data technique. *Production Planning & Control*, 28(11-12), 945-963.

In this article, consumer centric beef supply chain is developed by utilising amalgamation of systematic literature review, big data analytics and Interpretive Structural Modelling (ISM). This methodology assists in classifying the factors determining consumer's beef purchasing decisions into: dependent, drivers, independent and linkage variables and investigate their inter-relationships.

4. Singh, A., Shukla, N., & Mishra, N. (2017). Social media data analytics to improve supply chain management in food industries. *Transportation Research Part E: Logistics and Transportation Review.*

In this article, supply chain management issues within food industries are identified by utilising support vector machine and hierarchical clustering using multiscale bootstrap resampling. The findings of the study could assist supply chain managers in decision making regarding consumer feedback and concerns within the product flow/ quality of edible food products.

1.4.2 Conference articles

1. Singh, A., Mishra, N. (2014). Waste minimization at abattoir and processor end in beef supply chain, *in Proceedings of 24th International Conference on Flexible Automation and Intelligent Manufacturing (FAIM), Texas, USA 20th-23rd May, 2014.*

This article introduces methodology to identify the root causes of waste occurring at abattoir and processor end in beef supply chain and proposes suggestive measures to address them.

2. Singh, A., Mishra, N. (2015). Waste minimization at retailer end in beef supply chain. *International Interdisciplinary Business- Economics Advancement Conference, Nevada, USA, 26th-29th May, 2015.*

In this article, root causes of waste occurring at retailer end in beef supply chain is identified and corresponding good operation management practices have been recommended to mitigate them.

CHAPTER 2

Sustainability of beef supply chain and related work

2.1 Introduction

The term sustainability is derived from Latin word sustinere (to hold; sub, up). Incorporating sustainability into any process implies that it provides the necessities of current population without impeding the capacity of upcoming generations to fulfil their requirements. Often the three pillars of sustainability taken into account are environmental protection, economic development and social development. They could be mutually reinforcing rather than being mutually exclusive. In the domain of business and management, sustainability is referred as corporate sustainability which infers the synchronization and management of financial, environmental and social demands and issues to reassure accountable, ethical and incessant success. Economic, environmental and social demands are also considered as triple bottom line of corporate sustainability. In conventional corporate world, environmental and societal issues were deemed to be contradicting the financial aspirations. Adopting sustainability principles is associated with gradual returns on investment. However, they have the potential of raising financial dividends once the investment is made. For instance, using renewable sources (solar, wind, etc.) of energy rather than fossil fuels for generating electricity may lead to initial monetary expenditure. However, as the sources of energy (sun, wind, etc.) are freely available, the return on investment would be made in due course. Likewise, the implementation of socially ethical policies may involve initial financial outlay; nevertheless, it would assist in improved public relations, marketing and welfare of human resources.

In this research, environmental demands of beef supply have been considered. It has an impact on both financial (improving revenue by waste minimization) and societal aspect of the supply chain as well; however, they are beyond the scope of this study. This thesis aims to investigate the tools and techniques from the domain of operations and supply chain management to reduce the waste and carbon footprint in beef supply chain thereby reducing its environmental impact.

2.2 Beef supply chain

Beef supply chain consists of various stakeholders such as farmers, abattoirs, processors, retailers and consumers. The schematic diagram of beef supply chain is shown in figure 2.1. In the beef farms, cattle are raised from age of three months to thirty months as per their breed and demand in the market. When cattle reach their finishing age, they are transferred from farms to abattoir and processor using logistics. Then, cattle are slaughtered, boned and cut into primals. The primals are processed into various beef products such as mince, steak, burger, joint, dicer/stirfry, etc. These beef products are sent to retailers by logistics.

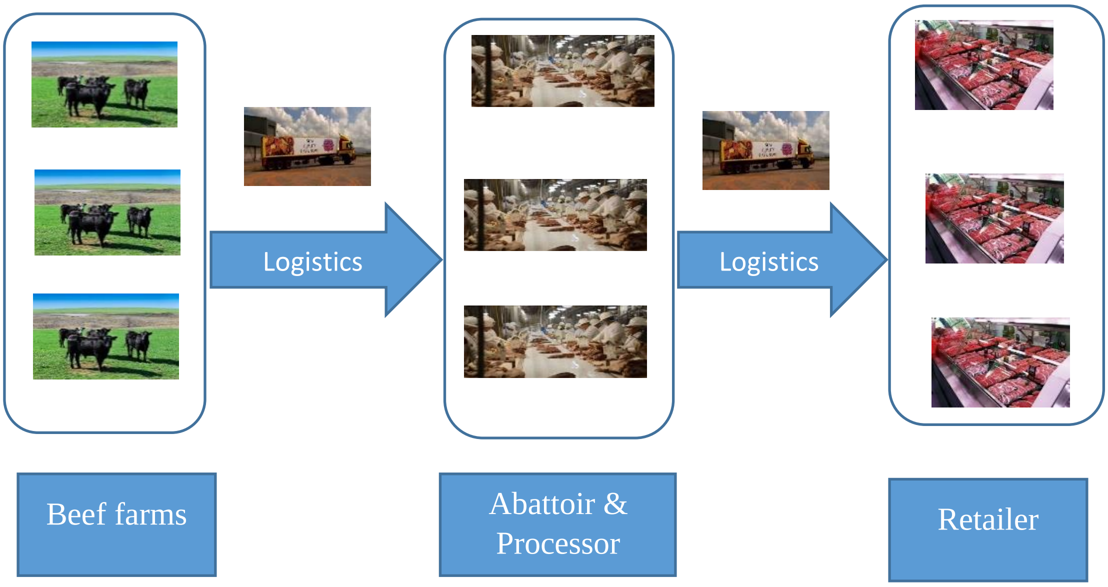

Figure 2.1 Product flow in beef supply chain (Mishra and Singh, 2016)

2.3 Waste in beef supply chain

OECD/Eurostat (2005) have defined waste as, "Those products which are not the principal product for which the manufacturer has no further utilization for their own manufacturing, processing or consuming and which they reject or aspire to reject or is needed to reject. Waste could be created while raw material extraction, their processing to end consumer products, while consumption of these products and while any distinct human occupation."

All the segments of beef supply chain viz. farmers, abattoirs, processors, logistics and retailers are generating waste. Different kinds of waste are generated across the supply chain, which can be classified into two broad categories: Animal byproducts and Product waste. These categories are briefly explained as following:

(1) Animal by-products – The non-edible carcass or secondary products derived from animals are known as Animal byproducts. They can be further divided into three subcategories as mentioned below:

   (a) Category 1 (High risk by-products) – The disposal of these byproducts is done either by incinerating or by processing in a government approved plant. They comprises of Specified Risk Material (SRM) such as spinal cord, brain, etc. Category 1 animal byproducts accounts for almost, 12.1% of aggregate live weight of the cattle (Whitehead et al., 2011).

   (b) Category 2 (medium risk by-products) – The disposal of these byproducts is done either by composting or by utilizing them in biogas production. These byproducts consist of digestive tract, blood and deceased animals. The Category 2 animal byproducts accounts for 1.9% of aggregate live weight of cattle (Whitehead et al., 2011).

   (c) Category 3 (Low risk material) – These byproducts are used for various purposes such as manufacturing of pet food, chemical fertilizer, oleo chemical, etc. The category 3 animal byproducts contribute to 19.2% of total live weight of cattle (Whitehead et al, 2011).

(2) Product waste – The loss of edible meat in the process of product flow along the beef supply chain is known as Product waste (Lundie et al, 2005; Papargyropoulou et al., 2014). It is not considered fit for human consumption and is rendered as animal byproducts. The product waste is the most crucial aspect in this thesis.

Products waste has an association with animal byproducts. Human error and inefficient management practices across the beef supply chain lead to the generation of product waste.

It is treated like animal byproducts based on the hazards associated with it. For example, during butchery and boning operations, meat dropped on floor is product waste and is rendered as category 3 waste. However, it could be disposed as category 2 waste if level of contamination is high. Product waste is being generated by all segments of beef supply chain: farmers, abattoirs, processors, logistics and retailers. These sources are described as following:

2.3.1 Farm

There are various factors at farm end, which lead to waste immediately or at the later end in the beef supply chain. These factors are described as following:

1. Deficiency of vitamin E – If the cattle are raised on grain based diet or mixed diet, they suffer from the deficiency of Vitamin E (Mishra and Singh, 2016). The meat derived from them have considerably shorter shelf life. This issue could be addressed by raising the cattle on fresh grass.

2. Inefficient cattle management – Lack of efficient cattle management procedures followed in the beef farms lead to cattle not meeting the weight and conformation specifications of the retailer and therefore gets rejected (Mishra and Singh, 2016).

3. Lack of animal welfare – If proper animal welfare framework is not being followed, cattle is more prone to get infection or to become physically injured. Abattoir and processor might reject these kinds of cattle (Miranda-De La Lama et al., 2014).

2.3.2 Abattoir and Processor

The product waste is generated at abattoir and processor end primarily because of inefficient butchering and boning operations. The root causes of waste occurring at this end of supply chain are mentioned as following:

1. Over trimming of primals – Considerable amount of edible beef is lost because of over trimming of primals performed by staff of abattoir and processor (Francis et al., 2008).

2. Machine waste – If periodic maintenance of machine is not done then their probability of breaking down while in operation is quite high, which leads to stopping of entire line and beef products stuck in the machine are discarded (Mishra and Singh, 2016).

3. Floor waste - The incompetent and inefficient butchering and boning operations leads to beef products falling on floor, which are not fit for human consumption and hence discarded as animal byproducts (Mena et al., 2014).

4. Takt time – If the butchering and boning operations are not performed at the pace of takt time calculated as per the forecasted demand of retailer then excess of beef products could be produced, which are left unsold (Francis et al., 2008). If less beef products are produced as per the demand of retailer, then it leads to financial waste for abattoir and processor.

5. Misbalancing of line - If proper line balancing procedures are not being followed, it creates bottleneck in butchery and boning operations and they consequently gets slowed down (Francis et al., 2008).

6. Over maturation of carcass – If carcass is matured more than the required amount of time then the shelf life derived from is quite shorter. It could be addressed by making sure that optimum amount of maturation is done based on the age, gender and breed of the cattle (Mishra and Singh, 2016).

7. Poor ergonomics – The efficiency of staff of abattoir and processor goes below the mark because of lack of periodic changeover of set of knives used or if they are performing against gravity (Francis et al., 2008). These issues could be mitigated by providing proper training to the staff and doing their regular inspection.

8. Over contact with metal blades - Some of the beef products are rejected in metal detection test if there was too much of contact with metallic blades (Mena et al., 2014). This process normally occurs in the production line of mince. Therefore, extra precaution needs to be taken so that beef products are not unnecessarily touching metallic blades.

9. Contamination and temperature abuse – Beef products gets contaminated if it is not washed appropriately or proper packaging is not done (Mena et al., 2014). If they are exposed to temperature abuse, it leads to microbial activity in the meat and hence they are discarded.

2.3.3 Retailer

Waste at retailer end is generated because of various reasons. Some of major reasons is lack of coordination between abattoir, processor and retailer, inaccurate forecasting of demand of the consumers, etc. The root causes of waste at Retailer end is mentioned as following:

1. Lack of coordination – If there is lack of vertical coordination between abattoir and processor and retailer then it leads to over or under delivery of beef products to the retailer as compared to the actual order (Halloran et al., 2014). The over delivery is often sent back by reverse logistics and crucial part of the shelf life of beef product is lost in this process. The under delivery creates financial waste for abattoir and processor.

2. Inaccurate forecasting - The inaccurate forecasting of the demand of consumers leads to over production of beef products, which remains unsold and therefore rendered as animal byproducts (Mena et al., 2011).

3. Inefficient cold chain management – The inefficient cold chain management at the retailer end leads to temperature abuse of beef products, which becomes inedible and is therefore discarded (Mena et al., 2011).

4. Inflation of orders – Some retailers offers excess of beef products to keep their shelf full of products irrespective of the forecasted demand of consumers (Mena et al., 2011). The excess products ordered are often left unsold and therefore goes waste.

5. Promotions – Lack of promotions management strategy by a retailer leads to cannibalization of products i.e. certain product is over sold at the expense of similar product thereby creating waste (Mena et al., 2011).

6. Stacking and shelving procedures – Lack of stacking and shelving procedures followed at retailer stores leads to beef products going past their shelf life and remaining unsold thereby creating waste (Mena et al., 2011).

7. Human resources – A dedicated management staff should be recruited which would map the entire operations of retailer starting from its distribution centers to their retail stores (Mena et al., 2011). They will identify the hotspots of waste and develop the efficient waste minimization strategy and implement it to mitigate the avoidable waste at retailer's end.

8. Packaging – Using conventional packaging such as Modified Atmosphere Packaging (MAP), which provides shorter shelf life (approximately 8-10 days), creates high probability of product remaining unsold and therefore getting waste. Modern technology in packaging like Vacuum Skin Packaging (VSP) should be used which provides longer shelf life (upto 21 days) (Meat Promotion Wales, (2012).

2.3.4 Logistics

There are numerous reasons for generation of waste at logistics end. The most important reason is the failure of cold chain management. The root causes of waste occurring at logistics are described as following:

1. Failure of cold chain management – The failure of cold chain management in logistics vehicle leads to temperature abuse of beef products and therefore they are discarded and rendered to waste (Francis et al., 2008).

2. Delayed delivery – Delayed delivery of beef products from abattoir and processor to retailer leads to shorter shelf life of beef products available on shelves of retailer's stores (Soysal et al., 2014). Often, the retailer rejects the beef products

with shorter shelf life and they are sent back to abattoir and processor. Considerable amount of reduced shelf life of these products is lost in logistics and most probably they surpass their shelf life without being consumed.

3. Inappropriate stacking – The beef products are damaged if beef products are not stacked properly in a logistics vehicle. Therefore, strong provision must be made for precise stacking of the beef products.

4. Injury/stress to cattle – Cattle might get injured or stressed during their journey from farms to abattoir and processor. Therefore, care must be taken so that number of cattle present in a vehicle, space allowance and journey time follows the guidelines prescribed by the government (Singh et al., 2015).

5. Utilization of cheaper channel – Some logistics firms carry extra load to make more profit, raising the probability of beef products getting damaged. Some firms also follow relatively longer routes, which leads to shorter shelf life of beef products delivered to retailer (Soysal et al., 2014).

2.4 Carbon footprint in beef supply chain

The greenhouse gas emissions are being generated by all stakeholders of beef supply chain viz. famers, abattoirs, processors, logistics and retailers. The carbon hotspots of all segments of beef supply chain are described in following subsections.

2.4.1 Farm

Maximum amount of greenhouse gases in beef supply chain are generated in the beef farms (EBLEX, 2012). The major root causes of the carbon emissions at beef farms is enteric fermentation and manure. The carbon hotspots at beef farms are described as following:

1. Enteric Fermentation – Enteric fermentation is one of the highest factors contributing to the carbon footprint of beef supply chain (Singh et al., 2015). This process is part of digestive system of cattle where they transform their feed intake into methane and release it in their ambient environment. Methane is very potent greenhouse gas. Its global warming potential is twenty-five times more than carbon

dioxide. The amount of methane released varies with the breed of the cattle. For instance, the digestive system of dairy cow generates more methane than bull beef.

2. Manure – The cattle of manure also significantly adds to the carbon footprint of the beef farms. It releases numerous hazardous greenhouse gases such as nitrous oxide, methane, ammonia and different oxides of nitrogen (Singh et al., 2015). Hence, carbon footprint of beef farms could be reduced by significant manure handling.

3. Fertilizers – The fertilizers used for the crops for feed of cattle and application of fertilizer on the grassland leads to the emission of different greenhouse gases primarily nitrous oxide. The global warming potential of nitrous oxide is two-hundred-ninety-eight times more than carbon dioxide (Forsteretal, 2007). An optimum rate of application of fertilizer (in Kg./Ha. of grassland) should be followed. There is need to raise awareness among the farmers growing feed for the cattle about the associated hazards of the excess application of fertilizers. The meat derived from the cattle could also be affected by the high dose of fertilizers.

4. Use of Energy – The greenhouse gases are also generated by the energy (diesel, electricity, etc.) used both in the beef farms and the farms used for growing feed of the cattle (Singh et al., 2015). The carbon footprint generated by use of energy is very less as compared to the carbon hotspots mentioned earlier. There is variation in the amount of emissions generated depending on the source of energy used. For instance, electricity has lower carbon footprint than the fossil fuels such as diesel, etc.

2.4.2 Logistics

The logistics employed in beef supply chain are sophisticated in nature. It should consider various factors such as vehicle should be temperature sensitive, restriction on the maximum journey carrying cattle and the maximum cattle allowed in a vehicle, etc. There are various sources of direct and indirect emissions in the logistics and the most significant of them is the greenhouse gases released from the exhaust of the vehicles carrying cattle or beef products. The carbon hotspots of logistics are described as following:

1. Distance – The carbon emissions by logistics has a positive correlation with the distance travelled by them. The beef farmers should follow government legislation in terms of maximum journey time allowed for transporting cattle. For instance, it is mandatory in UK to give a rest of one hour after a journey of 14 hours (DEFRA, UK, 2014).

2. Number of cattle – Maximum of number of cattle transported in a vehicle should abide by the space allowance described in the government legislations (DEFRA, UK, 2014). The space allowance varies with the weight of the cattle and if it is not followed, cattle will get stressed and it will have a negative impact on quality of meat and its shelf life.

3. Temperature sensitive vehicle – The ambient temperature guidelines by government bodies needs to be followed by the logistics firms. For instance, the temperature should not be below zero degree Celsius while transporting cattle in UK (Singh et al., 2015). Higher carbon emissions are generated in logistics of beef supply chain as a stable temperature needs to be maintained in logistics vehicle. Hence, the best quality catalytic converter needs to be used in the vehicle to reduce the emission of greenhouse gases.

4. Load optimization – Inefficient load optimization procedures leads to the deployment of extra logistic vehicles (Singh et al., 2015). These issues need to be addressed so that minimum number of logistics vehicles are used for transport of beef products.

5. Means of transport - The means of transport should be wisely chosen by considering the carbon footprint generated by them (Singh et al., 2015). For instance, rail freight could be deployed if possible instead of lorries as most of them run on electricity thereby generating less carbon footprint.

6. Alternative fuel - Burning of fuels generate lots of greenhouse gases. It could be reduced by using ecofriendly fuel options such as biodiesel or the mixture of petrol and ethanol (Singh et al., 2015).

2.4.3 Abattoir and Processor

The energy used at the premises of abattoir and processor contributes to most of carbon footprint generated by them. However, the animal byproducts produced in the processing of carcass also leads to emission of greenhouse gases. The carbon hotspots at abattoir and processor are described as following:

1. Energy – There is huge amount of consumption of energy by abattoir and processor to perform their operations which generates lot of carbon footprint. Hence, renewable sources of energy (solar, wind, hydroelectric, etc.) should be given priority to address this issue (Singh et al., 2015).

2. Animal byproducts – When the animal byproducts produced in the butchering and boning operations are disposed to landfill, it releases methane (Singh et al., 2015). These byproducts could be utilized in composting or for generation of biogas thereby reducing emission of greenhouse gases.

3. Packaging – The packaging of beef products is produced by consumption of huge resources, which produces considerable amount of emissions (Singh et al., 2015). The packaging material used could be blend with the recycled content. The green operations like reusing and recycling could be performed on bigger packaging materials like pallets and trays.

4. Forecasting – Incorrect forecasting of demand by abattoir and processor leads to the overproduction of beef products, which generates greenhouse gases (Singh et al., 2015). It could be addressed by utilizing modern forecasting techniques and dedicated human resources liaising with retailers.

5. Maturation of carcass – Maturation of hindquarter of cattle is done after the slaughtering of cattle. In this process, carcass is kept in a temperature of one degree Celsius from seven to twenty-one days depending on its age, breed and gender of cattle (Singh et al., 2015). Appropriate measures must be taken so that carcass are not over matured as huge amount of resources are exploited for maintaining freezing temperature

2.4.4 Retailer

The prime sources of greenhouse gas emissions are the energy consumed at their premises and inefficient management leading to beef products going to waste. The carbon hotspots at retailer end are described as following:

1. Energy- There is lot of consumption of energy by retailer in their operations such as refrigeration, air condition, lighting, etc. Use of renewable sources of energy should be preferred to mitigate this issue (Singh et al., 2015).

2. Forecasting – Inefficient forecasting of demand of beef products by retailers lead to beef products going to waste thereby considering avoidable carbon footprint (Singh et al., 2015). The transportation of the unsold beef products to anaerobic digestion plants and to landfill generates more carbon emissions. Hence, modern forecasting methods should be followed which consider the factors such as weather, promotions, etc.

3. Lack of coordination – Lack of coordination between retailer and abattoir and processor leads to extra beef products being delivered to retailer (Singh et al., 2015). These products are sent back to abattoir and processor using reverse logistics thereby generating carbon footprint. Moreover, considerable amount of shelf life of beef products is lost in reverse logistics. Hence, the probability of these beef products getting discarded is quite high.

4. Skilled labour - Mishandling of beef products by staff of retailers lead to damage of beef products (Singh et al., 2015). Lack of stacking and shelving procedures followed by retailer's staff also leads to expiry of shelf life of beef products, which goes to waste.

2.5 Related work

There is scarcity of research work done in the domain of beef supply chain. Therefore, the scope of related work in this thesis has been increased to red meat supply chains. The pork and lamb supply chains are facing the similar issues in terms of implementing sustainability practices to mitigate physical waste and their carbon footprint. Therefore, exploring the research work done in the broad category of red meat supply chains assisted in identifying the critical gap in the literature, which is being addressed in this thesis. Although, the frameworks proposed in this thesis are focused on beef supply chains, they are applicable on lamb and pork supply chains as well. The literature available on red meat supply chains is focused on various issues, which are vertical coordination, traceability, meat safety, waste minimization and reducing carbon footprint of red meat supply chains. These categories are described as following:

2.5.1 Vertical coordination in red meat supply chain

Strong vertical coordination in red meat supply chains represents transparency in flow of information, products and finance among all stakeholders of supply chain. It is key for their survival to deliver sustainable high quality products in today's competitive market. Strong vertical coordination improves the resilience of the supply chain towards internal and external disruptions. It is indispensable for achieving traceability of red meat products, which is gaining more prominence since the outbreak of horsemeat scandal in 2013 in United Kingdom. Usually, farmers receive the least share of profit among stakeholders of red meat products and they suffer the most from external disruptions like bullwhip effect. A strong vertical coordination in the supply chain would result in fair distribution of risks and profits among all the stakeholders of supply chain.

A considerable body of research is available on the vertical coordination of red meat supply chain in the literature. Hobbs (1996) has analyzed the procurement of beef by British retailers. Examining the hypothesis that transaction costs incurred in various supply relationships in terms of quality, traceability and animal welfare issues, impacts the selection of beef supplier by a retailer was crucial in this research. This study was conducted by the postal survey of various retailers in the UK. It was concluded that a strong vertical coordination in beef supply chain by having strategic alliance partnership among retailers, processors and farmers can reduce the transactional costs involved at various stage of the supply chain. Mulrony et al., (2005) have analyzed the strategic alliances in the US beef industry and their impact on the vertical coordination practices in beef supply chain. This study was performed by a survey of US strategic alliances, which was predominantly focused on contractual requirements, structure of organization, nature of participant's involvement, strategies of information sharing and marketing and services offered to alliance participants. The results showed that although these alliances differ in size, marketing strategy, organizational set up etc., they all have a common goal of adding value to the beef products and producing more consumer desired beef products.

Perez et al., (2009) has identified the major factors affecting the quality of pork products with respect to the demand of consumers. This study was conducted by a structured literature review of 230 publications, which included journal articles, book chapters in the domain of pork supply chain. It was revealed that only with a strong vertical coordination among all the stakeholders of pork supply chain, high quality pork products could be obtained which can meet the fluctuating demand of the consumers. Hueth & Lawrence (2006) have analyzed organizational behavior in US beef industry to overcome barriers for efficient information flow among all stakeholders. The qualitative assessment of Chariton valley beef alliance was performed. Sources of failure of vertical coordination in beef supply chain of US were identified and their mitigation strategies were briefly described. Palmer (1996) has evaluated the initiatives taken to motivate beef farmers to form alliances with other stakeholders of beef supply chain. The barriers to achieve this type of alliance were identified. Introduction of value based marketing/ processing could help to achieve effective alliance among farmers and processors.

Ward & Stevens, (2000) have determined the impact on vertical coordination in beef supply chain on price linkages throughout the supply chain. Mathematical modeling has been used for analysis. It was found out that price linkages have the potential to boost the market performance within the supply chain. Hornibrook et al., (2003) have investigated the potential of using vertical coordination strategy by foodservice supplier to manage perceived risk associated with fresh beef for catering customers. Results of a case study have been used for analysis. It was found out that stronger vertical coordination strategy has been successful to manage perceived risk among the customers. Lawrence et al., (2001) has identified the transformation in livestock procurement and practices associated with beef and pork merchandising. Marketing contracts and vertical integration among the whole supply chain has increased rapidly in procurement of pigs as compared to procurement of cattle. This transformation was observed by conducting a survey among packers and producers of beef and pork industry. The major reason behind this transformation was assurance of consistent high quality products meeting customer requirements and specifications. Han et al., (2011) have determined inter firm exchange relationships and quality management in China. Survey was conducted in Jiangsu, Shandong and Shanghai municipality in eastern China. A positive relation was found out between close vertical coordination and quality management.

2.5.2 Traceability in red meat supply chain

Traceability in red meat products refers to providing specific information, which assists in tracing these products back to the farms where the animals (from which meat was derived) were raised. Some retailers do robust traceability, which can trace the red meat products back to the specific animal they are derived from, the diet fed to it, its breed, gender, date and venue of slaughter, etc. A strong vertical coordination is a pre-requisite to achieve traceability in the red meat supply chains. Initially, it came into existence in the UK since the outbreak of Bovine Spongiform Encephalopathy (BSE) crisis in 1986. However, the horsemeat scandal in the Tesco leads to the vital acceptance of traceability procedures in British red meat industry. It is gradually becoming integral part of the British red meat supply chains due to government legislation and consumer preferences. The traceability provides the quality assurance (of the farm practices) to consumers and simultaneously provides opportunities to red meat industry to charge premium price to consumers. Hence, it is win-win situation for both consumers and stakeholders of red meat supply chain.

Shanahan et al., (2009) have described the current procedures followed in Ireland for accomplishing traceability of beef. These procedures are in compliance with the European Union laws and global standards. The main hurdle in keeping the traceability of cattle is the herd-keepers, because they are not liable to keep current records of status of their herds electronically. It has been proposed to employ the biometric techniques like retinal scanning to be more precise in maintaining the traceability of cattle. This study has briefly explained the method to convert the animal identification number in ISO 11784 compliant format to EPC (Electronic Product Code), which will help in storing and transferring the traceability information more conveniently. Crandall et al., (2013) have explained the significance of traceability of beef for all stakeholders viz. producers, processors, retailers, consumers and government agencies. The main advantages associated with traceability of beef were food safety, addressing animal diseases issues and the premium derived from these high-quality products. This study has particularly looked at the need for traceability in the USA and the main barriers to accomplish it. This study suggested that although the technology exists to trace a trim of meat back to the animal, it is feasible only at a very small scale, where processing is done by ‘carcass by carcass.’ In big industries, the traceability can only go back to the bunch of animals processed in a particular day. Mora & Menozzi (2005) has studied the structure of beef supply chain in Italy after the BSE crisis. The consequences of European regulations (EC) 1760/2000 and 1850/2000 on the reorganization of beef supply chain in Italy were discussed. This research was carried out with the case of COOP Italia, which is the most large-scale retailer in Italy. It revealed that enforcement mechanisms helped in reducing the opportunist behavior of stakeholders in supply chain and therefore increases the transparency, trust and high quality product.

Banterle & Stranieri (2008) has examined the significance of voluntary traceability regulation by EU (Regulation 1760/2000) to producers and consumers of meat especially beef. This study was carried out by conducting a survey on Italian meat organizations, which signed voluntary regulation and on a sample of 1025 Italian consumers. It was found out that improved traceability distributes the liability among all stakeholders of supply chain and improves the coordination among them. Consumers were found to be interested in meat labeling information like meat origin, cattle breed and feed, slaughtering date etc. Steiner & Yang (2010) have analyzed the value of beef labeling among consumers of Canada and US after 2003 BSE crisis. Consumer’s responses were collected by a survey. It was found out that consumers of Canada want beef to be tested for BSE whereas US consumers want steaks to be produced without genetically modified organisms. Lusk and Fox (2002) have estimated the value of policies that would mandate beef labeling from cattle raised through genetically modified corn and growth hormones. Mathematical modeling has been used for their analysis. It was found out that consumers were willing to pay 17% and 10.6% higher for mandatory labeling of beef raised through growth hormones and genetically modified corn.

2.5.3 Meat safety

Consumption of red meat products is associated with various kinds of illness if appropriate food safety procedures are not followed in their production. The digestive tract of ruminants consists of pathogenic microorganisms, which could lead to foodborne illness in humans. The pathogen is left on the hides and fleeces of ruminants during the process of excretion and could lead to bacterial contamination if appropriate health and safety procedures are not implemented in the process of butchering and boning. Therefore, visible cleanliness of live ruminants is considered to be one of critical control point for meat safety.

Brown et al., (2002) have discussed various issues associated with food safety of beef in China. They have explained the reasons for dominance of household slaughterhouse and wet markets in China. The negative social, economic, cultural implications associated with strict food safety regulations were identified. The eagerness and buying power of Chinese consumers towards high cost associated with food safety regulations were explored. Finally, the feasibility of framing policies for modernizing Chinese beef supply chains was critically reviewed. Polkinghorne et al., (2008) have investigated the potential of applying Meat Standards Australia (MSA) eating grade quality policies on beef retailing. Mathematical modeling has been used for analysis. It was revealed that consumer focus delivered by MSA could be implemented in real time beef retailing.

Jayasinghe Mudalige (2006) have determined the economic incentive for red meat and poultry firms to adopt food safety controls. Mathematical modeling has been used for analysis. It was found out that private incentives (market based) have more impact on food safety responsiveness than government regulatory actions. Hornibrook et al., (2005) have made an attempt to understand risk associated with pre-packed beef in Ireland. Survey and face-to-face interview are being used for analysis. It was found out that food safety and health are still main cause of concern in pre-packed beef consumers. Investment by retailers in their supply chain policies and strategies has played a crucial role to reduce perception of risk in consumers. Den Ouden et al., (1997) have analyzed the pig welfare perception of both consumers and pig welfare experts. The crucial stages for pig welfare were identified and the increase in price (22% to 30%) was noticed when all pig welfare attributes are included in production-marketing chains.

2.5.4 Waste minimization in red meat supply chain

Food waste is occurring at different stages of the supply chain from farms to the retailer. Various techniques have been employed in the past to address this issue by identifying the root causes of food waste and consequently mitigating them such as lean principles (Cox & Chicksand, 2005), value chain analysis (Taylor, 2006), six sigma (Nabhani & Shokri, 2009), and just in time principle. Simons et al., (2005) have applied the lean approach to the cutting room of red meat industry. This research consists of five case studies: involving two traditional and three advanced cutting rooms. A productivity gap of around 25% was observed between advanced and traditional cutting rooms because of application of lean procedures like Takt time and work standardization in advanced cutting rooms. Zokaei & Simons, (2006) has highlighted the advantages of application of lean techniques throughout the red meat supply chain in UK. The major aspects of lean techniques considered were Takt time and work standardization. These techniques were applied to eight value chains of red meat in UK. Results obtained showed that there is potential of 2-3% saving for all stakeholders of red meat supply chain viz. farmer, slaughterhouse, processor and retailer.

Cicatiello et al., (2016) have explored the waste occurring at retailer end and its environmental, economic and social implications. The data collected from an Italian supermarket project was utilized to develop food waste recovery strategy. In this research, both physical and monetary value of food was considered. Mena et al., (2011) have found out the principal causes leading to food waste in the supplier retailer interface. The management practices of UK and Spain have been compared using current reality tree method. Various good practices such as efficient forecasting, shelf life management, promotion management, cold chain management and proper training to employees, etc. have been suggested to mitigate the root causes of waste. Katajajuuri et al., (2014) has quantified the amount of avoidable waste occurring in the food production and consumption chain in Finland. It was found that households were creating 130 million Kg of food waste per year. The waste occurring in food service sector is about 75 to 85 million kg per year. The whole food industry in Finland was producing waste of 75-140 million kg per annum. It was concluded that overall 335-460 million kg of waste is generated in the Finnish food chain (excluding farming sector).

Francis et al., (2008) have employed value chain analysis technique to evaluate UK beef sector. Waste elimination strategy was developed at producer and processor level in UK beef supply chain by comparing them with Argentine counterparts. Also, good management practices are proposed to minimise the waste. Cox et al., (2007) has investigated the scope of application of lean techniques on lamb, pig and beef supply chains in UK. They have conducted an action research on above mentioned supply chains by interviewing various participants from farm to consumers at each stage of supply chain. Their research revealed that application of lean techniques is more sophisticated on beef and lamb as compared to pork. The participants of pork supply chain who followed lean techniques observed that commercial returns were not as high as expected. Simons & Taylor (2007) have used Food Value Chain Analysis (FVCA) on value added pork for a retailer to improve the product flow and reduce waste in their supply chain. System theory has been used in their analysis of FVCA on four subsystems of an organization, which are goal and values, human resources, logistics and management structure. The results obtained gave a positive indication of the potential of benefits in terms of logistics along the pork supply chain. Simultaneously, they identified two issues in implementation which are intercompany alignment of other subsystems apart from logistics and supply chain organizational stability through time.

Taylor (2006) has shown the opportunities for strategic modifications in UK agri food supply chains by using value chain analysis method. They have proposed a primitive model of integrated supply chain using lean principles. This research was built on the case study of two pork supply chains. Eventually, they highlighted the benefits of the integrated supply chain for agri food products. Perez et al., (2010) has investigated the performance of Catalan pork sector in terms of adoption of lean principles. The methods used for their research were multiple case studies and interviews along the whole Catalan pork supply chain from farm gate to consumers. It was found out that the Catalan pork sector has been actively utilizing productive techniques of lean principles especially demand management. De Steur et al., (2016) have demonstrated the application of value stream mapping in identifying the root causes of food waste, their mitigation and in retaining the nutritional value of food products throughout the supply chain. A systematic literature review of 24 research articles focused on reducing waste in the various stages of supply chain (production, processing, storage, retail, food service and consumption was performed. The findings of the study were discarding of food products and the losses of nutrients predominantly at the premises of processor were the major contributor of food waste. It was concluded that lead time is the most appropriate performance indicator among these studies.

Sgarbossa and Russo, (2017) presented a platform for creating closed loop supply chain models, enhancing their scale to retrieve resource value from waste by-products (such as unavoidable waste). Their framework was demonstrated by case study on meat supply chain utilising the waste generated as a form of resource thereby preventing their disposal to landfill. The resource recovery activities proposed in this study has facilitated a channel to accommodate the waste generated as a resource within the supply chain activities to accomplish an efficient supply chain.

The majority of waste in beef supply chain is generated at the consumer end. Waste is generated by various issues such as discolouration of beef products prior to expiry of shelf life (Jeyamkondan & Holley, 2000), lack of tenderness (Goodson et al., 2002; Huffman et al., 1996), presence of extra fat (Brunsø et al., 2005), oxidisation of beef (Brooks, 2007), presence of foreign bodies in beef products (FSA reports: Incident Report 2015) and inefficient cold chain management (Kim et al., 2012; Mena et al., 2011). These root causes are occurring at consumer end because of the issues within the beef supply chain. For instance, discoloration of beef could be due to lack of vitamin E in the diet of cattle (Liu et al., 1995; Houben et al. 2000; Cabedo et al., 1998; O’Grady et al., 1998; Lavelle et al., 1995; Mitsumoto et al., 1993) and temperature abuse of beef products along the supply chain (Rogers et al., 2014; Jakobsen & Bertelsen, 2000; Gill & McGinnis, 1995; van Laack et al., 1996; Jeremiah & Gibson, 2001; Greer & Jones, 1991).

Lack of tenderness is because of absence or inefficient maturation of carcass from which beef products are derived (Riley et al., 2005; Vitale et al., 2014; Franco et al., 2009; Gruber et al., 2006; Monsón et al., 2004; Sañudo et al., 2004; Troy and Kerry, 2010). Presence of extra fat could be due to cattle being not raised as per the weight and conformation specifications of the retailer (Hanset et al, 1987; Herva et al., 2011; Borgogno et al., 2016; AHDB Industry Consulting, 2008; Boligon et al., 2011) and inefficient trimming procedures in the boning hall in abattoir (Francis et al., 2008; Mena et al., 2014; Kale et al., 2010; Watson, 1994; Cox et al., 2007). The oxidisation of beef could be occurring because of improper packaging at abattoir and processor, damage of packaging along the supply chain and inappropriate packaging techniques being followed (Brooks, 2007; Lund, 2007; Singh et al., 2015). The presence of foreign bodies could be due to improper packaging because of machine error at abattoir and processor, lack of safety checks such as metal detection, physical inspection and lack of renowned food safety process management procedures being followed such as HACCP (Goodwin, 2014). The inefficient cold chain management could be because of lack of periodic maintenance of refrigeration equipment (Kim et al., 2012).

Table 2.1 Summary of research work on waste minimisation in red meat supply chain

S.No.	System Boundary	Method	Region	Reference
1.	Abattoir & processor	Lean principles	UK	Simons et al., (2005)
2.	Processor to retailer	Empirical research and current reality tree	UK and Spain	Mena et al., (2011)
3.	Retailer	Case study	Italy	Cicatiello et al., (2016)
4.	Farm to retailer	Lean principles, value chain analysis & systems theory	UK	Zokaei & Simons, (2006); Simons & Taylor (2007)
5.	Farm to foodservice restaurant	Value chain analysis	UK	Francis et al., (2008)
6.	Farm to consumer	Empirical research, value chain analysis, case studies, Systematic literature review	UK; Spain; Finland; Belgium	Cox et al., (2007); Taylor (2006); Perez et al., (2010); Katajajuuri et al., (2014); De Steur et al., (2016)

The maximum amount of food waste in the supply chains is generated by the consumers. It could be observed from Table 2.1 that most of studies involving consumers are done by empirical research (interview, survey, etc.). However, these techniques are not able to attract larger audiences and often they consist of biased responses. There is plenty of useful information available on social media, which reflects the true opinion of consumers, which could be analysed to explore consumer sentiments regarding various issues. Keeping this in mind, in this thesis, social media (Twitter) data has been used for waste minimisation and to develop consumer centric supply chains. The findings of the analysis have been linked to the upstream of the supply chain so that an appropriate waste minimisation strategy could be developed.

2.5.5 Carbon footprint in red meat supply chain

Beef has the highest carbon footprint among all the red meat products. It is estimated that 3.4% of the global greenhouse gas emission are generated because of livestock. The contribution of beef farms towards generating carbon footprint is highest among all the stakeholders of beef supply chain. The major root cause is the emission of methane via enteric fermentation occurring in cattle's stomach. Other stakeholders of beef supply chain viz. abattoir, processor, logistics and retailer are also generating carbon footprint primarily due to consumption of energy. Peters et al., (2010) have done a comparative study of carbon footprint associated with red meat supply chains in Australia with the global studies. Three supply chains viz. beef, sheep and premium beef from various geographical regions of Australia were taken into account. Their carbon footprint is measured using LCA (Life Cycle Assessment) method. It was concluded that red meat industries in Australia has average or below average carbon footprint in comparison to global studies. There was a revelation that feedlot based cattle are associated with lesser carbon footprint as compared to grassland based cattle.

Kythreotou et al., (2011) found out a technique to determine the greenhouse gas emissions occurring because of the energy consumption like LPG, diesel, electricity, etc. for breeding of cattle, poultry and pig in Cyprus. The consumption of energy from each energy source by livestock species and the corresponding greenhouse gas emission form these energy sources were calculated. The impact of anaerobic digestion and greenhouse gas emission due to transport is not being considered in this article. The results obtained were compared to the other major greenhouse gas emission sources in livestock breeding like enteric fermentation and manure management. Desjardins et al., (2012) have calculated the carbon footprint of beef in European Union, Canada, Brazil and USA. It was noticed that carbon footprint of beef production in these countries is declining in the past 30 years and the corresponding reasons were mentioned. They proposed to allocate the carbon emission to the byproducts of beef as well like offal, hide, fat and bones. Bustamante et al., (2012) have calculated the greenhouse gas emissions associated with breeding cattle in Brazil in the time period of five years from 2003 to 2008. Their root causes were explained. It was found out that the greenhouse gas emission from cattle farming is contributing to almost half of the greenhouse gas emissions done by Brazil. Finally, certain policies were recommended for both public and private sectors to curtail the greenhouse gas emission associated with the cattle farming.

Bellarby et al., (2013) have calculated the greenhouse emission from the supply chains of livestock starting from their production to consumption and the corresponding waste in EU27 in year 2007. The major root causes of these emissions were livestock farms, Land Use and Land Use Change (LULUC) and food waste. It was suggested to reduce waste, consumption and production to curtail greenhouse gas emissions. There was a proposal of utilizing grassland-based farm for cattle breeding instead of intensive production for them. Schroeder et al., (2012) have determined the carbon footprint of two beef supply chains from UK and one from Brazil. LCA techniques were used for this purpose and the phenomenon of carbon sequestration is included in them. It was observed that majority of emissions are occurring at farm end. There was a recommendation to increase the weaning rate and reduce the age of slaughter from 30 to 24 months for mitigating the carbon footprint of beef supply chain. Ogino et al., (2007) have evaluated the impact of cow calf system on environment in Japan. LCA techniques have been used and this study was confined to various operations and procedures involved in feed production, transport and animal welfare. The impact of one calf in its entire lifetime is being considered on environment in form of greenhouse gas emission, acidification, eutrophication and energy consumption. There was a suggestion to reduce the calving interval by one month and increasing the weaning rate to mitigate the impact on environment.

Darkow et al., (2015) have demonstrated how logistics firms in food supply chains can enhance their businesses as compared to their rivals by aligning towards eco-friendly sustainable principles in their operations. Acquaye et al., (2014) has generated supply chain carbon maps to identify hot spots of carbon emission so that they can be mitigated. It will also help in benchmarking with other supply chains of similar products and structures. Soosay et al., (2012) have identified lack of synergy between consumer preferences and allocation of resources by using sustainable value chain analysis. Rotz et al., (2013) has developed a simulation tool to explore the improvements achieved in environmental footprint of beef production system over past 40 years at US Meat Animal Research Center. This tool was pretty accurate as the simulated feed production and consumption; beef production costs and energy consumption for year 2011 were within 1% of actual records. This study provides a reference model to enhance the national and regional complete life cycle assessments of the sustainability of beef. Nguyen et al., (2010) have evaluated the environmental consequences of beef production in the EU employing life cycle assessment. In this study, four beef production systems were considered – three from intensively reared dairy calves and one from suckler herds. It was observed that beef derived from suckler herd does less contribution towards global warming, eutrophication, acidification and consumption of non-renewable energy as compared to dairy calves. The study also explained the significance of phenomenon of land use change in calculation of global warming from beef production. Overall, this research highlights the stages in beef production, which requires sustainable management practices to improve environmental performance of beef production.

O'Brien et al., (2011) has compared the Greenhouse Gas (GHG) emissions from dairy farms by IPCC (Intergovernmental Panel on Climate Change) method and LCA (Life Cycle Analysis) method. These methods were applied to nine dairy farms involving Holstein-Friesian breed of cow. It was observed by both the methods that reducing intensity of dairy farms would reduce the GHG emission. In the LCA method, the greenhouse gas emissions are measured by clearly defining system boundaries. For instance, in dairy farming the system boundary accounts for all the processes at dairy farm upto the point when milk leaves for consumption by consumers (Cederberg and Mattson, 2000). Hence, it also considers the carbon footprint generated in producing external inputs of dairy farms like concentrate feeds and fertilizers. Often this method is known as cradle to farm gate LCA. Unlike IPCC, this methodology may generate higher results for carbon emission but assures the aggregate impact of carbon footprint reducing strategies at farm results in reduction of gross greenhouse gas emissions in the entire supply chain. The IPCC method on the other hand performs the assessment of carbon footprint by taking into account only the emission factors listed in the agriculture domain of greenhouse gas national inventory of Ireland (Ireland EPA, 2009). The shortcoming of this methodology is that it only considers the generation and removal of greenhouse gases via hotspots and sinks, which are deemed to be significant by IPCC. For example, the sources of carbon footprint considered with respect to dairy farming are enteric fermentation, management of manure and soils of farmlands. This study recommended the use of LCA method as unlike IPCC method, it takes into account the pre-farm chains like emission due to farming of feed for cattle.

Edwards-Jones et al., (2009) has calculated the carbon footprint from beef and lamb production. They have done empirical analysis of data obtained from two Welsh farms. LCA techniques have been deployed to calculate the associated carbon footprint of beef and lamb production. There were two strategies followed to calculate carbon footprint: one with taking emissions from soil (nitrous oxide) into account and one without taking soil emission into account. The results obtained were in synchronism with the previous studies of this domain. Vergé et al., (2008) have evaluated the greenhouse gas emission from cattle industry from 1981-2001 using IPCC methods. It was revealed that overall emission has increased from 1981 to 2001 because of expansion of cattle industry. However, they have become more carbon efficient in terms of emission per kg of animal live weight from 1981 to 2001.

Pelletier et al., (2010) have compared the environmental impacts of three categories of beef viz. weaned directly to feedlots; weaned to out-of-state wheat pastures and finished wholly on managed pasture and hay. The factors taken into account for analysis were energy usage, carbon footprint and eutrophying emission. LCA methodology was used for their analysis. It was found out that pasture finished beef does most harm and feedlot finished beef does least harm. De Vries & De Boer (2010) has compared the environmental impacts of livestock: pork, chicken, beef, milk and eggs. LCA have been used for analysis. The factors taken into account were energy and land usage, global warming potential. Results showed that production of beef has higher impact followed by pork, chicken, eggs and milk. Stackhouse-Lawson et al., (2012) have calculated the carbon footprint and ammonia emission from the cattle production in California. The model deployed in their calculation was Integrated Farm System Model (IFSM). The results suggested that cow calf phase has the highest emission. Finally, the suggestive measures to mitigate these emissions were provided. Veysset et al., (2010) have evaluated the environmental and economic performance of five Charolais beef production systems. They have used two software models: OptINRA and PLANETE for their analysis. The calculated results suggested that mixed crop livestock system is financially more secured than grassland based systems.

Aramyan et al., (2011) have analysed pork supply chain in terms of economic and environmental perspective in Europe. Mixed integer linear programming model has been developed for analysis. Opportunities were identified for reducing carbon footprint and cost if some operations of supply chain are relocated to other countries. Krieter (2002) have evaluated various pig production systems in terms of economic, environmental and animal welfare aspects. The analysis was done by simulation on a computer model. It was found out that group housing for gestating sows increases the performance of pig production in terms of economic, environmental and animal welfare aspects. Wiskerke & Roep (2007) have described the techno-institutional dynamics of sustainable pork supply chain. They have used mathematical modeling along with case study for their analysis. The importance of agency and learning and negotiation process in the creation of new path for sustainable pork supply chain was highlighted.

Keeratiurai (2013) have determined the greenhouse gas emission from energy usage (electricity, petrol, LPG) in pork production. Mathematical modeling has been used for analysis. The results for greenhouse gas emission from each category of energy used were calculated. The highest emission was from fuel used in transportation. White et al., (2010) have calculated the production, financial and environmental implications of intensifying beef farming systems. They have used Farmex Pro as their modeling tool. It was found out that both feeding maize silage and applying nitrogen fertilizers increased beef production per hectare but feeding maize was associated with less greenhouse gas emission. Casey & Holden (2006) determined greenhouse gas emission from Irish suckler-beef production. They have used LCA methodology for their calculation. It was revealed that dairy- bred production have less greenhouse gas emission as compared to beef bred. Dietary supplements did not show major potential to reduce greenhouse gas emission. Foley et al., (2011) have evaluated the effect of different management strategies in pastoral beef production system on their greenhouse gas emission. Beef system greenhouse gas emission model (BEEFGEM) was developed for analysis. It was revealed that bull beef production at high stocking rate has the least emission among all the categories of pastoral beef production system.

Table 2.2 Summary of research work on carbon footprint in red meat supply chain

S.No.	**System Boundary**	**Method**	**Region**	**Reference**
1.	Farm	Life Cycle Assessment (LCA); Intergovernmental Panel for Climate Change (IPCC) methods; Partial LCA, Integrated Farm System	European Union; Wales, UK; Canada; USA, Cyprus; Brazil; Japan; Ireland; France; New Zealand; Ireland; Thailand	Nguyen et al., (2010); Edwards-Jones et al., (2009); Vergé et al., (2008); Pelletier et al., (2010); Stackhouse-Lawson et al., (2012); Kythreotou et al., (2011); Bustamante et al.,

		Model; OptINRA and PLANETE; Farmex Pro; Beef system greenhouse gas emission model (BEEFGEM)		(2012); Ogino et al., (2007); Rotz et al., (2013); O'Brien et al., (2011); Veysset et al., (2010); Keeratiurai (2013); White et al., (2010); Casey & Holden (2006); Foley et al., (2011)
2.	Farm to processor	Life Cycle Assessment (LCA), Literature Review and IPCC method,	OECD nations; Australia; Brazil; Canada, USA	De Vries & De Boer (2010); Peters et al., (2010); Desjardins et al., (2012);
3.	Farm to retailer	Life Cycle Assessment (LCA)	UK and Brazil	Schroeder et al., (2012)
4.	Farm to consumer	Literature review	EU 27	Bellarby et al., (2013)

It can be observed from Table 2.2 that most of research work done in the domain of reducing carbon footprint of red meat supply chain is focussed on either farms or from farm to processor. There is scarcity of studies spanning the entire supply chain from farm to retailer. It was found that measurement of greenhouse gas emissions in red meat supply chains were done at a segment level i.e. independently at farm, abattoir, processor, logistics and retailer level. There is deficiency of an integrated model capable of measuring carbon footprint of entire beef supply chain. Keeping this in mind, in this thesis, an integrated framework is proposed to calculate the carbon footprint of entire beef supply chain. The results of the emission of a particular segment of the supply chain would be visible to all stakeholders of supply chain via cloud computing technology.

2.6 Conclusion

This chapter consists of two segments. The first segments comprise of hotspots of waste and carbon footprint generation in beef supply chain. The second segment consists of related work section, which includes research work done on vertical coordination, traceability, meat safety, reducing carbon footprint in red meat supply chain and on waste minimisation in food supply chain.

The waste and carbon footprint generated by different stakeholders of supply chains viz. farms, processor, logistics and retailer were discussed. The research work done to address these issues and improve sustainability of beef supply chain was described in detail. The advantages and shortcomings of various frameworks used by researchers were explored.

This research makes an attempt to address the sustainability issues of beef supply chain which includes waste and carbon footprint generated by it. Various frameworks have been proposed for waste minimisation and reducing the greenhouse gas emissions of the beef supply chain, which are described in detail in upcoming chapters.

The maximum amount of waste in beef supply chain is being generated at the consumer end, who frequently mentions the reasons for discarding beef products on social media. The next chapter proposes a framework to analyse consumer posts on social media and link them to their root causes in the upstream of the supply chain. It will assist the beef retailers to develop waste minimisation strategy to prevent waste generated at consumer households and improve their satisfaction.

CHAPTER 3

Use of social media data in waste minimization in beef supply chain

3.1 Introduction

Global population is rising rapidly and is forecasted to reach nine million by 2050. Colossal amount of resources would be needed to feed them. Millions of people are losing their lives due to global hunger. Besides, the global food lost within the supply chain and wasted at the consumer end corresponds to one-third of the aggregate food produced (Food and Agriculture Organization of the United Nations, 2015). The monetary value of food waste is approximately US $680 per annum in developed nations and around US $ 310 billion per annum in developing nations (Save Food, 2015). All segments of food supply chain viz. farmers, wholesalers, logistics, retailers and consumers are contributing to the food waste. The generation of waste at one segment in beef supply chain might be having its root cause at other segment in supply chain. For instance, the discoloration of beef prior to expiry of its shelf life is because of deficiency of Vitamin E in diet of cattle in beef farms (Liu et al., 1995). The stakeholders of beef supply chain are generating distinct kinds of waste. There is enormous pressure on food retailers from government regulations, competition from rival brands to reduce waste in their supply chains. Beef retailers are capturing huge amount of data from farmers, abattoir and processor, retail stores and consumers as depicted in figure 3.1, which could be analyzed for improving production efficiency and reducing waste. Numerous methodologies have been employed in the past to mitigate different issues at farmer, processor and retailer end such as lean principles (Cox and Chicksand, 2005), six sigma (Nabhani and Shokri, 2009) and value chain analysis (Taylor, 2006). Consumers generate the major amount of waste in the beef supply chain. Beef retailers aim to make their supply chain consumer centric (A supply chain designed as per the requirements of end consumers by addressing organisational, strategic, technology, process and metrics factors) by taking into account various methods including market survey, market research, interviews and giving opportunity to consumers to give feedback within the retailer store. However, food retailers are not able to attract large audiences by following these procedures and thereby making the data sample small. Any decisions made based on smaller sample of customer feedback are prone to be ineffective. With the advent of online social media, there is lots of consumer information available on Twitter, which reflects the true opinion of customers (Liang and Dai 2013; Katal et al., 2013). Effective analysis of this information can give interesting insight into consumer sentiments and behaviours with respect to one or more specific issues generating waste. Using social media data, a retailer can capture a real-time overview of consumer reactions about an episodic event. Social media data is relatively cheap and can be very effective in gathering opinion of large and diverse audiences (Liang and Dai 2013; Katal et al., 2013). Using different information techniques, business organisations can collect social media data in real time and can use it for developing future strategies. However, social media data is qualitative and unstructured in nature and often large in volume, variety and velocity (He et al., 2013; Hashem et al., 2015; Zikopoulos and Eaton, 2011). At times, it is difficult to handle it using traditional operation management tools and techniques for business purposes.

In this study, Twitter was chosen amongst all the prominent social media platforms such as Facebook and Google+ because it is the most rapidly growing social media network (Bennett, 2013). Moreover, information on Twitter is deemed as ‘open’ unlike other social media platforms, which could be accessed via Twitter Application Programming Interface (API) (Twitter, 2013). It will generate numerous opportunities to gather information on a gigantic volume, variety and velocity for tedious problems in versatile domains. Even the literature suggests that Twitter is the most potent and comprehensive platform for data analytics among all social networking websites (Chae, 2015).

In the past, social media analytics have been implemented in various supply chain problems predominantly in manufacturing supply chains. The research on application of social media analytics in domain of food supply chain is in its primitive stage. In this chapter, an attempt has been made to use social media data in domain of food supply chain for waste minimisation and to make it consumer centric. The results from the analysis have been linked with all the segments of supply chain to improve customer satisfaction. For instance, the issues faced by consumers of beef products such as discoloration, presence of foreign bodies, extra fat, hard texture etc. has been linked to their root causes in the upstream of the supply chain. Firstly, data was extracted from Twitter (via Twitter streaming API) using relevant keywords related to consumer’s opinion about different food products. Thereafter, pre-processing and text mining has been performed to investigate the positive and negative sentiments of tweets using Support Vector Machine (SVM). Hierarchical clustering of tweets from different geographical locations (World, UK, Australia and USA) using multiscale bootstrap resampling is performed. Further, root causes of issues affecting consumer satisfaction are identified and linked with various segments of supply chain for waste minimisation and to develop consumer centric supply chain.

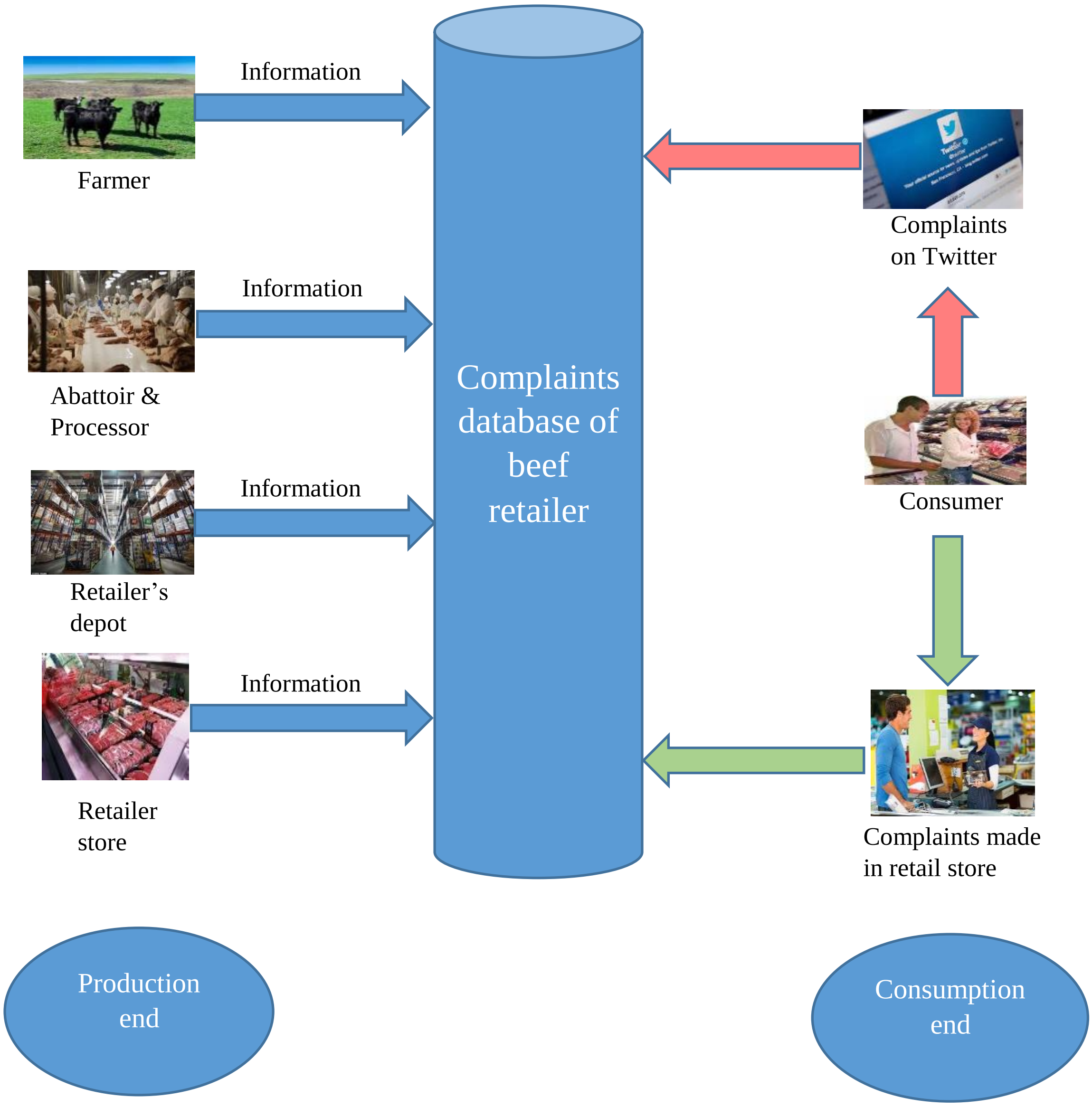

Figure 3.1 Various ways of receiving waste related information for beef retailer

3.2 Application of big data and social media in supply chains

In literature, various mechanisms have been developed to analyse big data to mitigate various challenges, bottlenecks in the supply chain. Hazen et al., (2014) identified the issues with data quality in the domain of supply chain management. Innovative techniques for data monitoring and controlling their quality were proposed. The significance of data quality in research and practice of supply chain management has been described. Vera-Baquero et al., (2016) have proposed a cloud-based framework using big data techniques to enhance the performance analysis of businesses efficiently. The capability of the mechanism was demonstrated to deliver business activity monitoring in big data environment in real time with minimal cost of hardware. Frizzo et al., (2016) have done a literature review of research publications associated with big data in business journals. The time period of the publications was from year 2009 to year 2014 and 219 peer reviewed research articles from 152 business journals were examined. Quantitative and qualitative analysis was performed using NVivo10 software. The biggest advantages and challenges of implementing big data in domain of business were found out. It remains fragmented and has lots of potential in terms of theoretical, mathematical and empirical research.

Twitter information has emerged as one of the most widely used data source for research in academia and practical applications. Various examples associated with practical applications of Twitter information are available in literature like brand management (Malhotra et al., 2012), stock forecasting (Arias et al., 2013) and crisis management (Wyatt, 2013). It is anticipated that there will be swift expansion in utilisation of Twitter information for numerous other purposes like market prediction, public safety and humanitarian relief and assistance (Dataminr, 2014). In the past, Twitter data based studies have been conducted in various domains. Most of the research work is being performed in the area of Computer science for various purposes such as sentiment analysis (Schumaker et al., 2016; Mostafa, 2013; Kontopoulos et al., 2013; Rui et al., 2013; Ghiassi et al. 2013; Hodeghatta & Sahney, 2016; Pak and Paroubek, 2010), topic detection (Cigarrán et al., 2016), gathering market intelligence (Li & Li, 2013; Lu et al., 2014; Neethu & Rajasree, 2013), insight of stock market (Bollen et al., 2011), etc. There are few studies conducted in the domain of disaster management like dispatching resources in a natural disaster by monitoring real time tweets (Chen et al., 2016), exploring the application of social media by non-profit organisations and media firms during natural disasters (Muralidharan et al., 2011), etc. Analysis of Twitter data has also been conducted by researchers in the domain of Operations Management such as capturing big data in form of tweets to improve supply chain innovation capabilities (Tan et al., 2015), investigating the state of logistics related customer service provided by e-retailers on Twitter (Bhattacharjya et al., 2016), examining the process of service recovery in the context of operations management (Fan et al., 2016), developing a framework for assimilating social media into supply chain management (Sianipar and Yudoko, 2014; Chae, 2015).

Researchers have used numerous methods for extracting intelligence from tweets. For instance, Ghiassi et al., (2013) have used n-gram analysis and artificial neural network for determining sentiments of brand related tweets. Their methodology gives better precision in classification of sentiments and minimised the complexity of modeling as compared to conventional sentiment lexicons. However, their study was conducted by offsetting the false positives and performed on a single brand. Hence, the efficacy of the framework needs to be verified on other brands. Bollen et al., (2011) have utilised Granger causality analysis and a Self-Organizing Fuzzy Neural Network to analyse tweets to measure the mood of people associated with stock market. Their framework was capable enough to measure the mood of people along six distinct dimensions (such as alert, sure, kind, happy, etc.) by accuracy of 86.7%. Li & Li, (2013), have developed a numeric opinion summarization framework for extracting market intelligence. The aggregated scores generated by the framework assists the decision maker to effectively gain the insights into market trends via fluctuation in tweet sentiments. However, their study doesn't take into account the synonym of terms while classifying the tweets into thematic topics as different users might use distinct terms in their tweets. For instance, a dictionary-based approach could be applied to incorporate all possible synonyms. Lu et al., (2014) have proposed a visual analytics toolkit to gather data from Bitly and Twitter to predict the ratings and revenue generated by the movies. The advantages of interactive environment for predictive analysis were demonstrated over statistical modelling methods using results from vast box office challenge, 2013. The proposed framework is flexible to be used in other social media platforms for analysis of advertisement and forecasting of sales. However, the data cleaning and sentiment analysis process employed is very challenging and it gets complicated for the larger data sets. Mostafa, (2013) have applied lexicon based sentiment analysis to explore the consumer opinion towards certain cosmopolitan brands. The text mining techniques utilised were capable to explore the hidden patterns of consumer's opinions. However, their framework was quite oversimplified and was not designed to perform some of the prevalent analysis such as topic detection. Tan et al., (2015) have developed deduction graph model for extracting big data to improve the capabilities for supply chain innovation. This model extracts and develop inter relations among distinct competence sets thereby generating opportunity for extensive strategic analysis of a firm's capabilities. The mathematical methodology followed to achieve the optimum results is quite sophisticated and monotonous considering it is not autonomous. Chae, (2015) have developed a Twitter analytics framework for evaluation of Twitter information in the field of supply chain management. An attempt has been made by them to fathom the potential engagement of Twitter in the application of supply chain management and further research and development. This mechanism is composed of three procedures, which are known as descriptive analysis, network analysis and content analysis. The shortcoming of this research is that data collection was performed using '#supply chain' instead of keywords. Therefore, the data collected may not be the true representative of the consumer's opinion. Bhattacharjya et al., (2016) have implemented inductive coding to examine the efficiency of e-retailer's logistics specific customer service communications on social media (Twitter). Their approach can depict informative interactions and was precisely able to distinguish the beginning and conclusion of interactions among e-retailers and consumers. However, the data mining mechanism utilised might be overlooking certain kinds of exchanges, which are relatively low in frequency. Kontopoulos et al., (2013) have used Formal Concept Analysis (FCA) to develop an ontology-based model for sentiment analysis. Their framework does efficient sentiment analysis of tweets by differentiating the features of the domain and allocates a respective sentiment grade to it. However, their framework was not robust enough to deal with advertisement tweets. It was either considered as positive tweets or rejected by their mechanism thereby reducing the precision of sentiment analysis. Similarly, Cigarran et al., (2016) have also utilised FCA approach for analysing tweets for topic detection. Although FCA approach is quite efficient, it is not robust enough to deal with tweets having lack of clarity and therefore creates uncertainty on its ability to give precise sentiment grades. Rui et al., (2013) have used an amalgamation of Naive Bayesian classifier and support vector machine to explore the impact of pre-consumer opinion and post-consumer opinion with respect to movie sales data. The algorithms utilised by them for sentiment analysis of tweets was good to classify them into positive, negative and neutral sentiments. The only limitation is that Naive

Bayesian classifier is considered to be oversimplified method and their accuracy results are not appreciable as compared to some of the more sophisticated tools available currently for sentiment analysis. Pak and Paroubek, (2010) have developed a Twitter corpus by gathering tweets via Twitter API. It was utilised to create a sentiment classifier derived from multinomial Naïve Bayes classifier (using N-gram and POS-tags as features). This framework leaves room for error as only polarity of emoticons was employed to label the tweet emotions in training data set. Only the tweets with emoticons are available in the training data set, which makes it fairly inefficient. Neethu & Rajasree, (2013) have utilised machine-learning approach to investigate the tweets on electronic products such as laptop, mobile phone, etc. A new feature vector is proposed for sentiment analysis and gathers intelligence from people's view on these products. During the study, they found that support vector machine classifier gives more accurate results than Naïve Bayes classifier.

Application of social media data in food supply chain is in primitive stage. This study addresses the gap in the literature by analysing social media data to identify issues in food supply chain and how they can be mitigated for waste minimisation and to achieve consumer centric supply chain. The consumer tweets regarding beef products were analysed using SVM and hierarchal clustering using multiscale bootstrap resampling to explore the major issues faced by consumers. For accumulation of ultimate opinions, the subjectivity and polarity associated with the opinions is identified and merged in the form of a numeric semantic score (SS). The identified issues from the consumer tweets have been linked to their root causes in different segments of supply chain. For instance, issues like bad flavour, unpleasant smell, discoloration of meat, presence of foreign bodies, etc. have been linked to their root causes in the upstream of the supply chain at beef farms, abattoir, processor and retailer. The corresponding mitigation of these issues is also provided in detail. The next section describes the Twitter data analysis process employed in this chapter.

3.3 Twitter data analysis process

In case of social media data analysis, three major issues are to be considered namely - data harvesting/capturing, data storage, and data analysis. Data capturing in case of twitter starts with finding the topic of interest by using appropriate keywords list (including texts and hashtags). This keywords list is used together with the twitter streaming APIs to gather publicly available datasets from the Twitter postings. Twitter streaming APIs allows data analysts to collect 1% of available Twitter datasets. There are other third party commercial data providers like Firehose with full historical Twitter datasets.

Morstatter et al., (2013) presented a good comparison on the data sample collected by Twitter Streaming API and full data stored by Firehose. This was done to test if the data obtained by Streaming API is a good/sufficient representation of user activity on Twitter. Their study suggested that there are various ways of setting up API to increase the representativeness of the data collected. One of the ways was to create more specific parameter sets with bounding boxes and keywords. This approach can be used to extract more data from the API. Another key issue highlighted in their study was – the representation accuracy (in terms of topics) increased when the data collected from streaming API was large. Following these recommendations, we have used set of specific keywords and regions to extract data from streaming API such that data coverage and in turn representation accuracy can be increased.

The Twitter streaming API allowed us to store/append Twitter data in a text file. Then, a parsing method was implemented to extract datasets relevant to this study (e.g. tweets, coordinates, hastags, urls, retweet count, follower count, screen name, favorited, location and others). See Figure 3.2 for details on the overall approach. The analysis of the gathered Twitter data is generally complex due to the presence of unstructured textual information, which typically requires natural language processing (NLP) algorithms. In this chapter, two main types of content analysis techniques are proposed– sentiment mining and clustering analysis for investigating the extracted Twitter data. More information about the proposed sentiment mining method and hierarchical clustering method is detailed in following subsections.

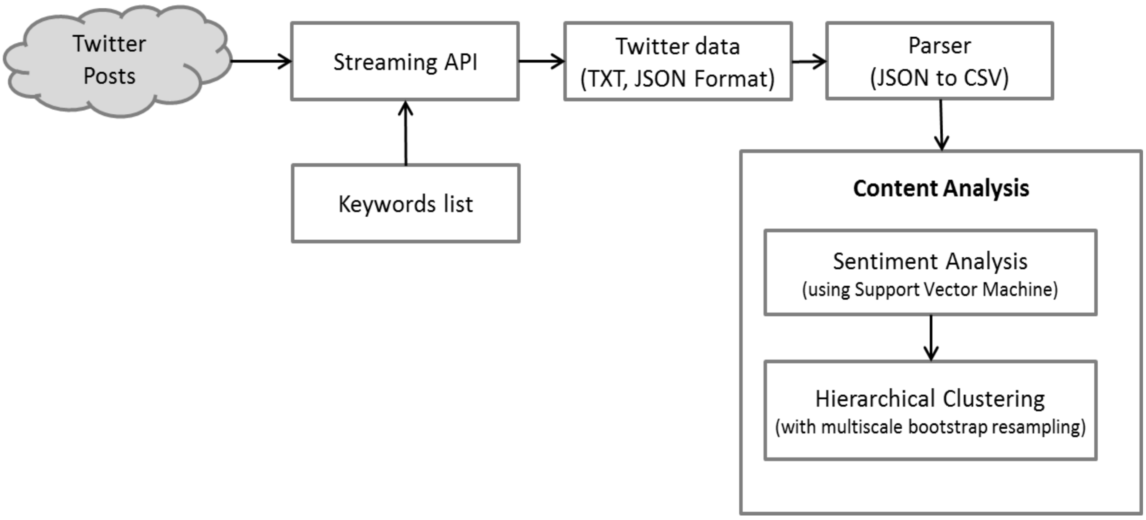

Figure 3.2 Overall approach for social media data analysis

3.3.1 Content Analysis

The information available on social media is predominantly in the unstructured textual format. Therefore, it is essential to employ Content Analysis (CA) approaches, which includes a wide array of text mining and NLP methods to accumulate knowledge from Web 2.0 (Chau and Xu, 2012). A tweet (with maximum of 140 characters) comprises small set of words, URLs, hashtags, numbers and emoticons. An appropriate cleaning of text and further processing is required for effective knowledge gathering. There is no best way to perform data cleaning and several applications have used their own heuristics to clean the data. A text cleaning exercise, which included removal of extra spaces, punctuation, numbers, symbols, and html links were used. Then, a list of major food retailers in the world (including their names and Twitter handles) was used to filter and select a subset of tweets, which are used for analysis.

3.3.1.1 Sentiment analysis based on SVM

Tweets contains sentiments as well as information about the topic. Thus, sophisticated text mining procedures like sentiment analysis are vital for extracting true customer opinion. The objective here is to categorise each tweet with positive and negative sentiment.

Sentiment analysis, which is also widely known as opinion mining is defined as the domain of research that evaluates public's sentiments, appraisals, attitudes, emotions, evaluations, opinions towards various commodities like services, corporations, products, problems, situations, subjects and their characteristics. It denotes a broad arena of issues. Many names exist with marginally distinguished actions like opinion mining, sentiment mining, sentiment analysis, opinion extraction, affect analysis, emotion analysis, subjectivity analysis, review mining. Nonetheless, all these names are covered under the broad domain of opinion mining or sentiment analysis. In literature, both opinion mining and sentiment analysis are intermittently utilised.

In the proposed sentiment mining approach, an opinion is elicited in form of numeric values from a microblog (in text format). This approach identifies the subjectivity and polarity associated with the opinions and merges them in the form of a numeric semantic score (SS) for accumulation of ultimate opinions. Following are the steps involved in this approach:

Identifying subjectivity from the text: While posts on microblogging websites are quite short in length, still some posts comprises of multiple sentences highlighting numerous subjects or views. The subjectivity of an opinion is investigated by determining the strength of an opinion for a topic. Bai (2005) and Duan & Whinston (2005) have classified the opinion into subjective and objective opinions. Objective opinions reveal the basic information associated with an entity and does not have subjective and emotional perspectives. On the other hand, subjective opinion represents personal viewpoints. As the purpose of this framework is to analyse Twitter user's perspective on food products, subjective opinion is more crucial. Mostly, people utilise emotional words while describing their opinions rather than objective information. Therefore, the Opinion Subjectivity (OS) of a post is defined as average sentimental and emotional word density in every sentence of microblog *m*, which describes topic *t* (in this study, words related to *beef*/*steak*).

The subjectivity level of opinions could be evaluated by developing a subjective word set, which comprises of sentimental and emotional words by expansion of word set using WordNet. WordNet is a web based semantic lexicon having the database of synonyms and antonyms of words. In this approach, a small set of seeds or sentiment words with defined positive and negative inclination is initially gathered manually. Then, the algorithm expands this set by exploring the online dictionary such as WordNet for their respective synonyms and antonyms. The fresh words found are transferred to the small set. Thereafter, next iteration is started. This iterative procedure is concluded when the search is complete and no fresh words could be found. This approach was followed in Hu and Liu (2004). Following this procedure, a subjective word set $\boldsymbol{\phi}$ is identified. The opinion subjectivity associated with a post *m* as per the topic *t*, represented as $OS_{m,t}$, is represented as:

$$OS_{m,t} = \frac{\left(\sum_{s \in S_t^m} \frac{|U_s \cap \boldsymbol{\phi}|}{U_s}\right)}{|S_t^m|}$$

where, U_s denotes the set of unigrams contained in sentence and S_t^m represents the set of sentences in tweet '*m'* which has topic '*t*'.

<u>*Sentiment classification module*</u>*:* The identification of polarity mentioned in opinion is crucial for transforming the format of opinion from text to numeric value. The performance of data mining methods such as support vector machine (SVM) is excellent for sentiment classification (Popescu & Etzioni, 2005). SVM model is employed in this approach for the division of polarity of opinions. The prerequisites for SVM are threefold. Initially, the features of the data must be chosen. Then, data set utilised in training process needs to be marked with its true classes. Finally, the optimum combination of model settings and constraints needs to be calculated. The Unigrams and Bigrams are the tokens of one-word and two-word respectively identified from the microblog. While there is a constraint on the length of the microblogging post, the probability of iterative occurrence of a characteristic in same post is quite low. As such, this study uses binary value {0,1} to represent the presence of these features in the microblog. The appearance of a feature in a message is denoted by "1" whereas the absence of a feature is denoted by "0".

SVM is a technique for supervised machine learning, which requires a training data set to identify best Maximum Margin Hyperplane (MMH). In the past, researchers have used approach where they have manually analysed and marked data prior to their use as training data set. Posts on a microblogging websites are short and therefore the numbers of features associated with them are also limited. In this case, we have examined the use of emoticons to identify sentiment of opinions. In this paper, Twitter data was pre-processed based on emoticons to create training dataset for SVM. Microblogs with ":)" were marked as "+1" representing positive polarity, whereas messages with ":(" were marked as "-1" representing negative polarity. It was observed that more than 89% messages were marked precisely by following this procedure. Thus, the training data set was captured using this approach for SVM analysis. Then, a grid search (Hsu et al., 2003) was employed to identify the optimum combination of variables γ and c for carrying out SVM along with a Radial Basis Function kernel. The polarity ($Pol_m \in \{+1, -1\}$) representing positive and negative sentiment respectively of microblog m can be predicted using trained SVM. Thus, the semantic score, SS, can be calculated by using resultant subjectivity and opinion polarity on for a topic t by following equation:

$$SS_{m,t} = Pol_m \times OS_{m,t}$$

where, $SS_{m,t} \in [-1,1]$

In real life, when consumers buy beef products, they leave their true opinion (feedback) on Twitter. In this chapter, the SVM classifier has been utilised to classify these sentiments into positive and negative and consequently gather intelligence from these tweets.

3.3.1.2 Word and Hashtag analysis

Another type of content analysis that is conducted in this chapter is word analysis. This type of analysis includes term frequency identification, summarisation of document and word clustering. Term frequency is commonly utilised in text data retrieval and identification of word clusters and word clouds. These analyses can help is identifying various issues being discussed in the tweets and their relevance to the food supply chain management practices. Term frequency can help in extracting popular hashtags and Twitter handles, which can give information about tweet features and its relevance. Other types of analysis include machine learning based clustering and association rules mining. The association rules mining can help to identify associations of different terms, which are frequently occurring in the tweets.

3.3.1.3 Hierarchical clustering with *p*-values using multiscale bootstrap resampling

In this research, we have employed a hierarchical clustering with *p*-values via multiscale bootstrap resampling (Suzuki and Shimodaira, 2006). The clustering method creates hierarchical clusters of words and also computes their significance using *p*-values (obtained after multiscale bootstrap resampling). This helps in easily identifying significant clusters in the datasets and their hierarchy. The agglomerative method used is ward.D2 (Murtagh and Legendre 2014). The pseudocode for the hierarchical clustering algorithm is presented in Figure 3.3.

$d_{i,j}$: distance between cluster i and j

C: set of all clusters

D*:* set of all $d_{i,j}$

n_i: number of data points in cluster i

Step 1: Find smallest element $d_{i,j}$ in ***D***

Step 2: Create new cluster k by merging cluster i and j (where $i, j \in C)$

Step 3: Compute new distances $d_{k,l}$ (where $l \in C$ and $l \neq k$) as

$$d_{k,l} = \alpha_i d_{i,l} + \alpha_j d_{j,l} + \beta d_{i,j}$$

Compute number of data points in cluster k as n_k as

$$n_k = n_i + n_j$$

where, $\alpha_i = \frac{n_i+n_l}{n_k+n_l}$, $\alpha_j = \frac{n_j+n_l}{n_k+n_l}$, $\beta = \frac{-n_l}{n_k+n_l}$ (Ward's minimum variance method)

Step 4: Repeat steps 1 to 3 until ***D*** contains a single group made of all data points.

Figure 3.3 Hierarchical Clustering Algorithm

Figure 3.3 illustrates how hierarchical clustering generates a dendrogram, which contains clusters. However, the support of the data for these clusters is not determined using the method detailed in Fig 3.3. One of the ways of determining the support of data for these clusters is by adopting multiscale bootstrap resampling. In this approach, the dataset is replicated by resampling for large number of times and the hierarchical clustering is applied (see Figure 3.3). During resampling, replicating sample sizes was changed to multiple values including smaller, larger and equal to the original sample size. Then, bootstrap probabilities are determined by counting the number of dendrograms, which contained a particular cluster and dividing it by the number of bootstrap samples. This is done for all the clusters and sample sizes. Then, these bootstrap probabilities are used to estimate p-value, which is also known as AU (approximately unbiased) value.

The result of hierarchical clustering with multiscale bootstrap resampling is a cluster dendrogram. At every stage, the two clusters, which have the highest resemblance are combined to form one new cluster (as presented in Figure 3.3). The distance or dissimilarity between the clusters is denoted by the vertical axis of dendrogram. The various items and clusters are represented on horizontal axis. It also illustrates several values at branches such as AU (approximately unbiased) p-values (left), BP (bootstrap probability) values (right), and cluster labels (bottom). Clusters with AU >= 95% are usually shown by the red rectangles, which represents significant clusters (as depicted in Figure 3.5).

3.4 Case study and Twitter data analysis

The proposed Twitter data analysis approach is used to understand issues related to the beef/steak supply chain based on consumer feedback on Twitter. This analysis can help to analyse reasons for positive and negative sentiments, identify communication patterns, prevalent topics and content, and characteristics of Twitter users discussing about beef and steak. Based on the result of the proposed analysis, a set of recommendations have been prescribed for developing customer centric supply chain.

The total number of tweets extracted for this research was 1,338,638 (as per the procedure discussed in Section 3.3). They were captured from 23/03/2016 to 13/04/2016 using the keywords beef and steak. Only tweets in English language were considered with no geographical constraint. Figure 3.4 illustrates the location of tweets, which has the geolocation data, on the world map. Then, keywords were selected to capture the tweets relevant to this study. In order to select the keywords, site visit was made to various main and convenience retail stores in the UK to find out the different negative and positive feedback left by the consumers with respect to beef products. The interviews of staff members of retail stores dealing with consumer complaints was performed, who provided access to database of consumer complaints regarding beef products. Interviews of some consumers were also conducted to explore the type of keywords used by them to express their views. A thorough investigation of the various complaints made by consumers in different stores worldwide was also performed. Different keywords employed on Twitter for beef products were captured and discussed with retailers and consumers. Consequently, a comprehensive list of the keywords (as shown in Table 3.1) was made to explore issues related to beef products highlighted by consumers on Twitter. The overall tweets were then filtered using this list of keywords so that only the relevant tweets (26,269) are retrieved. Then, country wise classification of tweets was performed by using the name of supermarket corresponding to each country. It was observed that tweets from USA, UK, Australia and World were 1605, 822, 338 and 15214 respectively. There were many hashtags observed in the collected tweets. The most frequently used hashtags (more than 1000) were highlighted in Table 3.2. Top Twitter handles (users who are mentioned very frequently) are identified among the extracted tweets. Those Twitter users who have been mentioned more than 2000 times are considered as top Twitter handles and they are presented in Table 3.3.

Table 3.1 Keywords used for extracting consumer tweets

Beef#disappointment	Beef#rotten	Beef# rancid	Beef#was very chewy
Beef#taste awful	Beef#unhappy	Beef#packaging blown	Beef#was very fatty
Beef#odd colour beef	Beef#discoloured	Beef#plastic in beef	Beef#gristle in beef
Beef#complaint	Beef#grey colour	Beef#oxidised beef	Beef#taste
Beef#flavour	Beef#smell	Beef#rotten	Beef#funny colour
Beef#horsemeat	Beef#customer support	Beef#bone	Beef#inedible
Beef#mushy	Beef#skimpy	Beef#use by date	Beef#stingy
Beef#grey colour	Beef#packaging	Beef#oxidised	Beef#odd colour
Beef#gristle	Beef#fatty	Beef#green colour	Beef#lack of meat
Beef#rubbery	Beef#suet	Beef#receipt	Beef#stop selling
Beef#deal	Beef#bargain	Beef#discoloured	Beef#dish
Beef#stink	Beef#bin	Beef#goes off	Beef#rubbish
Beef#delivery	Beef#scrummy	Beef#advertisement	Beef#promotion
Beef#traceability	Beef#carbon footprint	Beef#nutrition	Beef#labelling
Beef#price	Beef#organic/ inorganic	Beef#MAP packaging	Beef#tenderness

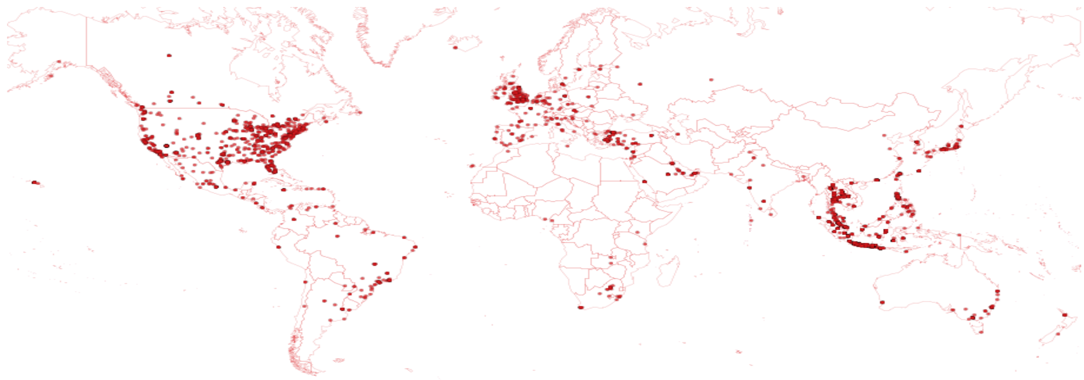

Figure 3.4: Visualisation of tweets with geolocation data

Table 3.2 Top hashtags used

Hashtag	Freq (>1000)	Freq (%)	Hashtag	Freq (>1000)	Freq (%)	Hashtag	Freq (>1000)	Freq (%)
#beef	17708	16.24 %	#aodafail	1908	1.75 %	#bmg	1255	1.15 %
#steak	14496	13.29 %	#earls	1859	1.70 %	#delicious	1243	1.14 %
#food	7418	6.80%	#votemainefp p	1795	1.65 %	#soundcloud	1169	1.07 %
#foodporn	5028	4.61%	#win	1761	1.62 %	#vegan	1131	1.04 %
#whcd	5001	4.59%	#ad	1754	1.61 %	#rt	1128	1.03 %
#foodie	4219	3.87%	#cooking	1688	1.55 %	#mrpoints	1116	1.02 %
#recipe	4106	3.77%	#mplusplaces	1686	1.55 %	#staydc	1116	1.02 %
#boycottearl s	3356	3.08%	#meat	1607	1.47 %	#wine	1072	0.98 %
#gbbw	3354	3.08%	#lunch	1577	1.45 %	#np	1069	0.98 %
#kca	2898	2.66%	#bbq	1557	1.43 %	#yelp	1052	0.96 %
#dinner	2724	2.50%	#yum	1424	1.31 %	#ufc196	1048	0.96 %
#recipes	2159	1.98%	#yummy	1257	1.15 %	#britishbeefwee k	1045	0.96 %
#accessibility	1999	1.83%	#bdg	1255	1.15 %			

As described in subsection 3.3.1.1**,** the collection of training data for SVM was done automatically based on emoticons. The training data was developed by collecting 10,664 messages from the Twitter data captured with emoticons “:)” and “:(”. The microblogs/tweets consisting of “:)” was marked as “+1” whereas messages comprising of “:(” were marked as a “-1.” The tweets consisting both “:)” and “:(” were removed. The automatic marking process concluded by generating 8560 positive, 2104 negative and 143 discarded messages. Positive and negative messages were then randomly classified into five categories. The 8531 messages in first four categories were utilised as training data set and the rest of the 2133 messages were utilised as the test data set.

Numerous pre-processing steps were employed to minimise the number of features prior to implement SVM training. Initially, the target query and terms related to topic (beef/steak related words) were deleted to prevent the classifier from categorising sentiment based on certain queries or topics. Then, numeric values in messages were replaced with a unique token “NUMBER”. A prefix “NOT_” was added to the words followed by negative word (such as “never”, “not” and words ending with “n’t”) in each sentence. In the end, Porter Stemming algorithm was utilised to stem the rest of the words (Rijsbergen et al., 1980).

Various feature sets were collected and their accuracy level was examined. Unigrams and bigrams representing one-word and two-word tokens were extracted from the microblog posts. In terms of performance of the classifier, we have used two types of indicators: (i) 5-fold cross validation (CV) accuracy, and (ii) the accuracy level obtained when trained SVM is used to predict sentiment of test data set. We have also implemented a Naïve Bayes classifier to compare the performance of the SVM classifier.

Table 3.4 reports the performance of Naïve Bayes (NB) and SVM based classifiers on the collected microblogs. The best performance is provided when using unigram feature set in both SVM and Naïve Bayes classifiers. It can be seen that the performance of SVM is always superior to the Naïve Bayes classifier in terms of sentiment classification. The unigram feature set gives better result than the other feature sets. This is due to the fact that additional casual and new terms are utilised to express the emotions. It negatively affects the precision of subjective word set characteristic as it is based on a dictionary. Also, the binary representation scheme produced comparable results, except for unigrams, with those produced by term frequency (TF) based representation schemes. As the length of micro blogging posts are quite short, binary representation scheme and TF representation scheme are similar and have almost matching performance levels. Therefore, the SVM based classifier with unigrams as feature set represented in binary scheme is used for estimating the sentiment score of the microblog.

The sentiment analysis based on SVM was performed on the country wise classification of tweets. Table 3.5 shows the example tweets and their sentiment scores.

Table 3.3 Top Twitter users

Twitter Handle	**Freq (>2k)**	**Freq (%)**	**Twitter Handle**	**Freq (>2k)**	**Freq (%)**	**Twitter Handle**	**Freq (>2k)**	**Freq (%)**
@historyflick	10903	9.16%	@chipotletweets	3701	3.11%	@shukzldn	2203	1.85%
@metrroboomin	10725	9.01%	@globalgrind	3626	3.05%	@zacefron	2201	1.85%
@jackgilinsky	8814	7.40%	@trapicalgod	3499	2.94%	@foodpornsx	2190	1.84%
@itsfoodporn	8691	7.30%	@viralbuzznewss	2964	2.49%	@redtractorfood	2166	1.82%
@kanyewset	7452	6.26%	@crazyfightz	2798	2.35%	@sza	2155	1.81%
@youtube	6593	5.54%	@soioucity	2795	2.35%	@therock	2131	1.79%
@earlsrestaurant	5822	4.89%	@kardashianreact	2765	2.32%	@tmzupdates	2093	1.76%
@hotfreestyle	3794	3.19%	@sexualgif	2564	2.15%	@ayookd	2031	1.71%
@audiesamuels	3775	3.17%	@cnn	2504	2.10%	@mcjuggernugets	2015	1.69%
@freddyamazin	3758	3.16%	@euphonik	2335	1.96%			

Table 3.4 Performance of SVM and Naïve Bayes based classifier on selected feature sets; CV – 5-fold cross validation, NB – Naïve Bayes

Representation scheme	**Feature Type**	**Number of Features**	**SVM**		**NB**
			CV (%)	Test data (%)	Test data (%)
Binary	Unigram	12,257	91.75	90.80	70.68
	Bigram	44,485	76.80	74.46	63.60
	Unigram + bigram	56,438	87.12	83.28	63.48
	Subjective word set ($\boldsymbol{\phi}$)	6,789	66.58	65.52	41.10
Term Frequency	Unigram	12,257	88.78	86.27	72.35
	Bigram	44,485	77.49	71.68	65.90
	Unigram + bigram	56,438	84.81	80.97	59.24
	Subjective word set ($\boldsymbol{\phi}$)	6,789	68.21	62.25	39.71

Table 3.5 Raw Tweets with Sentiment Polarity

Sentiment Polarity	Raw Tweets
Negative	*@Tesco just got this from your D'ham Mkt store. It's supposed to be Men's Health Beef Jerky...The smell is revolting https://t.co/vTKVRIARW5*
Negative	*@Morrisons so you have no comment about the lack of meat in your Family Steak Pie? #morrisons*
Negative	*@AsdaServiceTeam why does my rump steak from asda Kingswood taste distinctly of bleach please?*
Positive	*Wonderful @marksandspencer are now selling #glutenfree steak pies and they are delicious and perfect! Superb stuff.*
Positive	*Ive got one of your tesco finest* beef Chianti's in the microwave oven right now and im pretty pleased about it if im honest*
Positive	*@AldiUK beef chilli con carne! always a fav that goes down well in our house! of course with lots of added cheese on top! #WIN*

To identify meaningful topics and their content in the collected tweets, initially, we performed sentiment analysis to identify sentiments of each of the tweets. To gain more insights, the sentiment scores and country type was then used to perform content analysis.

The next section explains the results by sub-setting the captured data based on sentiment scores and country type.

3.4.1 Content analysis based on country type

3.4.1.1 Analysis of all the tweets from the world

The collected tweets were examined to identify the most frequently used words by consumers to express their views. Beef and steak are most frequently used words followed by fresh, taste, smell. Then, the association rule mining of these tweets is performed to find out which words are mostly used in conjunction with 'beef' and 'steak'. It was found out that the words 'celebrate', 'redtractorfood' are most widely used and words like 'smell', 'roast' are scarcely used with 'beef'. For instance, tweets like "*Celebrate St. Patrick's Day with dinner at the Brickstone! Irish Corned Beef and Cabbage tops the menu! https://t.co/vRnewdKZYd*" have very high frequency compared to the tweets similar to "*@Tesco just got this from your D'ham Mkt store. It's supposed to be Men's Health Beef Jerky...The smell is revolting https://t.co/vTKVRIARW5.*"

Further, cluster analysis is applied to classify them into some groups (or clusters) as per the similarities between tweets. The proposed clustering approach involves hierarchical cluster analysis (HCA) with uncertainty assessment. For each cluster in hierarchical clustering, *p*-values are calculated using multiscale bootstrap resampling. *P*-value of a cluster indicates its strength (*i.e.* how well it is supported by data). A parallel computing based HCA with *p*-values is implemented to quickly analyse the large number of tweets. The cluster, which has high *p*-values (approximate unbiased) are strongly supported by the capture tweets. These clusters can help us to explain user's opinion on beef and steak across the globe. The two predominant clusters identified (with significance >0.95 level) is represented in Figure 3.5 as red coloured rectangles. The first cluster consists of some closely related words like *gbbw, win, celebrate, and hamper, redtractorfood and dish*. It primarily highlights an event called *Great British Beef Week* in UK, where an organisation associated with farm assurance schemes called red tractor has asked customers to share their dish to win a beef hamper to celebrate this event. The second cluster consists of words like *bone*, which highlights presence of bone fragments in the beef and steak of the customers. The *taste, smell, freshness* and various *recipes* of the beef products are both appreciated and complained in the customer tweets. The details of the deals and promotions associated with food products primarily beef have been described.

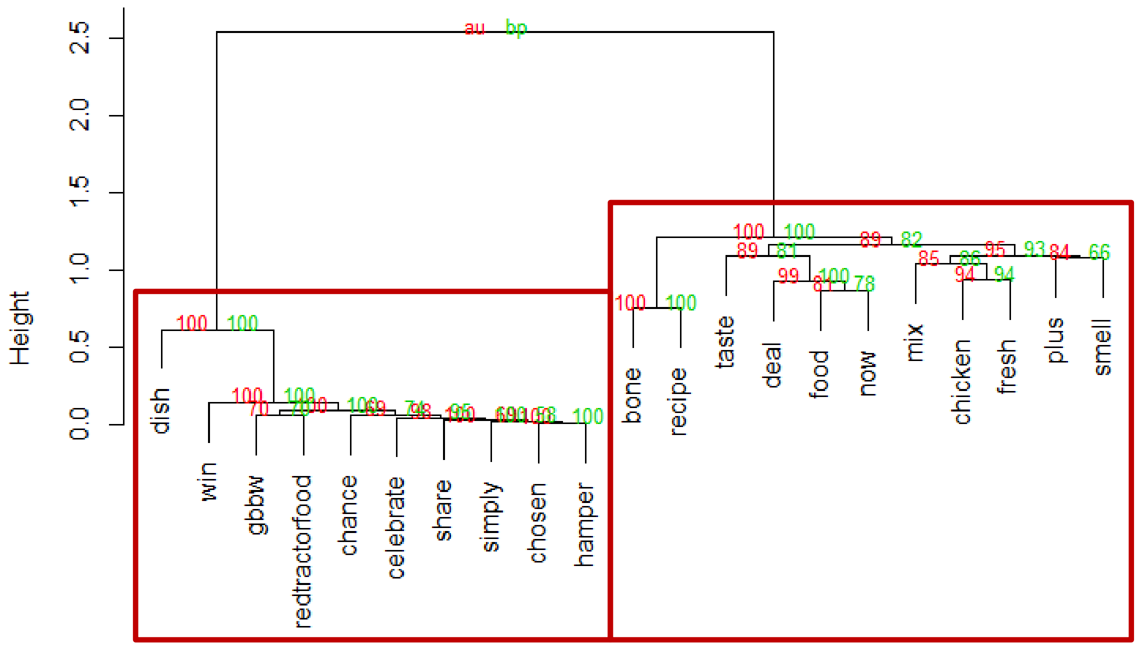

Figure 3.5 Hierarchical cluster analysis of the all tweets originating in the World; approximately unbiased p-value (AU, in red), bootstrap probability value (BP, in green)

During the analysis, it was found that Twitter data can be broadly classified in two clusters: tweets associated with episodic event and tweets associated with opinion of consumers on beef products. The intelligence gathered from episodic event cluster can help retailers in pursuing effective marketing campaigns of their new products. Retailers can also identify the factors having high influence within the network and their association with other related products. They can also use these medium to address consumer concerns. The second cluster will provide insight into likes and dislikes of consumers. Some tweets in this cluster were positive and others were negative, which are explained in next subsections.

3.4.1.2 Analysis of negative tweets from the world

The collected tweets were divided into positive and negative sentiment tweets. In negative sentiment tweets, the most frequently used words associated with 'beef' and 'steak', were 'smell', 'recipe', 'deal', 'colour', 'spicy', 'taste' and 'bone.'

Cluster analysis is performed on the negative tweets from the world to divide them into clusters in terms of resemblance among their tweets. The three predominant clusters identified (with significance >0.95 level) is represented in Figure 3.6 as red coloured rectangles. The first cluster consists of *bone and broth*, which highlights the excess of bone fragments in broth. The second cluster is composed of *jerky and smell*. The customers have expressed their annoyance with the bad smell associated with jerky. The third cluster consists of tweets comprising of *taste and deal*. Customers have often complained to the supermarket about the bad flavour of the beef products bought within the promotion (deal). The rest of the words highlighted in figure 3.6 do not lead to any conclusive remarks.

This cluster analysis will help global supermarkets to identify the major issues faced by customers. It will provide them opportunity to mitigate these problems and raise customer satisfaction and their consequent revenue.

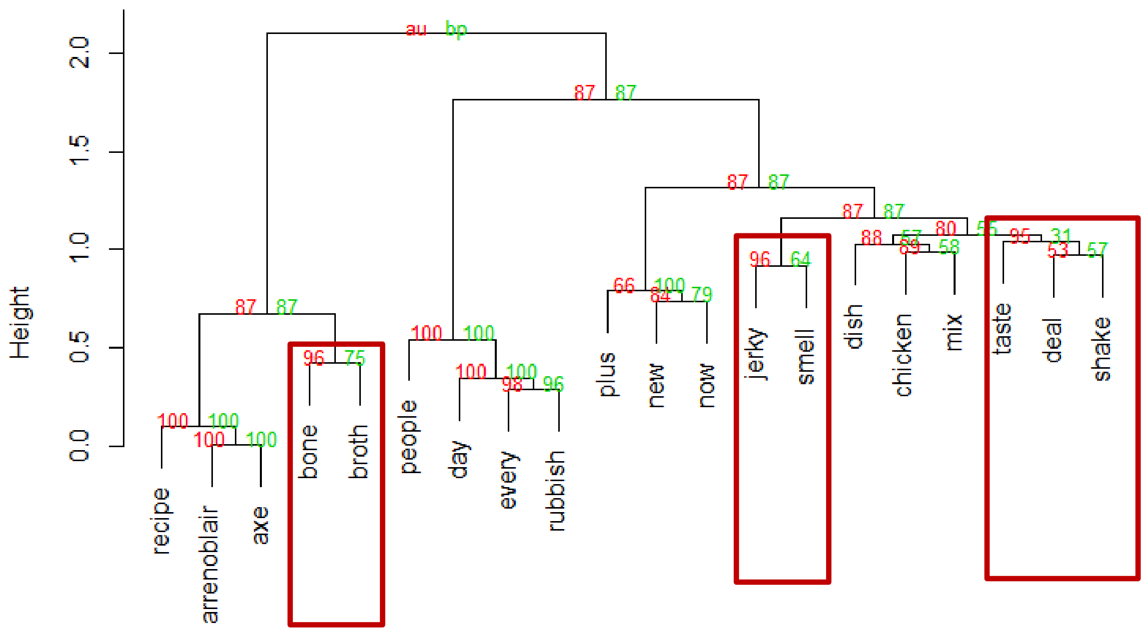

Figure 3.6 Hierarchical cluster analysis of the negative tweets originating in the World

3.4.1.3 Analysis of positive tweets from the world

The positive tweets from the world are analysed and most frequently used words after 'beef' and 'steak' were 'fresh', 'dish' and 'taste'.

The association rule mining evaluation of the positive tweets from around the world is performed. It is found that 'beef' was closely associated with words like 'celebrate', 'redtractorfood' and was rarely used with words like 'months' and 'ways'. The word 'steak' was frequently used with words like 'awards', 'kca' and was sparsely used with 'chew', 'night'.

The positive tweets from the world are classified into two clusters based on the similarity in their tweets. They are divided into two clusters as shown in Figure 3.7. The first cluster is composed of words like '*dish, win, gbbw, celebrate, redrtractorfood, share, hamper*'. These tweets are associated with the celebration of Great British beef week in the UK. A British farm assurance firm known as red tractor has asked customers to share their dish to win a beef hamper. The findings from this cluster do not contribute to the objective of this study to develop consumer centric supply chain and waste minimisation strategy. However, retailers can utilise it to develop a strategy to introduce appropriate promotional deals to capture larger market share than their rivals during events like great British beef week. The second cluster is composed of words like *love, taste, best roast, delicious food* where customers have praised the taste and overall quality (like smell, tenderness) of the beef products. The words like '*deal, great*' highlight the promotions, which were very popular among customers while purchasing beef products.

This cluster analysis will help global supermarkets to show their best performing beef products and their strength like taste, promotions. It will help them in the introduction of new products and promotions.

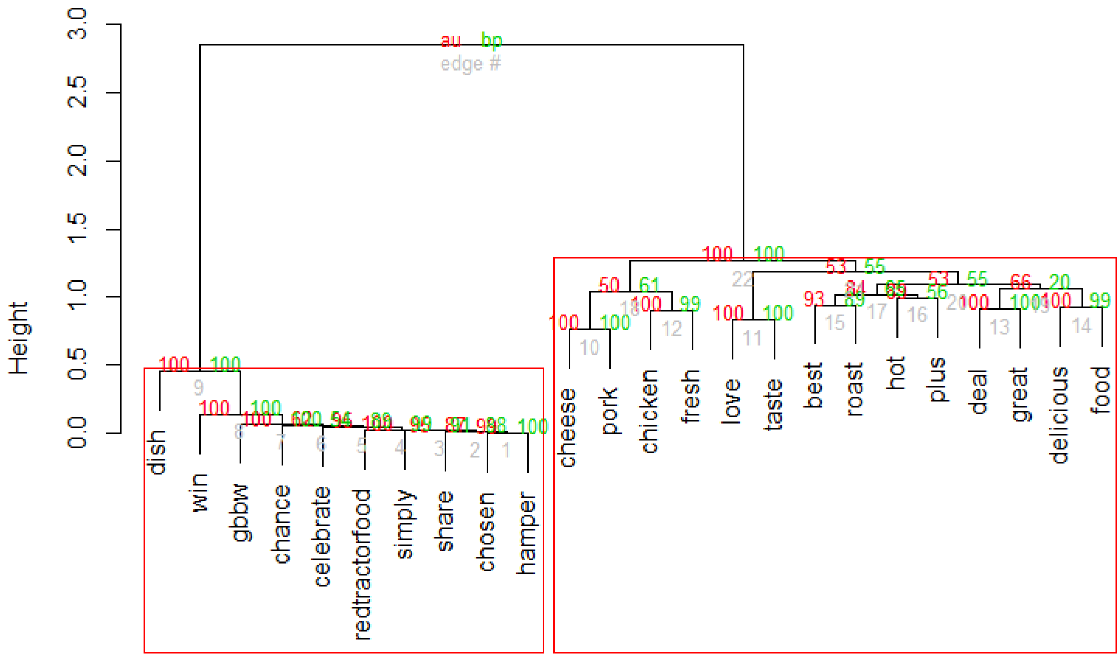

Figure 3.7 Hierarchical cluster analysis of the positive tweets originating in the World

3.4.1.4 Analysis of positive tweets from UK

The positive tweets from UK were analysed and most widely used words after 'beef' and 'steak' were 'adliuk, 'morrisons', 'waitrose' 'tesco'. The association rule mining of tweets from UK with positive sentiment was conducted and the word 'beef' was most closely associated with terms like 'roast britishbeef', 'Sunday' and least used with words like 'type', 'tell'. The term 'steak' was most frequently used with words like 'days', 'date', 'free' and was rarely used with terms like 'supper', 'quick', 'happy'.

The positive tweets from the UK are classified into three clusters based on the similarity among their tweets. The first cluster consists of words like '*leeds* and *nfunortheast'*, which highlights an event that took place in Leeds, UK where Asda has joined NFU Northeast in selling red tractor (farm assurance) approved beef products. The second cluster consists of words like '*delicious, roast, lunch, Sunday*', where customers are talking about cooking roast beef products on Sunday, which turn out to be delicious. Third cluster is composed of words like '*thanks, love, made, meal*', where customers are grateful for the good quality of beef products after cooking them.

The cluster analysis will help UK supermarkets to find out the preference of customers. For instance, they prefer the beef originating from the farms approved by farm assurance schemes (Red Tractor). They can also monitor their best performing beef products, which will assist them in launching their new products. It will help retailers to develop a strategy to align their products with the preference of the consumers.

3.4.1.5 Analysis of negative tweets from UK

The most widely used words after 'beef' and 'steak' were 'tesco', 'coffee', 'asda', 'aldi'. The association rule mining indicated that the word 'beef' was most closely associated with terms like '*brisket'*, '*rosemary'*, and '*cooker'*, etc. It was least used with terms like '*tesco'*, '*stock'*, '*bit'*. The word '*steak'* was highly associated with '*absolute', 'back', 'flat'* and rarely associated with words like 'stealing', 'locked', 'drug'.

The four predominant clusters are identified (with significance >0.95 level). The first cluster contains words – *man, coffee, dunfermline, stealing, locked, addict, drug*. When this cluster was analysed together with raw tweets, it was found that this cluster represents an event where a man was caught stealing coffee and steak from a major food store in Dunfermline. The finding from this cluster is not linked to our study. However, it could assist retailers for various purposes such as developing strategy for an efficient security system in stores to address shoplifting. Cluster 2 is related to the tweets discussing high prices of steak meal deals. Cluster 3 represents the concerns of users on the use of horsemeat in many beef products offered by major superstores. It reveals that consumers are concerned about the traceability of beef products. Cluster 4 groups tweets which discuss the lack of locally produced British sliced beef in the major stores (with #*BackBritishFarming*). It reflects that consumers prefer the beef derived from British cattle instead of imported beef. Rest of the clusters, when analysed together with raw tweets, did not highlight any conclusive remarks and users were discussing mainly one-off problems with cooking and cutting slices of beef.

The proposed HCA can help to identify (in an automated manner) root causes of the issues with the currently sold beef and steak products. This can help major superstores to monitor and respond quickly to the customer issues raised in the social media platforms.

3.4.1.6 Analysis of negative tweets from Australia

The tweets with negative sentiment from Australia were analysed and the most frequently used words after 'beef' and 'steak' were '*aldi'* and '*safeway'.* The association analysis shows that the term 'beef' was most closely associated with words like '*safeway'*, and '*corned'* and was least associated with '*grass, 'gross', packaged*'. The word '*steak'* was mostly used in conjunction with terms like '*woolworths', 'breast', 'complain*' and was rarely used with terms like '*waste', 'wine', 'tough*'.

Cluster analysis has been performed on the negative tweets from Australia and they have been classified into two clusters based on similarity in their tweets. The first cluster consists of words like '*feel, eat, complain*', which reflects customers complaining the quality of beef products especially tenderness and flavour. The second cluster comprises of words like '*disappointed, cuts, cook, sold, dinner*', which shows the annoyance of customers with beef products cooked for dinner especially in terms of smell, cooking time and overall quality.

This analysis will assist the Australian supermarkets to explore the issues faced by customers. It will help them to backtrack their supply chains and mitigate them in order to improve customer satisfaction and consequent revenue.

3.4.1.7 Analysis of positive tweets from Australia

The tweets from Australia having positive sentiment is analysed and the most frequently used words after 'beef' and 'steak' were 'aldi', 'woolworths', 'flemings', 'roast'. The association analysis indicated that the word 'beef' was most closely associated with terms like 'roast', 'safeway', 'sandwich' and was least used with terms like 'see', 'slow', 'far'. The word steak was commonly used with terms like 'flemings', 'plate' and is rarely used with words like 'spent', 'prime', house'.

Cluster analysis has been performed on the positive tweets from Australia. Two significant clusters were identified. The first cluster consists of words like '*new, sandwich, best, try*', where customers are praising the new beef sandwich they tried in different supermarkets. The second cluster includes words such as '*delicious, Sunday, well, roast, best*', in which customers are appreciating the flavour of roast beef cooked on Sunday, bought from different supermarkets.

The cluster analysis of positive tweets will help Australian supermarkets to see the best performing beef products among their brands and their rival brands. It will help them to identify the most popular beef products among customers. It will help them in launching the new beef products and strengthen their position in the market against their rivals.

3.4.1.8 Analysis of negative tweets from USA

The tweets from USA having negative sentiment is being analysed and the most frequently used words were 'beef', 'carnival', 'steak', 'walmart', 'sum', 'yall'. The association rule mining was performed and the results indicated that the term 'beef' was most closely associated with words like '*carnival', 'yall', dietz*' and is least associated with terms like '*cake', 'sum', 'ride', 'grow'*. The word 'steak' was most frequently used with terms like *'shake', 'walmart', 'stolen'* and is least frequently used with words like *'show', 'minutes', 'fries'*.

Cluster analysis is being performed on the negative tweets from the USA and they have been classified into two clusters based on the similarity in their tweets. The first cluster includes words like '*mars, corned, beef, cream, really, eggs, trending, bars, personally*'. There was a tweet which was retweeted many times, which has expressed the annoyance of a customer for the price of corned beef and has compared it to Mars bars and Cream eggs. The second cluster is composed of terms like *'jerky, eat, went*', where customers have gone to supermarket to buy steak or joint but they could only find beef jerky on the shelves.

The negative cluster analysis will help the US supermarket to understand the problem faced by customer. For instance, the high price of corned beef and unavailability of steak and joint were the major issues highlighted. The supermarkets can liaise with their supplier and develop appropriate strategy to satisfy their customers and thereby generate more revenue.

3.4.1.9 Analysis of positive tweets from USA

The positive tweets from USA were analysed and the most frequently used words were 'beef', 'lamb', 'lbs', 'steak', 'tops', 'walmart.' The association rule mining of tweets from USA were performed and the results indicated that term 'beef' was most closely associated with words like *'lamb', 'pork', 'lbs', 'generate*' and was least associated with terms like '*tops', 'cheese', 'equivalents'*. The word 'steak' was most frequently used with terms like 'butter', 'affordable' and is rarely used with terms like '*truffles', 'sea', 'honey'*.

Two significant clusters were identified. The first cluster consists of words like '*tops, equivalents, cheese, greenhouse, gases, generate, pork, every, list, lamb, lbs*'. Customers have compared the greenhouse gases generated by production of beef to that of lamb and cheese. They have suggested that beef has lower emissions than lamb. The second cluster comprises of terms such as '*top, new, publix, better, best*' where customers have appreciated the beef products sold by Publix to that of other supermarkets in terms of quality and price.

The cluster analysis of positive tweets will help US supermarkets to find out the qualities preferred by consumers. For instance, they were conscious of the carbon footprint generated in the production of beef, lamb and cheese. They were also looking for high quality beef products at reasonable price. It will help the US supermarket to develop their strategy for introduction of new products.

In the next section, it has been described how content analysis of Twitter data could help retailer in waste minimisation, quality control and efficiency improvement by linking them to upstream of the supply chain.

3.5 Root cause identification and waste mitigation strategy

The maximum amount of the waste in beef supply chain is generated at the consumer end because of different root causes as depicted in figure 3.8. The nature of consumer tweets related to beef products is vague. They lack the precision of consumer complaints made in the retail store, which includes information such as date of purchase, bar code, end of shelf life etc. The exact root causes of consumer complaints could be traced back in the supply chain by using the rich information available in the consumer complaints made in the retail store. However, this precision could not be replicated while using consumer complaints made on social media data as they are written in brief, informal and have a constraint of 140 characters in a tweet. Therefore, only probable root cause of the waste could be identified using social media data. The probable root causes of waste and preventive measures to address them are mentioned below:

a. Losing colour – In some cases, discoloration of beef products is observed prior to the end of their shelf life as shown in Table 3.6. Customers have a perception that the shelf life of these products (lacking fresh red colour) has ended and therefore refrain to purchase them thereby resulting in them going waste. The major root cause of this issue is deficiency of Vitamin E in diet of cattle indicating that cattle are not raised on fresh grass (Liu et al., 1995; Houben et al. 2000; Cabedo et al., 1998; Fornmanek et al., 1998; O'Grady et al., 1998; Lavelle et al., 1995; Mitsumoto et al., 1993). Other reasons might also be contributing to the discoloration of beef products such as temperature abuse (Rogers et al., 2014; Jakobsen & Bertelsen, 2000; Gill & McGinnis, 1995; Eriksson et al., 2016). Exposure of more than three degree Celsius results in beef products losing their fresh red colour (Rogers et al., 2014; van Laack et al., 1996; Jeremiah & Gibson, 2001; Greer & Jones, 1991). Hence, the issue of discoloration of beef products observed at consumer end could be addressed by raising cattle with fresh grass at beef farms and maintaining chilled temperature throughout the supply chain for beef products derived from carcass.

Table 3.6 Example of consumer tweets highlighting discoloration

S.No.	Consumer tweets
1.	*@AsdaServiceTeam what do I with beef i bought yesterday that's been cooked for Sunday dinner and comes out a funny colour and smells rancid?*
2.	*@sainsburys beef packaging blown and discoloured*
3.	*@Tesco joint was green in colour.*
4.	*@CooperativeFood check your stock in Chelmsford, the corn beef on the right was a very strange grey colour. https://t.co/YE28VjZnY6*
5.	*Colour of @Morrisons steak has gone off.*

b. Hard texture – The quality of beef products is often decided by the tenderness of beef products (Godson et al., 2002). The beef products lacking tenderness and inconvenient to chew results in disappointment of consumers and often get discarded (Huffman et al., 1996). These issues are primarily observed in beef products derived from hindquarter of cattle such as steak and joint as shown in Table 3.7. The major root cause of this issue is insufficient maturation of carcass post slaughtering (Riley et al., 2005; Vitale et al., 2014; Franco et al., 2009; Gruber et al., 2006; Monsón et al., 2004; Sañudo et al., 2004; Troy and Kerry, 2010). During the maturation process, carcass is preserved in chilled temperatures for duration of seven to twenty-one days based on breed, age and gender of cattle (Riley et al., 2005). Hence, the tenderness of beef products could be improved by appropriate maturation of carcass.

Table 3.7 Example of consumer tweets highlighting hard texture

S.No.	Consumer tweets
1.	*@asda v disappointed with pepper steak medallions tonight, really sinewy n chewy. Not much of a Fri night treat.*
2.	*Morissons rump steak awful, tough as boots and overpriced, Aldi in future.*
3.	*@Tesco Hi Aimee, after slow cooking the beef was inedible as it was so tough a dining knife could not cut through, ordered guests takeaway*
4.	*The worst steak @Outback in CC,Tx. My steak was midRare 2 salty, 2 tough 2 cut thru & chewy!! Ugh, so disappointing when dinner is ruined.*
5.	*@AldiUK very disappointing Specially Selected Fillet Steak full of inedible fibrous tissue, couldn't cut it #yuk https://t.co/oZW8bzIBun*

c. Excess of fat and gristle – During the study, it was revealed that beef products having excess of fat and gristle are discarded by consumers as waste as shown in Table 3.8. The root cause of this problem could be traced back to both beef farms and slaughterhouse. The meat derived from cattle, which are not raised as per the retailer’s conformation and weight specifications are expected to have excess of fat (Hanset et al, 1987; Herva et al., 2011; Borgogno et al., 2016; AHDB Industry

Consulting, 2008; Boligon et al., 2011). Similarly, extra layer of fat is left on beef products if proper trimming techniques are not being followed in the boning hall of the abattoir (Francis et al., 2008; Mena et al., 2014; Kale et al., 2010; Watson, 1994; Cox et al., 2007). Hence, optimum procedures of animal welfare should be followed so that cattle meet the weight and conformation specifications of the abattoir and appropriate trimming of primals should be done at the abattoir. Consumers also get disappointed by the extra gristle in the beef products. Appropriate butchering and boning methods for the beef products derived from chuck, shoulder and legs should be followed to minimise the amount of gristle present in beef cuts (Cobiac et al., 2003).

Table 3.8 Example of consumer tweets highlighting excess of fat and grsitle

S.No.	Consumer tweets
1.	@LidlUK so disappointed with my 5% lean frying steak. Over 1/2 one steak was fat & bone! #disappointed #canteatthat https://t.co/8SwpwfuJuv
2.	@Tesco I got some Steak from the butcher counter and had no idea how much fat was on it. Wouldn't have got it. https://t.co/Do8H4TITm2
3.	@Tesco really disappointed with the quality of this rump steak full of fat! Bought for 6year olds birthday tearuined https://t.co/lE0px0cuag
4.	Spend 5hours slow cooking beef the 6year old wants it for dinner, cut it to find its basically just fat @Morrisons #bin
5.	@sainsburys steak was all gristle and fat inedible

d. Bad flavour, smell and rotten – Oxidation of beef products i.e. oxidisation of their lipids and proteins because of being exposed to air is one of the major root cause of foul smell, poor flavour and beef products getting rotten (Brooks, 2007; Campo et al., 2006; Utrera and Estévez, 2013; Wang and Xiong, 2005). Consumers consider these products as inedible and hence discard them as shown in Table 3.9. Their root cause lies in the packaging process of beef products. Inappropriate packaging methods might be followed at abattoir and processor and damaging of packaging while product flow in the supply chain might be resulting in premature oxidization of beef products (Barbosa-Pereira et al., 2014; Brooks, 2007). This issue could be addressed by periodic maintenance of packaging machines, random sampling of beef products, implementation of modern packaging techniques, which delays the oxidization process in beef products (Cunningham, 2008). Retailer staff could be provided proper training so the beef products are not damaged because of mishandling. Bad smell, flavor and beef products getting rotten are also caused by inefficiency of cold chain (James and James, 2002, 2010; Raab et al., 2011). Maintenance of chilled temperature of 1-3 degree Celsius for beef products in the entire supply chain viz. abattoir, processor and retailer is crucial (Kim et al., 2012; Mena et al., 2011). Lack of periodic maintenance of refrigeration equipment also results in inefficient cold chain management (Kim et al., 2012). Periodic temperature checks should be performed at different segments in the supply chain so that chilled temperature within permissible limits (1-3 degree Celsius) is maintained for optimum product flow of beef products.

Table 3.9 Example of consumer tweets highlighting bad flavour, smell and rotten

S.No.	Consumer tweets
1.	*@Tesco just got this from your D'ham Mkt store. It's supposed to be Men's Health Beef Jerky...The smell is revolting https://t.co/vTKVRIARW5*
2.	@LidlUK @siogibbs beef bought for mothers day meal rancid + in bin. house stinks like rotten cheese and have ordered pizza bbd 08/03 #mumday
3.	@Tesco bought 2 beef joints from u. Smelt disgusting & taste even worse. Like iron. Totally inedible. Basically unfit 4 human consumption.
4.	The beef lasagne from woolworths smells like sweaty armpits siesðŸ˜·ðŸ˜·ðŸ˜·
5.	Woolies Cradlestone mall sold me rotten "slow cook steak/beef"@WoolworthsSA#unbelievable

e. Foreign bodies – Foreign bodies such as piece of metal, insect, piece of plastic have been found in beef products in some instances as shown in Table 3.10. These products are considered as inedible by the consumers and hence discarded. This issue is generated because of inefficiency of packaging machines at abattoir and processor, lack of food safety process management procedures like HACCP, lack of safety checks such as metal detection (Goodwin, 2014; Lund et al., 2007; Jensen et al., 1998; Piggott and Marsh, 2004). Random sampling of beef products and periodic maintenance of packaging machines should be performed at abattoir and processor. To address this issue, proper safety checks like physical inspection, metal detection should be conducted at different segments of abattoir and processor and a renowned food safety process management technique such as GMP, HACCP must be adopted (Bolton et al., 2001; Goodwin, 2014; Roberts et al., 1996). The packaging of beef products also gets damaged by mishandling within the supply chain (Goodwin, 2014; Singh et al., 2015). The workforce working at premises of all the stakeholders must be appropriately trained and supervised to address this issue. There should be quality checks performed at various stages in the supply chain so that beef products consisting of foreign bodies like piece of metal and insects are discarded prior to being sold to the consumers.

Table 3.10 Example of consumer tweets highlighting foreign bodies

S.No.	Consumer tweets
1.	@asda Just found a bit of bone in my ASDA corned beef. It must slip in at times, but it's a bit offputting. Luckily, it did no tooth damage.
2.	@CooperativeFood just found a small piece of hard plastic in my steak pastry?!
3.	@marksandspencer I found a piece of metal in one of your steak and kidney pie. Almost broke a tooth. https://t.co/GEN52q2f0M
4.	@sainsburys needle found in 5% fat mince
5.	@asda pieces of glass in 20% fat mince

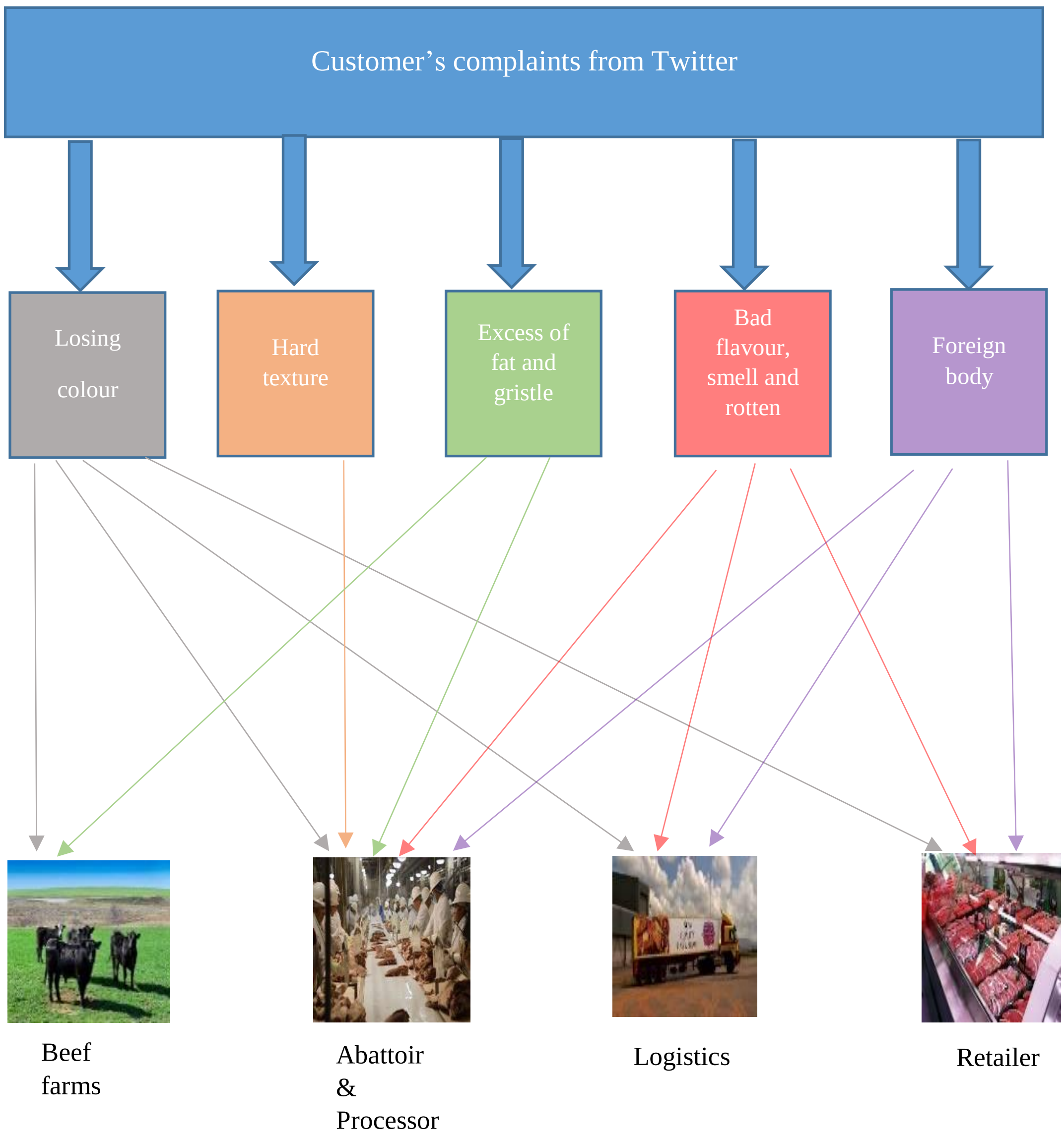

Figure 3.8 Association of issues occurring at consumer end with various stakeholders of beef supply chain

Table 3.11 Summary of issues identified from consumer tweets and their mitigation

S. No.	Issues identified from consumer tweets	Mitigation of issues
1	Bad flavour and unpleasant smell	Periodic maintenance of packaging machines at abattoir and processor (Barbosa-Pereira et al., 2014), efficient cold chain management (Kim et al., 2012), appropriate training of workforce in logistics and throughout the supply chain so that mishandling of beef products is avoided (Mishra and Singh, 2016).
2	Extra fat	Raising of cattle as per the weight and conformation specifications of retailer (Borgogno et al., 2016) and appropriate trimming of primals at abattoir and processor (Mena et al., 2014).
3	Discoloration of beef products	Raising cattle on fresh grass at beef farms and maintaining efficient cold chain management throughout the supply chain (Mishra and Singh, 2016).
4	Hard texture	Appropriate maturation of carcass after slaughtering (Singh et al., 2017).
5	Presence of foreign body	Following renowned food safety process management techniques like GMP, HACCP (Goodwin, 2014). Appropriate safety checks such as physical inspection, metal detection, random sampling (Bolton et al., 2001). Periodic maintenance of machines at abattoir and processor (Singh et al., 2017).

In the next section, managerial implications of proposed framework have been described in detail.

3.6 Managerial Implications

The finding of this study will assist the beef retailers to develop a consumer centric supply chain. During the analysis, it was found that sometimes, consumers were unhappy because of high price of steak products, lack of local meat, bad smell, presence of bone fragments, lack of tenderness, cooking time and overall quality. In a study, Wrap (2008) estimated that 161,000 tonnes of meat waste occurred because of customer dissatisfaction. The majority of food waste is because of discolouration, bad flavour, smell, packaging issues, and presence of foreign body. Discolouration can be solved by using new packaging technologies and by utilising natural antioxidants in diet of cattle. If the cattle consume fresh grass before slaughtering, it can help to increase the Vitamin E in the meat and have a huge impact on delaying the oxidation of colour and lipids. The issues related to bad smell and flavour can be caused due to temperature abuse of beef products. The efficient cold chain management throughout the supply chain, raising awareness and proper coordination among different stakeholders can assist retailers to overcome this issue. The packaging of beef products can be affected by mishandling during the product flow in the supply chain or by following inefficient packaging techniques by abattoir and processor, which can also lead to presence of foreign body within beef products. Inefficient packaging affects the quality, colour, taste and smell. Periodic maintenance of packaging machines and using more advanced packaging techniques like Modified Atmosphere Packaging and Vacuum Skin Packaging will assist retailers in addressing above mentioned issues. The high price of beef products can be mitigated by improving the vertical coordination within the beef supply chain. The lack of coordination in the supply chain leads to waste, which results in high price of beef products. Therefore, a strategic planning and its implementation can assist the food retailers to reduce price of their beef products more efficiently than their rivals.

The major issues revealed by customer's tweets helps to identify their root causes in supply chain. It can be at the premises of a stakeholder, at the interface of two stakeholders or at multiple places within the supply chain. The proposed framework in this study will help the policy makers of the retailer to prioritize the mitigation of various issues as per their impact on food waste. Normally, all the stakeholders in a beef supply chain work independently. If a common issue is identified in the whole supply chain leading to the waste in the customer end. Then, the retailer can assist all the stakeholders to improve their coordination (in terms of information sharing) and collectively address this issue. The improved coordination among stakeholders will not just help in waste minimisation but assist in improved product flow, efficiency and sustainability of the supply chain. These aspects would be beneficial for both the retailer firms and the society.

3.7 Conclusion

Rising population is a cause of concern globally as there are limited resources (land, water, etc.) to produce food for them. Millions of people are dying worldwide because of being deprived from food. These complications cannot be mitigated alone by development of innovative technologies to extract more harvest from the limited natural resources. Waste minimisation must be made a priority throughout the food supply chain including their consumption at consumer's end. Food waste financially affects all the stakeholders of food supply chain viz. farmers, food processors, wholesalers, retailers, and consumers. Majority of waste is being generated at consumer end. Often, consumers are not happy with the food products and discard them. Apart from food waste, retailers are losing their customers because of their dissatisfaction. Although, major retailers have made a provision for the customers to make a complaint in the store, still, customers are not doing so. They are using social media like Twitter to express their disappointment. Consumers usually tag the name of the retailer while making their complaints on social media, which is affecting the reputation of the retailers. There is plenty of useful information available on social media like Twitter, which can be used by food retailers for developing their waste minimisation strategy. In this study, Twitter data has been used to investigate the consumer sentiments. More than one million tweets related to beef products has been collected using different keywords. Sentiment mining based on SVM and HCA with multiscale bootstrap sampling techniques were proposed to investigate positive and negative sentiments of the consumers; as well as, to identify their issues/concerns about the food products. The collected tweets have been analysed to identify the main issues affecting consumer satisfaction. The root causes of these identified issues have been linked to their root causes in different segments of supply chain. During the analysis of the tweets collected, it was found that the main concern related to beef products among consumers were colour, food safety, smell, flavour and presence of foreign particles in beef products. These issues generate huge disappointment among consumers. There were lots of tweets related to positive sentiments where consumers had discovered and shared their experience about promotions, deals and a particular combination of food and drinks with beef products. Based on these findings, a set of recommendations have been prescribed for waste minimisation and to develop consumer centric supply chain.

The proposed framework assisted in addressing the waste occurring at the consumer end of the beef supply chain by data mining from social media. However, waste is being generated at the premises of other stakeholders (farmers, abattoir, processor and retailer) as well. The next chapter proposes a mechanism to mitigate the waste generated at these segments. The data collection is being done by interviews of different stakeholders which are analyzed by Current Reality Tree method to recommend good practices for waste minimization in beef supply chain.

CHAPTER 4

Sustainable Food Supply Chain: A Case Study on Indian Beef industry

4.1 Introduction

India is one of the largest exporters of beef in the world (United States Department of Agriculture, April, 2015). The consumption of beef is very less locally and majority of the products are being exported to around 65 countries across the globe (Agricultural and Processed Food Products Export Development Authority, 2014-15). This segregated scenario of production and consumption often leads to generation of waste. The amount of food lost along the supply chain is approximately, 25-50%, which is a huge number (Mena et al., 2011). Sustainable consumption and production is one of the most pressing challenges in this sector. It directly impacts some of the crucial issues across the globe. The foremost is that the millions of people are losing life because of food scarcity. The food wasted in the supply chain could be utilized to feed them. There are also environmental implications of wasting food as lots of resources (land, water and energy) are being exploited for producing it. The food waste generated is also being disposed to landfill leading to the generation of Methane, which is a very potent greenhouse gas, leading to global warming. Besides, the food wasted along the supply chain, financially affects all the stakeholders of supply chain including customers. Mitigation of the food waste can play a significant role in strengthening the fortunes of global food industries and thereby boost national economies around the world. In recent years' food waste, has started to draw the attention of government, private, academic and food industry practitioners.

Food waste is generally being ignored because the associated expenses are often under rated. Multi-national firms of food industry usually keep their waste figures confidential because of data sensitivity. Raising awareness will play a crucial role in drawing the attention of food industry towards the multi-dimensional consequences of food waste. It will improve the financial return to the farmers, who gets the least profit in the supply chain. Simultaneously, it will address the global issues of food security, environmental implications and financial crisis of food industries and will also help to achieve sustainable consumption and production. Keeping the same in mind, this study is focused on the waste minimisation in Indian beef supply chain. The aim of the study is to draw the attention of Indian beef industry towards sustainable production and consumption. Suggestive measures have been proposed at firms' levels to make a balance between production and consumption.

4.2 Beef Supply chain in India

According to USDA (United States Department of Agriculture), India is the largest exporter of beef (United States Department of Agriculture, April, 2015). It exports beef to 65 countries, which includes Vietnam, Thailand, Malaysia, Jordan, Egypt, Saudi Arabia, etc. (Agricultural and Processed Food Products Export Development Authority, 2014-15a). This beef is basically derived from buffalo as Indian government has imposed a ban on beef exports derived from cow. There is strict ban on few states of India for slaughtering of cow. The consumption of beef is very less in India as compared to its massive exports. The primary reason is 80% of population of India is Hindu, who abstain from eating beef.

India has approximately 115 million buffaloes, which is more than half of the global population of buffalo (Agricultural and Processed Food Products Export Development Authority 2014-15b). They are finished on fresh pastures instead of growth hormones. Hence, the demand of beef obtained from them is very high in south East Asian countries and Middle East nations. Recently, Russia and China has also opened their market for Indian beef. Hence, Indian beef exports are expected to grow more, which is termed as "Pink Revolution" in India. Beef exports in India have already surpass their previous most exported commodity (Basmati Rice) (Time.com, April, 2015).

The beef supply chain is complex in nature. It includes all the stakeholders from farmer to retailer. Figure 1 shows an illustrative diagram of beef supply chain. The Indian beef farms are of different sizes and contain varying number of cattle. The farmer raises the cattle in beef farms to the finishing age, which could be anywhere between 3 months to 30 months. The finishing age depends on the breed of cattle, gender and demand in market (local and abroad). The cattle are sent to abattoir and processor, when they reach their finishing age, by deploying logistics. The abattoir slaughters the cattle and slices them into primals. The processor then processes these primals into human consumable products like steak, joint, burger and meatball, etc. Then, packing and labelling of these fine products are completed and sent to retailers both local and abroad for consumption.

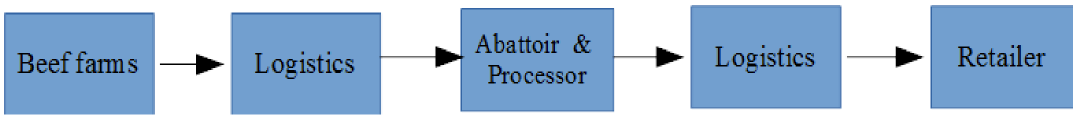

Figure 4.1 Product flow in Indian beef supply chain

Most of the Indian beef is exported to foreign countries for consumptions. It creates an imbalance between production and consumption and results in huge amount of waste. In order to investigate the root causes of waste and corresponding preventive measures, interview of different stakeholders is being conducted. The interview information is being analysed using Current Reality Tree method. The detailed information of interview data and outcome of analysis is being described in detail in upcoming sections. In the next section, with the help of interview we have classified different types of waste and their root causes.

4.3 Research Method

The goal of this chapter is to identify the root causes of waste in Indian beef supply chain and to suggest good practices to mitigate them. Biggest chunk of Indian beef export goes to Vietnam. Hence, in this study, one of the supply chain of Indian beef products (steak, joints, mince, stir fry, etc.) exported to Vietnam is being considered.

In beef supply chain, waste is occurring at all stages viz. farms, abattoirs, processors, retailers and logistics. Although, the reason of waste occurring at various segments is different, they are still interconnected. Initially, a thorough literature review is being conducted to explore the nature and types of waste. Thereafter, academic practitioners visited farms and processing units of different sizes located in various geographical locations to observe their operations and spoke to them in detail about the issues arising there with respect to waste. Based on literature review and initial collected data, interview questions are drafted. Thereafter, questionnaire was sent to experts of red meat supply chain at Aberystwyth University, UK for their comments. Their feedback was incorporated and a final interview questions were finalized.

Thirty interviews were conducted across the whole supply chain. It includes twenty beef farmers, four managers of abattoirs and processors, three managers of logistic firms and three managers of the Vietnam based retailer firm who were working in India. This process revealed valuable information about the potential waste occurring at various stages of beef supply chain. The interviews conducted lasted for one hour each and was carried on by two researchers. Interviews were not recorded for confidentiality reasons. One of the researchers was asking questions to the interviewee and the other was doing the note taking. These notes were sent to the interviewee later to take his consent. Company records and observation by researcher also helped in data collection. All the participating firms were concerned about the sensitivity of the information and were not very comfortable in sharing the waste data. Hence, their identity has been kept confidential. The developed report based on data collection was sent to the firms and farms involved. They cross checked all the information and added some valuable data and comments.

4.4 Analysis

To identify the root cause of waste and best waste management practices, collected primary data was analyzed using qualitative data analysis technique. At first, interview data were analyzed individually from farmer to retailer end. Each collected data were coded and put into standard format. Each interview was analyzed separately and key information was extracted to produce templates. Thereafter, these individual templates were analyzed so that the individual perception about waste of all the managers was being explored. However, waste occurring in the supply chain is the result of collective activities of all stakeholders. Therefore, all the templates are joined together and analyzed using Casual map to find out inter- relation between wastes occurring at premises of different stakeholders.

In the literature, Casual map method have been used for various purposes like identifying root causes (Jenkins and Johnson, 1997; Fiol and Huff, 1992), to develop cause and effect diagram (Ishikawa, 1990) and interrelation diagrams (Doggett, 2005) for quality management. Kaplan and Norton (2004) have used strategy maps to demonstrate the long-term strategy of a firm.

In Causal map, relationship between components of a framework are represented by graphs, where nodes denote problems, concepts or ideas and the unidirectional arcs connecting these nodes denotes the causal relationship between them (Scavarda et al., 2006). There are various kinds of causal maps available for root cause identification (Doggett, 2005). However, the CRT (Current Reality Tree) has been used in this study, considering its clear logical flow and capability to identify distinct and logical root causes (Walker and Cox, 2006; Doggett, 2005). The creation of CRT begins with finding out the surface issues or unwanted consequences (Walker and Cox, 2006). It utilizes three unique symbols: nodes represent unwanted consequences, arcs represent causal relationship and oval denotes the ‘AND’ logical function, which means that two or more causes are needed to generate an effect. The unwanted consequences are connected via an if-then logic. The process creates a graph or tree having the final issues or problem at the top and the root causes can be found out at the bottom.

In this study, CRT for Indian beef supply chain is being created as shown in figure 4.2. The top of the tree denotes the generation of waste across the beef supply chain, which is the major focus of this research. The central part of tree denotes the intermediate causes of waste generation. The root causes of generating waste in entire beef supply chain are located at the bottom of the tree, which will be discussed in detail in following section.

4.5 Results

The outcomes of Current Reality Tree are described in two subsections. Initially, major root causes of waste in Indian beef supply chain have been identified. Some of the root causes are interconnected. Then, each root cause was allocated a range (1-5%; 6-10%; >10%) based on the information collected in interviews and company records. These ranges were verified with the interviewees. Finally, the destination of the waste generated has been described.

A. *Root causes of waste occurring in beef supply chain and the corresponding ranges*

This section describes the root causes of waste occurring at the premises of various stakeholders in beef supply chain. They are identified using Current Reality Tree. These root causes are described as following and the corresponding waste range is given in brackets:

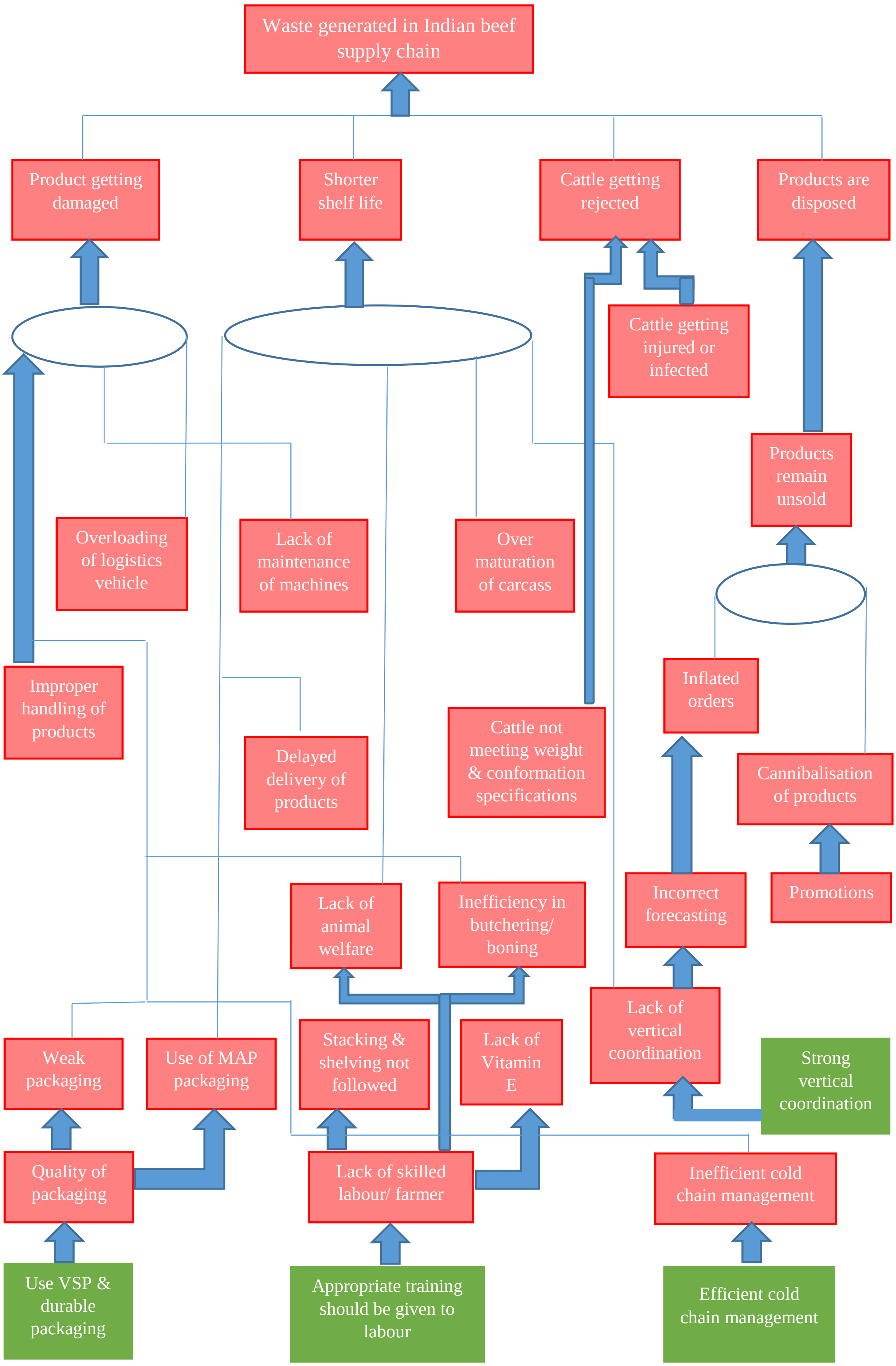

Fig. 4.2 Current Reality Tree highlighting root causes of waste and preventive measures

a. Farm – The main root causes of waste occurring at farm end are because of following reasons:

i. Cattle are not fed on fresh grass. So, they are deficient in vitamin E. Hence, the meat derived from them has shorter shelf life. Waste – (5-10%)
ii. Lack of cattle management leads to the cattle not meeting the weight and conformation specifications of retailer, when they reach the finishing age. Waste – (1-5%)
iii. Lack of animal welfare at beef farms might lead to cattle getting an infection or physically injured, which might lead to their rejection by abattoir. Waste – (1-5%)

b. Abattoir and Processor - The main root causes of waste occurring at abattoir and processor are because of following reasons:
i. Loss of edible beef because of over trimming by less skilful staff. Waste – (1-5%)
ii. Lack of maintenance of machines can lead to line getting stopped during operations and loss of product stuck in the line. Waste – (1-5%)
iii. Beef products falling on floor because of lack of competency and inefficiency in butchery and boning operations. Waste – (1-5%)
iv. Butchery and boning operations not based on takt time calculated on the forecasted demand of retailer. Waste – (5-10%)
v. Slowing of butchery and boning operations because of principle of line balancing not being followed. Waste – (1-5%)
vi. Over maturing of carcass in Maturation Park leading to shorter shelf life of beef products from it. Waste – (1-5%)
vii. Periodic changeover of set of knives not being followed regularly, leading to slow operation. Waste – (1-5%)
viii. Butchery and boning operations being performed against gravity. Hence, over spending the time and energy of abattoir staff. Waste – (1-5%)
ix. Too much contact with metallic blades leading to beef products being discarded in metal detection test. Waste – (1-5%)

x. Product getting contaminated if not washed properly, packed properly or there is a temperature abuse. Waste – (1-5%)

c. Retailer - The main root causes of waste occurring at retailer end are because of following reasons:

i. Lack of coordination between abattoir and processor and retailer leading to loss of beef. Waste – (>10%)
ii. Lack of efficient cold chain management leading to temperature abuse of beef products. Waste – (1-5%)
iii. Inflation of orders in retailer store for the sake of availability of products thereby neglecting the consequent potential waste. Waste – (5-10%)
iv. Stacking and shelving procedures being not followed at retailer store leading the beef products to go past their shelf life without getting sold. Waste – (1-5%)
v. Lack of promotions management by retailers leading to cannibalization of products. Hence, generating waste. Waste – (1-5%)
vi. Lack of dedicated waste management staff to frame the efficient waste management policy and their implementation leading to avoidable waste occurring at retailer's distribution centre and retail store. Waste – (5-10%)
vii. Utilisation of packaging providing shorter shelf life. For example, Modified Atmosphere Packaging (MAP) provides around 8-10 days of shelf life compared to Vacuum Skin Packs (VSP), which provide up to 21 days of shelf life. Waste – (5-10%)

d. Logistics- The main root causes of waste occurring at logistics end are because of following reasons:

i. Lack of cold chain management in logistic vehicle leading to temperature abuse of beef products. Waste – (1-5%)
ii. Delayed delivery of beef products to retailer leading to shorter shelf of beef products available for sale. Waste – (5-10%)
iii. Improper stacking of beef products leading to their damage. Waste – (1-5%)
iv. Using cheaper transport channels, which often take full truck load leading to more probability of damage of beef products. They also follow longer

routes leading to shorter shelf life of beef products available for sale. Waste – (1-5%)

v. Cattle getting injured or stressed during transportation from farm to abattoir. Waste – (1-5%)

B. ***Destination of waste occurring in Indian beef supply chain***

Landfill has been the conventional destination of waste for Indian beef industry. However, in past two decades, the scenario has changed. Now, they must be disposed at government approved site as per the government laws in the form of incineration, rendering, composting, etc. The waste occurring in Vietnam like edible beef products left unsold on retails shelves were being channelized to charities to a limited extent. Some products were also sent to pet food manufacturing firms. However, in India, it could not be done because of lack of management and absence of such active charities. In terms of packaging waste, the primary packaging must go to landfill. The secondary packaging is being recycled. The tertiary packages like pallets were reused.

4.6 Discussion

The analysis of root causes map shown in figure 4.2 suggested that the root causes of waste in beef supply chain can be broadly classified into two groups: Natural limitations and Management issues. The former includes factors that are associated with the characteristic of product or processes involved like short shelf life of beef products, variation in weather, etc. The latter consists of factors generating waste because of inefficiency in management practices across the beef supply chain. The first group is beyond the control of the stakeholders involved in beef supply chain. However, the second group points towards the decision making of managers of all the stakeholders of beef supply chain, which can potentially lead to avoidable waste. The rest of the analysis will focus on second group, considering these are the problems where improvement in management practices will make a difference. Some basic management inconsistencies have been identified across the whole beef supply chain and they are explained along with their preventive measures for all the stakeholders of Indian beef supply chain as following:

(a) Farm- During the interview of Indian beef farmers, it was observed that they lack awareness in terms of modern practices of raising the cattle. They should be given appropriate training in terms of proper diet of buffaloes, animal welfare and overall animal husbandry. The cattle should be fed on fresh grass, which is rich in Vitamin E. It will help to improve the shelf life of beef derived from them. During the interview, farmers mentioned that sometimes animals get rejected because of health reasons. A regular health check-up will help farmers to avoid getting their cattle rejected due to infection. If there is any health issue diagnosed, it can be cured well on time. The beef farmers should be made aware that cattle on medium to high dose of medication should not be sent to abattoir as they will get rejected. There should be ample time given to the sick cattle to recover and then sent to abattoir and processor. Similarly, their weight and conformation specifications should be observed regularly so that appropriate alterations in their diet can be done. It will help to meet the weight and conformation specifications of abattoir and processor, when the cattle reach their finishing age. The root causes of waste occurring at farm end, the corresponding preventive measures and some relevant quotes from interviewee have been summarised in Table 4.1.

Table 4.1 Main root causes of waste at farm and preventive measures along with relevant quotes from interviewee

S. No.	Root Cause	Preventive Measure	Interviewee quotes
1.	Cattle are not fed on fresh grass. So, they are deficient in vitamin E. Hence, the meat derived from them has shorter shelf life.	Cattle should be fed on fresh grass especially in winter when natural antioxidants are low. It will improve the shelf life of beef derived from them.	*Often, we follow in-house farming and raise the cattle on grain based diet.*
2.	Lack of cattle management leads to the cattle not meeting the weight and conformation specifications of retailer, when they reach the	Cattle management should be done in skilful way in terms of feeding, care of cattle and timely inspection. It will help the cattle to meet the weight and conformation	*Inefficient cattle management is one of the major root causes for cattle not being sold at premium price as the improper weight and conformation*

	finishing age.	specifications of abattoir and processor.	*leads to their rejection by reputed abattoirs.*
3.	Lack of animal welfare at beef farms might lead to cattle getting an infection or physically injured, which might lead to them being rejected by abattoir.	Proper care should be taken of cattle and those on medication should not be sent for slaughtering.	*Due to lack of education and exposure to modern farming practices, standards of animal welfare are fairly low.*

(b) Abattoir and Processor end – The interview of managers of abattoirs and processors suggested that the lack of coordination between them and retailer is the major root cause of waste at their premises. It should be improved and the information sharing between these two stakeholders should be increased. It will help abattoir and processor to forecast their demand more precisely, which will help to reduce waste because of overproduction and loss of revenue in the event of under production. Moreover, it was observed during site visit to abattoir and processors that there was some need of improvement in the butchery and boning operations of their labour. Certain good practices should be adopted in butchery and boning operations like takt time principle, line balancing, etc. It will improve their efficiency and reduce waste. The working staff should be given appropriate training so that there is no loss of beef because of over trimming and meat is handled carefully so that it doesn't fall on the floor. They should be made aware of the hygiene and temperature requirements of the beef products. There should be provision made for reliable auxiliary power supply in the event of power failure so that the cold chain is maintained and there is no temperature abuse of beef products. The knives used by the working staff should be changed periodically to avoid the slowing of operations. Care should be taken so that there is no unnecessary contact of beef products with metallic blade or knives or else they will be rejected in metal detector test. Finally, the provisions must be made for regular maintenance of machines used in the premises. These practices will collectively help to mitigate the root causes of waste occurring at abattoir and processor end. A summary of root causes of waste occurring at abattoir and processor end, their corresponding preventive measure and some relevant quotes from interviewee are provided in the Table 4.2.

Table 4.2 Main root causes of waste at abattoir and processor and preventive measures along with relevant quotes from interviewee

S. No.	Root Cause	Preventive Measure	Interviewee quotes
1.	Loss of edible beef because of over trimming by less skilful staff.	Staff should be given appropriate training so that trimming of fat is done carefully.	*Carelessness of staff in butchering and boning hall leads to avoidable product waste.*
2.	Lack of maintenance of machines can lead to line getting stopped during operations and loss of product stuck in the line.	Regular maintenance of machines should be done to avoid the stopping of line and loss of product.	*Machine waste is attributed to lack of periodic maintenance of the packaging and mincing machines.*
3.	Beef products falling on floor because of lack of competency and inefficiency in butchery and boning operations.	Butchery and boning operations of beef products should be performed carefully so that it does not fall on floor.	*Sometimes, beef primals fell on the floor while butchering and boning by inexperienced staff.*
4.	Butchery and boning operations not being based on takt time calculated as per the forecasted demand of retailer.	Butchery and boning operations should be based on takt time calculated as per the forecasted demand of retailer.	*Bullwhip effect is observed as the production is not linked to the forecasted demand of the retailer.*
5.	Slowing of butchery and boning operations because of principle of line balancing not being followed.	Line balancing should be actively followed to improve the efficiency of butchery and boning operations.	*Lean principles are not being explicitly followed in the abattoir and processor creating bottlenecks.*
6.	Over maturing of carcass in Maturation Park leading to shorter shelf life of beef products from it.	Carcass should be appropriately matured so that their shelf life is not affected.	*Sometimes, carcass is over matured due to human error in the maturation park.*

7.	Periodic changeover of set of knives not being followed, leading to slow operations.	Periodic changeover of set of knives should be done to avoid slow operations.	*Employees are not keen to change set of knives as frequently as instructed by us.*
8.	Butchery and boning operations being performed against gravity. Hence, over spending the time and energy of abattoir staff.	Butchery and boning operations should not be performed against gravity.	*Poor ergonomics due to some operations being performed against gravity.*
9.	Too much contact with metal blades leading to beef products being discarded in metal detection test.	Unnecessary contact of beef products with metal blades must be avoided.	*Some mince products often fail metal detection test because of over exposure to blades.*
10.	Products getting contaminated if not washed properly, packed properly or there is a temperature abuse.	Proper care should be taken of beef products in terms of their hygiene, packing and efficient cold chain management.	*Temperature abuse and contamination caused due to discrepancies in cleaning and packing of beef products also generates waste.*
11	Waste generated because of overproduction due to lack of coordination with retailer.	There should be strong vertical coordination between abattoir and processor and retailer so that forecasting of demand is done more precisely. Hence, less waste is generated.	*Lack of vertical coordination in the supply chain leads to overproduction.*

(c) Retailer – In the interview of managers of retailer, it was revealed that majority of waste is occurring at retailer end because of lack of coordination between abattoir, processor and retailer. Retailer should share their real-time sales information with the abattoir and processor so that they can do accurate forecasting at their end. It will reduce the phenomenon of over and under delivery of beef products to them. The retailer should employ the latest forecasting techniques and updated data mining framework to lower the error in forecasting at their premises. It was observed that retailer was still using the conventional packaging technique - Modified Atmosphere Packaging (MAP) instead of latest Vacuum Skin Packaging (VSP). They were losing shelf life of around 11 days because of this practice. Hence, the retailers should adopt VSP to avoid the waste and improve their revenue. They should make an appropriate trade-off between availability of products and waste generated. The beef products in a retail store should only be ordered based on demand or sales of previous stock. It will help to reduce the unnecessary overstocking of beef products on retail shelves, which are left unsold. The managers of retailer told that stacking and shelving procedures are not being followed properly. The staff in retail store should be given proper training to do so and must be regularly supervised by the store manager or their supervisor. There should be efficient cold chain management both in retails depots and retail stores so that there is no loss of beef products because of temperature abuse. It was observed from the past records of company that promotions of a certain product were leading to waste of anther beef product. The retailer must closely study the behaviour of customer and employ a clear strategy for promotions so that it does not lead to generation of waste. The analysis of the interview of retailer manager pointed out that the waste occurring in the whole supply chain is not being properly quantified and there is no workforce to address it. Recruitment of a dedicated team for the waste minimisation can help in quantifying waste, which helps in identifying the hotspots of waste in retailer's supply chain. These hotspots can then be mitigated to avoid waste. A summary of root causes of waste, the corresponding preventive measure and some relevant quotes from interviewee are shown in the Table 4.3.

Table 4.3 Main root causes of waste at retailer, preventive measures along with relevant quotes from interviewee

S. No.	Root Cause	Preventive Measure	Interviewee quotes
1.	Lack of coordination between abattoir and processor and retailer leading to waste in beef supply chain.	There should be strong coordination and exchange of information between abattoir and processor and retailer to avoid waste in beef supply chain.	*Mis-coordination with abattoir and processor leads to overs and unders.*

2.	Lack of efficient cold chain management leading to temperature abuse of beef products.	There should be proper investment in reliable and innovative freezing equipment to avoid the equipment failure and poor storage and hence reducing the waste.	*Inefficient cold chain management is responsible for considerable amount of product waste.*
3.	Inflation of orders in retailer store for the sake of availability of products thereby neglecting the consequent potential waste.	Proper balance should be maintained between product availability and waste generated.	*Lack of trade-off between availability of products and consequent waste generation is a matter of concern.*
4.	Stacking and shelving procedures being not followed at retailer store leading the beef products to go past their shelf life without getting sold.	Staff should be trained in stock rotation and efficient stacking, shelving procedures.	*Incompetency in following stacking and shelving procedures leads to expiry of beef products.*
5.	Lack of promotion management by retailers leading to cannibalization of products. Hence, generating waste.	A clear strategy should be framed and implemented in promoting a certain product to avoid cannibalization and consequent waste.	*Promotion management lacks vision and causes cannibalisation.*
6.	Lack of dedicated waste management staff to frame the efficient waste management policy and their implementation leading to avoidable waste occurring at retailer's distribution centre and retail store.	A separate set of staff should be hired to constantly monitor and assess all the processes of a retailer. Then, they should frame a relevant waste minimization strategy and act so that it is implemented at all stages.	*There is no dedicated team specifically looking after waste management which often undermines the development of efficient waste minimisation strategy.*
7.	Utilisation of packaging providing shorter shelf life. For example, Modified Atmosphere Packaging (MAP) provides around 8-10 days of shelf life compared to	Vacuum Skin Packs (VSP) should be used for packing of beef products, which provide up to 21 days of shelf life. Awareness should be raised both in beef industry and	*Negligence in adopting modern packaging techniques like VSP creates lot of avoidable waste.*

	Vacuum Skin Packs (VSP), which provide up to 21 days of shelf life.	customers to discard the conventional packaging.	

(d) Logistics- Logistics plays a crucial role throughout the supply chain. It was revealed during the interview of managers of logistics firm that most losses were occurring because of delayed delivery of beef products from abattoir and processor to retailer. The retailer was receiving some products below their threshold shelf life. Hence, the retailer was rejecting them. Retailer must hire an efficient logistic firm, which will deliver the products on time. The logistics company must be penalised for the delay so their performance keeps up to the mark. There should be utilization of reliable technology for refrigeration in logistics vehicle so that the beef products are not spoiled. It was observed during site visit to logistics firm's premises that they were taking full truckload and following the longer route (to avoid toll tax, etc.) to save expenses. These practises should be avoided and an optimum load optimization procedure must be followed. A safe and quick transport route should be followed to avoid unnecessary delay in delivery of products. The practitioners noticed during their site visit to logistics firms that the beef products were not stacked properly which were causing damage to products. The logistics personnel should be trained about the appropriate stacking procedures so that product damage is avoided. It was revealed in the interview that cattle were found to be stressed and injured when transported from beef farms to abattoir and processor. The logistic vehicle must follow the guidelines of government and should not over crowd their vehicle with cattle. There should be enough space allowance given to each individual cattle and extra care should be taken in loading and unloading the logistics vehicle with cattle. A summary of root causes of waste in logistics, their corresponding preventive measures and some relevant quotes from interviewee are shown in Table 4.4.

Table 4.4 Main root causes of waste at logistics, preventive measures along with relevant quotes from interviewee

S. No.	Root Cause	Preventive Measure	Interviewee quotes
1.	Lack of cold chain management in logistic vehicle leading to temperature abuse of beef products.	There should be proper investment in reliable and innovative freezing equipment in logistics vehicle to avoid the equipment failure, poor storage and hence reducing the waste.	*Sometimes, optimum cooling is not generated by refrigeration equipment within the logistic vehicle.*
2.	Delayed delivery of beef products to retailer leading to shorter shelf of beef products available for sale.	Efficient logistics firm must be hired so that beef products are delivered on time to retail store with maximum shelf life left for sale to customers.	*Shelf life of beef products is shortened by delayed delivery of beef products.*
3.	Improper stacking of beef products leading to their damage.	Beef products should be stacked properly in logistics vehicle to avoid them getting damaged.	*Products get damaged if not stacked properly.*
4.	Using cheaper transport channels, which often take full truck load leading to more probability of damage of beef products. They also follow longer routes leading to shorter shelf life of beef products available for sale.	Efficient load optimization techniques must be followed to avoid the damage of beef products. Shorter and safe routes should be followed for the transportation of beef products so that their maximum shelf life is left when they reach shelves of retail store.	*Sometimes, full truck load leads to product damage. Moreover, following longer routes to avoid toll tax also results in delayed deliveries.*
5.	Cattle getting injured or stressed during transportation from farm to abattoir.	Principle of animal welfare must be strictly followed while transportation of cattle.	*Lack of animal welfare standards followed in transportation of cattle could lead to injury or stress in them.*

During the analysis, it was found that some root causes of waste were associated with a stakeholder of beef supply chain. For each stakeholder, the root causes and preventive measures were suggested above in detail. It was revealed in the interview of beef farmers that some farms were generating more waste as compared to others. Therefore, there is an opportunity for high waste generating farms to learn the good practices from low waste generating beef farms. Some root causes of waste were dependent on more than one stakeholder. There is a need of strong vertical coordination in the Indian beef supply chain to address them. To achieve this, a holistic approach is needed to bring all stakeholders on one platform and exchange information thereby minimising the waste in Indian beef supply chain.

(e) Potential biases and their impact on results - The data collection performed in this study via interviews could have some trivial amount of bias. For instance, the responses from Indian farmers could consist of a bit of acquiescence bias in which respondent agrees and is positive towards whatever presented by interviewer. It may be due to Indian farmers being less educated, still indulged in traditional farming techniques and not used to being interviewed about the waste generated in their farming practices. However, to mitigate this potential bias, maximum numbers of interviews (20) in this study were conducted at the farm end so that the bigger sample size would generate unbiased results.

Another possible bias could be in the data obtained from interview of managers of abattoirs and processor. As the motivation behind the study was to identify the factors generating waste in the beef supply chain, the respondents at abattoir and processor end were quite apprehensive to admit that their operations generate any significant amount of avoidable product waste. To address this potential bias, the responses of all four managers at abattoir and processor end were thoroughly studied and any possible contradiction was nullified by the information derived from company records and observations made during the site visit to their premises.

4.7 Conclusion

This chapter is focussed on exploration of waste occurring in beef supply chain in India, predominantly highlighting their root causes to establish a balance between production and consumption. The interviews with different stakeholders has been conducted and collected data were analysed by using Current Reality Tree method to find out the root causes and preventive measures to overcome them. The results revealed that amount of waste are primarily because of natural characteristics of beef products like short shelf life, temperature sensitivity and variations in demand.

Apart from natural characteristics, there were abundant opportunities for minimizing waste by working on the different management root causes of waste identified across the supply chain. The main root causes are: poor quality of meat, lack of vitamin E in diet of cattle, scarcity of information exchange, management of cold chain, lack of skilled labour, forecasting issues, promotions, quality of packaging, lack of waste minimisation strategy, etc. It was observed that a strong vertical coordination within the beef supply chain is the foremost action needs to be taken to address the root causes of waste. It will help in mitigating all the root causes mentioned above. It will improve the information exchanged between the stakeholders of supply chain.

The proposed framework recommends a mechanism for waste minimisation at all stakeholders of beef supply chain viz farmers, abattoir, processor, logistics and retailer. The frameworks proposed in chapter 3 and 4 assists in mitigating the physical waste in the beef supply chain. However, in order to improve the sustainability of beef supply chain, its carbon footprint also needs to be addressed. The next section proposes an Information and Communications Technology (ICT) based framework to measure the carbon footprint of beef farms and incorporate it into the supplier selection process of abattoir and processor. TOPSIS method is used to make an optimum trade-off between conventional quality attributes (breed, age, diet, average weight of cattle, conformation, fatness score, traceability and price) and carbon footprint generated in farms, to select the most appropriate supplier.

CHAPTER 5

Employing cloud computing technology to mitigate carbon footprint of beef supply chain

5.1 Introduction

Carbon footprint is drawing the attention of policy makers from around the globe as it has huge implications for both climate change and society. For instance, British government has made a legislation to cut down the carbon footprint by 80% in 2050 (from 1990 levels) (Barker et al., 2014). The supply chains of various organisations are making attempts to make their supply chain greener. A considerable uncertainty is associated with the kinds of techniques adopted for measuring greenhouse gas emissions in current and future industries. The issue of carbon footprint in the supply chain of an organisation is currently addressed at segment level. The carbon footprint generated at a particular segment of supply chain is linked to other segments of supply chain as well. There has been lack of availability of integrated framework for mitigating carbon footprint of entire supply chain.

Both academia and industries are equally laying emphasis on the vital implications of rising carbon footprint in the modern world. Carbon Trust, (2012) have defined carbon footprint as, "The aggregate greenhouse gas emissions generated directly or indirectly by people, event, or businesses."

Beef is considered to be rich source of protein and contributes to 24% of meat production across the globe (Boucher et al, 2012). The Environment Protection Agency asserts that 3.4% of the greenhouse gas emissions in the world are attributed to livestock. All segments of beef supply chain generate carbon footprint. Nonetheless, beef farms contribute to majority of the greenhouse gas emissions (EBLEX, 2012). These emissions are generated primarily due to emission of methane by enteric fermentation in the stomach of cattle. The potency of methane is twenty-five times higher than carbon (Forster et al., 2007). There are numerous methods described in literature to measure carbon footprint. It is very complicated for a beef farmer to select an appropriate tool and use it. These carbon calculators are often very expensive. So, it is quite a challenge for them to do the record keeping of carbon footprint. There is need to raise the awareness in farmers and to select the most eco-friendly beef cattle supplier. The other stakeholders of beef supply chains are also releasing significant amount of greenhouse gases. Most of these emissions are because of consumption of energy in their premises such as electricity, fossil fuels, etc.

Generally, the measurement of greenhouse gas emissions in beef supply chains is done at a segment level i.e. independently at farm, abattoir, processor, logistics and retailer level. There is deficiency of an integrated model capable of measuring carbon footprint of entire beef supply chain. However, in this chapter, the Life Cycle Assessment (LCA) principles are employed, which takes into account the carbon footprint generated during the product flow of beef products from farm to fork. Figure 5.1 shows the proposed LCA model for beef supply chain. These analysis maps the beef supply chain from farm to retailer.

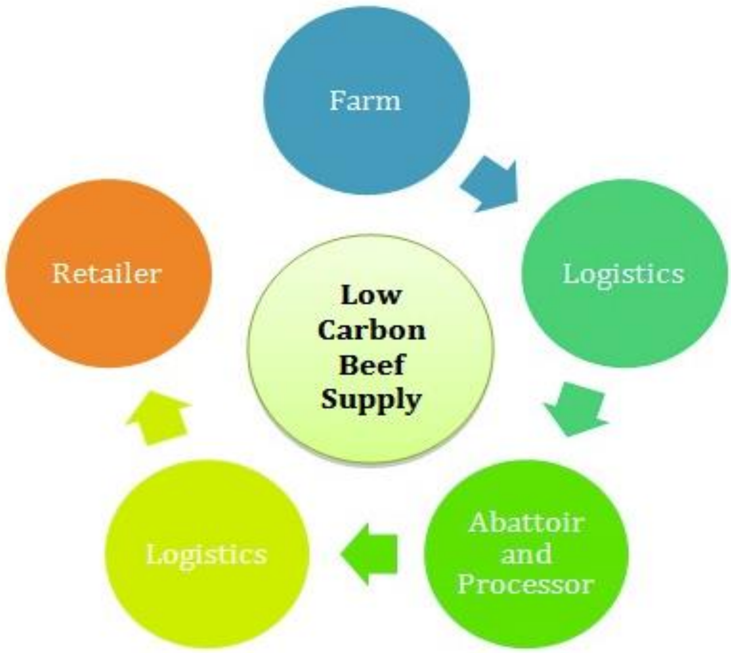

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Figure 5.1 The proposed LCA model for beef supply chain

Cloud Computing Technology (CCT) has been utilised over the years to integrate distinct stakeholders of an industry within minimal resources. The implementation of CCT has delivered excellent results in diverse industries such as manufacturing, service industry, etc. The information visibility is enhanced to different segments of a particular industry by employing the service delivery frameworks of CCT: Software as a Service (SaaS), Infrastructure as a Service (IaaS) and Platform as a Service (PaaS). Keeping these characteristics of CCT in consideration, it is utilised in this study to mitigate carbon footprint of the whole beef supply chain. A private cloud mapping the whole supply chain would be developed by the retailer. Retailer has uploaded the best and user friendly carbon calculator for each stakeholder on the cloud. The data associated with greenhouse gas emissions of all segments of beef supply chain would be visible to all stakeholders via private cloud.

In order to achieve the target of carbon footprint reduction by 80% in 2050 from 1990 levels, all stakeholders of beef supply chain have to take appropriate steps to achieve it. The maximum emissions are being generated at farm end and farmers are doing relatively less contribution to improve the sustainability of beef supply chain as compared to other stakeholders. There is pressure on beef retailers to reduce carbon footprint in their supply chain from both government legislation and consumers. The farmers are not taking this initiative seriously. In current scenario, it is not feasible to meet the target of reducing carbon emissions considering the inefficient practices of farmer. Therefore, in this study a CCT framework is proposed for abattoir and processor to incorporate carbon footprint in the supplier selection process of beef cattle along with other conventional attributes (price, quality, etc.).

5.2 Cloud Computing Technology (CCT)

Cloud computing technology is convenient to implement via basic and modern architecture (Hutchison et al., 2009). Information Technology (IT) is presented by CCT as remunerated service considering its employment and maintenance (Sean et al., 2011). Distinct models of CCT make its implementation convenient for any domain based on its requirement. The collaboration among different businesses is enhanced by this innovative technology (XunXu, 2012). The major advantages of deploying CCT are financial savings in software and hardware, boost in information visibility, rapid deployment and efficient management of resources via software as a service.

The major service delivery models of CCT are Software as a Service (SaaS), Infrastructure as a Service (IaaS) and Platform as a Service (PaaS). The delivery of these services is done via industry standards like service oriented architecture (SOA). SaaS is referred to as an application hosted as a service and delivered to consumers via Internet. The support and maintenance of the software is provided by the service providers such as Google Office, Netsuite, etc. PaaS assists in providing a platform for computing such as servers, networks, storage facilities, etc. The development of the software, its implementation and configuration of settings is performed by consumers such as Salesforce, Google App Engine, etc. The storage facilities, network capability and various computing resources are provided by IaaS on rental basis. Consumers employ IaaS to employ the software and services. They do the operation and maintenance of OS, network components, applications, etc. Some examples of IaaS ae Blizzard, Gogrid, etc.

The different models available for deployment of CCT are public, private and hybrid cloud as depicted in Figure 5.2. Third party service providers such as Google provide the public cloud via internet. It is convenient and cheaper means to implement IT solution via pay as you go approach. Apart from providing numerous benefits like public cloud, the private cloud provides greater command over framework of CCT and is ideal for large size facilities. It could also be controlled and managed by third party service providers (Sean et al, 2011). A hybrid cloud is an amalgamation of public and private cloud which sends non-confidential data to public cloud and confidential information is retained by the businesses (Sean et al, 2011).

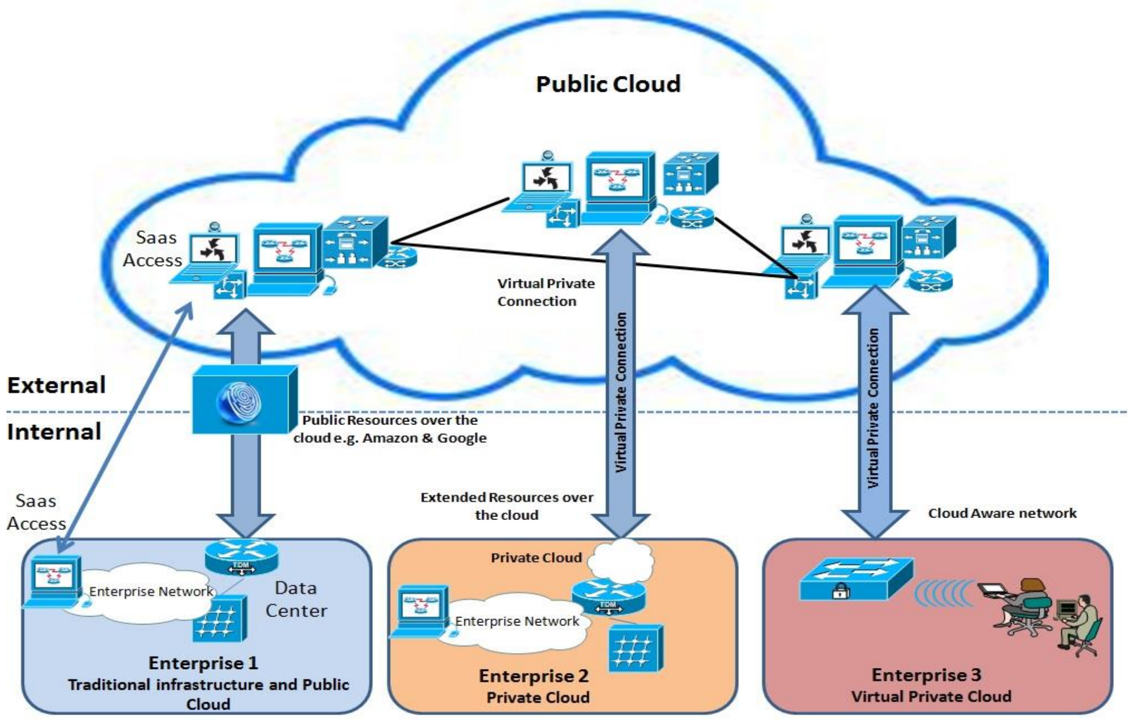

Figure 5.2 Various models of deployment of CCT

The model of CCT depicted in Figure 5.2 makes it an attractive option for different businesses of all sizes. Major corporations having vast IT architectures who couldn’t expand due to agility of business environment could also purchase services from third party service providers such as Google and use CCT to address their technology requirements. The industries having their subsidiaries around the world could employ CCT for connectivity and upload their generic apps on the cloud via SaaS. The SMEs also find CCT as an easy to adopt technical innovation. These firms are often deficient in financial resources and they could also access the services of third party service providers by following the concept of pay as you go. SMEs could employ SaaS to make a profile on the cloud and provide their services to the global businesses.

The application of CCT is scarce in the domain of food industry. In this chapter, CCT framework as depicted in Figure 5.3 is developed to mitigate the carbon footprint of beef supply chain. All the segments of supply chain: farms, abattoirs, processors, logistics and retailers are mapped using CCT framework and they make their respective accounts over the cloud to utilise carbon calculators uploaded on cloud via SaaS. The CCT framework would assist in information exchange regarding carbon emissions between the stakeholders. The next section describes the root causes of carbon emission at different segments of beef supply chain.

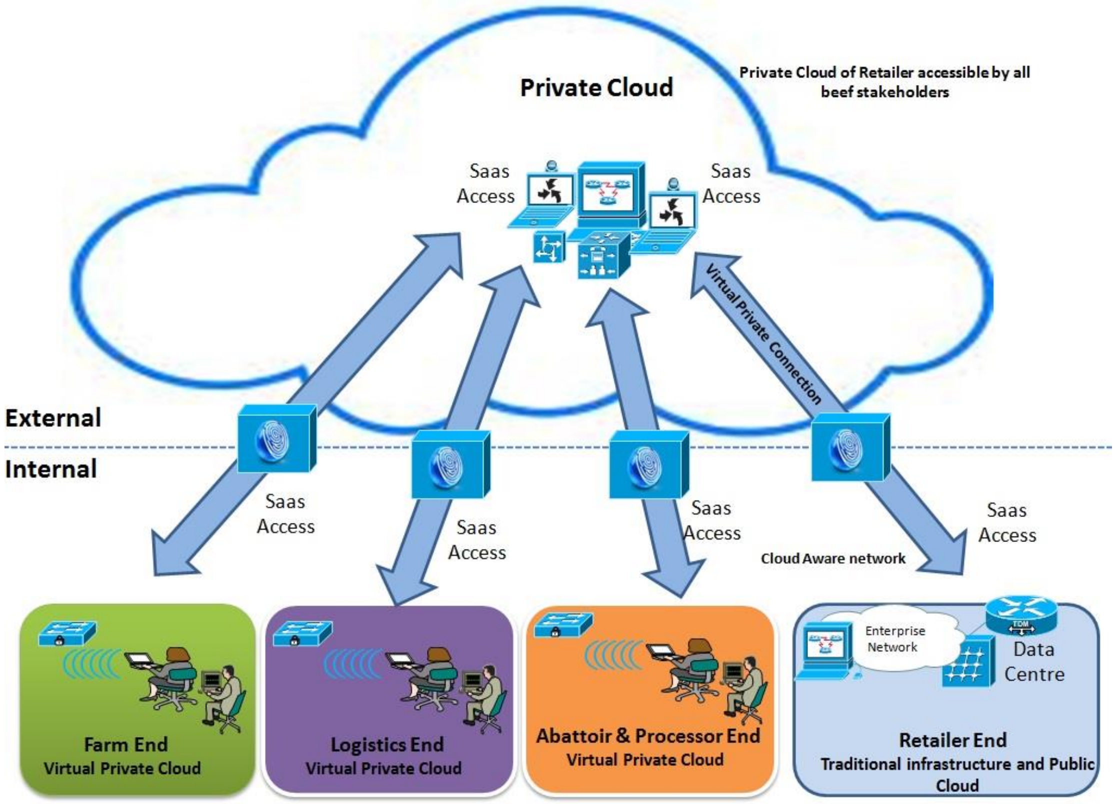

Figure 5.3 CCT framework for beef supply chain

5.3 Beef Supply Chain employing CCT and its Carbon Footprint

Carbon footprint is generated by numerous sources in the beef supply chain, which are referred to as carbon hotspots. These hotspots and how various segments of beef supply chain would employ CCT framework for reducing carbon footprint is described as following:

5.3.1 Farm- The carbon hotspots responsible for carbon footprint generated at beef farms are described in detail in section 2.2.1. The major root causes are enteric fermentation, manure and the fertilizers utilised for feed. Different carbon calculators available in modern world have distinct advantages and shortcomings. The costs of these calculators are usually very high. Generally, farmers of small and medium sized farms are deficient in technical and monetary resources. It is challenging process for them to select a carbon calculator to measure carbon footprint of their farms accurately. In the proposed framework, an easy to use and optimum calculator would be uploaded on private cloud for the farmers, who can employ it to address the carbon emission of their farms via SaaS.

When they enter the information associated with their farms in the calculator, it will process it and generate the emission results along with feedback to mitigate it. This process is depicted in Figure 5.4 and the detailed information on these calculators is provided in the section 5.4. It will assist farmers in sustainable decision making and implement necessary modifications in their farming practices. The results of carbon footprint at beef farms would be visible to every stakeholder of the supply chain. This framework would enhance the vertical and horizontal coordination in the supply chain, increase the efficiency of product flow and reduce the carbon footprint.

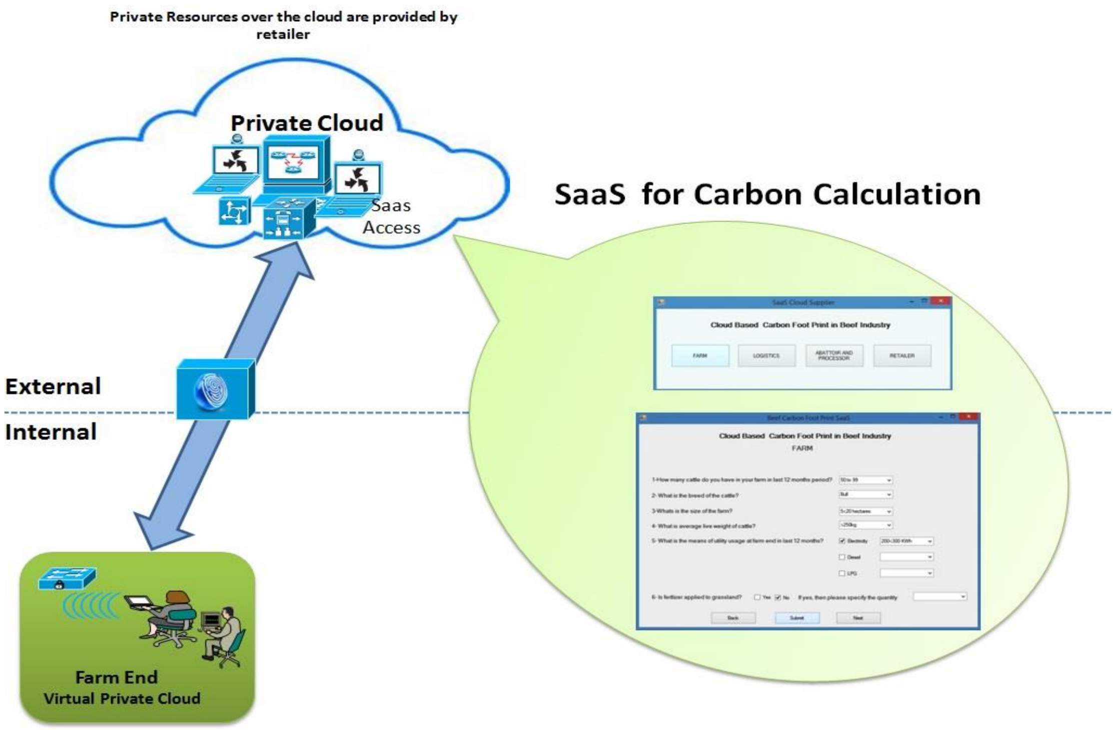

Figure 5.4: Software as a Service at beef farms

5.3.2 Logistics- The root causes of carbon footprint generated by logistics firms are mentioned in section 2.2.2. The priority of logistics companies is growth of their business and enhancing financial revenues. A significant pressure is there on all business firms to mitigate their carbon emissions. Certain firms primarily SMEs lack the financial and technical resources to choose a carbon calculator to measure their greenhouse gas emissions. Considering these issues, retailer has uploaded an optimum carbon calculator on a private cloud. It would assist logistics firms in doing appropriate decision making for mitigating their carbon footprint. The carbon emission data of logistics firm would be visible to every stakeholder of beef supply chain via private cloud. It would also assist in strengthening the coordination among logistics and other segments of beef supply chain. For instance, the beef farmers would get an update about the timing to stop feeding cattle for their efficient transport from farm to abattoir.

5.3.3 Abattoir & Processor – The primary root cause of the carbon footprint generated by abattoir and processor as highlighted in section 2.2.3 is due to the energy consumed in their butchering and boning activities. The retailers have chosen an appropriate carbon calculator for them after thoroughly investigating their operations and uploaded it on private cloud. The abattoir and processor can utilise the carbon calculator via computer and internet infrastructure in the form of SaaS. The carbon calculator will assist them in measuring their carbon footprint and provide them feedback to mitigate it. The abattoir and processor could use this feedback to make necessary changes to reduce their carbon emissions. The results of their carbon footprint would be visible to every stakeholder of beef supply chain.

5.3.4 Retailer – The factors responsible for carbon emission at the premises of all retailer depots and stores is described in section 2.2.4. The retailer has uploaded an optimum carbon calculator for retailer depots and stores on private cloud. The retailer stores can measure their carbon footprint and receive feedback to mitigate by using carbon calculator. The results of their carbon emissions would be visible to very stakeholder of the beef supply chain. The next section demonstrates the step by step execution of the proposed integrated framework to mitigate the carbon footprint of beef supply chain.

5.4 Implementation of CCT based framework to reduce carbon footprint of beef supply chain

In this section, the step by step execution of the mechanism mentioned in section 5.2 is provided. It comprises of a beef products retailer having multiple stores around the nation. These products are sourced from cattle raised in various farms. An abattoir and processor enterprise having numerous branches does the butchering and boning of these cattle. The final processed beef products are then transported to retailer using logistics to be sold to customers. Due to pressure from government legislation, the retailer wants to mitigate the carbon footprint of its supply chain. It could not be accomplished by just making the activities of retailer stores green. Hence, it approaches all stakeholders of beef supply chain to make the entire supply chain green. During the discussion of retailer's staff with beef farmers, it was revealed that farmers are deficient in financial and technical resources to address it. There are numerous carbon calculators in the market with distinct benefits and limitations. The farmers were finding it challenging to select and employ an optimum calculator for their businesses. Other stakeholders also mentioned similar issues in addressing their carbon footprint. The logistics team mentioned that they are taking active measures to make their operations greener such as taking shortest possible route, etc. Nonetheless, they would not be enough to accomplish the eco-friendly supply chain target. It was also revealed that lack of vertical coordination in supply chain is also contributing to considerable amount of carbon footprint, which could be avoided. Hence, the retailers concluded the need of a framework to assist all segments of beef supply chain for reducing carbon emissions and sharing their carbon emission results within the supply chain. The retailer has opted for the CCT infrastructure to accomplish this aim within minimal financial resources. The private cloud would map all segments of beef supply chain. Thereafter, an efficient, accurate and convenient to use carbon calculator would be selected by retailer for all stakeholders and uploaded on private cloud. Every segment of beef supply chain has access to it by internet and computing infrastructure in the form of SaaS. All stakeholders of beef supply chain would be provided user manuals and relevant training regarding operating CCT framework. The CCT framework comprises of carbon footprint calculator and feedback to address carbon emission of each segment of supply chain. SaaS at the premises of beef farms is depicted in Figure 5.5.

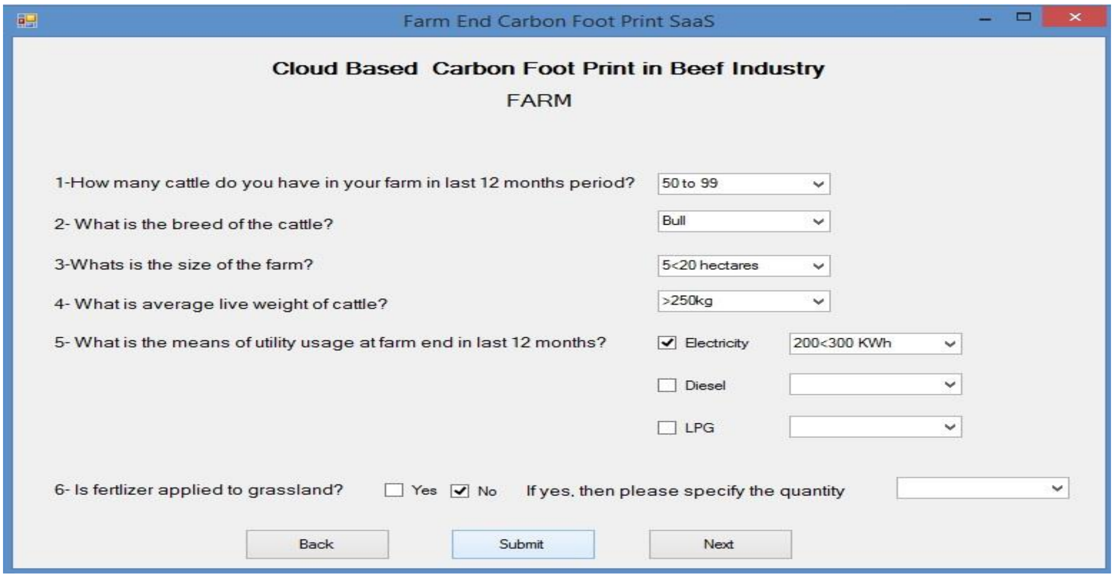

Figure 5.5 CCT interface at beef farms.

Farmers would utilise internet and basic computing infrastructure to access CCT. A window will open as depicted in Figure 5.5 asking the relevant information for generating carbon footprint results. When the farmer would enter this information, a new window would open having carbon footprint results and suggestive measures to address it. This process is depicted in Figure 5.6.

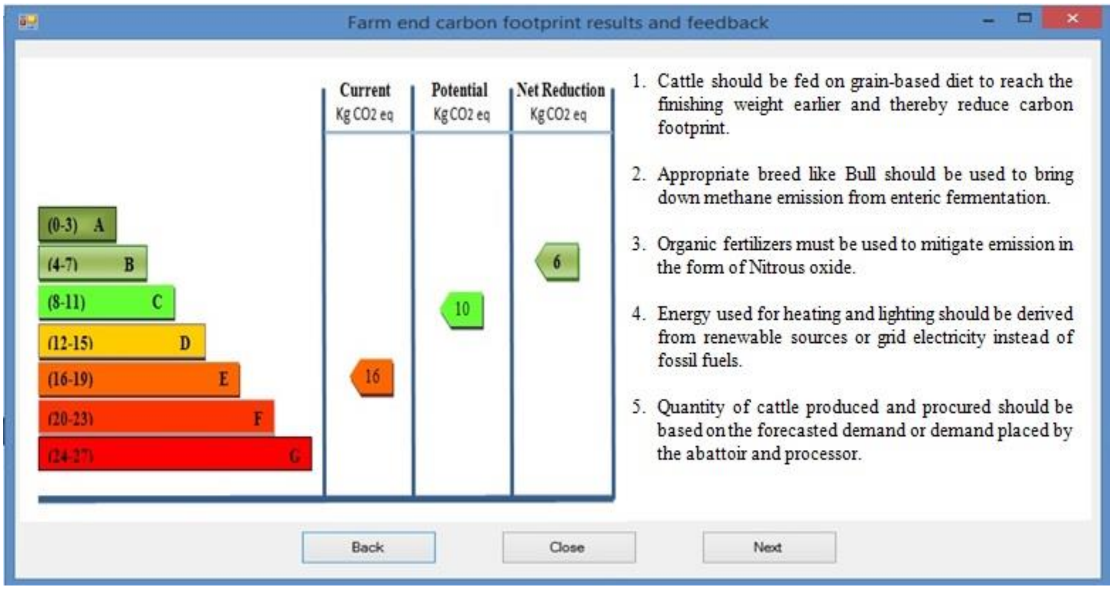

Figure 5.6 Carbon footprint results and suggestive measures for beef farms.

The carbon calculator processes the information entered by farmers and gives results in this case as 16 Kg CO_2 eq. A list of suggestive measure to mitigate this is also being generated. For instance, farmers would be given guidance about the breed of cattle and their feed, which will generate minimal carbon footprint. It also reveals how much reduction (2 kg CO_2 eq.) could be accomplished in the current carbon footprint by following these suggestive measures. The farmers will do the appropriate decision making and change their farming practices as per the prescribed suggestions. Then, they will measure their carbon emissions again by using the calculator. The data fed by farmers and the carbon footprint results would be visible to every segment of supply chain by private cloud. This information could be utilised by remaining segments of supply chain to minimise their carbon emission by addressing the inter-dependent factors. For instance, logistics would be able to diagnose if any delay or incompetence at their end is contributing to avoidable carbon footprint at beef farms. They will liaise with beef farmers and mitigate that problem. The logistics firms would also employ CCT interface and a separate window would pop up. They will feed the required information and get their carbon emission results along with suggestive measures to mitigate it. For instance, they would be given guidance to use eco-friendly fuels and modes of transport. They will follow these guidelines and then measure their carbon emissions again. The information fed by logistics and the results generated would be accessible to every stakeholder in the supply chain. It will create novel prospects for all stakeholders to assist logistics in minimising their carbon emissions by working on inter dependent factors. For instance, logistics will obtain the necessary inputs from farmers such as number of animals, address of beef farms, etc. using private cloud. Other information would also be retrieved beforehand like gender, weight of cattle in order to prepare the logistics vehicle to provide ample space allowance and abide by other government legislation. These processes would boost the coordination of logistics with rest of the supply chain. The calculator would guide the logistics firms in terms of optimum route to reach the destination within the permissible limits of regulation in a carbon efficient manner. As the carbon footprint results of every stakeholder are visible to each other, a logistics firm could learn from the good practices of other logistics firms to make their operations eco-friendly. The various wings of abattoir and processor firm would feed their carbon footprint related information into calculator and get the results along with suggestive measures. They would also implement these suggestions to reduce their emissions. Retailer stores at diverse locations would employ the CCT interface and feed the required information and obtain the carbon footprint results along with suggestive measures. For instance, they would be asked to utilise renewable energy instead of those derived from fossil fuels. Suggestions would be given to learn from the good practices of other stores in terms of product handling and efficient stacking and shelving procedures. It will stress on the deployment of innovative technologies for demand forecasting. The retailer stores would follow these suggestive measures to make their operations greener. The proposed CCT based framework would assist retailer's stores to work on their interdependent factors leading to unnecessary carbon footprint.

The CCT framework developed by retailer would assist all stakeholders of beef supply chain in a cost-effective manner. It is extremely advantageous to SMEs of beef industry as they are not able to afford carbon calculators. The optimum, convenient to operate carbon calculators are made accessible to all segments of supply chain as minimal expenses. This integrated approach would assist in reducing the carbon footprint of whole beef supply chain.

This section demonstrates how cloud computing technology could assist all stakeholders of beef supply chain including farmers in measuring their carbon footprint in a convenient and cost effective way.

In order to meet the UK government target to reduce carbon emission by 80% in 2050 from 1990 levels, all stakeholders of beef supply chains have to contribute in reducing their carbon emissions. The farmers are not motivated to actively take measures for reducing emission at their farms. There is need of a mechanism (post CCT framework) to raise pressure on them to adopt sustainable practices. An eco-friendly supplier selection framework is proposed for abattoir and processor to incorporate carbon footprint in their cattle supplier selection process along with other conventional attributes (price, quality, etc.). These mechanisms have been implemented in manufacturing industries. However, their application in the domain of food industries is scarce. The proposed mechanism will utilise the same carbon calculator as described in previous sections of this chapter to calculate the carbon footprint at farm end. The captured information of carbon footprint from farm end via CCT framework would be utilised along with other conventional attributes of cattle for low carbon supplier selection of beef cattle. The details of this mechanism are described in upcoming sections.

5.5 Application of Cloud based framework for eco-friendly supplier selection of cattle

Conventionally, the major focus of beef industries was to meet the demands of customers, which are improving quality (flavour, colour, and tenderness), reducing price, traceability and animal welfare. However, the awareness is growing gradually among customers for carbon footprint associated with all the edible products they are consuming. Simultaneously, there is a constant pressure from the government on beef industries to curb their emission or else their business might be in danger. The abattoir and processor is taking various steps to reduce the carbon emission at their end like reducing the emission in their butchering and boning operations by using renewable sources of energy. However, the 90% of the emissions occurring in beef supply chain is taking place at beef farms. There is need to mitigate this and integrate it with the beef cattle supplier selection process by abattoir and processor. The main root causes are enteric fermentation and manure. It has been demonstrated in previous sections that how cloud computing technology can help farmers to measure their carbon footprint in cost effective way. This section shows how the captured information of carbon footprint (using CCT framework proposed in previous sections) can be utilized by abattoir and processor in eco-friendly supplier selection of beef cattle.

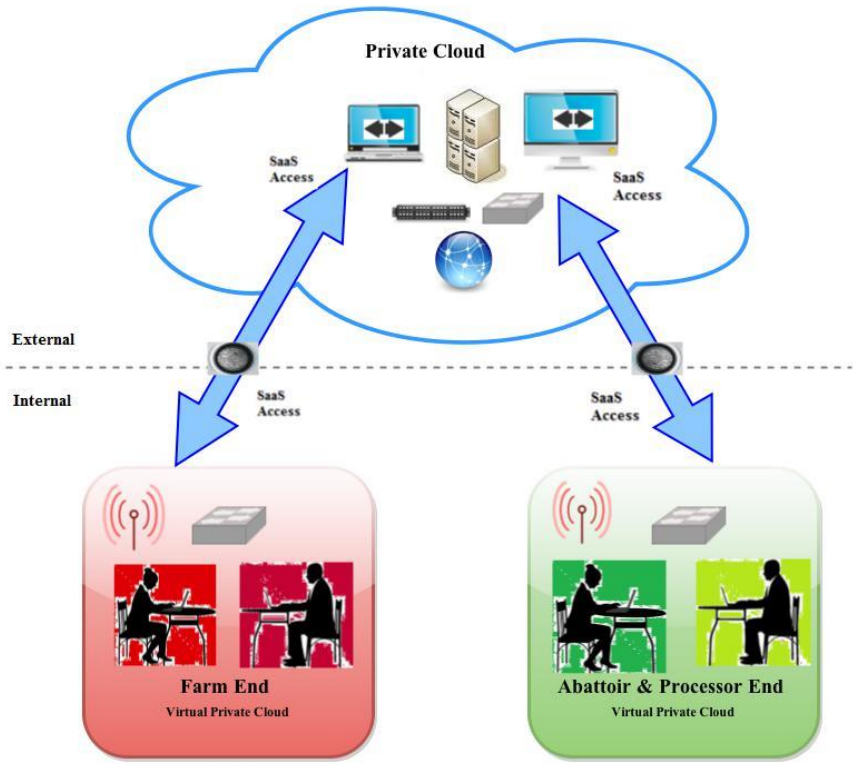

Figure 5.7 showing beef farmers being connected to abattoir and processor via private cloud

In this study, an Indian beef abattoir and processor is maintaining a private cloud which can be accessed by them and their listed suppliers as shown in figure 5.7. The listed beef farmers in India will open an account on the private cloud and enter the information of their cattle and farm as shown in figure 5.8. This information includes the breed of cattle being raised in their farms, their age, the feeding procedures followed, and number of cattle in a farm, average price of individual breed of cattle, fatness score and conformation of cattle, compliance with traceability techniques. The characteristics of above mentioned attributes are described in detail below:

a. Breed- Quality of meet varies with the breed of cattle. Meat derived from some of the cattle has premium quality where as some of them are of just mediocre quality, which is being sold at an economical price. The different breeds of cattle are also associated with different amount of carbon footprint. It is basically dependent on the process of enteric fermentation. Usually, an Indian farm consists of breeds like Brahman, Guzerat, Gir, Kangayam, etc. Farmer will select the type of breed raised by them and if they are raising more than one breed, they will select all of them and enter number of cattle corresponding to each breed in the private cloud.

b. Age – The age of cattle also affects the quality of beef. The cattle sent for slaughtering at the age of around 24 months generates less tender meat as compared to those of 20 months or lesser in age. The carbon footprint generated by cattle is directly proportional to the age of the cattle. Usually, Indian farmers raise their cattle till the age of eighteen to twenty-four months. The farmers will enter the age of their cattle of different breed in private cloud.

c. Diet- The diet fed to the cattle affects the shelf life of the beef derived from them. The meat derived from grass fed cattle has considerably higher shelf life as compared to those raised on grain or mixed diet. However, in terms of carbon footprint grain based diet is having an advantage over grass-based diet. The cattle reach the finishing age earlier on the grain-based diet. Hence, less carbon emission is done in raising them. The farmer will enter the different dietary procedures followed for various breed of cattle on private cloud.

d. Average weight – There is certain weight range, which matches the specification of abattoir and processor. The cattle having weight more or lesser of this range would lead to over burden on slaughterhouse in trimming the excess fat to make it lean to be able to sell it on premium price. Indian beef cattle have average weight from three hundred twenty to four hundred fifty kilograms. Farmers will enter the average weight corresponding to individual cattle.

e. Conformation – The conformation category is evaluated by visual assessment of shape of cattle considering the development of muscles in hindquarter and carcass blockiness. Cattle with excellent conformation assists in producing high quality beef. When farmer will make its profile on private cloud, it will enter the conformation values for each cattle over the cloud.

f. Fatness score –The fatness score is also determined by visual assessment of external fat development on cattle. Usually, the cattle ranges from very lean to very fat category. Cattle having optimum fatness leads to higher quality meat. Farmers will enter the value of fatness score of their individual cattle so that their cattle could be considered during the process of supplier selection.

g. Traceability – There is an increasing pressure of government legislation and customers on all stakeholders of beef supply chain to accommodate traceability in their operations. They must provide detailed information of the beef they are selling like breed of cattle, the location of farms where they were raised, and the diet fed to them, etc. It also helps the retailers and wholesalers of beef to charge premium price to consumers for traceability associated with their products. Farmers will enter the status of their traceability standards into cloud.

h. Price- The price of the cattle plays a crucial role in supplier selection by abattoir and processor. They look for the optimum quality cattle at a cheaper or reasonable price. The farmers will enter the desired price range for selling their cattle in the cloud.

As soon as farmers will enter this information, artificial intelligence present on cloud will generate values corresponding to different supplier selection attributes. For example, carbon calculator will extract all information entered by farmer and calculate the carbon emissions generated by farmer in raising their cattle. GRA (Grey Relational Analysis) will be used to combine breed, conformation and fatness score to generate value corresponding to quality of beef. Thereafter, AHP and TOPOSIS will be used to make trade-off between all supplier selection attributes to select high quality beef at cheaper price with least carbon footprint. In the next section, the methodology used in this mechanism is described in detail.

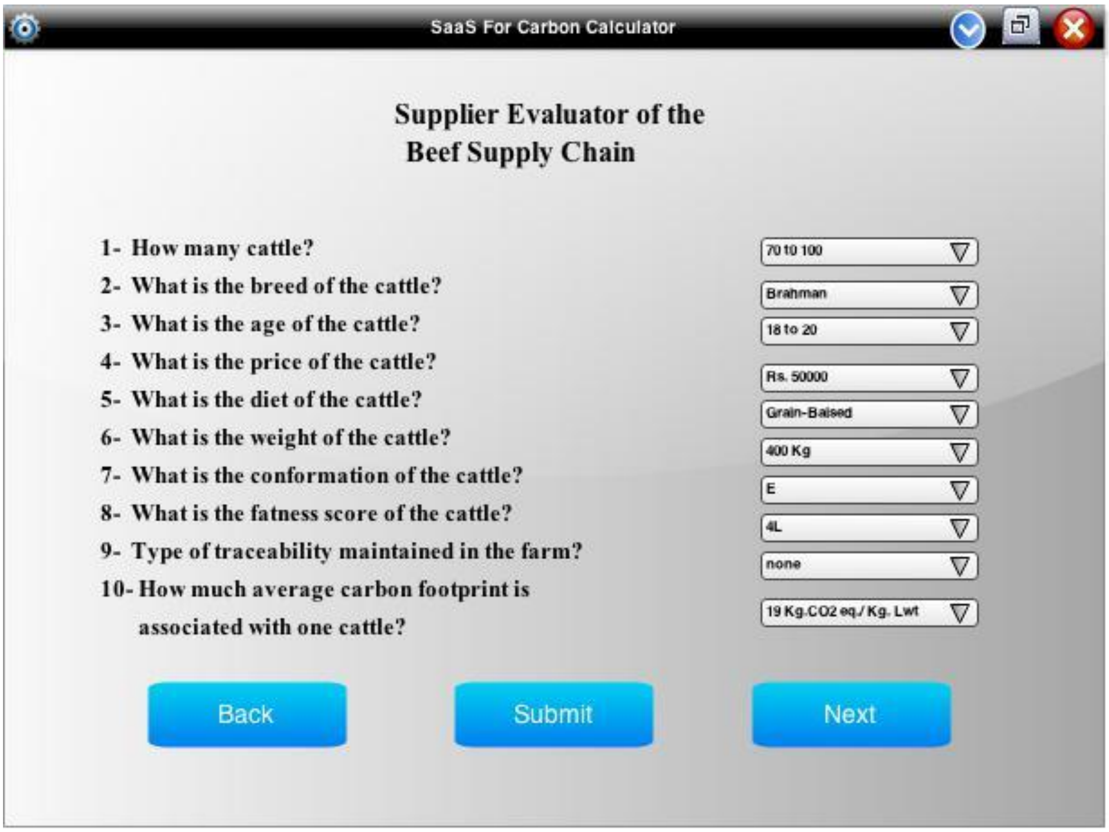

Figure 5.8 Showing information asked by carbon calculator uploaded on cloud.

5.6 Methodology

The major criteria for beef supplier selection are quality, price, traceability, carbon footprint, etc. as mentioned in section 5.5. The quality of cattle is obtained by combining the breed, conformation and fatness score. These three variables can be combined and transformed into a single variable by using Grey Relational Analysis (GRA). Now, the resultant variable of quality and the remaining variables as mentioned in section 5.5 are assigned a weightage as per the preference of customers, quality inspectors of abattoir and processor, etc. This process is achieved by using Analytic Hierarchy Process (AHP) method. Then, the information of various beef suppliers in terms of these variables is being processed using Toposis method. It will prepare a ranking list of all the suppliers, starting from the most appropriate to the least appropriate. The detailed procedure of this method is explained below:

One of the significant criteria of beef supplier selection is quality of beef. Quality is dependent on breed, conformation and fatness score of cattle. Importance of each of these variables varies with the preference of quality inspector. The determination of weightage corresponding to each variable is tedious job. Usually, they use their experience to assign weightage to these variables. To overcome this difficulty, Grey relational analysis is being used in this study, which is being described below:

Grey relational analysis:

Ju-Long (1982) proposed Grey Relational Analysis, which is an effective tool to deal with uncertainty in decision making and solves problems in the event of incomplete information. Grey relational analysis (GRA) can be used to show correlations between the reference/aspirational –level (desired) factors and other compared (alternatives) factors of a system (Chen & Tzeng, 2004; Kuo et al., 2006). Some basic concepts of grey theory are explained below.

Assume, A is the universal set. Therefore, a grey set S of A can be represented by $\acute{\mu}_S(a)$ and $\acute{\mu}_{-S}(a)$

$$\begin{cases} \acute{\mu}_S(a): a \rightarrow [0,1] \\ \acute{\mu}_{-S}(a): a \rightarrow [0,1] \end{cases}$$

$\acute{\mu}_S(a) \geq \acute{\mu}_{-S}(a)$, a A, A = R, $\acute{\mu}_S(a)$ and $\acute{\mu}_{-S}(a)$ denotes the upper and lower membership functions in S. When $\acute{\mu}_S(a)$ = $\acute{\mu}_{-S}(a)$, the grey set S is transformed into fuzzy set. It can be concluded that grey theory takes into account the condition of fuzziness and is capable of coping with it.

When it is only possible to estimate the lower limit of A and A is known as lower limit grey number.

$$\otimes A = [\underline{A}, \infty)$$

Explanation 5 When it is only possible to estimate the upper limit of A and A is known as lower limit grey number.

$$\otimes A = (-\infty, A]$$

Explanation 6 When it is possible to estimate the lower and upper values of G and G is known as interval grey number

$$\otimes A = [\underline{A}, \acute{A}]$$

Explanation 7 Grey number operation is defined on set of intervals. It cannot be defined on real numbers. If $A_1 = [\underline{A}_1, \overline{A}_1]$ and $A_2 = [\underline{A}_2, \overline{A}_2]$ then the main operations on grey numbers is done through following:

$\otimes$A1 + $\otimes$A2 = $[\underline{A1} + \underline{A2}, \overline{A1} + \overline{A2}]$

$\otimes$A1 − $\otimes$a2 = $[\underline{A}1 - \overline{A2}, \overline{A1} - \underline{A2}]$

$\otimes$A1 × $\otimes$A2 = [min($\underline{A1A2}, \underline{A1}\overline{A2}, \overline{A1}\underline{A2}, \overline{A2A1}$), max($\underline{A1A2}, \underline{A1}\overline{A2}, \overline{A1}\underline{A2}, \overline{A2A1}$)]

$\otimes$A1 ÷ $\otimes$A2 = $[\underline{A1}, \overline{A1}] \times \left[\frac{1}{\underline{A2}}, \frac{1}{\underline{A2}}\right]$

In order to make a decision by applying Grey Relational Analysis, the grey relation between the alternatives with the referential point needs to be calculated. Therefore, Grey Relational coefficient is being used and the grey relational coefficient between the point x_{ij} and referential point x_{oj} is obtained through formula (1).

$$\gamma\left(x_{oj}, x_{ij}\right) = \frac{\min_i \min_j \Delta_{ij} + \zeta \max_i \max_j \Delta_{ij}}{\Delta_{ij} + \zeta \max_i \max_j \Delta_{ij}} \tag{1}$$

In above equation: $\Delta_{ij} = \left|x_{oj} - x_{ij}\right|$ and ζ is a coefficient which is ($\zeta \in [0,1]$).

In order to do the final evaluation between the alternatives, there is need to calculate grade of grey relation based on formula (2). Alternatives with higher grade have more relation to our reference point.

$$\gamma(x_o, x_i) = \sum_{j=1}^{n} \gamma\left(x_{oj} - x_{ij}\right) \tag{2}$$

Fuzzy set theory

The nature, scale and units of measurement are distinct for different variables of supplier selection of beef. Also, some decision makers are more confident in expressing their judgment by using interval values rather than numeric exact values. In order to deal with ambiguities, uncertainties and vagueness as well as above mentioned problems, the use of fuzzy set theory has become popular among researchers. By application of fuzzy set theory, the decision-maker is able to incorporate unquantifiable information, incomplete information, non-obtainable information and partially ignorant facts into decision model (Zadeh, 1965; Kulak, Durmusoglu, & Kahraman, 2005).

The mathematical aspects of fuzzy set theory assume that there is a universe of discourse *U* and its fuzzy subset A is represented mathematically by membership value denoted by $\mu_A(x)$, with x as an element of the universe of discourse that conceptually denotes the grade of membership of x. The fuzzy subset A is $A = \{\mu_A(u)/u | u \in U\}$ and the linguistic variable are represented in natural language by the name, e.g. x and the set term S(x) of the linguistic value of x. In case of triangular fuzzy number (TFN), the membership function of $M = (a_i, b_i, c_i)$ is based on formula (3) and this triplet is shown in figure ():

$$\mu_M(x) = \begin{cases} 0 & if \quad x \leq a_i \\ \frac{x-a_i}{b_i-a_i} & if \quad a_i \leq x \leq b_i \\ \frac{b_i-x}{c_i-b_i} & if \quad b_i \leq x \leq c_i \\ 0 & if \quad x \geq c_i \end{cases} \tag{3}$$

Now, let $\widetilde{M}$ and $\widetilde{N}$ be two triangular fuzzy numbers which are parametrized with two triplets of (a_1, b_1, c_1) and (a_2, b_2, c_2) respectively. Then, the following operational laws for these two number are applied:

$\widetilde{M} + \widetilde{N} = (a_1 + a_2, b_1 + b_2, c_1 + c_2)$

$\widetilde{M} - \widetilde{N} = (a_1 - a_2, b_1 - b_2, c_1 - c_2)$

$\widetilde{M} \times \widetilde{N} = (a_1 . a_2, b_1 . b_2, c_1 . c_2)$

$\widetilde{M} / \widetilde{N} = (a_1/c_2, b_1/b_2, c_1/a_2)$

The triangular fuzzy numbers are selected in this research not only because of their intuitive easiness for decision makers to calculate, but also for proven effectiveness of modelling decision making problems through them (Chang et al 2007, Zimmerman 1996).

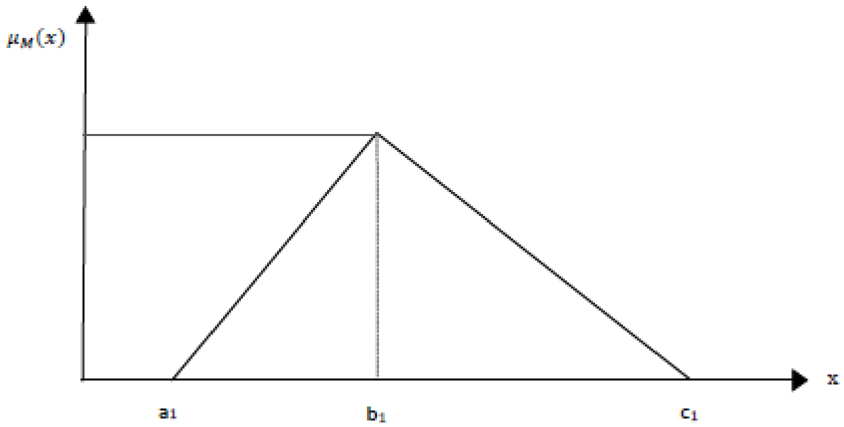

Figure 5.9 Triangular fuzzy number M

Fuzzy TOPSIS

Hwang and Yoon (1981) introduced the TOPSIS (Technique for Order Preference by Similarity to Ideal Solution). TOPSIS is a technique which ranked the alternative based on their distances from ideal positive and negative solution (PIS, NIS). The alternatives with closer distance to PIS and further distance from NIS are ranked higher by TOPSIS. Thus, the best alternative should not only have the shortest distance from the positive ideal solution, but also should have the largest distance from the negative ideal solution. Ideal solutions are set of the best and worth, respectively for PIS and NIS, performance of the alternatives within our criteria. The following steps indicate how the Fuzzy TOPSIS calculated the evaluation of alternatives:

Assume, there are m alternatives and n criteria through which the performance of criteria is going to be evaluated. The decision Matrix D with m row and n column is formed based on equation (4).

$$D = [x_{ij}] = \begin{bmatrix} \tilde{x}_{11} & \cdots & \tilde{x}_{1n} \\ \vdots & \ddots & \vdots \\ \tilde{x}_{m1} & \cdots & \tilde{x}_{mn} \end{bmatrix} \quad (4)$$

$Where\ x_{ij} = (a_{ij}, b_{ij}, c_{ij})$

1- Normalize the decision Matrix using following formula and obtain $\tilde{R} = [\tilde{r}_{ij}]_{m\times n}$:

$$\tilde{r}_{ij} = \left(\frac{a_{ij}}{c_j^*}, \frac{b_{ij}}{c_j^*}, \frac{c_{ij}}{c_j^*}\right), \qquad j \in B \quad (5)$$

$$\tilde{r}_{ij} = \left(\frac{a_j^-}{c_{ij}}, \frac{a_j^-}{b_{ij}}, \frac{a_j^-}{a_{ij}}\right), \qquad j \in C \quad (6)$$

In above formula, B is for a benefit criteria and C is for a cost criteria. Also, $c_j^* = \max_i c_{ij}$ if $j \in C$ and $a_j^- = \min_i a_{ij}$ if $j \in B$.

2- Specify the Fuzzy Positive Ideal Solution (FPIS) and Fuzzy Negative Ideal Solution (FNIS) as below:

$$FPIS = (r_1^+, r_2^+, r_3^+, \ldots\ldots r_n^+) \quad (7)$$

$$FNIS = (r_1^-, r_2^-, r_3^-, \ldots\ldots r_n^-) \quad (8)$$

where

$$\upsilon_j^+ = (p, p, p)\ \ \forall j = (1, 1, 1) \quad (9)$$

$$\upsilon_j^- = (k, k, k)\ \ \forall j = (0, 0, 0) \quad (10)$$

3- Calculate the weighted distance of each alternative from positive and negative ideal solutions. Euclidean distance measure is used for this purpose. Distance d between two triangular fuzzy numbers (Let $A = (a_1, a_2, a_3)\ and\ B = (b_1, b_2, b_3\ )$) can be calculated by the following formula:

$$d(A,B) = \frac{1}{2}\{max(|a_1 - b_1|, |a_3 - b_3|) + |a_2 - b_2|\} \tag{11}$$

If we assume the weight matrix obtained from fuzzy AHP is $w_j = \left(w_{xj}, w_{yj}, w_{zj}\right)$ and each of our normalized Matrix arrays are $r_{ij} = \left(r_{xij}, r_{yij}, r_{zij}\right)$ so then distance from FPIS can be calculated from formula (12):

$$d_i^+ = \sum_{j=1}^{n} \frac{1}{2}\left\{max\left(w_{xj}\left|r_{xij} - 1\right|, w_{zj}\left|r_{zij} - 1\right|\right) + w_{yj}\left|r_{yij} - 1\right|\right\} \tag{12}$$

Distance from FNIS can be calculated from formula (13):

$$d_i^- = \sum_{j=1}^{n} \frac{1}{2}\left\{max\left(w_{xj}\left|r_{xij} - 0\right|, w_{zj}\left|r_{zij} - 0\right|\right) + w_{yj}\left|r_{yij} - 0\right|\right\} \tag{13}$$

4- In final step, the relative closeness coefficient to the ideal solution is computed through formula (14). The higher the value is, alternative obtain better rank.

$$CR = \frac{d_i^-}{d_i^+ + d_i^-} \tag{14}$$

Application of GRA to calculate the quality of beef

As mentioned above, in this chapter, the Grey Relational Analysis is used to combine three related criteria (breed, conformation and fatness score) and form one comprehensive criteria (Quality of meat). The above-mentioned criteria are in linguistic form and in order to take them into account along with other variables, firstly, it is converted into linguistic term by using triangular fuzzy number as shown in Table 5.1. In order to explain, how values in the column 'Quality of meat' in Table 5.3 are calculated, an example of farmer S2 is considered and the calculation procedure is described as following:

Firstly, the grey linguistic numbers are being assigned to breed, conformation and fatness score as per decision maker's opinion as shown in Table 5.2.

Table 5.1 Assigning of linguistic term by using triangular fuzzy number

Fuzzy linguistic Terms	Triangular Fuzzy Number	Grey linguistic terms	Grey Numbers
Very Good	(9 10 10)	Very good	[9 10]
Good	(7 9 10)	Good	[7 9]
Medium Good	(5 7 9)	Fair	[5 7]
Fair	(3 5 7)	Medium	[3 5]
Medium Poor	(1 3 5)	weak	[1 3]
Poor	(0 1 3)		
Very Poor	(0 0 1)		

Table 5.2 Grey values for creating a comprehensive criterion of meat quality

	Breed	Confirmation	Fat score
S1	[9 10]	[9 10]	[9 10]
S2	[1 3]	[9 10]	[9 10]
S3	[1 3]	[5 7]	[7 9]
S4	[5 7]	[5 7]	[3 5]
S5	[3 5]	[5 7]	[9 10]
S6	[7 9]	[7 9]	[7 9]
S7	[1 3]	[9 10]	[3 5]
S8	[9 10]	[5 7]	[7 9]
S9	[3 5]	[5 7]	[7 9]
S10	[5 7]	[5 7]	[7 9]

Table 5.3 Information of ten suppliers in terms of various criteria

Weights	0.247	0.032	0.151	0.031	0.057	0.224	0.235
Criteria Suppliers	Quality of Meat	Age	Diet	Average Weight	Traceability	Carbon Footprint	Price
S1	3	MP	VG	G	VG	F	50000
S2	2.33	MG	MG	MP	P	G	45000
S3	1.55	MP	G	MG	MG	MG	41000
S4	1.42	G	F	G	VG	MG	46000
S5	1.91	VG	G	P	P	G	42000
S6	2.13	MP	G	G	VG	MG	47000
S7	1.73	MP	F	G	MG	F	48500
S8	2.22	F	G	P	VG	VG	42500
S9	1.62	MP	F	MP	P	F	46500
S10	1.73	F	MG	VG	VG	VG	40500

In order to normalize the values in table 5.3, all the values are divided by the [10 10] to obtain a normalized matrix. The Ideal values for all the three criteria are [0.9 1]. The distances of S2 criteria values from ideal points are calculated.

$\Delta_{2,1} = (1 - 0.3) + (0.9 - 0.1) = 1.5$

$\Delta_{2,2} = (1 - 1) + (0.9 - 0.9) = 0$

$\Delta_{2,3} = (1 - 1) + (0.9 - 0.9) = 0$

In the next step $\min_i \min_j \Delta_{ij}$ and $\max_i \max_j \Delta_{ij}$ values are obtained. Thereafter, based on equation 1, the grey relational coefficient for each array in decision matrix based on table 5.3 will be calculated. For example, for second supplier:

$$\gamma(x_{o1}, x_{21}) = \frac{0 + (0.5 \times 1.5)}{1.5 + (0.5 \times 1.5)} = 0.33$$

$$\gamma(x_{o2}, x_{22}) = \frac{0 + (0.5 \times 1.5)}{0 + (0.5 \times 1.5)} = 1$$

$$\gamma(x_{o3}, x_{23}) = \frac{0 + (0.5 \times 1.5)}{0 + (0.5 \times 1.5)} = 1$$

And in the final step, grey degree of supplier S2 is calculated based on equation 2 as follows:

$$\gamma(x_{o1}, x_{21}) + \gamma(x_{o2}, x_{22}) + \gamma(x_{o3}, x_{23}) = 2.33$$

In above calculation, we have assumed $\xi = 0.5$

In the next section, the complete execution process of proposed method is demonstrated.

5.7 Execution of the CCT based eco-friendly supplier selection of cattle

This section demonstrates the working of the proposed methodology. A beef abattoir and processor company is operating in India. The maximum chunk of their products are being exported to foreign countries. However, they do sell some amount of their products in local markets as well. In the past, the decision of selection of their cattle supplier was driven by the conventional requirements of consumers (both local and abroad), which were high quality, minimum price, traceability, etc. However, there is lot of pressure on this firm both from the government and the consumers to cut down the carbon emission in their supply chains. This company has ample resources to optimize the carbon emission at their end. However, the majority of emission in their supply chain takes place at beef farms. In order to cut down the carbon emission in their beef supply chain, the abattoir and processor company has to make both their and their beef farms operations eco-friendly. The farmers have less knowledge and no mechanism to measure the carbon emission and take preventive measures to mitigate them. They lack the awareness and resources to purchase a carbon calculator to quantify the carbon footprint in their farms. The carbon calculators are very expensive and often very sophisticated to utilize. The abattoir and processor firm will select an appropriate carbon calculator which is both precise and user friendly and install them on a private cloud maintained by them. All the potential suppliers (beef farmers) to this firm can access this calculator via cloud by just having Internet connection. These beef farmers have to make an account on the cloud and enter the details of their farm like breed, age, diet, weight, etc. of cattle as shown in figure 5.8. The values of farmer profile are being shown in Table 5.3. The carbon calculator installed on the cloud will process these details as shown in figure 5.10 and generate the results of carbon emission for these farmers. Thereafter, the cloud will extract the breed, conformation and fatness score for all the farmers and utilize Grey Relational Analysis as described above (section 5.6) to calculate the quality of beef corresponding to various breed. The calculated linguistic terms and grey numbers representing the quality of meat for each farmer are shown in table 5.1 and 5.2. The higher the value of variable for quality, the better is the quality of meat. For example, supplier S1 has better quality of meat compared to that of S2. Thereafter, abattoir and processor will set the importance of different attributes over the cloud depending on demand of market, consumer preference, country of sale, etc. For example, in this case, quality of meat, price and carbon footprint are the three variables having highest importance in descending order. As soon as importance of various attributes of supplier selection, quality of meat and carbon footprint are calculated, the Topsis method will generate the ranking of the supplier from most appropriate to least appropriate, which is shown in table 5.4, while making trade-off between different attributes. Based on the criteria set by abattoir and processor and farmer's profile, supplier S8 is the most appropriate supplier, who produces high quality of meat in minimum carbon emission. The abattoir and processor will start negotiating with these suppliers starting from the most appropriate supplier. When both the parties mutually agree, then the cattle are procured from the most fitting supplier.

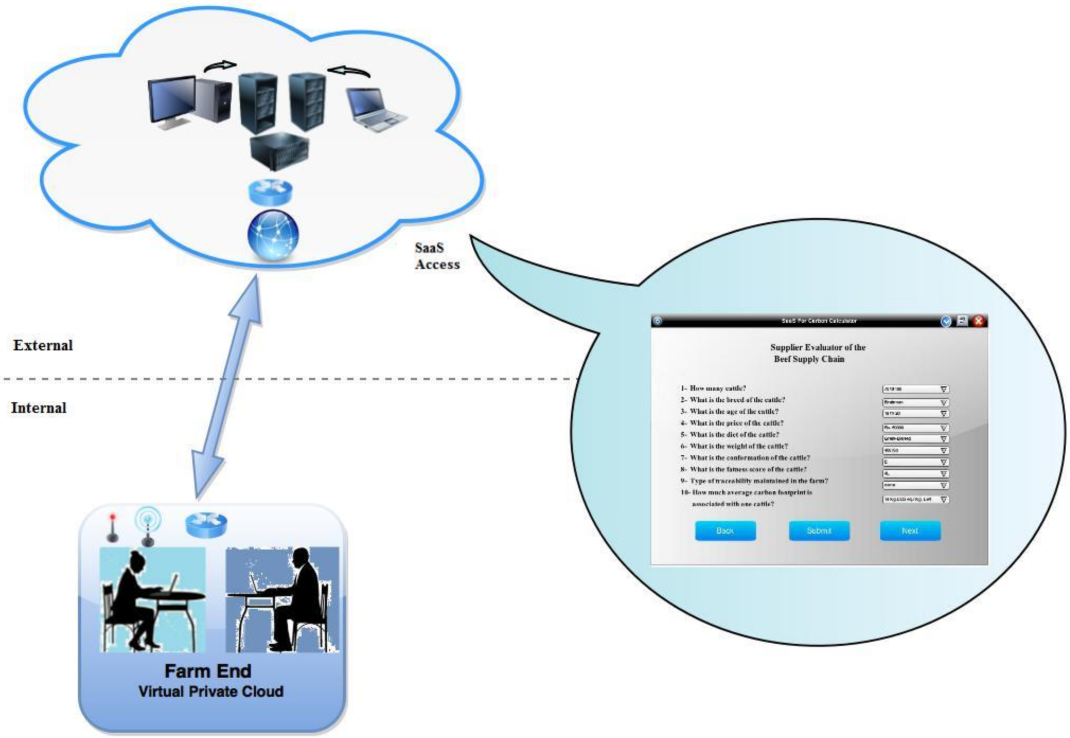

Figure 5.10 showing information entered by farmer is being processed by carbon calculator uploaded on private cloud

Table 5.4 Ranking of beef cattle supplier obtained by Topsis method

Rank	**Supplier**	**Relative Closeness**
1	S8	0.7051
2	S10	0.60853
3	S1	0.55855
4	S5	0.50763
5	S2	0.49106
6	S6	0.4886
7	S3	0.30528
8	S4	0.26601
9	S7	0.14268
10	S9	0.098091

5.8 Managerial implications

An integrated framework is proposed in this chapter to measure and mitigate the carbon footprint generated by the whole beef supply via CCT infrastructure. It would be very beneficial to SMEs of beef supply chain as they are deficient of resources and knowledge of carbon footprint generated by their farms. The proposed framework would prevent them from procuring expensive carbon calculator on their own as it could be utilised via SaaS from private cloud in a cost-effective manner.

Every segment of beef supply chain could utilise carbon calculator uploaded on cloud and obtain their carbon footprint results, which would be visible to managers and decision makers of other segments of beef supply chain. A feedback in the form of suggestive measures would also be provided by carbon calculator. It would assist managers of different segments of the supply chain in optimum decision making to reduce their carbon footprint and improve efficiency. For instance, the farmers would be given guidance about the breed of cattle associated with lowest carbon footprint. The integrated framework would assist policy makers of retailer to identify the segments associated with high carbon footprint and inefficient product flow, which could be addressed by the feedback given by carbon calculators.

The private cloud developed by the retailer is encompassing the entire beef supply chain and it would assist in addressing carbon footprint of a particular segment generated because of its interdependency on other segments of supply chain. For instance, it will suggest the logistics firm various means to mitigate their carbon hotspots, which are inter-dependent on retailer. It would also assist in revealing the good and bad practices followed by a specific segment of supply chain with regards to their carbon footprint. For instance, distinct logistics firms might be employed in the interface of farm to abattoir and from processor to retailer. The carbon footprint information of both the firms could be used by the managers of these logistics firms to replace their bad practices with good practices of the other firm. This research has a huge impact of the traditional approach of measurement of carbon emissions at one segment of beef supply chain. It would assist in enhancing the vertical and horizontal coordination in the whole supply chain resulting in improved and sustainable product flow within the supply chain. For instance, the coordination among the managers of farming enterprises and logistics firms would be strengthened in terms of efficient planning of shipping of cattle and specific measures to be considered such as ample space allowance, journey time within permissible limits, etc.

Consumers have adopted a very selective approach towards traceability associated with beef products post horsemeat scandal on one of the supermarket in the UK. The information sharing attribute of the proposed framework would assist in mitigating this problem. Hence, it will create the opportunities for retailer managers to raise the price of beef products following traceability procedures. Simultaneously, there is a rise in the consumer's awareness about the carbon footprint of all the products consumed by them. It could be mitigated by this study and could be beneficial for retailer in promoting their sustainable beef products and draw the attention of consumers. It would assist the decision maker of retailer to identify the stakeholders of beef supply chain which has to be altered to meet the government target of eco-friendly businesses.

The integrated framework proposed in this study would assist all segments of beef supply chain to identify, measure and prioritise their carbon hotspots while addressing them. Also, all managers of beef supply chain could track their progress in reducing their carbon emissions as their history of carbon footprint results would be saved in the private cloud database.

During the process of supplier selection by abattoir and processor, there will be a trade-off made between the carbon emission occurring at farm end and the conventional factors like breed, conformation, fatness score etc. The manager of abattoir and processor will have to curb emissions both at their premises and also carbon footprint generated at the premises of their suppliers to make their supply chain eco-friendly. Hence, they have to consider the carbon emission at beef farms while doing the supplier selection. This framework will give a broader view to the manager of abattoir and processor, as those farmers will also be able to connect to them via cloud, which were out of range earlier. The manager of abattoir and processor will be able to target different segments of market preferring different quality parameters with this system. The manager will utilize GRA (Grey Relation Analysis) to vary the three different quality parameters viz. breed, conformation and fatness score and select the most appropriate supplier for a particular market segment. The cloud-based framework will help farmers to optimize their carbon emission and other conventional factors as per their requirement of abattoir and processor. It will make them aware of modern trends and also help them to raise their cattle as per demand of abattoir and processor. Simultaneously, farmers will also learn from the good practices of the other farmers to reduce their carbon emission, as the relevant information of all the farmers will be visible on cloud. The abattoir and processor will also upload guidelines on the cloud-based framework for farmers on procedures and techniques to reduce their carbon footprint and improve other factors. It will help the farmers to save money and develop an appropriate strategy. They will be aware of what breed of cattle needs to be raised, what to feed them, etc.

5.9 Conclusion

All segments of beef supply chain are generating carbon footprint. Traditionally, these segments were only concerned about their financial revenue. Nonetheless, due to the pressure from government legislation, they have to take into account the carbon emissions done by their operations. The SMEs of beef supply chain could not address this issue pertaining to their deficiency in financial and technological resources. There is weak vertical coordination in the supply chain as there is no integrated framework to share the carbon footprint results of different stakeholders among each other. In order to address these shortcomings, this chapter proposes an integrated and collaborative framework based on CCT to optimise and measure carbon footprint of entire beef supply chain. Firstly, the carbon hotspots associated with all segments of supply chain: farms, abattoirs, processors, logistics and retailers are identified. Then, a private cloud is created by the retailer to encompass the whole beef supply chain irrespective of their locations. The carbon footprint generated in the process of product flow of beef products from farm to retailer would be mitigated and quantified. The vertical and horizontal coordination in the supply chain would also be strengthened resulting in improved efficiency and sustainability of supply chain. The execution of the proposed framework has been demonstrated via case study method.

This chapter also highlights eco-friendly supplier selection of beef cattle by abattoir and processor. It shows how carbon footprint generated in beef farms can be taken into account along with breed, age, diet, average weight of cattle, conformation, fatness score, traceability and price. Quality of beef is dependent on combination of breed, conformation and fatness score of the cattle. GRA (Grey Relation Analysis) is being used to combine these three factors and the resultant factor is being known as Quality. Then, quality, carbon footprint and other previously mentioned factors detrimental for supplier selection are assigned a weightage according to the priority of customers and quality inspector of abattoir and processor. Topsis method will process the information of various beef cattle suppliers in terms of above mentioned factors and generate a ranking list of suppliers, starting from most appropriate to least appropriate supplier. The proposed technique in this study is being successfully demonstrated on Indian beef industry in case study section. This research will not only help abattoir and processor in reducing their carbon footprint but will also help beef farmers to cut down their carbon emission. As most of the carbon footprint of beef supply chain is being generated in farms, this study will help in curbing these emissions. More farmers would be able to connect to abattoir and processor by using the cloud-based framework described in this chapter. These farmers will learn the modern trends associated with beef beyond conventional factors like price and breed. There will be an opportunity for farmers to learn from the good practices of other farmers in minimizing their carbon emission and also improving in terms of other factors.

This study has some operational limitations. Some of the farmers in India are uneducated and reluctant to adopt modern practices. They need to be motivated to engage in sustainable practices in the beef farms by raising awareness about the numerous benefits associated with it. Also, the weightage assigned to all the variables quality, price, traceability, carbon footprint, etc. could be biased due to the limited information collected from consumer's preferences and quality inspector of abattoir and processor. It could be mitigated by increasing the sample size of the information collected from both the sources to optimise the allocated weightage to all the variables. Some parts of rural India are still deprived of internet connectivity. Therefore, this cloud based framework could not be implemented at such locations. Government and private players associated with the Digital India plans could play a crucial role is addressing this situation.

The proposed mechanism utilised CCT for measuring and minimising carbon footprint of all stakeholders of beef supply chain and helped abattoir and processor in eco-friendly supplier selection of cattle. The frameworks proposed in chapter 3-6 assists in reducing carbon footprint and physical waste of beef supply chain to improve its sustainability. These objectives, could be achieved if consumer centric beef supply chain is developed, which is associated with less waste, low carbon footprint and assists retailer to capture larger market share. The next chapter is focused on making beef supply chain consumer centric by using amalgamation of big data analytics, Interpretive Structural Modelling (ISM) and MICMAC techniques. A thorough literature review and big data analytics is utilised to identify the most significant factors influencing the beef purchasing decision of consumers. Then, ISM and MICMAC analysis was performed to investigate the relationship between these factors to develop a consumer centric beef supply chain.

CHAPTER 6

Interpretive Structural Modelling and Fuzzy MICMAC Approaches for Customer Centric Beef Supply Chain: Application of a Big Data Technique

6.1 Introduction

The main objective of modern industry is to please consumers. Usually, supply chains are designed using customer driven approach. The businesses are framing their operations to become more efficient in terms of time and money to meet the expectations of consumers. The implementation of these policies becomes complicated in food industry considering the perishable nature of food products (Aung and Chang, 2014). The food products reaching the consumers should have the virtue of good taste, quality, ample shelf life, high nutrition, appearance, good flavour in minimum cost or else the food retailers and their suppliers might lose their market share (Banović et al., 2009; Bett, 1993; Killinger et al., 2004b; Neely et al., 1998; Oliver, 2012; O'Quinn et al., 2016; Sitz et al., 2005; van Wezemael et al., 2010; van Wezemael et al., 2014; Verbeke et al., 2010). After the horsemeat scandal, major retailers are in pressure to assure the food safety, quality and precise labelling to reflect the actual content of beef products by strengthening the relation with the key suppliers (Yamoah and Yawson, 2014). There is a lot of pressure from government legislation and consumers about the carbon footprint generated in producing the food products (Weber and Matthews, 2008). The aforementioned factors influence the consumer's purchasing decisions and food industries are aware of them. However, they don't know how these factors are linked with each other and how to assimilate these factors in their operations to achieve a consumer centric supply chain. Incorporating consumer perception is very crucial for food retailers to survive in today's competitive market. Food retailers make an attempt to receive consumer feedback via market survey, market research, interview of consumers and providing the opportunity to consumers to leave feedback in retail stores and use this information for improving their supply chain strategy. However, the response rates for these techniques are quite low, often the responses are biased and consist of false information; consumers are reluctant to participate due to privacy issues. Therefore, these techniques give limited outlook of the expectations of majority of customers. There is plenty of useful information available on social media. Such information includes the true opinion of consumers (Katal et al., 2013; Liang and Dai, 2013). The rapid development in information and technology will assist business firms to collect the online information to use it in developing their future strategy. On the contrary, the social media data is qualitative and unstructured in nature and often huge in terms of velocity, volume and variety (Hashem et al., 2015; He et al., 2013; Zikopoulos and Eaton, 2011).

Outcome of operations management tools and techniques are usually based on limited data collected from various sources such as survey, interview, expert opinion, etc. Decision making could be more precise and accurate if these analyses are supplemented by social media data. This study attempts to incorporate social media data using Interpretive Structural Modelling (ISM) and fuzzy MICMAC to develop a framework for consumer centric sustainable supply chain. The involvement of information from social media data will give consumers 'sense of empowerment.' There is no mechanism mentioned in the literature for using Twitter analytics to explore the interrelationships among factors mandatory to achieve consumer centric supply chain. This chapter explicitly investigates the interaction among these factors using big data (social media data) supplemented with ISM and fuzzy MICMAC analysis. A systematic literature review was conducted to identify the drivers influencing the consumer's decision of buying beef products and supply chain performance. Thereafter, ISM is developed to investigate factors influencing the beef purchasing decision of consumers and the relationship between them. Usually, structural models are composed of graphs and interaction matrices, signal flow graphs, delta charts, etc., which doesn't provide enough explanation of the representation system lying within. In this chapter, using ISM and fuzzy MICMAC techniques, the variables influencing consumers' decision are segregated into four different categories: driving, linkage, autonomous and dependent variables and generate the hierarchical structure to represent the linkage between the variables for interpretive logic of system engineering tools. Based on the findings, the recommendations have been prescribed to develop a consumer centric sustainable supply chain.

6.2 Variables influencing consumer's purchasing behaviour of beef products

Using systematic literature review, different variables influencing customers buying behaviour of beef products are identified. The research papers were extracted from prominent databases like ScienceDirect, Springer, Emerald, Taylor & Francis and Google Scholar. The keywords utilised were 'consumer purchasing beef', 'factors affecting beef buying behaviour', 'why purchase steak', 'variables influencing beef purchase', 'consumer attitude towards beef purchase', 'purchase behaviour for beef', 'consumer perception on buying beef', 'drivers influencing intention for beef purchase.' More than hundreds of research articles and reports from above mentioned search engines were selected for this research. The exhaustive analysis of the extracted content yields eleven drivers as shown in Table 6.1, which influence the consumer's decision to purchase beef products and are essential to achieve consumer centric supply chain. The extracted drivers are described as follows:

Table 6.1. List of variables influencing consumer's beef purchasing behaviour

S. No.	Variables	Sources
1	Quality	Banović et al. (2009); Becker (2000); Brunsø et al. (2005); Grunert (1997); Grunert et al. (2004); Krystalli et al. (2007); Verbeke et al. (2010)
2	Taste	Bett (1993); Killinger et al. (2004a); Killinger et al. (2004b); McIlveen & Buchanan (2001); Neely et al. (1998); Oliver (2012); O'Quinn et al, (2016); Sitz et al. (2005)
3	Packaging	Issanchou (1996); Zakrys et al. (2009); Brody and Marsh (1997); Kerry, O'grady & Hogan, (2006); Grobbel et al. (2008); Carpenter et al. (2001); Verbeke et al. (2005); Bernués et al. (2003)
4	Price	Acebrón & Dopico (2000); Erickson & Johansson (1985); Hocquette et al. (2015); Kukowski et al. (2005); Levin, & Johnson (1984); Lichtenstein et al. (1993); Liu & Ma (2016); Marian et al. (2014); Völckner & Hofmann (2007)
5	Promotion	Belch & Belch (1998); Cairns et al. (2009); Eertmans et al. (2001); Elliott (2016); Hawkes (2004); Kotler & Armstrong (2006); Rossiter & Percy (1998)
6	Organic/inorganic	Bartels & Reinders (2010); Bravo et al. (2013); Guarddon et al. (2014); Hughner et al. (2007); Mesías et al. (2011); Napolitano et al. (2010); Ricke (2012); Squires et al. (2001); Średnicka-Tober et al. (2016)
7	Advertisement	De Chernatony and McDonald (2003); Dickson and Sawyer (1990); Jung et al. (2015); Mason & Nassivera (2013); Mason & Paggiaro (2010); Quelch (1983); Simeon & Buonincontri (2011)
8	Colour	Brody and Marsh (1997); Grunert (1997); Guzek et al. (2015); Issanchou (1996); Jeyamkondan et al. (2000); Kerry et al. (2006); McIlveen & Buchanan, (2001); Realini et al. (2015); Savadkoohi et al. (2014); Suman et al. (2016); Viljoen et al. (2002)
9	Nutrition (Fat label)	Barreiro-Hurlé et al. (2009); da Fonseca & Salay (2008); Lähteenmäki (2013); Lawson (2002); McAfee et al. (2010); Nayga (2008); Rimal (2005); van Wezemael et al. (2010); van Wezemael et al. (2014)
10	Traceability	Becker (2000); Brunsø et al. (2002); Clemens & Babcock (2015); Giraud & Amblard (2003); Grunert (2005); Lee et al. (2011); Menozzi et al. (2015); Ubilava & Foster (2009); van Rijswijk & Frewer (2008); van Rijswijk et al. (2008a); Verbeke & Ward (2006); Zhang et al. (2012)
11	Carbon footprint	Grebitus et al. (2013); Grunert (2011); Lanz et al. (2014); Nash (2009); Onozaka et al. (2010); Röös & Tjärnemo (2011); Singh et al. (2015); Vermeir & Verbeke (2006); Vlaeminck et al. (2014)

6.2.1 *Quality of the meat* – International Organization for Standardization (ISO) has defined food quality as the entirety of traits and characteristic of a food product that has the capability to appease fixed and implicit requirements (ISO 8402). The eating quality is the foremost thing taken into account by customers while purchasing beef, which includes tenderness, juiciness, freshness, minimum gristle and free from bad smell or rancidity and absence of infections (Banovic et al., 2009; Brunsø et al., 2005; Krystallis et al., 2007). Good quality beef products boost the customer satisfaction and consequently raise the rate of consumption of beef products. It will lead to the increase in revenue of beef industry, which is crucial in modern era of economic crisis, uncertainty in food prices and intensive competition (Verbeke et al., 2010). The determinants of quality as mentioned above are normally assessed after cooking of beef products (Grunert, 1997). Some consumers also consider credence characteristics of beef products while evaluating their quality (Geunert et al., 2004). Sometimes, the quality is also judged by the labels associated with reputed farm assurance schemes such as Red Tractor. It confirms that appropriate animal welfare procedures or farm assurance schemes have been implemented in the beef farms associated with beef products in the retails stores. Therefore, the quality of beef products plays a vital role in deciding whether a particular beef product consumed by a consumer will be bought again or recommended by him or her to their friends and relatives.

6.2.2 *Taste* – Certain consumers give equal preference to the flavour profile of beef products rather than to the aggregate sensory experience (Neety et al., 1998). Flavour of beef products often becomes the most crucial determinant for eating satisfaction if the associated tenderness is within tolerable range (Killinger et al., 2004a). The flavour associated with beef products is not easy to anticipate and define (McIlveen and Buchanan, 2001). The determinants of beef flavour have been recognised as cooked beef fat, beefy, meaty/brothy, serum/bloody, grainy/cowy, browned and organ/liver meat (Bett, 1993). Many of these determinants are unfavourable for customers. O'Quinn et al. (2016) revealed that customers prefer the beef with high cooked beef fat, meaty/brothy, beefy and sweet flavour whereas organ/livery, gamey and sour flavour were disliked. In most of the cases, customers assess the aggregate intensity of the flavour. Although the studies based on consumer’s sensory have revealed that beef customers have distinct priorities for a certain attribute of beef flavour (Oliver, 2012; Killinger et al, 2004b). These individual flavour priorities are emulated in their decisions regarding purchase of beef products (Sitz et al., 2005).

6.2.3 *Packaging* – Packaging is one of the crucial visual determinants affecting the customer's decision to purchase beef (Issanchou, 1996). Packaging plays a vital role in increasing the shelf life of beef products and impedes the deterioration of food quality and insures the safety of meat (Zakrys et al., 2009). Brody and Marsh (1997) and Kerry et al. (2006) have further defined the role of packaging as to prevent from microbial infection, hamper spoilage and provide opportunity for activities by enzymes to boost tenderness, curtail loss of weight and if relevant to maintain the cherry red colour in beef products at retail shelves. Various packaging methods are followed by supermarkets, all of them have distinct characteristics and modes of application. Some of the major packaging systems followed are: overwrap packaging designed for chilled storage for shorter duration, Modified Atmosphere Packaging (MAP) intended for storing at chilled temperature or display at retail shelves for longer duration and Vacuum Skin Packaging (VSP), which is capable for storage at chilled temperature for a very long time (Kerry et al., 2006). As the packaging used has a great influence on colour of beef products, the packaging method used also have a great impact on consumer's approach towards beef products (Grobbel et al., 2008). A close association has been documented among the preference of colour and making a decision to purchase beef product (Carpenter, Cornforth and Whittier, 2001). Packaging of beef products also plays a crucial role in terms of marketing such as a mode of differentiation among products, value adding and a bearer of brands, labels, origin, etc. (Bernués, Olaisola and Corcoran, 2003). Visual cues like packaging and packaging associated traits considerably affect the decision of customers for purchasing beef products (Grobbel et al., 2008; Verbeke et al., 2005).

6.2.4 *Colour* – It is considered as one of the important determinants of quality of beef products (Issanchou, 1996). Colour of the meat gives an intrinsic cue to the customers regarding the freshness of beef products (McIlveen and Buchanan, 2001). Customers attempt to judge the tenderness, taste, juiciness, nutrition, and freshness from the colour of the beef products prior to purchase (Grunert, 1997). Most of the customers prefer the fresh red cherry like colour in their beef products (Brody and Marsh, 1997; Kerry et al., 2006). Customers are very reluctant to buy beef products if the fresh red colour is missing despite the fact its shelf life has not expired. Modified Atmosphere Packaging (MAP) is very popular among them where they could see the colour of beef products to make a decision to buy or not to buy beef products. The discoloration of meat hampers the shelf life post preparation at retail, which is an important financial concern in beef industry (Jeyamkondan and Holley, 2000). Dark cutting beef products have always been rejected by customers and have caused significant loss to the beef industry (Viljoen et al., 2002). Usually, the colour of beef products has significant impact on consumer's perception.

6.2.5 *Carbon footprint* – Beef products contain one of the highest carbon footprints among the agro products (Singh et al., 2015). Therefore, sustainable consumption is considered to be of vital significance (Nash, 2009). The cost of food product rises in order to reduce their carbon footprint. Price is considered as the major obstacle for the purchase of sustainable product by consumers (Grunert, 2011; Röös and Tjärnemo, 2011). Sustainable consumption can be encouraged by involvement of consumers, recognizing the impact of sustainable products and by increasing the peer pressure in society (Veremeir and Verbeke, 2006). Consumers are increasingly demonstrating their awareness towards sustainable consumption by doing eco-friendly shopping especially food products including beef (Grebitus et al., 2013; Onozaka et al., 2010). It was observed that if low carbon footprint alternative exists for products with higher carbon footprint at similar or lesser prices then consumers would be prioritising the lower carbon footprint option (Lanz et al., 2014; Vlaeminck et al., 2014). The carbon footprint associated with beef product will be an important driver for the consumer to purchase beef products.

6.2.6 *Organic/Inorganic* – Consumers buy organic food because of various reasons like nutrition value, eco-friendly nature of organic products, welfare of animals, safety of food products etc. (Hughner et al., 2007). The organic beef is assumed to be derived from livestock raised by free-range procedures (Mesías et al., 2010). It was found that consumers were happy to pay extra for organic beef if sufficient information about organic farming is provided (Napolitano et al., 2010). The literature suggests distinct behaviour of consumers towards organic food products based on social demographics (Padilla et al., 2013; Squires et al., 2001). Consumers are persuaded by social identification while purchasing organic food products (Bartels and Reinders, 2010).

6.2.7 *Price* – Price plays a crucial role in assessment of products by consumers (Marian et al., 2014). Price could be perceived as an amount of money spent by consumers for a particular transaction (Linchtenstein and Netemeyer, 1993). It is usually considered as a determinant of quality i.e. high price products are often associated with better quality (Erickson and Johansson, 1985; Völckner and Hofmann, 2007). Price could also be a barrier for low income consumers to buy high quality or organic food products (Marian et al., 2014). Price of beef product is affected by the packaging system used as well. Kukowski, Maddock and Wulf (2004) observed that consumers gave similar ratings to beef products in terms of prices based on their overall liking of the beef products. Price is a crucial factor affecting the customer’s decision to purchase beef products.

6.2.8 *Traceability* – Traceability labels are considered to be the most potent means for developing trust among consumers regarding quality and food safety (Becker, 2000). Consumers are laying more emphasis on food traceability because of the rising concern associated with food safety (Zhang and Wahl, 2012). Especially after horsemeat scandal, customers are more conscious of traceability of food products. Consumers gave equal importance to traceability as quality certificate (Ubilava and Foster, 2009). It was revealed that people were ready to pay considerable amount of premium for traceable beef products as compared to conventional beef products (Lee et al., 2011). Apart from assisting customers in speculating the quality of beef products, traceability labels impact the complete attitude of consumers towards purchasing of food products, preparation of dishes, contentment and forthcoming buying decision (Brunsø et al., 2002; Grunert, 2005).

6.2.9 *Nutrition* – Consumers have mixed perception about the nutrition value of beef products (Van Wezemael et al., 2010). Some customers have concerns about the amount of fat in beef products and its consequences on their cholesterol levels (Van Wezemael et al., 2014). However, the beef is a very rich source of good quality protein, minerals like zinc and iron, Vitamin-D, B12, B3, Selenium and essential Omega-3 fatty acid, all of which are essential components for healthy human body (McAfee et al., 2010). Nutrition labelling has a good influence over consumer decision of buying food products (da Foneseca and Salay, 2008; Nagya, 2008; Rimal, 2005). Some consumers who are conscious about their health also refer to the nutritional labelling. Food and health are interrelated to each other and they have a direct impact on body functions and disease risk reduction. Both nutrition and health claims are based on nutrition labelling and usually consumers process this information during decision making process (Lähteenmäki, 2012; Lawson, 2012). During the study, it was found that health claims outperform nutrition claims (Barreiro-Hurlé et al., 2009).

6.2.10 *Promotion* – Promotion is a valuable tool for marketing to make an impact on consumer’s purchase behaviour (Kotler and Armstrong, 2006). Food promotion could be defined as sales and marketing promotions utilised on food packaging for the purpose of alluring consumers to buy food products at the retailer’s point of sale (Hawkes, 2004). It may comprise of prime deals like discounts, contests and advocacy by celebrities (Hawkes, 2004). Basically, marketing promotion has a precise function of developing awareness of a brand, benign perception towards a brand and encourage desire to purchase (Belch and Belch, 1998; Rossiter and Percy, 1998). As beef products are usually expensive in nature, promotions and deals play a crucial role in prompting consumers to purchase beef products in larger quantities.

6.2.11 *Advertisement* – Advertising is an effective tool for retailers to promote their products and develop into persuasive brand (De Chernatony and McDonald, 2003). There are some barriers in promoting beef products via advertising. They are increased expenses, unreliability of advertisements and intangibility of content of advertisement messages (Dickson and Sawyer, 1990; Quelch, 1983). Advertisement via different channels such as newspaper, radio, television influences consumer's buying behaviour. Sometimes, retailers attempt to launch their new products at farm festivals, food shows etc. (Mason and Nassivera, 2013). Retailers launch their new products like organic beef products, high nutrition low fat products via these channels. During the study, it was found that festivals help food industry to raise awareness about quality and satisfaction of food products and consequently help them to gain broader market share.

To investigate the association among the above identified variables, consumer perception from social media data along with experts' opinions have been combined and analysed using ISM and fuzzy MICMAC, which is explained in detail in following section.

6.3 **Methodology**

Initially, consumers' opinion is extracted from social media (Twitter), which is rich in nature and provides unbiased opinion unlike consumer interviews, surveys, etc. Social media data is true representation of consumers' attitude, sentiments, opinions and thoughts. Cluster analysis is performed on the data collected from Twitter to find out the relation among above identified eleven variables. Thereafter, ISM and fuzzy MICMAC have been implemented to develop a theoretical framework. In the next subsection, firstly, the social media and cluster analysis are explained. Thereafter, ISM and fuzzy MICMAC are implemented to develop frameworks with the factors interlinked to each other at the various levels.

6.3.1 **Social media data and cluster analysis**

In order to capture, real time observation of consumers' reactions, attitudes, thoughts, opinions and sentiments towards the purchase of beef products, social media data from Twitter has been utilised. Using NCapture tool of NVivo 10 software, tweets were extracted using keywords shown in Table 6.2. In total, 1,338,638 tweets were extracted from Twitter. These tweets were filtered so that only English tweets will be captured. Then, they were further refined so that tweets corresponding to only our domain of study i.e. 'factors influencing purchasing behaviour or disappointment of beef products of consumers' are selected. After refining, 26,269 tweets were left for analysis, which are associated with the domain of this study. These tweets were then carefully investigated by the experts in the area of marketing management, supply chain management, meat science and couple of them as the big data professionals. Content analysis has been performed. In the initial stage, conceptual analysis is employed to determine the frequency corresponding to each factor. Thereafter, the collected tweets have been classified into eleven clusters as mentioned above. The association among these clusters is examined using total linkage clustering method. Pearson correlation coefficient is used to evaluate the relationship between variables. The distance between the clusters is calculated based on frequency and likeness of occurrence. The results of the analysis are depicted in Table 6.3. The pairs of variables having score 0.9 or above are considered to be interrelated. The remaining pairs of variables or clusters are not related to each other. The results of Pearson correlation coefficient test suggested that consumers are looking for good quality beef products at reasonable price while purchasing meat. They put great emphasis on taste and nutritional value associated with it as they are the significant drivers for the purchase of beef products. The traceability of beef products is also sought by consumers because of the food safety concern along with the carbon footprint generating in producing them considering the rising environmental concern. Finally, the packaging of the beef products and the organic/inorganic label have a significant influence on consumers' preference while purchasing beef products.

The outcome of cluster analysis is transferred to ISM to identify the driver, dependent, independent, linkage variables and interrelationship between them. The detailed description of ISM is illustrated in the following subsections.

Table 6.2. Keywords used for extracting consumer tweets

Beef#disappointment	Beef#Rotten	Beef# rancid	Beef#was very chewy
Beef#taste awful	Beef#unhappy	Beef#packaging blown	Beef#was very fatty
Beef#Odd colour beef	Beef#discoloured	Beef#Plastic in beef	Beef#Gristle in beef
Beef#complaint	Beef#Beefgrey colour	Beef#Oxidised beef	Beef#Taste
Beef#complaint	Beef#Beefgrey colour	Beef#Oxidised beef	Beef#Taste
Beef#Flavour	Beef#Smell	Beef#Rotten	Beef#Funny colour
Beef#Horsemeat	Beef#Customer support	Beef#Bone	Beef#Inedible
Beef#Mushy	Beef#Skimpy	Beef#Use by date	Beef#Stingy
Beef#Grey colour	Beef#Packaging	Beef#Oxidised	Beef#Odd colour
Beef#Gristle	Beef#Fatty	Beef#Green colour	Beef#Lack of meat
Beef#Rubbery	Beef#Suet	Beef#Receipt	Beef#Stop selling
Beef#Deal	Beef#Bargain	Beef#discoloured	Beef#Dish
Beef#Stink	Beef#Bin	Beef#Goes off	Beef#Rubbish
Beef#Delivery	Beef#Scrummy	Beef#Advertisement	Beef#Promotion
Beef#Traceability	Beef#Carbon footprint	Beef#Nutrition	Beef#Labelling
Beef#Price	Beef#Organic/ Inorganic	Beef#MAP packaging	Beef#Tenderness

Table 6.3. Pearson Correlation Test of the Cluster Analysis (Partial Results)

S. No.	Variable I	Variable II	P.C.C. Score
1	Quality	Taste	0.99
2	Promotion	Advertisement	0.98
3	Quality	Nutrition	0.92
4	Price	Nutrition	0.95
5	Colour	Packaging	0.95
6	Organic/ Inorganic	Quality	0.95
7	Organic/inorganic	Carbon Footprint	0.92
8	Price	Quality	0.94
9	Organic/ Inorganic	Taste	0.94
10	Packaging	Quality	0.94
11	Quality	Carbon footprint	0.95
12	Packaging	Price	0.93
13	Price	Traceability	0.96
14	Price	Promotion	0.93
15	Price	Colour	0.93
16	Price	Carbon footprint	0.93
17	Packaging	Taste	0.93
18	Price	Taste	0.92
19	Quality	Traceability	0.92
20	Price	Organic/inorganic	0.94

[Legend: P.C.C: Pearson Correlation Coefficient S. No.: Serial Number]

6.3.2 Interpretive Structural Modelling (ISM) methodology

ISM is a methodology for identifying and summarising relationships among specific items, which define an issue or a problem (Mandal and Deshmukh, 1994). The method is interpretive in a sense that group's judgement decides whether and how the variables are related. It is primarily intended as a group learning process. It is structural in a sense that an overall structure is extracted from the complex set of variables based on their relationships. It is a modelling technique to depict the specific relationships and overall structure in the digraph model (Agarwal et al., 2007). The ISM methodology helps to enforce order and direction on the complexity of the relationships among the variables of a system (Haleem et al. 2012; Purohit et al., 2016; Sage, 1977). For problems, such as understanding the factors considered by the customers while purchasing beef, several of them may be impacting each other at different levels. However, the direct and indirect relationships between the factors describe the situation far more precisely than the individual factors considered in isolation. ISM develops insights into the collective understanding of these relationships.

For example, Hughes et al., (2016) have employed ISM to identify the root causes of failure of information systems project and interrelationship between them. Gopal and Thakkar, (2016) have used ISM and MICMAC analysis to investigate the critical success factors (and their contextual relationships) responsible for sustainable practices in supply chains of Indian automobile industry. Kumar et al., (2016) have utilised ISM to identify barriers for implementation of green lean six sigma product development process. Haleem et al., (2012) have applied ISM techniques to develop a hierarchical framework for examining the relationship among critical success factors behind the successful implementation of world leading practices in manufacturing industries. Mathiyazhagan et al., (2013) have used ISM to identify the barriers in implementing green supply chain management in Indian SMEs manufacturing auto components. Mani et al., (2015a) have employed ISM to explore different enablers and the interactions among them in incorporating social sustainability practices in their supply chain. Mani et al., (2015b) have developed ISM model to investigate the barriers (and their contextual relationships) to adoption of social sustainability measures in Indian manufacturing industries. Dubey and Ali, (2014) have applied ISM, fuzzy MICMAC and Total Interpretive Structural Modelling

(TISM) to explore the major factors responsible for flexible manufacturing systems. Sindhu et al., (2016) have used ISM and fuzzy MICMAC to identify and analyse the barriers to solar power installation in rural sector in India. Singh et al., (2007) used ISM for improving competitiveness of small and medium enterprises (SMEs). Agarwal et al., (2007) used ISM to understand the interrelationships of the variables influencing the supply chain management. Similarly, Pfohl et al., (2011) used ISM to perform the structural analysis of potential supply chain risks. Talib et al., (2011) used the ISM to analyse the interaction among the barriers to total quality management implementation. The application of ISM typically forces managers to reassess perceived priorities and improves their understanding of the linkages among key concerns (Singh et al., 2007).

ISM starts with identifying variables, which are pertinent to the problem and then extends with a group problem-solving technique. A contextually significant subordinate relation is chosen. Having decided on the element set and the contextual relation, a structural self-interaction matrix (SSIM) is developed based on pair-wise comparison of variables. In the next step, the SSIM is converted into a reachability matrix and its transitivity is checked. Once transitivity embedding is complete, a matrix model is obtained. Then, the partitioning of the elements, development of the canonical form of the reachability matrix, driving power and dependence diagram and an extraction of the structural model, called ISM is derived (Agarwal et al., 2007). The execution process of ISM is shown in Figure 6.1.

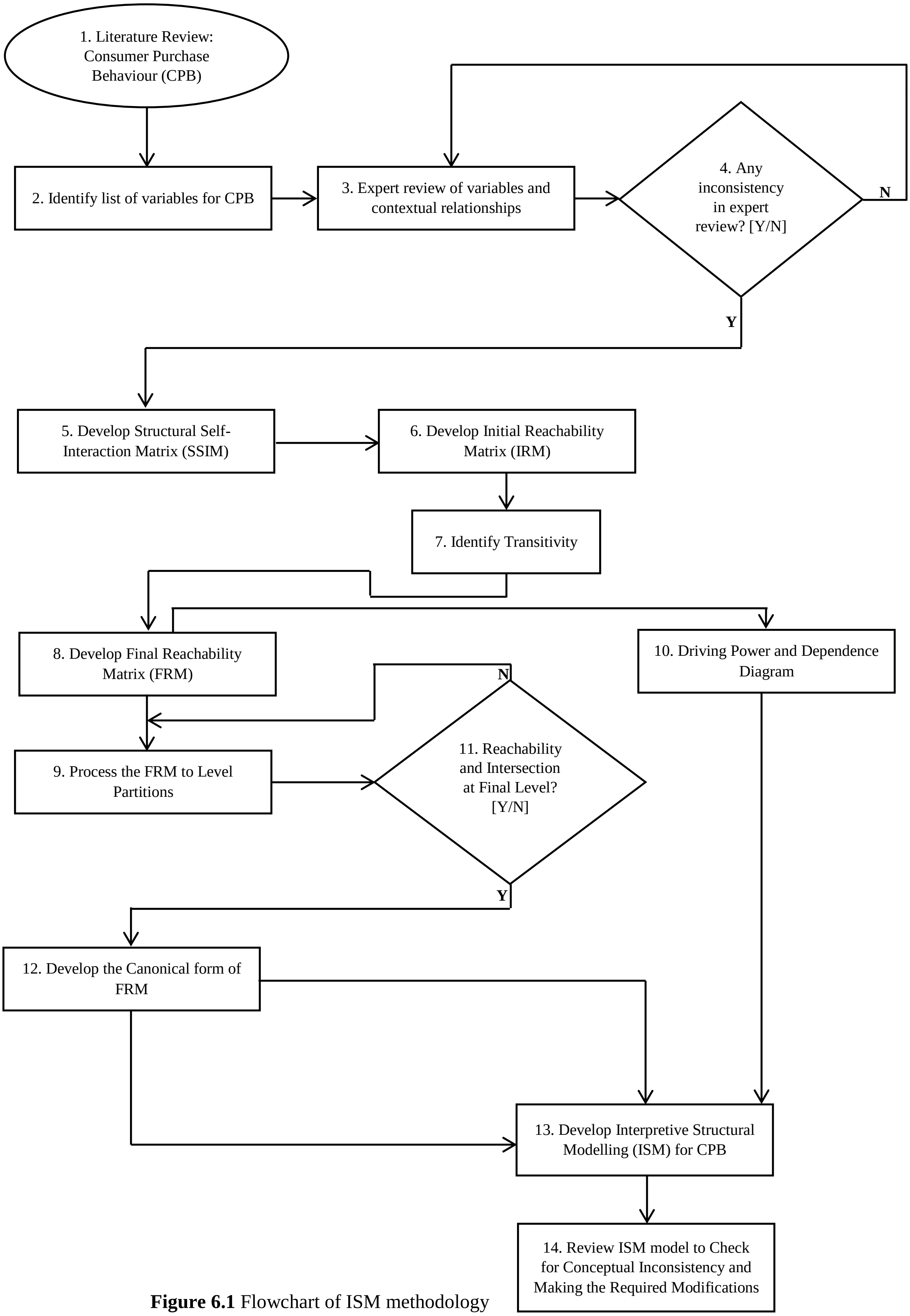

Figure 6.1 Flowchart of ISM methodology

In this research, ISM has been applied to develop a framework for the factors considered by the consumers while purchasing beef to achieve the following broad objectives: (a) to derive interrelationships among the variables that affect each other while consumers make decisions to purchase beef, and (b) to classify the variables according to their driving and dependence power using a 2x2 matrix, which represents the relationship between different factors that decide the consumers' intention to purchase beef.

6.3.2.1. Interpretive logic matrix

Although, the Pearson correlation coefficient test has revealed the association between factors, it is not clear what kind of association or relationship they have among themselves. In order to identify the relationship, the experts' opinion has been collected. Experts having considerable experience and operating at crucial stages in food supply chain were approached. The results obtained from big data analysis have been circulated to the experts and session was organised to establish the relationships between each pair of variable. The brainstorming session was conducted for several hours and then final consensus was reached on the SSIM matrix as shown in Table 6.4. To express the relationships between different factors (i.e. Price, quality, packaging, taste, organic/inorganic, promotion, advertisement, carbon footprint, traceability, colour and nutrition) that decide the consumers' intention to purchase beef, four symbols were used to denote the direction of relationship between the parameters i and j (here $i < j$):

V – Construct i helps achieve or influences j,

A - Construct j helps achieve or influences i,

X – Constructs i and j help achieve or influence each other, and

O – Constructs i and j are unrelated

The following statements explain the use of symbols V, A, X, O in SSIM:

[1] Quality (Variable 1) helps achieve or influences quality (Variable 4) (V)

[2] Packaging (Variable 3) helps achieve or influences quality (Variable 1) (A)

[3] Promotion (Variable 5) and advertisement (Variable 7) help achieve or influence each other (X)

[4] Advertisement (Variable 7) and traceability (Variable 10) are unrelated (O)

Based on contextual relationships, the SSIM is developed as shown in Table 6.4.

Table 6.4. Structural Self-Interactional Matrix (SSIM)

V[i/j]	11	10	9	8	7	6	5	4	3	2	1
1	X	A	X	O	O	A	O	V	A	X	
2	O	O	O	O	O	A	O	V	A		
3	O	O	O	V	O	O	O	V			
4	A	A	A	A	O	A	A				
5	O	O	O	O	X	O					
6	X	O	O	O	O						
7	O	O	O	O							
8	O	O	O								
9	O	O									
10	O										
11											

[Legend: [1] Quality, [2] Taste, [3] Packaging, [4] Price, [5] Promotion, [6] Organic/Inorganic, [7] Advertisement, [8] Colour, [9] Nutrition, [10] Traceability and [11] Carbon Footprint, V[i/j] = Variable i/Variable j]

6.3.2.2 Reachability matrix

The SSIM has been converted into a binary matrix, called the initial reachability matrix, by substituting V, A, X, and O with 1 and 0 as per the case. The substitution of 1s and 0s are as per the following rules:

[1] If the (i, j) entry in the SSIM is V, the (i, j) entry in the reachability matrix becomes 1 and the (j, i) entry becomes 0.

[2] If the (i, j) entry in the SSIM is A, the (i, j) entry in the reachability matrix becomes 0 and the (j, i) entry becomes 1.

[3] If the (i, j) entry in the SSIM is X, the (i, j) entry in the reachability matrix becomes 1 and the (j, i) entry becomes 1.

[4] If the (i, j) entry in the SSIM is O, the (i, j) entry in the reachability matrix becomes 0 and the (j, i) entry becomes 0.

Following these rules, the initial reachability matrix for the trustworthiness factors influencing the beef purchasing decision is shown in Table 6.5.

Table 6.5 Initial Reachability Matrix

V[i/j]	1	2	3	4	5	6	7	8	9	10	11
1	1	1	0	1	0	0	0	0	1	0	1
2	1	1	0	1	0	0	0	0	0	0	0
3	1	1	1	1	0	0	0	1	0	0	0
4	0	0	0	1	0	0	0	0	0	0	0
5	0	0	0	1	1	0	1	0	0	0	0
6	1	1	0	1	0	1	0	0	0	0	1
7	0	0	0	0	1	0	1	0	0	0	0
8	0	0	0	1	0	0	0	1	0	0	0
9	1	0	0	1	0	0	0	0	1	0	0
10	1	0	0	1	0	0	0	0	0	1	0
11	1	0	0	1	0	1	0	0	0	0	1

[Legend: [1] Quality, [2] Taste, [3] Packaging, [4] Price, [5] Promotion, [6] Organic/Inorganic, [7] Advertisement, [8] Colour, [9] Nutrition, [10] Traceability and [11] Carbon Footprint, V[i/j] = Variable i/Variable j]

We used ‘transitivity principle’ to develop the final reachability matrix (Dubey and Ali, 2014; Dubey et al., 2015a, 2015b; Dubey et al., 2016). This principle can be clarified by the use of following example: if ‘a’ leads to ‘b’ and ‘b’ leads to ‘c’, the transitivity property implies that ‘a’ leads to ‘c’. This property assists to eliminate the gaps among the variables if any (Dubey et al., 2016). By following the above criteria, the final reachability matrix is created and is shown in Table 6.6, where the driving and dependence power of each variable is also shown. The driving power for each variable is the total number of variables (including itself), which it may help to achieve. On the other hand, dependence power is the total number of variables (including itself), which may help in achieving it. As per Dubey and Ali (2014), driving power is calculated by adding up the entries for the possibilities of interactions in the rows whereas the dependence is determined by adding up such entries for the possibilities of interactions across the columns. These driving power and dependence power will be used later in the classification of variables into the four groups including autonomous, dependent, linkage and drivers (Agarwal et al., 2007; Singh et al., 2007).

Table 6.6 Final Reachability Matrix

V[i/j]	1	2	3	4	5	6	7	8	9	10	11	DRP
1	1	1	0	1	0	1*	0	0	1	0	1	6
2	1	1	0	1	0	0	0	0	1*	0	1*	5
3	1	1	1	1	0	0	0	1	1*	0	1*	7
4	0	0	0	1	0	0	0	0	0	0	0	1
5	0	0	0	1	1	0	1	0	0	0	0	3
6	1	1	0	1	0	1	0	0	1*	0	1	6
7	0	0	0	1*	1	0	1	0	0	0	0	3
8	0	0	0	1	0	0	0	1	0	0	0	2
9	1	1*	0	1	0	0	0	0	1	0	1*	5
10	1	1*	0	1	0	0	0	0	1*	1	1*	6
11	1	1*	0	1	0	1	0	0	1*	0	1	6
DNP	7	7	1	11	2	3	2	2	7	1	7	50

[Legend: 1*: shows transitivity, DNP: Dependence Power, DRP: Driving Power, V: Variable]

6.3.2.3 Level partitions

The matrix is partitioned by assessing the reachability and antecedent sets for each variable (Warfield, 1974). The final reachability matrix leads to the reachability and antecedent set for each factor relating to consumer's purchase of beef. The reachability set $R(s_i)$ of the variable s_i is the set of variables defined in the columns that contained 1 in row s_i. Similarly, the antecedent set $A(s_i)$ of the variable s_i is the set of variables defined in the rows, which contain 1 in the column s_i. Then, the interaction of these sets is derived for all the variables. The variables for which the reachability and intersection sets are same are the top-level variables of the ISM hierarchy. The top-level variables of the hierarchy would not help to achieve any other variable above their own level in the hierarchy. Once the top-level variables are identified, it is separated out from the rest of the variables. Then, the same process is repeated to find out the next level of variables and so on. These identified levels help in building the digraph and the final ISM model (Agarwal et al., 2007; Singh et al., 2007). In the present context, the variables along with their reachability set, antecedent set, and the top level is shown in Table 6.7. The process is completed in 3 iterations (in Tables 6.7-6.10) as follows:

In Table 6.7, only one variable price (Variable 4) is found at level I as the element (i.e., Element 4 for Variable 4) for this variable at reachability and intersection set are same. So, it is the only variable that will be positioned at the top of the hierarchy of the ISM model.

Table 6.7 Partition on Reachability Matrix: Interaction I

Element P(i)	Reachability Set: R(Pi)	Antecedent Set: A(Pi)	Intersection Set: R(Pi)∩A(Pi)	Level
1	1,2,4,6,9,11	1,2,3,6,9,10,11	1,2,6,9,11	
2	1,2,4,9,11	1,2,3,6,9,10,11	1,2,9,11	
3	1,2,3,4,8,9,11	3	3	
4	4	1,2,3,4,5,6,7,8,9,10,11	4	I
5	4,5,7	5,7	5,7	
6	1,2,4,6,9,11	1,6,11	1,6,11	
7	4,5,7	5,7	5,7	
8	4,8	3,8	8	
9	1,2,4,9,11	1,2,3,6,9,10,11	1,2,9,11	
10	1,2,4,9,10,11	10	10	
11	1,2,4,6,9,11	1,2,3,6,9,10,11	1,2,6,9,11	

In Table 6.8, maximum seven variables including 1 (i.e., quality), 2 (i.e., taste), 5 (i.e., promotion), 7 (i.e., advertisement), 8 (i.e., colour), 9 (i.e., nutrition) and 11 (i.e., carbon footprint) are put at level II as the elements (i.e., elements 1, 2, 6, 9 and 11 for variable 1; elements 1, 2, 9 and 11 for Variable 2; elements 5 and 7 for each of the variables 5 and 7; Element 8 for Variable 8; elements 1, 2, 9 and 11 for Variable 9; and elements 1, 2, 6, 9 and 11 for Variable 11) for these variables at reachability and intersection set are same. Thus, they will be positioned at level II in the ISM model. Moreover, we also remove the rows corresponding to Variable 4 from Table 6.8, which are already positioned at the top level (i.e., Level I).

Table 6.8 Partition on Reachability Matrix: Interaction II

Element P(i)	Reachability Set: R(Pi)	Antecedent Set: A(Pi)	Intersection Set: R(Pi)∩A(Pi)	Level
1	1,2,6,9,11	1,2,3,6,9,10,11	1,2,6,9,11	II
2	1,2,9,11	1,2,3,6,9,10,11	1,2,9,11	II
3	1,2,3,8,9,11	3	3	
5	5,7	5,7	5,7	II
6	1,2,6,9,11	1,6,11	1,6,11	
7	5,7	5,7	5,7	II
8	8	3,8	8	II
9	1,2,9,11	1,2,3,6,9,10,11	1,2,9,11	II
10	1,2,9,10,11	10	10	
11	1,2,6,9,11	1,2,3,6,9,10,11	1,2,6,9,11	II

The same process of deleting the rows corresponding to the previous level and marking the next level position to the new table is repeated until we reach to the final variable in the table. In Table 6.9, Variable 3 (i.e., packaging), Variable 6 (i.e., organic/inorganic) and Variable 10 (i.e., traceability) are kept at Level III as the elements (i.e., Element 3 for Variable 3; Element 6 for Variable 6; and Element 10 for Variable 10) at reachability set and intersection set for all these variables are same. Thus, it will be positioned at Level III in the ISM model.

Table 6.9 Partition on Reachability Matrix: Interaction III

Element P(i)	Reachability Set: R(Pi)	Antecedent Set: A(Pi)	Intersection Set: R(Pi)∩A(Pi)	Level
3	3	3	3	III
6	6	6	6	III
10	10	10	10	III

6.3.2.4 Developing canonical matrix

A canonical matrix is developed by clustering variables in the same level, across the rows and columns of the final reachability matrix as shown in Table 6.10. This matrix is just the other more convenient form of the final reachability matrix (i.e., Table 6.6) as far as drawing the ISM model is concerned.

Table 6.10. Canonical Form of Final Reachability Matrix

V[i/j]	4	1	2	5	7	8	9	11	3	6	10	LVL
4	1	0	0	0	0	0	0	0	0	0	0	I
1	1	1	1	0	0	0	1	1	0	1	0	II
2	1	1	1	0	0	0	1	1	0	0	0	II
5	1	0	0	1	1	0	0	0	0	0	0	II
7	1	0	0	1	1	0	0	0	0	0	0	II
8	1	0	0	0	0	1	0	0	0	0	0	II
9	1	1	1	0	0	0	1	1	0	0	0	II
11	1	1	1	0	0	0	1	1	0	1	0	II
3	1	1	1	0	0	1	1	1	1	0	0	III
6	1	1	1	0	0	0	1	1	0	1	0	III
10	1	1	1	0	0	0	1	1	0	0	1	III
LVL	I	II	II	II	II	II	II	II	III	III	III	

[Legend: LVL: Level, V: Variable]

6.3.2.5 Classification of factors considered by the customers while purchasing beef

The factors considered by the consumers while purchasing beef are classified into four categories based on driving power and dependence power. They include autonomous, dependent, linkage, and drivers (Mandal and Deshmukh, 1994). The driving power and dependence power of each of these factors is shown in Table 6.6. The driver power – dependence power diagram is drawn as shown in Figure 6.2.

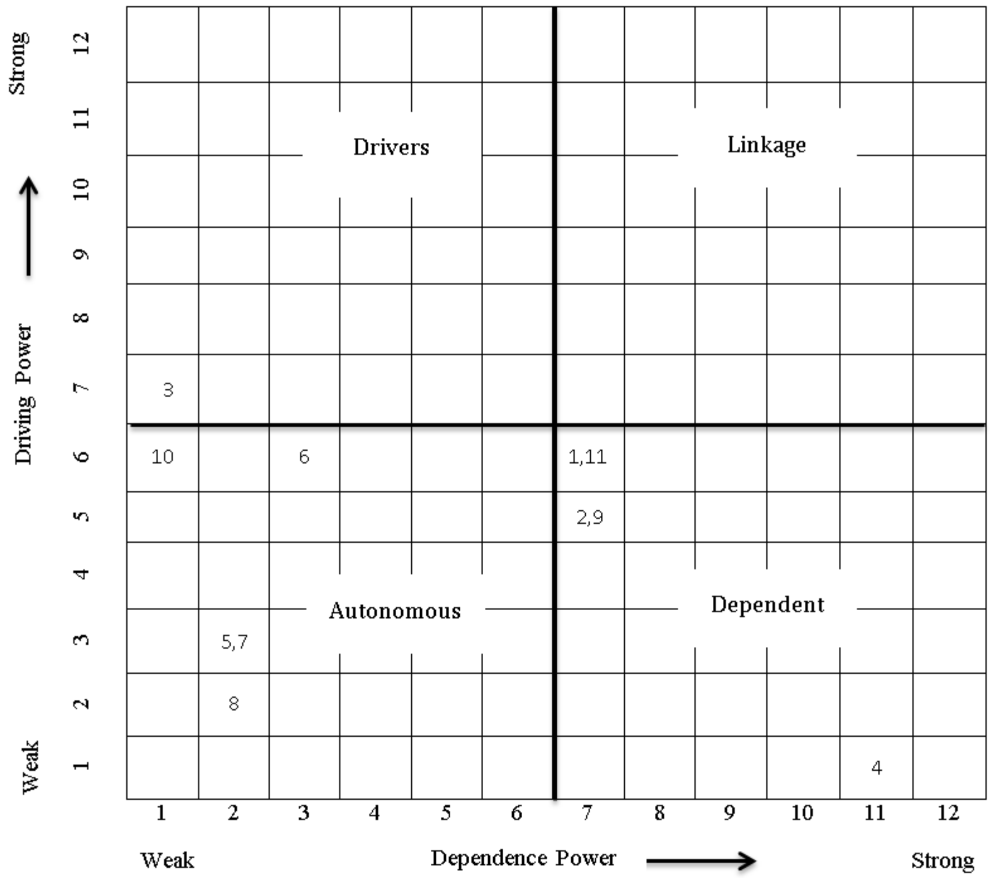

Figure 6.2 Driving Power and Dependence Diagram

This figure has four quadrants that represent autonomous, dependent, linkage and drivers. For example, a factor that has a driving power of 1 and dependence power of 11 is positioned at a place with dependence power of 11 in the X-axis and driving power of 1 on the Y-axis. Based on its position, it can be defined as a dependent variable. Similarly, a factor having a driving power of 7 and a dependence power of 1 can be positioned at dependence power of 1 at the X-axis and driving power of 7 on the Y-axis. Based on its position, it can be defined as a driving variable. The objective behind the classification of the factors considered by the consumers while purchasing beef is to analyse the driving power and dependency of the factors related to consumer's purchasing behaviour. The first cluster includes autonomous trustworthiness factors that have weak driver power and weak dependence. These factors are relatively disconnected from the system. In the context of the current research, factors such as promotion (i.e., Variable 5), organic/inorganic (i.e., Variable 6), advertisement (i.e., Variable 7), colour (i.e., Variable 8) and traceability (i.e., Variable 10) belong to this cluster.

The second cluster consists of the dependent variables that have weak driver power but strong dependence. Quality (i.e., Variable 1), taste (i.e., Variable 2), price (i.e., Variable 4), nutrition (Variable 9) and carbon footprint (i.e., Variable 11) belong to this cluster. The third cluster has the linkage variables that have strong driver power and dependence. Any action on these variables will have an effect on the others and also a feedback effect on themselves. No variable belongs to this category. The fourth cluster includes drivers or independent variables with strong driving power and weak dependence. Only variable that belongs to this cluster is packaging (i.e., Variable 3).

6.3.2.6 Formation of ISM

From the canonical form of the reachability matrix as shown in Table 6.10, the structural model is generated by means of vertices and nodes and lines of edges. If there is a relationship between the factors i and j considered by the consumers while purchasing beef, this is shown by an arrow that points from i to j. This graph is called directed graph or digraph. After removing the indirect links as suggested by the ISM methodology, the digraph is finally converted into ISM-based model as depicted in Figure 6.3.

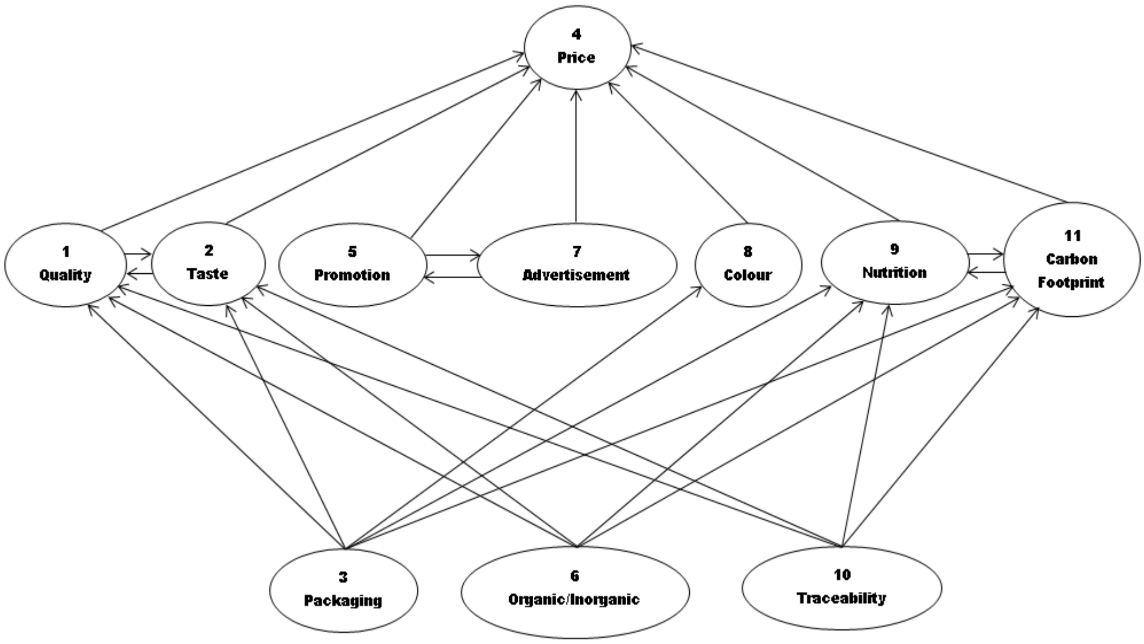

Figure 6.3 ISM Model

In the ISM methodology, binary digits (0 and 1) are considered. If there is a linkage then relationship is denoted by 1 and if there is no linkage then, 0 is used to denote the relationship. The strength of relationship between two factors is not being taken into account in this methodology. The relationship among two factors could be no relationship, very weak, weak, strong and very strong. The shortcoming of this methodology is overcome by using ISM fuzzy MICMAC analysis, which is described in the next section.

6.4. ISM fuzzy MICMAC analysis

In the ISM model, we have considered binary digits i.e. 0 or 1. If there is no linkage between the variables, then the relationship is denoted by 0 and if there is linkage then the relationship is denoted by 1. However, there is no scope for discussion in this matrix about the strength of relationship. The relationship between any two variables in the matrix could be defined as very weak, weak, strong and very strong or there is no relationship between them at all. To overcome the limitations of ISM modelling, a fuzzy ISM is used for MICMAC analysis (Gorane and Kant, 2013). The steps for ISM fuzzy MICMAC analysis are performed as follows:

6.4.1 Synthesis of Direct Relationship Matrix (DRM)

Making diagonal entries zero and ignoring transitivity in the final reachability matrix generate DRM (see Table 6.11). In the current context, it is essentially the calculation of direct relationship among the variables influencing consumers' beef purchasing behaviour.

Table 6.11 Binary direct relationship matrix

V[i/j]	1	2	3	4	5	6	7	8	9	10	11
1	0	1	0	1	0	0	0	0	1	0	1
2	1	0	0	1	0	0	0	0	0	0	0
3	1	1	0	1	0	0	0	1	0	0	0
4	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	1	0	0	1	0	0	0	0
6	1	1	0	1	0	0	0	0	0	0	1
7	0	0	0	0	1	0	0	0	0	0	0
8	0	0	0	1	0	0	0	0	0	0	0
9	1	0	0	1	0	0	0	0	0	0	0
10	1	0	0	1	0	0	0	0	0	0	0
11	1	0	0	1	0	1	0	0	0	0	0

[Legend: 1-Quality, 2-Taste, 3-Packaging, 4-Price, 5-Promotion, 6-Organic/Inorganic, 7-Advertisement, 8-Colour, 9-Nutrition, 10-Traceability, 11-Carbon Footprint]

6.4.2 Developing Fuzzy Direct Relationship Matrix (FDRM)

A fuzzy direct relationship matrix (FDRM) was constructed by putting a diagonal series of zero values into the correlation matrix (Table 6.13), and, by ignoring the transitivity rule of the initial RM. The traditional MICMAC analysis considers only a binary interaction and therefore to improve the sensitivity of traditional MICMAC analysis, fuzzy set theory has been used. The investigation is more enhanced as it considers the "possibility of reachability/achievement" in addition to the simple deliberation of reachability used thus far. According to the theory of fuzzy set, the possibilities of additional interactions between the variables on the scale 0-1 (Qureshi et al., 2008) are constructed (see Table 6.12).

Table 6.12. Consideration of various numerical values of the reachability

Possibility of reachability	No	Negligible	Low	Medium	High	Very High	Full
Value	0	0.1	0.3	0.5	0.7	0.9	1

By using values provided in above Table 6.12, again the judgments of same experts are considered to rate the relationship between two key variables influencing consumers' beef purchasing behavior. Fuzzy direct relationship matrix (FDRM) for key variables influencing consumers' beef purchasing behavior is presented in Table 6.13.

Table 6.13. FDRM for variables influencing consumers' beef purchasing behaviour

V[i/j]	1	2	3	4	5	6	7	8	9	10	11
1	0	0.9	0	0.7	0	0	0	0	0.7	0	0.5
2	0.9	0	0	0.5	0	0	0	0	0	0	0
3	0.5	0.3	0	0.5	0	0	0	0.7	0	0	0
4	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0.1	0	0	0.1	0	0	0	0
6	0.5	0.5	0	0.5	0	0	0	0	0	0	0.7
7	0	0	0	0	0.1	0	0	0	0	0	0
8	0	0	0	0.1	0	0	0	0	0	0	0
9	0.5	0	0	0.5	0	0	0	0	0	0	0
10	0.7	0	0	0.9	0	0	0	0	0	0	0
11	0.5	0	0	0.3	0	0.7	0	0	0	0	0

[Legend: 1-Quality, 2-Taste, 3-Packaging, 4-Price, 5-Promotion, 6-Organic/Inorganic, 7-Advertisement, 8-Colour, 9-Nutrition, 10-Traceability, 11-Carbon Footprint]

6.4.3. Developing fuzzy stabilised matrix

The concept of fuzzy multiplication is used on FDRM to obtain stabilization (Saxena and Vrat, 1992). This notion states that matrix is multiplied until the values of driving and dependence powers are stabilized (Qureshi et al., 2008). Driving and dependence power are obtained by adding row and column entries separately. The stabilized matrix for fuzzy MICMAC for variables influencing consumers' beef purchasing behaviour is obtained in Table 6.14.

Table 6.14. Stabilized matrix for variables influencing consumers' beef purchasing behaviour

V[i/j]	1	2	3	4	5	6	7	8	9	10	11	Driving Power
1	0.9	0.5	0	0.5	0	0.5	0	0	0.5	0	0.5	3.4
2	0.5	0.9	0	0.7	0	0.5	0	0	0.7	0	0.5	3.8
3	0.5	0.5	0	0.5	0	0.5	0	0	0.5	0	0.5	3.0
4	0	0	0	0	0	0	0	0	0	0	0	0.0
5	0	0	0	0	0.1	0	0	0	0	0	0	0.1
6	0.5	0.5	0	0.5	0	0.7	0	0	0.5	0	0.5	3.2
7	0	0	0	0.1	0	0	0.1	0	0	0	0	0.2
8	0	0	0	0	0	0	0	0	0	0	0	0.0
9	0.5	0.5	0	0.5	0	0.5	0	0	0.5	0	0.5	3.0
10	0.5	0.7	0	0.7	0	0.5	0	0	0.7	0	0.5	3.6
11	0.5	0.5	0	0.5	0	0.5	0	0	0.5	0	0.7	3.2
Dependence Power	3.9	4.1	0.0	4.0	0.1	3.7	0.1	0.0	3.9	0.0	3.7	**23.5**

6.4.4. Classification of categories of variables using MICMAC analysis

The classification of variables has been divided into four categories based on dependence and driving powers by using fuzzy MICMAC analysis. Figure 6.4 shows that there are four categories in which these 11 variables are assigned as per their new driving and dependence power. The first region belongs to autonomous variables, which have less driving and less dependence power. These variables lie nearby origin and remain disconnected to entire system. Three variables 5 (i.e. promotion), 7 (i.e. advertisement) and 8 (i.e. colour) fall under this cluster. The second region belongs to dependence variables, which have high dependence and low driving power. The only variable falls under this cluster is 4 (i.e. price), which indicates price as the ultimate dependent variable as it can be visualized from the previous MICMAC analysis as well. The third region belongs to linkage variables, which have high driving and high dependence power. In the modified MICMAC analysis, highest five variables including 1 (i.e. quality), 2 (i.e. taste), 6 (i.e. organic/inorganic), 9 (i.e. nutrition) and 11 (i.e. carbon footprint) fall in this category. The fourth and final category of variables belongs to independent variables, which have high driving and low dependence power. Two variables 3 (i.e. packaging) and 10 (i.e. traceability) fall under this region. These are the key driving variables and are generally found at the bottom of the ISM model.

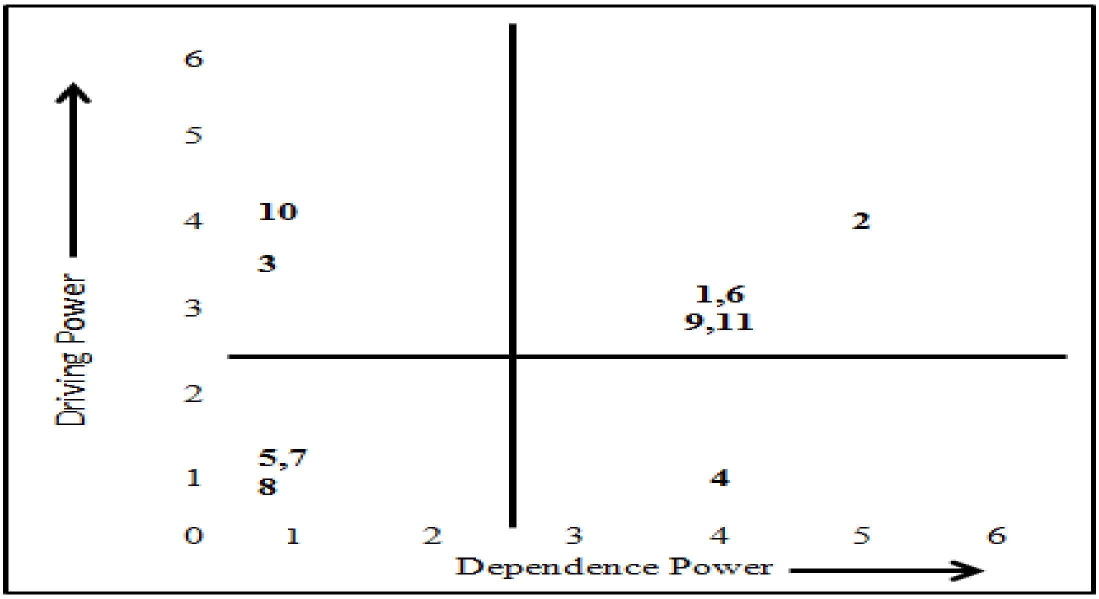

Figure 6.4 Cluster of variables

6.4.5. Integrated ISM model development

An integrated ISM model is developed using the driving and dependence powers obtained from fuzzy stabilized matrix. The value of dependence power is subtracted from driving power to obtain the effectiveness of each variable, which is shown in Table 6.15. The variables having low value of effectiveness are placed at the bottom levels in the model. The integrated model of variables influencing consumers' beef purchasing behaviour is drawn from the values of effectiveness as shown in Figure 6.5.

Table 6.15 Effectiveness and ranking of variables

V[i/j]	Driving Power (DR)	Dependence Power (DP)	Effectiveness (DR-DP)	Level
1	3.4	3.9	-0.5	III
2	3.8	4.1	-0.3	IV
3	3.0	0.0	3.0	VII
4	0.0	4.0	-4.0	I
5	0.1	0.1	0.0	V
6	3.2	3.7	-0.5	III
7	0.2	0.1	0.1	VI
8	0.0	0.0	0.0	V
9	3.0	3.9	-0.9	II
10	3.6	0.0	3.6	VIII
11	3.2	3.7	-0.5	III

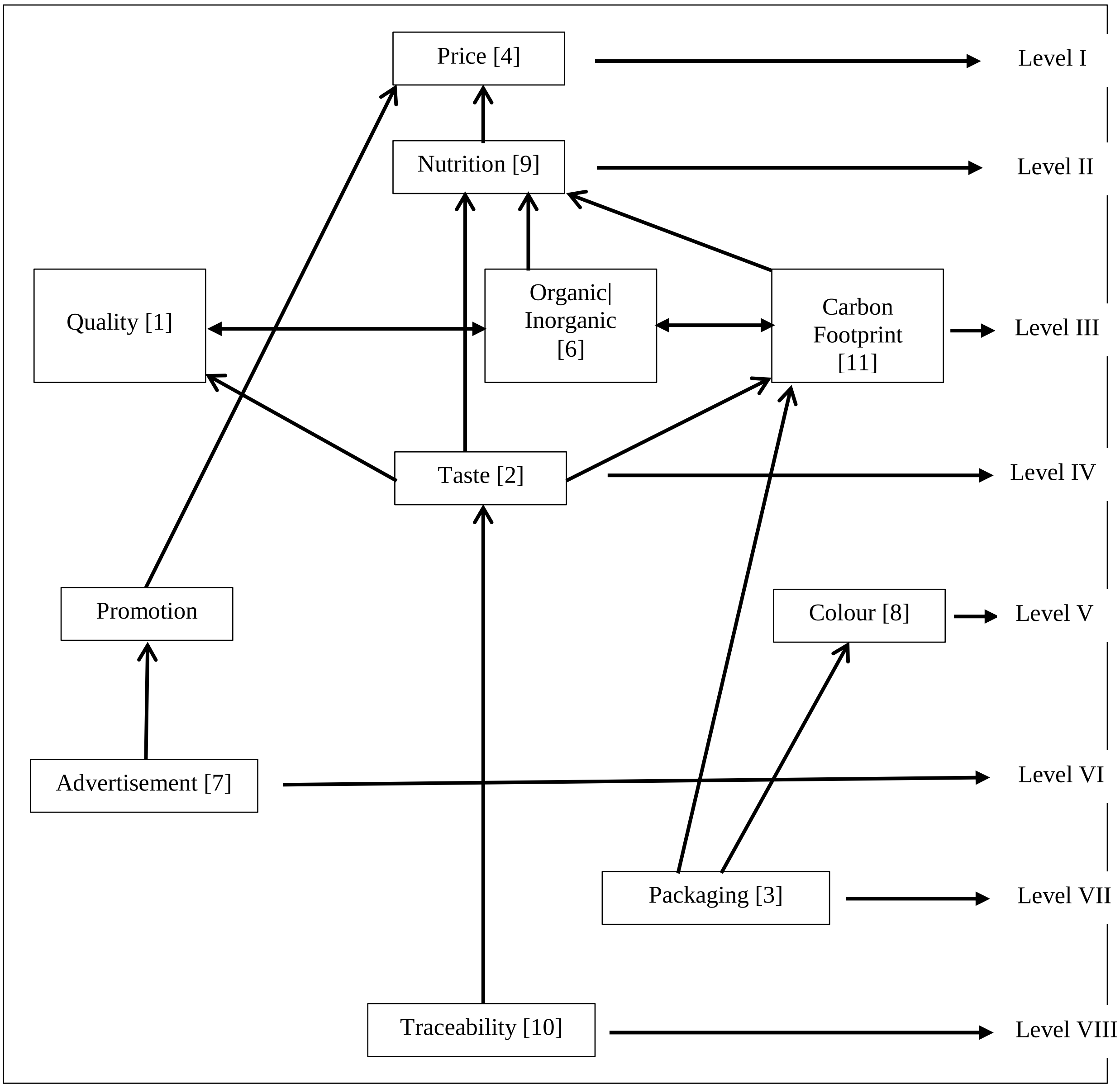

Figure 6.5 Integrated ISM Model

6.5 Discussion

During the investigation, it was found that consumer buying preferences while purchasing beef products are vastly dependent on their price. The variable 'price' has high dependence and low driving power. It is dependent on nutritional value and ongoing promotions. The beef derived from grass-fed cattle is higher in nutrition in terms of omega-3 fatty acid, conjugated linoleic acid (CLA) and have lower amounts of saturated and monounsaturated fats as compared to grain-fed cattle (Daley et al., 2010). The grass-fed cattle takes more time to reach finishing age (Profita, 2012) and are more expensive than grain-fed cattle (Gwin, 2009). The ongoing promotions in retail stores have a direct influence on the price of the beef products (Darke and Chung, 2005).

The variables like quality, taste, carbon footprint, organic/inorganic and nutrition have high dependence and high driving power in terms of influencing consumer's decision for purchasing beef products. Quality and organic/inorganic are interrelated variables as depicted in Figure 6.5. The organic/inorganic label in beef products reflects the sustainable practices used in the production of beef products and are associated with high quality, lower carbon footprint, higher nutrition, better taste and colour stability for longer duration of time (Fernandez and Woodward, 1999; Kahl et al., 2014; Nielsen and Thamsborg, 2005; Załęcka et al., 2014; Zanoli et al., 2013). Organic food is usually sold at a higher price than their conventional produced counterparts. However, still, some consumers are ready to pay extra because they are worried about the food safety, environment and use of pesticides, hormones and other veterinary drugs in beef farms. Organic food assists in solving the problems of animal welfare, rural development and numerous issue of food production (Capuano et al., 2013). Organic/inorganic and carbon footprint also have an interrelationship. The organic beef products associated with higher nutrition are derived from grass-fed cattle, which took more time to reach finishing age (Ruviaro et al., 2015). Hence, the beef products derived from grass-fed cattle have higher carbon footprint. Similarly, the beef products having higher carbon emissions are associated with beef products derived from grass-fed cattle (organic beef) as majority of the carbon emission is generated in terms of cattle taking longer time to reach finishing age (Capper, 2012). Nutrition of beef products is found to be dependent on taste, organic/inorganic and carbon footprint as depicted in Figure 6.6. Excellent flavour and organic beef are considered to be a determinant of the nutritional value of beef products (Yiridoe et al., 2005). Beef products having high carbon footprint (grass-fed) have better nutritional value (Profita, 2012).

The variables promotion, advertisement and colour have low driving and dependence power. Advertisement via television, radio, social media etc. has a direct impact on promotions in retail store. Colour of beef products is significantly influenced by the variant of packaging used. For instance, beef products in Modified Atmosphere Packaging (MAP) have shelf life of around eight to ten days where as Vacuum Skin Packaging (VSP) provides shelf life of up to 21 days (Meat Promotion Wales, 2012).

Traceability and packaging have the highest driving power and have very low dependence. The beef products produced with strict traceability procedures are often attributed with better taste, nutrition, and quality (Giraud and Amblard, 2003; Verbeke and Ward, 2006; van Rijswijk et al., 2008a; van Rijswijk and Frewer, 2008). During the study, it was found that traceability helps consumers to find different information related to animal breed, slaughtering, food safety and quality. Generally, retailers use traceability information to boost consumer confidence (van Rijswijk and Frewer, 2008). The variant of packaging employed in beef products affects the carbon footprint. Vacuum Skin Packaging (VSP) are lightweight, requires fewer corrugate for logistics, gives longer shelf life and thereby reduces retailer food loss and consumer food waste and requires less fuel in transport as compared to Modified Atmosphere packaging (MAP) (Mashov, 2009).

The bottom level variables viz. traceability and packaging have high driving power but no dependence on them. They strongly affect the middle level variables like promotion, advertisement, colour, quality, taste, carbon footprint, organic/inorganic and nutrition. The middle level variables in turn affect the price, which has the highest influence on the consumer's willingness to purchase beef products. Therefore, it can be concluded that two variables traceability and packaging influence the price of the beef products, which in turn has an impact on consumer's decision for purchasing beef products.

This study reveals two factors: traceability and packaging, which needs to be improved and maintained throughout the supply chain of beef retailers in order to allure consumers. For instance, many retailers utilise superior quality packaging for the beef products, however, it gets damaged within the supply chain, which could be due to mishandling at logistics, warehouse or in the retailer's store. Hence, a strong vertical coordination should be developed within the whole beef supply chain so that the quality of packaging is retained till the beef products are sold to consumers. The stronger vertical coordination among all stakeholders of beef supply chain viz. farmer, abattoir and processor, logistics and retailer will also assist in achieving the traceability of beef products, which is another crucial driving factor influencing consumer's buying preference.

Usually, retailers consider price of beef products as the most strategic tool for market capturing. Nowadays, consumers are very conscious about their health and nutrition. They are looking for food products having high nutrition and safe to consume. Specially, after horsemeat scandal, customers are prone towards traceability information i.e. information related to animal breed, slaughtering method, animal welfare, use of pesticides, hormones and other veterinary drugs in beef farms. During the ISM fuzzy MICMAC analysis, it was found that customers make a trade-off between price and quality, taste, food safety, nutrition, colour while purchasing the beef products. Using proper packaging, labelling information, retailers can boost customer confidence.

Further, the beef industry could utilise modern technology like cloud computing technology to bring all the stakeholders on one platform (Singh et al., 2015) and can manage the information flow effectively, which will result in high quality beef products at lower carbon footprint in minimum cost and can get maximum market share.

In modern era, food industries struggle to anticipate the quantity and quality of food products to meet the expectations of consumers, which leads to overproduction of food products and reducing market share of food companies. This scenario is a mutual loss to both food industries and consumers. In order to fulfil this gap, major food retailers have taken lots of attempts to receive consumer feedback via market survey, market research, interviews of consumers and providing the opportunity to consumers to leave feedback in retail stores and use this information for improving their supply chain strategy. Still, they cannot get the inputs from the larger audiences and sometimes the information gathered by these methods is biased and inaccurate. The current study utilises the social media data, which covers larger audience and consists of real time true opinion of consumers. The amalgamation of Twitter analytics and ISM has identified the most crucial factors (and their inter-relationships) needed to achieve consumer centric supply chain. It will assist business firms to have an edge over their rivals and enhance their market share. The analysis of the crucial factors and their interrelationships will assist business firms in prioritising their actions, appropriate decision making in terms of where to start making modification to achieve consumer centric supply chains. This study will help them to develop a short and long term strategy to develop an efficient, resilient, and sustainable supply chain.

This chapter provides novel directions for developing consumer centric beef supply chain. In the past, quality and price of beef products were the crucial factors driving the purchasing behaviour of consumers (Acebron and Dopico, 2000; Levin and Johnson, 1984;

Becker, 2000; Brunso et el., 2005; Epstein et al. 2012). Nonetheless, it was revealed during the study that traceability of beef products has emerged as an influential driving factor having significant impact on consumer’s decision making. Since the horsemeat scandal in Europe in 2013, the consumers are extremely cautious about the traceability of beef products (Clemens and Babcock, 2015; Henchion, McCarthy and Resconi, 2017; Menozzi et al., 2015; Barnett el al., 2016). Along with the traceability, packaging also emerged as one of the strongest driving factor affecting consumer’s beef purchasing behaviour (Grobbel et al., 2008; Verbeke et al., 2005). Apart from visual cues, it has a direct influence on shelf life of beef products (Grobbel et al., 2008). Experts within the beef industry also unequivocally reaffirm this finding. This chapter would assist industrial practitioners within beef industry to reconsider their priorities to develop a productive, robust and sustainable supply chain to gain a competitive advantage over their rivals in foreseeable future.

6.5.1 Managerial implications and theoretical contributions

The proposed framework is vital for both academia and industry in streamlining the supply chain and improving participation of all stakeholders. The revealing of interaction of various mandatory factors to achieve consumer centric supply chain would assist in improving vertical and horizontal collaboration within the supply chain. Consequently, an efficient strategy would be developed by taking the drivers into account for increasing market share of a business firm, having advantage over their rivals and developing a consumer centric supply chain. This mechanism will assist in appropriate partner selection within the supply chain to improve sustainability. It will assist the managers of small and medium size stakeholders in the supply chain, who lacks awareness about consumer priorities, such as farmers lack awareness of consumers seeking traceability in meat products.

The chapter has a two-fold contribution to the literature on the consumer interest in beef. Firstly, although many research studies (e.g., Reicks et al., 2011; Robbins et al., 2003; Thilmany et al., 2006) in the beef industry have focused on the motivational factors affecting consumers’ purchasing decisions while purchasing beef, none of them have offered an alternative approach to theory building emerging from the various quality characteristics and other factors that could be considered while purchasing beef. This research undertakes a comprehensive review of literature generating the most important eleven factors or clusters and devises a theoretical framework based on the interrelationships of those variables emerging from the consumers (social media data) and experts' opinion using ISM and fuzzy MICMAC analysis. Secondly, this research further extends the existing literature on consumers' decisions toward purchasing beef by offering a strategic framework, which is not only based on literature but also validated using the big data clustering technique that divide all such potential variables in the most important clusters that influence consumers' beef purchasing decisions. In the current research, the number of such clusters coincides to eleven factors. Therefore, the proposed theoretical framework extrapolates eleven factors at eight different layers and their interrelationships highlighting the specific roles of these variables.

6.6 Conclusion

Food is a significant commodity for enduring human life as compared to other essentials. In today's competitive market, consumers are very selective. To sustain in this competitive scenario, retailers have to investigate the purchasing behaviour of consumers and the factors influencing it. They must investigate how these factors are linked with each other and which of the factors belong to the category of driver, dependent, linkage and autonomous respectively. It will help the retailers in waste minimisation, streamlining their supply chain, improving its efficiency and making it more consumer centric.

In this study, initially, systematic literature review was conducted to identify the factors influencing the consumers' decision for buying beef products. Then, cluster analysis on consumers' information from Twitter in the form of big data was conducted. It assists in finding how the variables determining the consumers' beef products buying preference are influenced. Then, experts' opinion, ISM and fuzzy MICMAC analysis are used to classify eleven variables into: linkage, dependent, driver, independent variables and their interrelationships are explored. During the study, it was observed that price of the beef products is the most important criteria driving the purchasing decision of consumers. It is followed by nutrition, quality, organic/inorganic, carbon footprint, taste, promotion, colour and advertisement. Based on the findings, recommendations were given for making consumer centric supply chain.

CHAPTER 7

Conclusions and future research work

One third of the food products including beef are lost within the supply chain and majority of this waste is being generated at the consumer end. For instance, UK households discard 34,000 tonnes of beef products on an annual basis, which is worth £260 million approximately and is equivalent of 300 million beef burgers. The mitigation of waste in the beef supply chain would improve the financial return to all stakeholders of supply chain including farmers, who gets the least share in profit. Waste minimisation would also assist in addressing the global challenges of food security and climate change. Retailers of beef products are analysing the consumer complaints made in the retail store for waste minimisation. However, only few consumers participate in this activity, which inhibits the retailers to get the insights into the issues faced by them. Therefore, they employ additional means such as surveys, interviews, etc. Sometimes, consumers give biased feedback to these channels and often the response rate of these methods are quite low. Nonetheless, unhappy consumers post their complaints frequently on social media. During the study, it was found that 45000 tweets associated with beef products are made on daily basis. The information available on social media represents the true opinion of consumers, which could be utilised by retailers to explore the issues faced by consumers and identify their root causes within the supply chain. This information could be utilised to develop a waste minimisation strategy.

Beef is considered to be one of the most resource intensive food products. It generates the highest carbon footprint among all the agricultural products. Generally, the preference of beef industries is aligned to conventional attributes of beef products such as quality (colour, tenderness and flavor), price, animal welfare, traceability, etc. Consumers are getting more cautious about the carbon footprint of all the products consumed by them. Simultaneously, there is pressure from government legislation to curb the emissions of beef industry. The abattoir and processor are adopting various green technologies to mitigate their carbon footprint such as employing renewable sources of energy for their butchering and boning operations. However, 90% of greenhouse gas emissions are generated at beef farms. In order to cut down the carbon footprint in their supply chains, abattoir and processor have to incorporate the virtue of low carbon footprint while doing supplier selection of beef cattle. The majority of carbon footprint at beef farms is generated because of enteric fermentation and manure of cattle. Beef farmers find it expensive and challenging to select the optimum carbon calculator to measure the carbon footprint in their farms. The abattoir and processor could assist the farmers by raising the awareness and adopt an ecofriendly supplier selection process. Conventionally, the measurement of carbon footprint of beef industry is being done in a segregated way i.e. independently at segment level by beef farms, abattoir, processor and retailer. There was lack of an integrated holistic model for measuring the carbon footprint and provide feedback to optimize it.

Keeping the above-mentioned issues in mind, in this thesis, novel methodologies were developed to address the waste and carbon footprint of beef supply chain to improve its sustainability. All the stakeholders of beef supply chain viz. farmers, abattoir, processor, logistics and retailer would be assisted by these frameworks in identifying the hotspots of carbon footprint, root causes of waste in the supply chain and their consequent mitigation. Various quantitative and qualitative research techniques were employed to generate these methodologies such as current reality tree method, big data analytics, interpretive structural modelling, toposis and cloud computing technology. In these analyses, real data set from interviews of different segments of beef supply chain and from social media were used.

7.1 Contribution

In this thesis, various methodologies were developed to mitigate the waste and carbon footprint generated in the beef supply chain. The major contributions of this study are as following:

a. This research presents a thorough literature review on waste and carbon emissions generated during the product flow in the beef supply chain. Different issues, limitations and the frameworks developed for waste minimization in beef supply chain were discussed. The research work done in the domain of reducing carbon footprint of beef supply chain was examined.

b. During the research, it was revealed that 45000 tweets associated with beef products are made on daily basis on an average. These tweets are focused on quality attributes and issues related to rancidity, flavour, discoloration and presence of foreign bodies, etc. The retailer of beef products could use this valuable data to identify the root causes of waste underlying the supply chain and consequently develop waste minimization strategy. The consumer complaints on Twitter are unstructured in format and vague in nature. The literature is deficient of a framework to link these complaints to root causes of waste with various segments of beef supply chain (Singh et al., 2017; Mishra and Singh, 2016). In this thesis, a novel mechanism is proposed to capture and examine this Twitter data and back track it to the root causes of waste in the beef supply chain. The root causes of waste in beef supply chain could be addressed for waste minimization, boosting consumer satisfaction, enhancing brand value and thereby improving the financial revenue of retailer. Hence, this thesis makes a vital contribution to existing literature by linking the consumer complaints on Twitter in the downstream of beef supply chain to their respective root causes in the upstream of beef supply chain.

c. A thorough investigation of waste generated in Indian beef supply chain was performed to identify its root causes to address the imbalance between production and consumption. Various stakeholders of beef supply chain were interviewed, which was analyzed via Current Reality Tree method to explore the root causes and preventive measures to mitigate them. During the study, it was revealed that majority of waste in beef supply chain is attributed to natural characteristics such as short shelf life, fluctuations in demand and temperature sensitivity. There were numerous management root causes leading to significant amount of waste such as poor quality of meat, lack of vitamin E in diet of cattle, scarcity of information exchange, management of cold chain, lack of skilled labour, forecasting issues, promotions, quality of packaging, lack of waste minimisation strategy, etc. It was concluded that a strong vertical coordination within the beef supply chain is the foremost action needs to be taken to address the root causes of waste. It will improve the information exchanged between the stakeholders of supply chain.

d. Usually, measurement of carbon footprint in beef supply chain is done on a segment level (Nguyen et al., (2010); Ogino et al., (2007); Bustamante et al., (2012); Kythreotou et al., (2011)) i.e. at farms, abattoir and processor, logistics and retailer level. The availability of integrated model for mapping carbon emission of entire beef industry is quite rare (Singh et al., 2015). In this thesis, an integrated, collaborative and centric framework is proposed for measuring and optimizing carbon footprint of entire beef supply chain using cloud computing technology. Firstly, carbon hotspots are identified for all segments of supply chain (farms, logistics, abattoir, processor and retailer). Then, a private cloud is developed by retailer to map the whole beef supply chain irrespective of their geographical locations. Apart from optimizing and measuring the carbon footprint of entire beef supply chain, it also improves the vertical and horizontal coordination of supply chain making their operations eco-friendly and efficient. The efficacy of proposed system is demonstrated via case study. Therefore, this research addresses the shortcoming of existing literature by mitigating the carbon footprint of entire beef supply chain from farm to retailer.

e. The cloud based framework for eco-friendly supplier selection of beef cattle would provide opportunity to more farmers to connect with abattoir and processor using cloud based framework. There will be rise in awareness of beef farmers about the modern trends of raising cattle beyond the conventional characteristics of price and breed. It will assist farmers to replicate the good practices of other farmers in reducing carbon footprint and also improving in terms of conventional characteristics.

f. In the past, stakeholders of beef supply chain were only concerned about their profit and productivity. However, in current scenario, they must also consider the carbon footprint generated by their operations because of pressure from government legislation. The small and medium size stakeholders of beef supply chain are not capable to address this issue due to lack of awareness and financial resources (Singh et al., 2015). The cloud based integrated framework proposed in this thesis would assist the small and medium size stakeholders to mitigate this issue in a cost-effective way. Therefore, the small and medium size farmers could overcome the financial, technological barriers and contribute in developing ecofriendly beef supply chain by implementing the proposed integrated framework in this thesis.

g. A novel mechanism for eco-friendly supplier selection of beef cattle by abattoir and processor is proposed, which would take into account carbon footprint along with conventional characteristics of cattle such as breed, age, diet, average weight of cattle, conformation, fatness score, traceability and price. These characteristics are assigned a weightage as per the priority of consumers and quality inspector of abattoir and processor. The aforementioned information of different cattle suppliers is analysed by Toposis method to generate a ranking list of suppliers from most appropriate to least appropriate supplier. The execution of proposed framework is demonstrated on a case study on Indian beef supply chain. It will assist both beef farmers, abattoir and processor in reducing carbon footprint

h. The food industries are aware of the factors influencing consumer's purchasing decisions. Nonetheless, they could not fathom how these factors are linked with each other. The food retailers employ various means to receive consumer feedback such as market research, interview of consumers, collecting consumer feedback within retail stores, etc. However, the response rates of these methods are low and usually they are biased in nature. Hence, these methods give limited outlook of the consumer priorities (Mishra et al., 2017). The information available on social media reflects the true opinion of consumers, which could give precise insights to decision makers of retailers. In this thesis, Twitter analytics is being used to identify the consumer preferences for buying beef products to give them 'sense of empowerment' and therefore made an attempt to bridge the gap in the existing literature and provide an insightful framework to industrial practitioners for capturing consumer feedback.

i. This study has a two-fold contribution to the literature on the consumer interest in beef. Firstly, although many research studies in the beef industry have focused on the motivational factors affecting consumers' purchasing decisions while purchasing beef (Clark et al., 2017; Lewis et al., 2016; Morales et al., 2013; Hocquette et al., 2014), none of them have offered an alternative approach to theory building emerging from the various quality characteristics and other factors that could be considered while purchasing beef (Mishra et al., 2017). This research undertakes a comprehensive review of literature generating the most important eleven factors or clusters and devises a theoretical framework based on the interrelationships of those variables emerging from the consumers (social media data) and experts' opinion using Interpretive Structural Modelling (ISM) and fuzzy Matriced' Impacts Croise's Multiplication Appliquée a UN Classement (MICMAC) analysis. Secondly, this research further extends the existing literature on consumers' decisions toward purchasing beef by offering a strategic framework, which is not only based on literature but also validated using the big data clustering technique that divide all such potential variables in the most important clusters that influence consumers' beef purchasing decisions. In the current research, the number of such clusters coincides to eleven factors. Therefore, the proposed theoretical framework extrapolates eleven factors at eight different layers and their interrelationships highlighting the specific roles of these variables. In conclusion, this thesis makes a contribution to the existing literature by highlighting the most significant drivers behind purchase of beef products and their interrelationships which are crucial in developing consumer centric beef supply chain.

7.2 Limitations

The proposed methodologies in this thesis are significantly dissimilar from the frameworks existing in the literature. The efficacy of these methodologies has been demonstrated using case studies and computational experiments. It can be concluded that these novel methodologies are proficient in addressing real world sustainability issues of food supply chain. There are numerous benefits of these frameworks and has significant theoretical and practical contribution. However, it has some limitations, which are described as following:

a. Some of the results of hierarchical clustering analysis were not linked to the beef supply chains. These findings do not contribute towards the objective of the study to develop consumer centric supply chain and therefore are not being described in detail. However, these results could be used for different purposes and is a topic for future research.

b. The methodologies proposed in this thesis assists in reducing the waste and carbon footprint of beef supply chain thereby improving its sustainability. The literature on sustainability of beef supply chain is still in its primitive stage. Further research work needs to be done to safeguard the capability, precision and implications of the methodologies to improve sustainability of beef supply chain.

7.3 Application to other domains

The basic principles employed in this research for improving the sustainability of beef supply chain are generic in nature, which could be applied to address similar real world sophisticated issues. The algorithm of the proposed frameworks does not require tailoring for new problems and are flexible to be implemented in the domain of meat supply chains (lamb, pork and chicken) and on other food supply chains to address their sustainability issues. However, the parameters of the sustainability issues being mitigated in these supply chains needs to be adjusted in terms of their scale and measurement units depending on the nature of the problem.

7.4 Future research work

This thesis consists of novel methodologies to improve the sustainability of beef supply chain via reducing their physical and environmental waste. Case studies and computational experiments demonstrates the efficacy of these frameworks. This study has vital scope for future research. Certain research directions for future studies associated with improving sustainability of beef supply chain have been mentioned.

In this study, Twitter data has been used to investigate the consumer sentiments. More than one million tweets related to beef products has been collected using different keywords. Sentiment mining based on Support Vector Machine (SVM) and Hierarchical Cluster Analysis (HCA) with multiscale bootstrap sampling techniques were proposed to investigate positive and negative sentiments of the consumers; as well as, to identify their issues/concerns about the food products. The collected tweets have been analysed to identify the main issues affecting consumer satisfaction. The root causes of these identified issues have been linked to their root causes in different segments of supply chain. In future, Latent Dirichlet Algorithm could be used instead of keyword based approach for better understanding of consumer behaviours. A larger volume of tweets could be captured using Twitter firehose instead of streaming API, which have better representativeness of the data.

In proposed methodology, consumer's tweets related to complaints of beef products were mined using a set of keywords. The tweets were captured from duration of around one month. The issues identified from consumer tweets were then linked to their root causes in the upstream of the supply chain for waste minimization. In future, an enhanced list of keywords could be used for further analysis of the issues. Twitter analytics could be employed for longer time duration to give more insight into the issues generating waste at consumer end of beef supply chain.

This thesis has investigated the waste generated in beef supply chain in India because of imbalance between production and consumption. The method of qualitative research (conducting interviews) has been followed in this study, which helped to identify the root causes of waste in Indian beef supply chain. The corresponding good management practices to mitigate them were discussed. Future studies could be conducted by utilising the quantitative methods like surveys to find out the waste generated corresponding to each root cause. Future research could concentrate on other geographical regions having prominent beef industries such as Brazil, which is another leading exporter of beef products.

In this research, a collaborative, integrated and centric approach of optimizing and measuring carbon footprint of entire beef supply chain by using Cloud Computing Technology (CCT) was proposed. The identification of carbon hotspots for entire beef supply chain is done. Then, retailer develops a private cloud to map the whole chain, which would assist in optimizing and measuring carbon footprint of complete beef supply chain from farm to retailer. This research has the further scope of being a pilot study with real time data from all the stakeholders.

This study explores the interrelationships among factors mandatory to develop consumer centric supply chain by amalgamation of Twitter analytics, ISM and fuzzy MICMAC analysis. Future studies could be performed to develop a theoretical mechanism for sustainable consumer centric supply chain by assimilating some additional factors. Furthermore, confirmatory investigation of variables could be conducted to validate the theoretical framework developed. The proposed model could be validated by using Systems Dynamic Modelling (SDM) and Structural Equation Modelling (SEM). The factors identified to develop consumer centric beef supply chain could be quantified by employing Analytical Network Process (ANP) and Analytical Hierarchical Process (AHP). These factors could be further ranked by utilising Interpretive Ranking Process (IRP) to develop consumer centric beef supply chain.

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Appendix A

Abbreviations

AHP	Analytic Hierarchy Process
BEEFGEM	Beef system greenhouse gas emission model
BSE	Bovine Spongiform Encephalopathy
CCT	Cloud Computing Technology
FAO	Food and Agriculture Organisation of United Nations
FCA	Formal Concept Analysis
FVCA	Food Value Chain Analysis
GRA	Grey Relational Analysis
IaaS	Infrastructure as a Service
ICT	Information and Communications Technology
IFSM	Integrated Farm System Model
IPCC	Intergovernmental Panel on Climate Change
ISM	Interpretive Structural Modelling
LCA	Life Cycle Assessment
LULUC	Land Use and Land Use Change
MAP	Modified Atmosphere Packaging
MSA	Meat Standards Australia
PaaS	Platform as a Service
SaaS	Software as a Service
SME	Small and Medium-sized Enterprises
SRM	Specified Risk Material

SVM	Support Vector Machine
USDA	United States Department of Agriculture
VSP	Vacuum Skin Packaging

APPENDIX B

Journal Article 1

Interpretive Structural Modelling and Fuzzy MICMAC Approaches for Customer Centric Beef Supply Chain: Application of a Big Data Technique

Interpretive Structural Modelling and Fuzzy MICMAC Approaches for Customer Centric Beef Supply Chain: Application of a Big Data Technique

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Abstract

The food retailers have to make their supply chains more customer driven to sustain in modern competitive environment. It is essential for them to assimilate consumer's perception to improve their market share. The firms usually utilise customer's opinion in the form of structured data collected from various means such as conducting market survey, customer interviews and market research to explore the interrelationships among factors influencing consumer purchasing behaviour and associated supply chain. However, there is abundance of unstructured consumer's opinion available on social media (Twitter). Usually, retailers struggle to employ unstructured data in above decision-making process. In this paper, firstly, by the help of literature and social media Big Data, factors influencing consumer's beef purchasing decisions are identified. Thereafter, interrelationships between these factors are established using big data supplemented with ISM and Fuzzy MICMAC analysis. Factors are divided as per their dependence and driving power. The proposed frameworks enable to enforce decree on the intricacy of the factors. Finally, recommendations are prescribed. The proposed approach will assist retailers to design consumer centric supply chain.

Keywords: Big Data, Interpretive Structural Modelling (ISM), Fuzzy MICMAC, Beef Supply Chain, Twitter

1. Introduction

The main objective of modern industry is to please consumers. Usually, supply chains are designed using customer driven approach. The businesses are framing their operations to become more efficient in terms of time and money to meet the expectations of consumers. The implementation of these policies becomes complicated in food industry considering the perishable nature of food products (Aung and Chang, 2014). The food products reaching the consumers should have the virtue of good taste, quality, ample shelf life, high nutrition, appearance, good flavour in minimum cost or else the food retailers and their suppliers might lose their market share (Banović et al., 2009; Bett, 1993; Killinger et al., 2004b; Neely et al., 1998; Oliver, 2012; O'Quinn et al., 2016; Sitz et al., 2005; van Wezemael et al., 2010; van Wezemael et al., 2014; Verbeke et al., 2010). After the horsemeat scandal, major retailers are in pressure to assure the food safety, quality and precise labelling to reflect the actual content of beef products by strengthening the relation with their key suppliers (Yamoah and Yawson, 2014). There is a lot of pressure from government legislation and consumers about the carbon footprint generated in producing the food products (Weber and Matthews, 2008). The aforementioned factors influence the consumer's purchasing decisions. In the past, studies have been conducted to examine the impact of these factors individually (Lewis et al., 2016; Morales et al., 2013; Clark et al., 2017) or in a group of two to three factors (Hocquette et al., 2014) on consumer's buying preferences. However, literature lacks the documentary evidence on how these factors collectively impact consumer's purchasing behaviour and their interrelationship among each other. The food industries are aware of these factors. However, they do not have the insights of the linkage among the factors and the knowhow to assimilate these factors in their operations to achieve a consumer centric supply chain. Incorporating consumer's perception is very crucial for food retailers to survive in today's competitive market. Food retailers make an attempt to receive consumer feedback via market surveys, market research, interview of consumers and providing the opportunity to consumers to leave feedback in retail store and use this information for improving their supply chain strategy. However, the response rates for these techniques are quite low, often the responses are biased and consists of false information; consumers are reluctant to participate due to privacy issues. Therefore, these techniques give limited outlook of the expectation of majority of customers. There are plenty of useful information available on social media. Such information includes the true opinion of consumers (Katal et al., 2013; Liang and Dai, 2013). The rapid development in information and technology will assist business firms to collect the online information to use it in developing their future strategy. On the contrary, the social media data is qualitative and unstructured in nature and often huge in terms of velocity, volume and variety (Mishra & Singh, 2016; Hashem et al., 2015; He et al., 2013; Zikopoulos and Eaton, 2011).

Outcome of operation management tools and techniques are usually based on limited data collected from various sources such as surveys, interviews, expert opinions, etc. Decision making could be more precise and accurate if these analyses are supplemented by social media data. This study attempts to incorporate social media data using Interpretive Structural Modelling (ISM) and fuzzy MICMAC to develop a framework for consumer centric sustainable supply chain. The involvement of information from social media data will give consumers 'sense of empowerment.' There is no mechanism mentioned in the literature for using Twitter analytics to explore the interrelationships among factors mandatory to achieve consumer centric supply chain. This article explicitly investigates the interaction among these factors using big data (social media data) supplemented with ISM and fuzzy MICMAC analysis. A systematic literature review was conducted to identify the drivers influencing the consumer's decision of buying beef products and supply chain performance. Thereafter, ISM is developed to investigate factors influencing the beef purchasing decision of consumers and the relationships between them. Usually, structural models are composed of graphs and interaction matrices, signal flow graphs, delta charts, etc., which do not provide enough explanation of the representation system lying within. In this article, using ISM and fuzzy MICMAC techniques, the variables influencing consumers' decision are segregated into four different categories: driving, linkage, autonomous and dependent variables and generate the hierarchical structure to represent the linkage between the variables for interpretive logic of system engineering tools. Based on the findings, the recommendations have been prescribed to develop a consumer centric sustainable supply chain.

The organisation of the article is as follows: Section 2 consists of literature review. In Section 3, cluster analysis and ISM methodology are described in detail. Section 4 introduces and analyses ISM fuzzy MICMAC Analysis. Section 5 includes discussion, managerial implications and theoretical contribution. Finally, Section 6 provides conclusion and recommendations for future research.

2. Literature review

Food supply chain consists of all the operations that explain how food is transferred from farm to fork. It includes various processes like production, processing, distribution, marketing, retailing, consumption and disposal. The beef supply chain is composed of various segments viz. farmers, abattoir, processor, logistics and retailer. The beef farmers raise the cattle in beef farms from the age of three to thirty months based on the breed and demand of the cattle within the market. The cattle are transferred to abattoir and processor when they reach their finishing age. Then, they are butchered and cut into primals, which is followed by processing them into beef products like joint, steak, mince, burger, veal, dicer/stir-fry etc. The packaging and labelling of these fine beef products are performed and then they are transferred to retailer by employing logistics. In order to flourish in the competitive environment, food retailers have to provide excellent quality products at minimal cost, at precise time in right condition by incorporating virtues like food safety, eco-friendly products, good flavour, high nutrition etc.

Using systematic literature review, different variables influencing customer’s buying behaviour of beef products are identified. The research papers were extracted from prominent databases like ScienceDirect, Springer, Emerald, Taylor and Francis and Google Scholar. The articles considered in this study were published in the duration of 2000-2016. The keywords utilised for searching the aforementioned databases are shown in Table 1. Initially, 3295 articles are obtained using these keywords, which included leading journal articles, international conference proceedings and reputed government reports predominantly in the domain of food quality, meat safety, marketing, meat sciences, environmental sciences and animal sciences. A preliminary screening was performed on these articles by assessing the title and abstract of article to filter the articles based on relevance to this study. The articles in non-English language and duplicates were also eliminated. The preliminary screening generated 374 articles. A deeper analysis of these articles was performed to limit the system boundary of the articles to retail beef cuts only, which are sold to customers in retail stores. The full text analysis of these studies revealed that some of them were not directly related to our domain of study as they were based on processed beef products and meals cooked from beef. Also, some of the articles were repetitive in nature considering the similarity in their findings. The elimination of the aforementioned studies via full text analysis yielded 87 most relevant articles to our research.

Table 1 Keywords used for extracting research articles from prominent databases

S. No.	Keywords
1.	Priority OR Attitude OR Perception OR Intention OR Behaviour AND Customer AND Beef OR Steak
2.	Expectations OR Experience AND Beef OR Steak AND Consumer
3.	Quality cues OR quality attributes AND Beef OR Steak AND Consumer
4.	Preference OR Choices AND Beef OR Steak AND Consumer
5.	Like OR Dislike OR Prefer AND Beef OR Steak AND Consumer
6.	Driver OR Enabler OR Purchase behaviour AND Beef OR Steak AND Consumer
7.	Carbon footprint OR Sustainability OR Greenhouse gases OR Emissions OR Global Warming AND Beef OR Steak AND Consumer
8.	Colour OR Discoloured OR Grey OR Red OR Brown AND Beef OR Steak AND Consumer
9.	Price OR Cost OR Expensive OR Cheap AND Beef OR Steak AND Consumer
10.	Taste OR Flavour OR Delicious AND Beef OR Steak AND Consumer
11.	Advertisement OR Campaign OR Media OR Marketing AND Beef OR Steak AND Consumer
12.	Nutrition OR Fat OR Protein OR Vitamins OR Minerals OR Healthy AND Beef OR Steak AND Consumer
13.	Packaging OR MAP OR VSP AND Beef OR Steak AND Consumer
14.	Organic OR Premium OR Animal Welfare AND Beef OR Steak AND Consumer
15.	Promotion OR Deal OR Offer OR Bargain AND Beef OR Steak AND Consumer
16.	Traceability OR Labelling OR Food safety OR Origin AND Beef OR Steak AND Consumer
17.	Smell OR Odour OR Aroma AND Beef OR Steak AND Consumer
18.	Tenderness OR Chewy OR Maturation AND Beef OR Steak AND Consumer

The exhaustive analysis of these studies along with interviews of consumers of beef products, supermarket technologists monitoring the performance of beef products and prominent academics working in the domain of beef supply chain generated eleven drivers as shown in Table 2, which influence the consumer's decision to purchase beef products and are essential to achieve consumer centric supply chain. The extracted drivers are described as follows:

Table 2. List of variables influencing consumer's beef purchasing behaviour

S. No.	Variables	Sources
1	Quality	Banović et al. (2009); Becker (2000); Brunsø et al. (2005); Acebron & Dopico, (2000); Grunert et al. (2004); Krystalli et al. (2007); Verbeke et al. (2010); Koohmaraie and Geesink, 2006
2	Taste	Killinger et al. (2004a); Killinger et al. (2004b); McIlveen & Buchanan (2001); Oliver (2012); O'Quinn et al, (2016); Sitz et al. (2005)
3	Packaging	Zakrys et al. (2009); Kerry et al., 2006; Grobbel et al. (2008); Carpenter et al. (2001); Verbeke et al. (2005); Bernués et al. (2003)
4	Price	Acebrón & Dopico (2000); Hocquette et al. (2015); Kukowski et al. (2005); Liu & Ma (2016); Marian et al. (2014); Völckner & Hofmann (2007)
5	Promotion	Cairns et al. (2009); Eertmans et al. (2001); Elliott (2016); Hawkes (2004); Kotler & Armstrong (2006)
6	Organic/inorganic	Bartels & Reinders (2010); Bravo et al. (2013); Guarddon et al. (2014); Hughner et al. (2007); Mesías et al. (2011); Napolitano et al. (2010); Ricke (2012); Squires et al. (2001); Średnicka-Tober et al. (2016)
7	Advertisement	De Chernatony and McDonald (2003); Jung et al. (2015); Mason & Nassivera (2013); Mason & Paggiaro (2010); Simeon & Buonincontri (2011)
8	Colour	Guzek et al. (2015); Jeyamkondan et al. (2000); Kerry et al. (2006); McIlveen & Buchanan, (2001); Realini et al. (2015); Savadkoohi et al. (2014); Suman et al. (2016); Viljoen et al. (2002); Font-i-Furnols and Luis Guerrero, (2014)
9	Nutrition (Fat label)	Barreiro-Hurlé et al. (2009); da Fonseca & Salay (2008); Lähteenmäki (2013); Lawson (2002); McAfee et al. (2010); Nayga (2008); Rimal (2005); van Wezemael et al. (2010); van Wezemael et al. (2014); De Smet and Vossen, (2016); Egan et al., (2001); Pethick et al., (2011)
10	Traceability	Becker (2000); Brunsø et al. (2002); Clemens & Babcock (2015); Giraud & Amblard (2003); Grunert (2005); Lee et al. (2011); Menozzi et al. (2015); Ubilava & Foster (2009); van Rijswijk & Frewer (2008); van Rijswijk et al. (2008a); Verbeke & Ward (2006); Zhang et al. (2012)
11	Carbon footprint	Grebitus et al. (2013); Grunert (2011); Lanz et al. (2014); Nash (2009); Onozaka et al. (2010); Röös & Tjärnemo (2011); Singh et al. (2015); Vermeir & Verbeke (2006); Vlaeminck et al. (2014)

2.1 *Quality of the meat* – International Organization for Standardization (ISO) has defined food quality as the entirety of traits and characteristic of a food product that has the capability to appease fixed and implicit requirements (ISO 8402). The eating quality is the foremost thing taken into account by customers while purchasing beef, which includes tenderness, juiciness, freshness, minimum gristle and free from bad smell or rancidity and absence of infections (Banovic et al., 2009; Brunsø et al., 2005; Krystallis et al., 2007; Koohmaraie and Geesink, 2006). Good quality beef products boost the customer satisfaction and consequently raise the rate of consumption of beef products. It will lead to the increase in revenue of beef industry, which is crucial in modern era of economic crisis, uncertainty in food prices and intensive competition (Acebron & Dopico, 2000; Verbeke et al., 2010). The determinants of quality as mentioned above are normally assessed after cooking of beef products (Grunert, 1997). Some consumers also consider credence characteristics of beef products while evaluating their quality (Geunert et al., 2004). Sometimes, the quality is also judged by the labels associated with reputed farm assurance schemes such as Red Tractor. It confirms that appropriate animal welfare procedures or farm assurance schemes have been implemented in the beef farms associated with beef products in the retail stores. Therefore, the quality of beef products plays a vital role in deciding whether a particular beef product consumed by a consumer will be bought again or recommended by him or her to their friends and relatives.

2.2 *Taste* – Certain consumers give equal preference to the flavour profile of beef products rather than to the aggregate sensory experience (Neety et al., 1998). Flavour of beef products often becomes the most crucial determinant for eating satisfaction if the associated tenderness is within tolerable range (Killinger et al., 2004a). The flavour associated with beef products is not easy to anticipate and define (McIlveen and Buchanan, 2001). The determinants of beef flavour have been recognised as cooked beef fat, beefy, meaty/brothy, serum/bloody, grainy/cowy, browned and organ/liver meat (Bett, 1993). Many of these determinants are unfavourable for customers. O'Quinn et al. (2016) revealed that customers prefer the beef with high cooked beef fat, meaty/brothy, beefy and sweet flavour whereas organ/livery, gamey and sour flavour were disliked. In most of the cases, customers assess the aggregate intensity of the flavour. Although the studies based on consumer's sensory have revealed that beef customers have distinct priorities for a certain attribute of beef flavour (Oliver, 2012; Killinger et al, 2004b). These individual flavour priorities are emulated in their decisions regarding purchase of beef products (Sitz et al., 2005).

2.3 *Packaging* – Packaging is one of the crucial visual determinants affecting the customer's decision to purchase beef (Issanchou, 1996). Packaging plays a vital role in increasing the shelf life of beef products and impedes the deterioration of food quality and insures the safety of meat (Zakrys et al., 2009). Brody and Marsh (1997) and Kerry et al. (2006) have further defined the role of packaging as to prevent from microbial infection, hamper spoilage and provide opportunity for activity by enzymes to boost tenderness, curtail loss of weight and if relevant to maintain the cherry red colour in beef products at retail shelves. Various packaging methods are followed by supermarkets, all of them have distinct characteristics and modes of application. Some of the major packaging systems followed are: overwrap packaging designed for chilled storage for shorter duration, Modified Atmosphere Packaging (MAP) intended for storing at chilled temperature or display at retail shelves for longer duration and Vacuum Skin Packaging (VSP), which is capable for storage at chilled temperature for a very long time (Kerry et al., 2006). As the packaging used has a great influence on colour of beef products, the packaging method used also have a great impact on consumer's approach towards beef products (Grobbel et al., 2008). A close association has been documented among the preference of colour and making a decision to purchase beef product (Carpenter, Cornforth and Whittier, 2001). Packaging of beef products also plays a crucial role in terms of marketing such as a mode of differentiation among products, value adding and a bearer of brands, labels, origin, etc. (Bernués, Olaisola and Corcoran, 2003). Visual cues like packaging and packaging associated traits considerably affect the decision of customers for purchasing beef products (Grobbel et al., 2008; Verbeke et al., 2005).

2.4 *Colour* – It is considered as one of the important determinants of quality of beef products (Issanchou, 1996). Colour of the meat gives an intrinsic cue to the customers regarding the freshness of beef products (McIlveen and Buchanan, 2001). Customers attempt to judge the tenderness, taste, juiciness, nutrition, and freshness from the colour of the beef products prior to purchase (Grunert, 1997; Font-i-Furnols and Luis Guerrero, 2014). Most of the customers prefer the fresh red cherry like colour in their beef products (Brody and Marsh, 1997; Kerry et al., 2006). Customers are very reluctant to buy beef products if the fresh red colour is missing despite the fact its shelf life has not expired. Modified Atmosphere Packaging (MAP) is very popular among them where they could see the colour of beef products to make a decision to buy or not to buy beef products. The discoloration of meat hampers the shelf life post preparation at retail, which is an important financial concern in beef industry (Jeyamkondan and Holley, 2000). Dark cutting beef products have always been rejected by customers and have caused significant loss to the beef industry (Viljoen et al., 2002). Usually, the colour of beef products has significant impact on consumer's perception.

2.5 *Carbon footprint* – Beef products contain one of the highest carbon footprints among the agro products (Singh et al., 2015). Therefore, sustainable consumption is considered to be of vital significance (Nash, 2009). The cost of food product rises in order to reduce their carbon footprint. Price is considered as the major obstacle for the purchase of sustainable product by consumers (Grunert, 2011; Röös and Tjärnemo, 2011). Sustainable consumption can be encouraged by involvement of consumers, recognizing the impact of sustainable products and by increasing the peer pressure in society (Veremeir and Verbeke, 2006). Consumers are increasingly demonstrating their awareness towards sustainable consumption by doing eco-friendly shopping especially food products including beef (Grebitus et al., 2013; Onozaka et al., 2010). It was observed that if low carbon footprint alternative exists for products with high carbon footprint at similar or lesser prices then consumers would be prioritising the low carbon footprint option (Lanz et al., 2014; Vlaeminck et al., 2014). The carbon footprint associated with beef product will be an important driver for the consumers to purchase beef products.

2.6 *Organic/Inorganic* – Consumers buy organic food because of various reasons like nutrition value, eco-friendly nature of organic products, welfare of animals, safety of food products etc. (Hughner et al., 2007). The organic beef is assumed to be derived from livestock raised by free-range procedures (Mesías et al., 2010). It was found that consumers were happy to pay extra for organic beef if sufficient information about organic farming is provided (Napolitano et al., 2010). The literature suggests distinct behaviour of consumers towards organic food products bases on social demographics (Padilla et al., 2013; Squires et al., 2001). Consumers are persuaded by social identification while purchasing organic food products (Bartels and Reinders, 2010).

2.7 *Price* – Price plays a crucial role in assessment of products by consumers (Marian et al., 2014). Price could be perceived as an amount of money spent by consumers for a particular transaction (Linchtenstein and Netemeyer, 1993). It is usually considered as a determinant of quality i.e. high price products are often associated with better quality (Erickson and Johansson, 1985; Völckner and Hofmann, 2007). Price could also be a barrier for low income consumers to buy high quality or organic food products (Marian et al., 2014). Price of beef product is affected by the packaging system used as well. Kukowski, Maddock and Wulf (2004) observed that consumers gave similar ratings to beef products in terms of prices based on their overall liking of the beef products. Price is a crucial factor affecting the customer’s decision to purchase beef products.

2.8 *Traceability* – Traceability labels are considered to be the most potent means for developing trust among consumers regarding quality and food safety (Becker, 2000). Consumers are laying more emphasis on food traceability because of the rising concern associated with food safety (Zhang and Wahl, 2012). Especially after horsemeat scandal, customers are more conscious of traceability of food products. Consumers gave equal importance to traceability as quality certificate (Ubilava and Foster, 2009). It was revealed that people were ready to pay considerable amount of premium for traceable beef products as compared to conventional beef products (Lee et al., 2011). Apart from assisting customers in speculating the quality of beef products, tractability labels affect the complete attitude of consumers towards purchasing of food products, preparation of dishes, contentment and forthcoming buying decision (Brunsø et al., 2002; Grunert, 2005).

2.9 *Nutrition* – Consumers have mixed perceptions about the nutrition value of beef products (Van Wezemael et al., 2010). Some customers have concerns about the amount of fat in beef products and its consequences on their cholesterol levels (Van Wezemael et al., 2014). However, the beef is a very rich source of good quality protein, minerals like zinc and iron, Vitamin-D, B12, B3, Selenium and essential Omega-3 fatty acid, all of which are essential components for healthy human body (McAfee et al., 2010; De Smet and Vossen, 2016; Egan et al., 2001; Pethick et al., 2011). Nutrition labelling has a good influence over consumer decision of buying food products (da Foneseca and Salay, 2008; Nagya, 2008; Rimal, 2005). Some consumers who are conscious about their health also refer to the nutritional labelling. Food and health are interrelated to each other and they have a direct impact on body functions and disease risk reduction. Both nutrition and health claims are based on nutrition labelling and usually consumers process this information during decision making process (Lähteenmäki, 2012; Lawson, 2012). During the study, it was found that health claims outperform nutrition claims (Barreiro-Hurlé et al., 2009).

2.10. *Promotion* – Promotion is a valuable tool for marketing to make an impact on consumer's purchase behaviour (Kotler and Armstrong, 2006). Food promotion could be defined as sales and marketing promotions utilised on food packaging for the purpose of alluring consumers to buy food products at the retailer's point of sale (Hawkes, 2004). It may comprise of prime deals like discounts, contests and advocacy by celebrities (Hawkes, 2004). Basically, marketing promotion has a precise function of developing awareness of a brand, benign perception towards a brand and encourage desire to purchase (Belch and Belch, 1998; Rossiter and Percy, 1998). As beef products are usually expensive in nature, promotions and deals play a crucial role in prompting consumers to purchase beef products in larger quantities.

2.11. *Advertisement* – Advertising is an effective tool for retailers to promote their products and develop into persuasive brand (De Chernatony and McDonald, 2003). There are some barriers in promoting beef products via advertising. They are increased expenses, unreliability of advertisements and intangibility of content of advertisement messages (Dickson and Sawyer, 1990; Quelch, 1983). Advertisement via different channels such as newspapers, radio, television influences consumer's buying behaviour. Sometimes, retailers attempt to launch their new products at farm festivals, food shows etc. (Mason and Nassivera, 2013). Retailers launch their new products like organic beef products, high nutrition low fat products via these channels. During the study, it was found that festivals help food industries to raise awareness about quality and satisfaction of food products and consequently help them to gain broader market share.

To investigate the association among the above identified variables, consumer's perception from social media data along with experts' opinions have been combined and analysed using ISM and fuzzy MICMAC, which is explained in detail in following section.

3. **Methodology**

Initially, consumers' opinion is extracted from social media (Twitter), which is rich in nature and provides unbiased opinion unlike consumer interviews, surveys, etc. Social media data is true representation of consumers' attitude, sentiments, opinions and thoughts. Cluster analysis is performed on the data collected from Twitter to find out the relation among above identified eleven variables. Thereafter, ISM and fuzzy MICMAC have been implemented to develop a theoretical framework. In the next subsection, firstly, the social media and cluster analysis are explained. Thereafter, ISM and fuzzy MICMAC are implemented to develop frameworks with the factors interlinked to each other at the various levels.

3.1 **Social media data and cluster analysis**

In order to capture, real time observation of consumers' reactions, attitudes, thoughts, opinions and sentiments towards the purchase of beef products, social media data from Twitter has been utilised. Using NCapture tool of NVivo 10 software, tweets were extracted using keywords shown in Table 3. In total, 1,338,638 tweets were extracted from Twitter. These tweets were filtered so that only English tweets will be captured. Then, they were further refined so that tweets corresponding to only our domain of study i.e. 'factors influencing purchasing behaviour or disappointment of beef products of consumers' are selected. After refining, 26,269 tweets were left for analysis, which are associated with the domain of this study. These tweets were then carefully investigated by the experts in the area of marketing management, supply chain management, meat science and couple of them as the Big Data professionals. Content analysis has been performed. In the initial stage, conceptual analysis is employed to determine the frequency corresponding to each factor. Thereafter, the collected tweets have been classified into eleven clusters as mentioned above. The association among these clusters is examined using total linkage clustering method. Pearson correlation coefficient is used to evaluate the relationship between variables. The distance between the clusters is calculated based on frequency and likeness of occurrence. The results of the analysis are depicted in Table 4. The pairs of variables having score 0.9 or above are considered to be interrelated. The remaining pairs of variables or clusters are not related to each other. The results of Pearson correlation coefficient test suggested that consumers are looking for good quality beef products at reasonable price while purchasing meat. They put great emphasis on taste and nutritional value associated with it as they are the significant drivers for the purchase of beef products. The traceability of beef products is also sought by consumers because of the food safety concern along with the carbon footprint generating in producing them considering the rising environmental concern. Finally, the packaging of the beef products and the organic/inorganic label have a significant influence on consumers' preferences while purchasing beef products.

The outcome of cluster analysis is transferred to ISM to identify the driver, dependent, independent and linkage variable and interrelationships between them. The detailed description of ISM is illustrated in the following subsections.

Table 3. Keywords used for extracting consumer tweets

Beef#disappointment	Beef#Rotten	Beef# rancid	Beef#was very chewy
Beef#taste awful	Beef#unhappy	Beef#packaging blown	Beef#was very fatty
Beef#Odd colour beef	Beef#discoloured	Beef#Plastic in beef	Beef#Gristle in beef
Beef#complaint	Beef#Beefgrey colour	Beef#Oxidised beef	Beef#Taste
Beef#complaint	Beef#Beefgrey colour	Beef#Oxidised beef	Beef#Taste
Beef#Flavour	Beef#Smell	Beef#Rotten	Beef#Funny colour
Beef#Horsemeat	Beef#Customer support	Beef#Bone	Beef#Inedible
Beef#Mushy	Beef#Skimpy	Beef#Use by date	Beef#Stingy
Beef#Grey colour	Beef#Packaging	Beef#Oxidised	Beef#Odd colour
Beef#Gristle	Beef#Fatty	Beef#Green colour	Beef#Lack of meat
Beef#Rubbery	Beef#Suet	Beef#Receipt	Beef#Stop selling
Beef#Deal	Beef#Bargain	Beef#discoloured	Beef#Dish
Beef#Stink	Beef#Bin	Beef#Goes off	Beef#Rubbish
Beef#Delivery	Beef#Scrummy	Beef#Advertisement	Beef#Promotion
Beef#Traceability	Beef#Carbon footprint	Beef#Nutrition	Beef#Labelling
Beef#Price	Beef#Organic/ Inorganic	Beef#MAP packaging	Beef#Tenderness

Table 4. Pearson Correlation Test of the Cluster Analysis (Partial Results)

S. No.	Variable I	Variable II	P.C.C. Score
1	Quality	Taste	0.99
2	Promotion	Advertisement	0.98
3	Quality	Nutrition	0.92
4	Price	Nutrition	0.95
5	Colour	Packaging	0.95
6	Organic/ Inorganic	Quality	0.95
7	Organic/inorganic	Carbon Footprint	0.92
8	Price	Quality	0.94
9	Organic/ Inorganic	Taste	0.94
10	Packaging	Quality	0.94
11	Quality	Carbon footprint	0.95
12	Packaging	Price	0.93
13	Price	Traceability	0.96
14	Price	Promotion	0.93
15	Price	Colour	0.93
16	Price	Carbon footprint	0.93
17	Packaging	Taste	0.93
18	Price	Taste	0.92
19	Quality	Traceability	0.92
20	Price	Organic/inorganic	0.94

[Legend: P.C.C: Pearson Correlation Coefficient S. No.: Serial Number]

3.2 Interpretive Structural Modelling (ISM) methodology

ISM is a methodology for identifying and summarising relationships among specific items, which define an issue or a problem (Mandal and Deshmukh, 1994). The method is interpretive in a sense that group's judgement decides whether and how the variables are related. It is primarily intended as a group learning process. It is structural in a sense that an overall structure is extracted from the complex set of variables based on their relationships. It is a modelling technique to depict the specific relationships and overall structure in the digraph model (Agarwal et al., 2007). The ISM methodology helps to enforce order and direction on the complexity of the relationships among the variables of a system (Haleem et al. 2012; Purohit et al., 2016; Sage, 1977). For problems, such as understanding the factors considered by the customers while purchasing beef, several of them may be impacting each other at different levels. However, the direct and indirect relationships between the factors describe the situation far more precisely than the individual factors considered in isolation. ISM develops insights into the collective understanding of these relationships. ISM methodology has been successfully implemented in various domains. Hughes et al., (2016) have employed ISM to identify the root causes of failure of information systems project and interrelationship between them. Gopal and Thakkar, (2016) have used ISM and MICMAC analysis to investigate the critical success factors (and their contextual relationships) responsible for sustainable practices in supply chains of Indian automobile industry. Kumar et al., (2016) have utilised ISM to identify barriers for implementation of green lean six sigma product development process. Haleem et al., (2012) have applied ISM techniques to develop a hierarchical framework for examining the relationship among critical success factors behind the successful implementation of world leading practices in manufacturing industries. Mathiyazhagan et al., (2013) have used ISM to identify the barriers in implementing green supply chain management in Indian SMEs manufacturing auto components. Mani et al., (2015a) have employed ISM to explore different enablers and the interactions among them in incorporating social sustainability practices in their supply chain. Mani et al., (2015b) have developed ISM model to investigate the barriers (and their contextual relationships) to adoption of social sustainability measures in Indian manufacturing industries. Dubey and Ali, (2014) have applied ISM, fuzzy MICMAC and Total Interpretive Structural Modelling (TISM) to explore the major factors responsible for flexible manufacturing systems. Sindhu et al., (2016) have used ISM and fuzzy MICMAC to identify and analyse the barriers to solar power installation in rural sector in India. Singh et al., (2007) used ISM for improving competitiveness of small and medium enterprises (SMEs). Agarwal et al., (2007) used ISM to understand the interrelationships of the variables influencing the supply chain management. Similarly, Pfohl et al., (2011) used ISM to perform the structural analysis of potential supply chain risks. Talib et al., (2011) used the ISM to analyse the interaction among the barriers to total quality management implementation. The application of ISM typically forces managers to reassess perceived priorities and improves their understanding of the linkages among key concerns (Singh et al., 2007).

ISM starts with identifying variables, which are pertinent to the problem and then extends with a group problem-solving technique. A contextually significant subordinate relation is chosen. Having decided on the element set and the contextual relation, a structural self-interaction matrix (SSIM) is developed based on pair-wise comparison of variables. In the next step, the SSIM is converted into a reachability matrix and its transitivity is checked. Once transitivity embedding is complete, a matrix model is obtained. Then, the partitioning of the elements, development of the canonical form of the reachability matrix, driving power and dependence diagram and an extraction of the structural model, called ISM is derived (Agarwal et al., 2007). The execution process of ISM is shown in Figure 1.

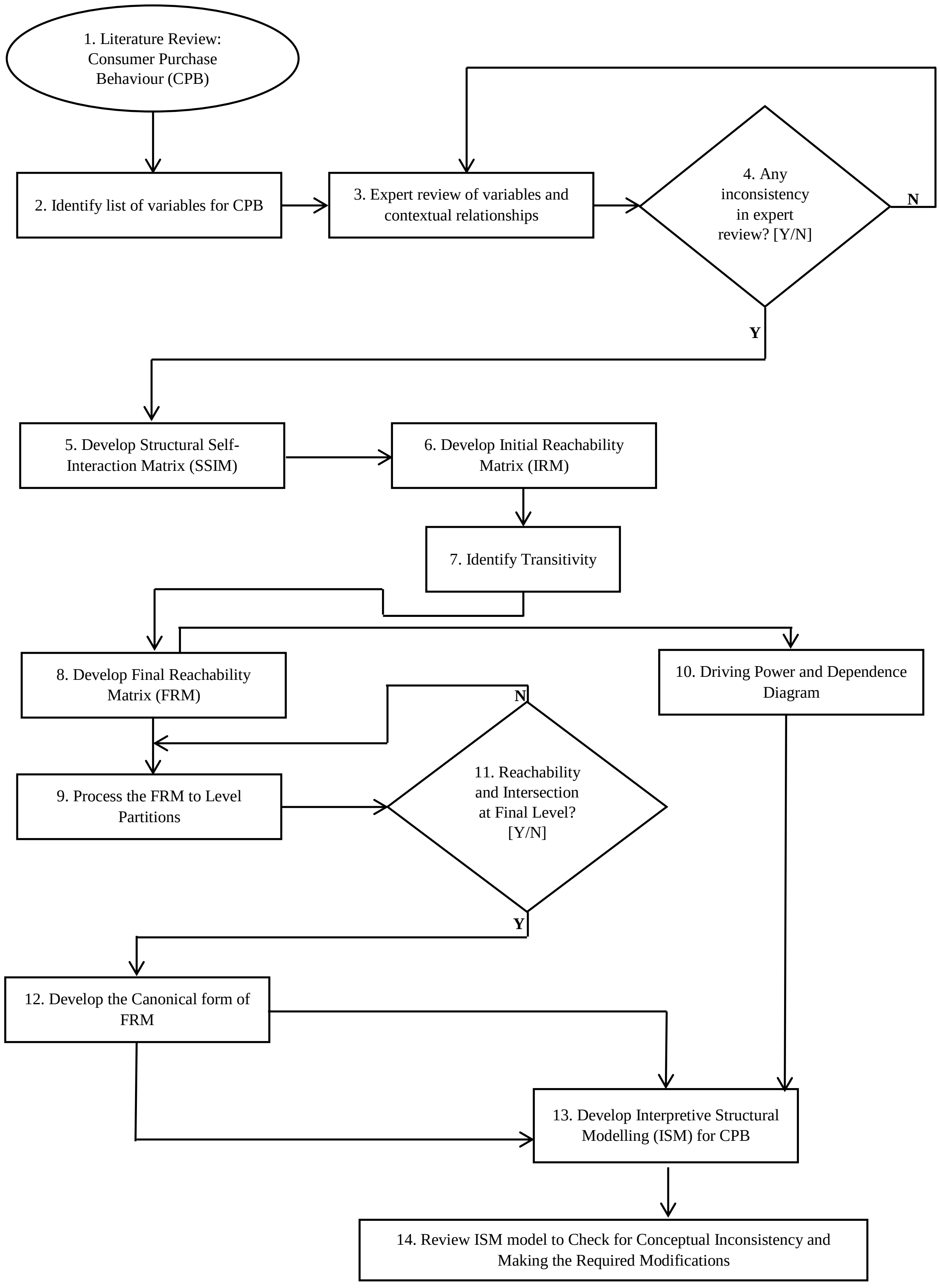
1. Literature Review: Consumer Purchase Behaviour (CPB)
2. Identify list of variables for CPB
3. Expert review of variables and contextual relationships
4. Any inconsistency in expert review? [Y/N]
N
Y
5. Develop Structural Self-Interaction Matrix (SSIM)
6. Develop Initial Reachability Matrix (IRM)
7. Identify Transitivity
8. Develop Final Reachability Matrix (FRM)
10. Driving Power and Dependence Diagram
N
9. Process the FRM to Level Partitions
11. Reachability and Intersection at Final Level? [Y/N]
Y
12. Develop the Canonical form of FRM
13. Develop Interpretive Structural Modelling (ISM) for CPB
14. Review ISM model to Check for Conceptual Inconsistency and Making the Required Modifications

Figure 1. Flowchart of ISM methodology

In this research, ISM has been applied to develop a framework for the factors considered by the consumers while purchasing beef to achieve the following broad objectives: (a) to derive interrelationships among the variables that affect each other while consumers make decisions to purchase beef, and (b) to classify the variables according to their driving and dependence power using a 2x2 matrix, which represents the relationships between different factors that decide the consumers' intention to purchase beef.

3.2.1. Interpretive logic matrix

Although, the Pearson correlation coefficient test has revealed the association between factors, it is not clear what kind of association or relationship they have among themselves. In order to identify the relationship, the experts' opinion has been collected. Experts having considerable experience and operating at crucial stages in food supply chain were approached. The results obtained from Big Data analysis have been circulated to the experts and session was organised to establish the relationships between each pair of variable. The brainstorming session was conducted for several hours and then final consensus was reached on the SSIM matrix as shown in Table 5. To express the relationships between different factors (i.e. Price, quality, packaging, taste, organic/inorganic, promotion, advertisement, carbon footprint, traceability, colour and nutrition) that decide the consumers' intention to purchase beef, four symbols were used to denote the direction of relationship between the parameters i and j (here $i < j$):

V – Construct i helps achieve or influences j,

A - Construct j helps achieve or influences i,

X – Constructs i and j help achieve or influence each other, and

O – Constructs i and j are unrelated

The following statements explain the use of symbols V, A, X, O in SSIM:

[1] Quality (Variable 1) helps achieve or influences quality (Variable 4) (V)

[2] Packaging (Variable 3) helps achieve or influences quality (Variable 1) (A)

[3] Promotion (Variable 5) and advertisement (Variable 7) help achieve or influence each other (X)

[4] Advertisement (Variable 7) and traceability (Variable 10) are unrelated (O)

Based on contextual relationships, the SSIM is developed as shown in Table 5.

Table 5. Structural Self-Interactional Matrix (SSIM)

V[i/j]	11	10	9	8	7	6	5	4	3	2	1
1	X	A	X	O	O	A	O	V	A	X	
2	O	O	O	O	O	A	O	V	A		
3	O	O	O	V	O	O	O	V			
4	A	A	A	A	O	A	A				
5	O	O	O	O	X	O					
6	X	O	O	O	O						
7	O	O	O	O							
8	O	O	O								
9	O	O									
10	O										
11											

[Legend: [1] Quality, [2] Taste, [3] Packaging, [4] Price, [5] Promotion, [6] Organic/Inorganic, [7] Advertisement, [8] Colour, [9] Nutrition, [10] Traceability and [11] Carbon Footprint, V[i/j] = Variable i/Variable j]

3.2.2 Reachability matrix

The SSIM has been converted into a binary matrix, called the initial reachability matrix, by substituting V, A, X, and O with 1 and 0 as per the case. The substitution of 1s and 0s are as per the following rules:

[1] If the (i, j) entry in the SSIM is V, the (i, j) entry in the reachability matrix becomes 1 and the (j, i) entry becomes 0.

[2] If the (i, j) entry in the SSIM is A, the (i, j) entry in the reachability matrix becomes 0 and the (j, i) entry becomes 1.

[3] If the (i, j) entry in the SSIM is X, the (i, j) entry in the reachability matrix becomes 1 and the (j, i) entry becomes 1.

[4] If the (i, j) entry in the SSIM is O, the (i, j) entry in the reachability matrix becomes 0 and the (j, i) entry becomes 0.

Following these rules, the initial reachability matrix for the trustworthiness factors influencing the beef purchasing decision is shown in Table 6.

Table 6. Initial Reachability Matrix

V[i/j]	1	2	3	4	5	6	7	8	9	10	11
1	1	1	0	1	0	0	0	0	1	0	1
2	1	1	0	1	0	0	0	0	0	0	0
3	1	1	1	1	0	0	0	1	0	0	0
4	0	0	0	1	0	0	0	0	0	0	0
5	0	0	0	1	1	0	1	0	0	0	0
6	1	1	0	1	0	1	0	0	0	0	1
7	0	0	0	0	1	0	1	0	0	0	0
8	0	0	0	1	0	0	0	1	0	0	0
9	1	0	0	1	0	0	0	0	1	0	0
10	1	0	0	1	0	0	0	0	0	1	0
11	1	0	0	1	0	1	0	0	0	0	1

[Legend: [1] Quality, [2] Taste, [3] Packaging, [4] Price, [5] Promotion, [6] Organic/Inorganic, [7] Advertisement, [8] Colour, [9] Nutrition, [10] Traceability and [11] Carbon Footprint, V[i/j] = Variable i/Variable j]

We used 'transitivity principle' to develop the final reachability matrix (Dubey and Ali, 2014; Dubey et al., 2015a, 2015b; Dubey et al., 2016). This principle can be clarified by the use of following example: if 'a' leads to 'b' and 'b' leads to 'c', the transitivity property implies that 'a' leads to 'c'. This property assists to eliminate the gaps among the variables if any (Dubey et al., 2016). By following the above criteria, the final reachability matrix is created and is shown in Table 7. Table 7 also shows the driving and dependence power of each variable. The driving power for each variable is the total number of variables (including itself), which it may help to achieve. On the other hand, dependence power is the total number of variables (including itself), which may help in achieving it. As per Dubey and Ali (2014), driving power is calculated by adding up the entries for the possibilities of interactions in the rows whereas the dependence is determined by adding up such entries for the possibilities of interactions across the columns. These driving power and dependence power will be used later in the classification of variables into the four groups including autonomous, dependent, linkage and drivers (Agarwal et al., 2007; Singh et al., 2007).

Table 7. Final Reachability Matrix

V[i/j]	1	2	3	4	5	6	7	8	9	10	11	DRP
1	1	1	0	1	0	1*	0	0	1	0	1	6
2	1	1	0	1	0	0	0	0	1*	0	1*	5
3	1	1	1	1	0	0	0	1	1*	0	1*	7
4	0	0	0	1	0	0	0	0	0	0	0	1
5	0	0	0	1	1	0	1	0	0	0	0	3
6	1	1	0	1	0	1	0	0	1*	0	1	6
7	0	0	0	1*	1	0	1	0	0	0	0	3
8	0	0	0	1	0	0	0	1	0	0	0	2
9	1	1*	0	1	0	0	0	0	1	0	1*	5
10	1	1*	0	1	0	0	0	0	1*	1	1*	6
11	1	1*	0	1	0	1	0	0	1*	0	1	6
DNP	7	7	1	11	2	3	2	2	7	1	7	50

[Legend: 1*: shows transitivity, DNP: Dependence Power, DRP: Driving Power, V: Variable]

3.2.3 Level partitions

The matrix is partitioned by assessing the reachability and antecedent sets for each variable (Warfield, 1974). The final reachability matrix leads to the reachability and antecedent set for each factor relating to consumer's purchase of beef. The reachability set $R(s_i)$ of the variable s_i is the set of variables defined in the columns that contained 1 in row s_i. Similarly, the antecedent set $A(s_i)$ of the variable si is the set of variables defined in the rows, which contain 1 in the column s_i. Then, the interaction of these sets is derived for all the variables. The variables for which the reachability and intersection sets are same are the top-level variables of the ISM hierarchy. The top-level variables of the hierarchy would not help to achieve any other variable above their own level in the hierarchy. Once the top-level variables are identified, it is separated out from the rest of the variables. Then, the same process is repeated to find out the next level of variables and so on. These identified levels help in building the digraph and the final ISM model (Agarwal et al., 2007; Singh et al., 2007). In the present context, the variables along with their reachability set, antecedent set, and the top level is shown in Table 8. The process is completed in 3 iterations (in Tables 8-11) as follows:

In Table 8, only one variable price (Variable 4) is found at level I as the element (i.e., Element 4 for Variable 4) for this variable at reachability and intersection set are same. So, it is the only variable that will be positioned at the top of the hierarchy of the ISM model.

Table 8. Partition on Reachability Matrix: Interaction I

Element P(i)	Reachability Set: R(Pi)	Antecedent Set: A(Pi)	Intersection Set: R(Pi)∩A(Pi)	Level
1	1,2,4,6,9,11	1,2,3,6,9,10,11	1,2,6,9,11	
2	1,2,4,9,11	1,2,3,6,9,10,11	1,2,9,11	
3	1,2,3,4,8,9,11	3	3	
4	4	1,2,3,4,5,6,7,8,9,10,11	4	I
5	4,5,7	5,7	5,7	
6	1,2,4,6,9,11	1,6,11	1,6,11	
7	4,5,7	5,7	5,7	
8	4,8	3,8	8	
9	1,2,4,9,11	1,2,3,6,9,10,11	1,2,9,11	
10	1,2,4,9,10,11	10	10	
11	1,2,4,6,9,11	1,2,3,6,9,10,11	1,2,6,9,11	

In Table 9, maximum seven variables including 1 (i.e., quality), 2 (i.e., taste), 5 (i.e., promotion), 7 (i.e., advertisement), 8 (i.e., colour), 9 (i.e., nutrition) and 11 (i.e., carbon footprint) are put at level II as the elements (i.e., elements 1, 2, 6, 9 and 11 for variable 1; elements 1, 2, 9 and 11 for variable 2; elements 5 and 7 for each of the variables 5 and 7; element 8 for variable 8; elements 1, 2, 9 and 11 for variable 9; and elements 1, 2, 6, 9 and 11 for variable 11) for these variables at reachability and intersection set are same. Thus, they will be positioned at level II in the ISM model. Moreover, we also remove the rows corresponding to variable 4 from Table 9, which are already positioned at the top level (i.e., Level I).

Table 9. Partition on Reachability Matrix: Interaction II

Element P(i)	Reachability Set: R(Pi)	Antecedent Set: A(Pi)	Intersection Set: R(Pi)∩A(Pi)	Level
1	1,2,6,9,11	1,2,3,6,9,10,11	1,2,6,9,11	II
2	1,2,9,11	1,2,3,6,9,10,11	1,2,9,11	II
3	1,2,3,8,9,11	3	3	
5	5,7	5,7	5,7	II
6	1,2,6,9,11	1,6,11	1,6,11	
7	5,7	5,7	5,7	II
8	8	3,8	8	II
9	1,2,9,11	1,2,3,6,9,10,11	1,2,9,11	II
10	1,2,9,10,11	10	10	
11	1,2,6,9,11	1,2,3,6,9,10,11	1,2,6,9,11	II

The same process of deleting the rows corresponding to the previous level and marking the next level position to the new table is repeated until we reach to the final variable in the table. In Table 10, variable 3 (i.e., packaging), variable 6 (i.e., organic/inorganic) and variable 10 (i.e., traceability) are kept at Level III as the elements (i.e., element 3 for variable 3; element 6 for variable 6; and element 10 for variable 10) at reachability set and intersection set for all these variables are same. Thus, it will be positioned at Level III in the ISM model.

Table 10. Partition on Reachability Matrix: Interaction III

Element P(i)	Reachability Set: R(Pi)	Antecedent Set: A(Pi)	Intersection Set: R(Pi)∩A(Pi)	Level
3	3	3	3	III
6	6	6	6	III
10	10	10	10	III

3.2.4 Developing canonical matrix

A canonical matrix is developed by clustering variables in the same level, across the rows and columns of the final reachability matrix as shown in Table 11. This matrix is just the other more convenient form of the final reachability matrix (i.e., Table 7) as far as drawing the ISM model is concerned.

Table 11. Canonical Form of Final Reachability Matrix

V[i/j]	4	1	2	5	7	8	9	11	3	6	10	LVL
4	1	0	0	0	0	0	0	0	0	0	0	I
1	1	1	1	0	0	0	1	1	0	1	0	II
2	1	1	1	0	0	0	1	1	0	0	0	II
5	1	0	0	1	1	0	0	0	0	0	0	II
7	1	0	0	1	1	0	0	0	0	0	0	II
8	1	0	0	0	0	1	0	0	0	0	0	II
9	1	1	1	0	0	0	1	1	0	0	0	II
11	1	1	1	0	0	0	1	1	0	1	0	II
3	1	1	1	0	0	1	1	1	1	0	0	III
6	1	1	1	0	0	0	1	1	0	1	0	III
10	1	1	1	0	0	0	1	1	0	0	1	III
LVL	I	II	II	II	II	II	II	II	III	III	III	

[Legend: LVL: Level, V: Variable]

3.2.5 Formation of ISM

From the canonical form of the reachability matrix as shown in Table 11, the structural model is generated by means of vertices and nodes and lines of edges. If there is a relationship between the factors i and j considered by the consumers while purchasing beef, this is shown by an arrow that points from i to j. This graph is called directed graph or digraph. After removing the indirect links as suggested by the ISM methodology, the digraph is finally converted into ISM-based model as depicted in Figure 2.

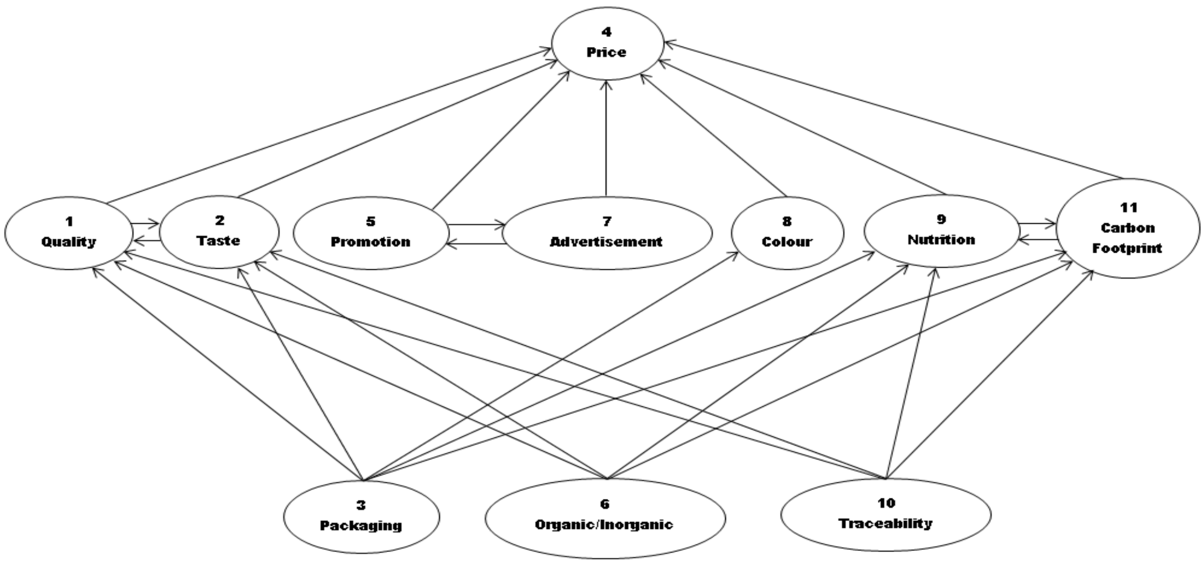

Figure 2. ISM Model

In the ISM methodology, binary digits (0 and 1) are considered. If there is a linkage then relationship is denoted by 1 and if there is no linkage then, 0 is used to denote the relationship. The strength of relationship between two factors is not being taken into account in this methodology. The relationship among two factors could be no relationship, very weak, weak, strong and very strong. The shortcoming of this methodology is addressed by using ISM fuzzy MICMAC analysis, which is described in the next section.

4. ISM fuzzy MICMAC analysis

In the ISM model, we have considered binary digits i.e. 0 or 1. If there is no linkage between the variables, then the relationship is denoted by 0 and if there is linkage then the relationship is denoted by 1. However, there is no scope for discussion in this matrix about the strength of relationship. The relationship between any two variables in the matrix could be defined as very weak, weak, strong and very strong or there is no relationship between them at all. To overcome the limitations of ISM modelling, a fuzzy ISM is used for MICMAC analysis (Gorane and Kant, 2013). The steps for ISM fuzzy MICMAC analysis are performed as follows:

4.1 Synthesis of Direct Relationship Matrix (DRM)

Making diagonal entries zero and ignoring transitivity in the final reachability matrix generate DRM (see Table 12). In the current context, it is essentially the calculation of direct relationships among the variables influencing consumers' beef purchasing behaviour.

Table 12. Binary direct relationship matrix

V[i/j]	1	2	3	4	5	6	7	8	9	10	11
1	0	1	0	1	0	0	0	0	1	0	1
2	1	0	0	1	0	0	0	0	0	0	0
3	1	1	0	1	0	0	0	1	0	0	0
4	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	1	0	0	1	0	0	0	0
6	1	1	0	1	0	0	0	0	0	0	1
7	0	0	0	0	1	0	0	0	0	0	0
8	0	0	0	1	0	0	0	0	0	0	0
9	1	0	0	1	0	0	0	0	0	0	0
10	1	0	0	1	0	0	0	0	0	0	0
11	1	0	0	1	0	1	0	0	0	0	0

[Legend: 1-Quality, 2-Taste, 3-Packaging, 4-Price, 5-Promotion, 6-Organic/Inorganic, 7-Advertisement, 8-Colour, 9-Nutrition, 10-Traceability, 11-Carbon Footprint]

4.2 Developing Fuzzy Direct Relationship Matrix (FDRM)

A fuzzy direct relationship matrix (FDRM) was constructed by putting a diagonal series of zero values into the correlation matrix (Table 13), and, by ignoring the transitivity rule of the initial RM. The traditional MICMAC analysis considers only a binary interaction and therefore to improve the sensitivity of traditional MICMAC analysis, fuzzy set theory has been used. The investigation is more enhanced as it considers the "possibility of reachability/achievement" in addition to the simple deliberation of reachability used thus far. According to the theory of fuzzy set, the possibilities of additional interactions between the variables on the scale 0-1 (Qureshi et al., 2008) are constructed using the specifications: No -0, Negligible – 0.1, Low - 0.3, Medium – 0.5, High - 0.7, Very High – 0.9 and Full -1. By using these values, again the judgments of same experts are considered to rate the relationship between two key variables influencing consumers' beef purchasing behavior. Fuzzy direct relationship matrix (FDRM) for key variables influencing consumers' beef purchasing behavior is presented in Table 13.

Table 13. FDRM for variables influencing consumers' beef purchasing behaviour

V[i/j]	1	2	3	4	5	6	7	8	9	10	11
1	0	0.9	0	0.7	0	0	0	0	0.7	0	0.5
2	0.9	0	0	0.5	0	0	0	0	0	0	0
3	0.5	0.3	0	0.5	0	0	0	0.7	0	0	0
4	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0.1	0	0	0.1	0	0	0	0
6	0.5	0.5	0	0.5	0	0	0	0	0	0	0.7
7	0	0	0	0	0.1	0	0	0	0	0	0
8	0	0	0	0.1	0	0	0	0	0	0	0
9	0.5	0	0	0.5	0	0	0	0	0	0	0
10	0.7	0	0	0.9	0	0	0	0	0	0	0
11	0.5	0	0	0.3	0	0.7	0	0	0	0	0

[Legend: 1-Quality, 2-Taste, 3-Packaging, 4-Price, 5-Promotion, 6-Organic/Inorganic, 7-Advertisement, 8-Colour, 9-Nutrition, 10-Traceability, 11-Carbon Footprint]

4.3. Developing fuzzy stabilised matrix

The concept of fuzzy multiplication is used on FDRM to obtain stabilization (Saxena and Vrat, 1992). This notion states that matrix is multiplied until the values of driving and dependence powers are stabilized (Qureshi et al., 2008). Driving and dependence power are obtained by adding row and column entries separately. The stabilized matrix for fuzzy MICMAC for variables influencing consumers' beef purchasing behaviour is obtained in Table 14.

Table 14. Stabilized matrix for variables influencing consumers' beef purchasing behaviour

V[i/j]	1	2	3	4	5	6	7	8	9	10	11	Driving Power
1	0.9	0.5	0	0.5	0	0.5	0	0	0.5	0	0.5	3.4
2	0.5	0.9	0	0.7	0	0.5	0	0	0.7	0	0.5	3.8
3	0.5	0.5	0	0.5	0	0.5	0	0	0.5	0	0.5	3.0
4	0	0	0	0	0	0	0	0	0	0	0	0.0
5	0	0	0	0	0.1	0	0	0	0	0	0	0.1
6	0.5	0.5	0	0.5	0	0.7	0	0	0.5	0	0.5	3.2
7	0	0	0	0.1	0	0	0.1	0	0	0	0	0.2
8	0	0	0	0	0	0	0	0	0	0	0	0.0
9	0.5	0.5	0	0.5	0	0.5	0	0	0.5	0	0.5	3.0
10	0.5	0.7	0	0.7	0	0.5	0	0	0.7	0	0.5	3.6
11	0.5	0.5	0	0.5	0	0.5	0	0	0.5	0	0.7	3.2
Dependence Power	3.9	4.1	0.0	4.0	0.1	3.7	0.1	0.0	3.9	0.0	3.7	**23.5**

4.4. Classification of categories of variables using MICMAC analysis

The classification of variables has been divided into four categories based on dependence and driving powers by using fuzzy MICMAC analysis. Figure 3 shows that there are four categories in which these 11 variables are assigned as per their new driving and dependence power. The first region belongs to autonomous variables, which have less driving and less dependence power. These variables lie nearby origin and remains disconnected to entire system. Three variables 5 (i.e. promotion), 7 (i.e. advertisement) and 8 (i.e. colour) falls under this cluster. The second region belongs to dependence variables, which have high dependence and low driving power. The only variable falls under this cluster is 4 (i.e. price), which indicates price as the ultimate dependent variable as it can be visualized from the previous MICMAC analysis as well. The third region belongs to linkage variables, which have high driving and high dependence power. In the modified MICMAC analysis, highest five variables including 1 (i.e. quality), 2 (i.e. taste), 6 (i.e. organic/inorganic), 9 (i.e. nutrition) and 11 (i.e. carbon footprint) fall in this category. The fourth and final category of variables belongs to independent variables, which have high driving and low dependence power. Two variables 3 (i.e. packaging) and 10 (i.e. traceability) fall under this region. These are the key driving variables and are generally found at the bottom of the ISM model.

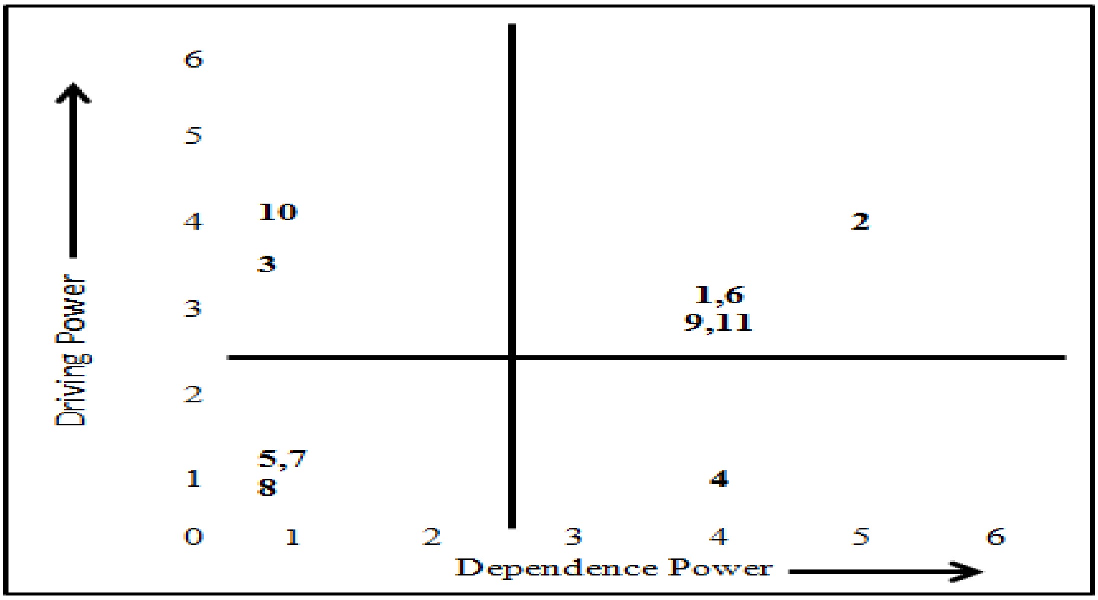

Figure 3. Cluster of variables

4.5. Integrated ISM model development

An integrated ISM model is developed using the driving and dependence powers obtained from fuzzy stabilized matrix. The value of dependence power is subtracted from driving power to obtain the effectiveness of each variable, which is shown in Table 15. The variables having low value of effectiveness are placed at the bottom levels in the model.

The integrated model of variables influencing consumers' beef purchasing behaviour is drawn from the values of effectiveness as shown in Figure 4.

Table 15. Effectiveness and ranking of variables

V[i/j]	Driving Power (DR)	Dependence Power (DP)	Effectiveness (DR-DP)	Level
1	3.4	3.9	-0.5	III
2	3.8	4.1	-0.3	IV
3	3.0	0.0	3.0	VII
4	0.0	4.0	-4.0	I
5	0.1	0.1	0.0	V
6	3.2	3.7	-0.5	III
7	0.2	0.1	0.1	VI
8	0.0	0.0	0.0	V
9	3.0	3.9	-0.9	II
10	3.6	0.0	3.6	VIII
11	3.2	3.7	-0.5	III

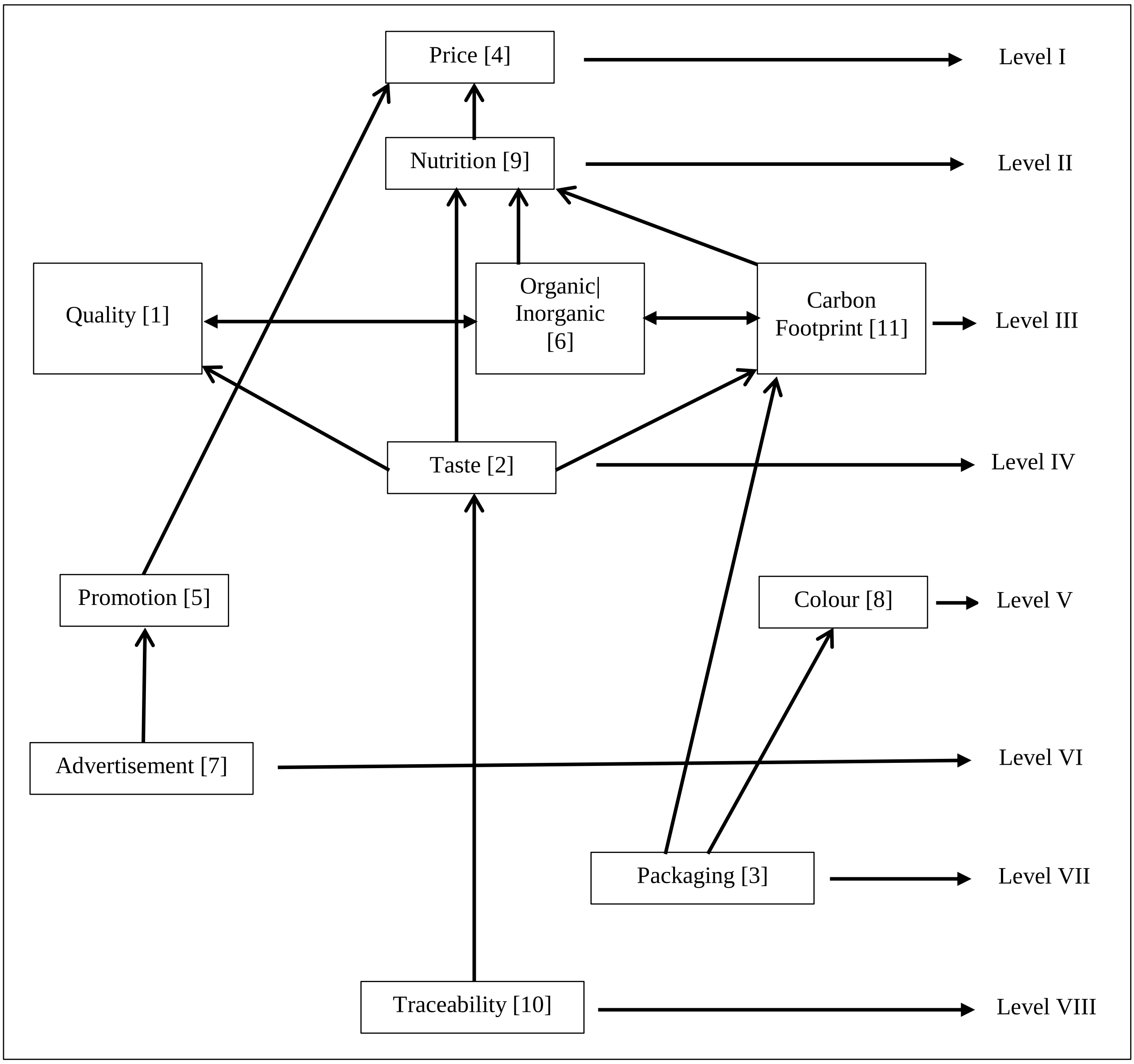

Figure 4. Integrated ISM Model

4.6 Comparison of ISM and ISM-Fuzzy MICMAC based models

This research first identified factors influencing consumer's beef purchasing decisions using literature survey and social media Big Data analysis and implemented ISM based model to understand the interrelationships between these factors across different levels. In the ISM model, we have considered binary digits i.e. 0 and 1, however this methodology does not provide any further details about the strength of relationship. The relationship between two factors could be very weak, weak, strong or very strong or there is no relationship. To overcome the limitations of ISM model, the Fuzzy ISM is used for the

MICMAC analysis (Dubey and Ali, 2014). The ISM model splits the factors only into three levels whereas integrated ISM expands it into eight levels. The ISM model shown in Figure 2 shows the contribution of factors such as packaging (3), organic/inorganic (6) and traceability (10) at Level 3 and form the foundation of the ISM hierarchical structure for the factors influencing consumer's beef purchasing decisions. However, in the integrated ISM model only traceability (10) is shown to be at the very bottom level indicating it as a key driving factor to identify other factors influencing consumer's beef purchasing decisions whereas the other two factors i.e. packaging (3) and organic/inorganic (6) were found at Level 7 and Level 3 respectively. This clearly indicates that factors 3 (i.e. packaging) and 10 (i.e. traceability) have higher effectiveness in terms of drivers in the integrated ISM as well. However, organic/inorganic factor has been found more toward the upper level (i.e. Level 3) in the integrated ISM model. There are six variables in the ISM model at Level 2, which have got scattered over five different levels in between the top and the bottom levels (i.e. from Level 2 to Level 6) in the integrated ISM model. In other words, the integrated ISM model (see Figure 4) provides more detailed levelling of each one of the factors shown in Level 2 in the ISM model (see Figure 2). However, from the integrated ISM model, it can be understood that a factor placed at a definite level will not aid in accomplishing any other factor placed at the level above it. For example, the factors placed at Level 5 such as promotion (5) and colour (8) would not facilitate in accomplishing any other factors such as taste (2), quality (1), carbon footprint (11) and nutrition (9) which are placed above them and were not distinguished at different levels in the ISM model. As far as the key dependent variable (i.e. price (4)) is concerned, it remains same for both ISM and integrated ISM models. This indicates that all middle level variables, no matter what levels they are placed at, can influence price, which has the highest influence on the consumer's willingness to purchase beef products.

5. Discussion

During the investigation, it was found that consumers' buying preferences while purchasing beef products are vastly dependent on their price. The variable 'price' has high dependence and low driving power. It is dependent on nutritional value and ongoing promotions. The beef derived from grass-fed cattle is higher in nutrition in terms of omega-3 fatty acid, conjugated linoleic acid (CLA) and have lower amounts of saturated and monounsaturated fats as compared to grain-fed cattle (Daley et al., 2010). The grass-fed cattle takes more time to reach finishing age (Profita, 2012) and are more expensive than grain-fed cattle (Gwin, 2009). The ongoing promotions in retail stores have a direct influence on the price of the beef products (Darke and Chung, 2005).

The variables like quality, taste, carbon footprint, organic/inorganic and nutrition have high dependence and high driving power in terms of influencing consumer's decision for purchasing beef products. Quality and organic/inorganic are interrelated variables as depicted in Figure 4. The organic/inorganic label in beef products reflects the sustainable practices used in the production of beef products and are associated with high quality, lower carbon footprint, higher nutrition, better taste and colour stability for longer duration of time (Fernandez and Woodward, 1999; Kahl et al., 2014; Nielsen and Thamsborg, 2005; Załęcka et al., 2014; Zanoli et al., 2013). Organic food is usually sold at a higher price than their conventionally produced counterparts. However, still, some consumers are ready to pay extra because they are worried about the food safety, impact on environment and use of pesticides, hormones and other veterinary drugs in beef farms. Organic food assists in solving the problems of animal welfare, rural development and numerous issue of food production (Capuano et al., 2013). Organic/inorganic and carbon footprint also have an interrelationship. The organic beef products associated with higher nutrition are derived from grass-fed cattle, which took more time to reach finishing age (Ruviaro et al., 2015). Hence, the beef products derived from grass-fed cattle have higher carbon footprint. Similarly, the beef products having higher carbon emission are associated with beef products derived from grass-fed cattle (organic beef) as majority of the carbon emission is generated in terms of cattle taking longer time to reach finishing age (Capper, 2012). Nutrition of beef products is found to be dependent on taste, organic/inorganic and carbon footprint as depicted in Figure 4. Excellent flavour and organic beef are considered to be a determinant of the nutritional value of beef products (Yiridoe et al., 2005). Beef products having high carbon footprint (grass-fed) have better nutritional value (Profita, 2012).

The variables promotion, advertisement and colour have low driving and dependence power. Advertisement via television, radio, social media etc. has a direct impact on promotions in retail stores. Colour of beef products is significantly influenced by the variant of packaging used. For instance, beef products in Modified Atmosphere Packaging (MAP) have shelf life of around eight to ten days where as Vacuum Skin Packaging (VSP) provides shelf life of up to twenty one days (Meat Promotion Wales, 2012).

Traceability and packaging have the highest driving power and have very low dependence. The beef products produced with strict traceability procedures are often attributed with better taste, nutrition, and quality (Giraud and Amblard, 2003; Verbeke and Ward, 2006; van Rijswijk et al., 2008a; van Rijswijk and Frewer, 2008). During the study, it was found that traceability helps consumers to find different information related to animal breed, slaughtering, food safety and quality. Generally, retailers use traceability information to boost consumer confidence (van Rijswijk and Frewer, 2008). The variant of packaging employed in beef products affects the carbon footprint. Vacuum Skin Packaging (VSP) are lightweight, requires fewer corrugate for logistics, gives longer shelf life and thereby reduces retailer food loss and consumer food waste and requires less fuel in transport as compared to Modified Atmosphere packaging (MAP) (Mashov, 2009).

The bottom level variables viz. traceability and packaging have high driving power but no dependence on them. They strongly affect the middle level variables like promotion, advertisement, colour, quality, taste, carbon footprint, organic/inorganic and nutrition. The middle level variables in turn affect the price, which has the highest influence on the consumer's willingness to purchase beef products. Therefore, it can be concluded that two variables traceability and packaging influence the price of the beef products, which in turn has an impact on consumer's decision for purchasing beef products.

This study reveals two factors: traceability and packaging, which needs to be improved and maintained throughout the supply chain of beef retailers in order to allure consumers. For instance, many retailers utilise superior quality packaging for the beef products, however, it gets damaged within the supply chain, which could be due to mishandling at logistics, warehouse or in the retailer's store. Hence, a strong vertical coordination should be developed within the whole beef supply chain so that the quality of packaging is retained till the beef products are sold to consumers. The strong vertical coordination among all stakeholders of beef supply chain viz. farmer, abattoir, processor, logistics and retailer would also assist in achieving the traceability of beef products, which is another crucial driving factor influencing consumer's buying preferences.

Nowadays, consumers are very conscious about their health and nutrition (Van Wezemael et al., 2014; Cavaliere et al., 2015; Van Doorn and Verhoef, 2015). They are looking for food products having high nutrition and safe to consume (Liu et al., 2013; Van Wezemael et al., 2014). During the ISM fuzzy MICMAC analysis, it was found that customers makes a trade-off between price and quality, taste, food safety, nutrition, colour while purchasing the beef products. Using proper packaging, labelling information, retailers can boost customer confidence. Further, the beef industry could utilise modern technology like cloud computing technology to bring all the stakeholders on one platform (Singh et al., 2015) and can manage the information flow effectively which will result in high quality beef products at lower carbon footprint in minimum cost and can get maximum market share.

In modern era, food industries struggle to anticipate the quantity and quality of food products to meet the expectations of consumers, which lead to overproduction of food products and reducing market share of food companies (Corrado et al., 2017; Silvennoinen et al., 2014; Garrone et al. 2014). This scenario is a mutual loss to both food industries and consumers. In order to fulfil this gap, major food retailers have taken lots of attempts to receive consumer feedback via market survey, market research, interview of consumers and providing the opportunity to consumers to leave feedback in retail store and use this information for improving their supply chain strategy (Mishra and Singh, 2016). Still, they cannot get the inputs from the larger audiences and sometimes the information gathered by these methods are biased and inaccurate. The current study utilises the social media data, which covers larger audience and consists of real time true opinion of consumers. The amalgamation of Twitter analytics and ISM has identified the most crucial factors (and their inter-relationships) needed to achieve consumer centric supply chain. It will assist business firms to have an edge over their rivals and enhance their market share. The analysis of the crucial factors and their interrelationships will assist business firms in prioritising their actions, appropriate decision making in terms of where to start making modification to achieve consumer centric supply chains.

The current study provides some new insights into developing consumer centric beef supply chain. In the past, price and quality of beef products used to be the detrimental factors for consumers purchasing beef products (Acebrón & Dopico, 2000; Kukowski et al., 2005; Brunsø et al., 2005; Becker, 2000). However, during the study, it was observed that apart from quality and price, traceability has emerged as a high driving factor and it influences consumer's buying behaviour. After the horsemeat scandal in Europe in 2013, traceability of beef products has gained vital significance among the consumers (Henchion et al., 2017; Clemens & Babcock, 2015; Menozzi et al., 2015). Apart from traceability, packaging also appeared as one of the prime driver influencing the consumer's beef purchasing behaviour (Verbeke et al., 2005; Grobbel et al., 2008). Along with visual cues, it has great impact on the shelf life of beef products (Grobbel et al., 2008). Experts working in beef industry also unequivocally rated it as a crucial factor affecting choices made by the consumers. This study will help beef industry to restructure their priorities to develop an efficient, resilient, and sustainable supply chain in longer run.

5.1 Managerial implications and theoretical contributions

The proposed framework is vital for both academia and industry in streamlining the supply chain and improving participation of all stakeholders. The revealing of interaction of various mandatory factors to achieve consumer centric supply chain would assist in improving vertical and horizontal collaboration within the supply chain. Consequently, an efficient strategy would be developed by taking the drivers into account for increasing market share of a business firm, having advantage over their rivals and developing a consumer centric supply chain. This mechanism will assist in appropriate partner selection within the supply chain to improve sustainability. It will assist the managers of small and medium size stakeholders in the supply chain, who lacks awareness about consumer priorities, such as farmers lack awareness of consumers seeking traceability in meat products.

The paper has a two-fold contribution to the literature on the consumer interest in beef. Firstly, although many research studies (e.g., Reicks et al., 2011; Robbins et al., 2003; Thilmany et al., 2006) in the beef industry have focused on the motivational factors affecting consumers' purchasing decisions while purchasing beef, none of them have offered an alternative approach to theory building emerging from the various quality characteristics and other factors that could be considered while purchasing beef. This research undertakes a comprehensive review of literature generating the most important eleven factors or clusters and devises a theoretical framework based on the interrelationships of those variables emerging from the consumers (social media data) and experts' opinion using ISM and fuzzy MICMAC analysis. Secondly, this research further extends the existing literature on consumers' decisions toward purchasing beef by offering a strategic framework, which is not only based on literature but also validated using the big data clustering technique that divides all such potential variables in the most important clusters that influence consumers' beef purchasing decisions. In current research, the number of such clusters coincides to eleven factors. Therefore, the proposed theoretical framework extrapolates eleven factors at eight different layers and their interrelationships highlighting the specific roles of these variables.

6. Conclusion and future research

Food is a significant commodity for enduring human life as compared to other essentials. In today's competitive market, consumers are very selective. To sustain in this competitive scenario, retailers have to investigate the purchasing behaviour of consumers and the factors influencing it. They must investigate how these factors are linked with each other and which of the factors belong to the category of driver, dependent, linkage and autonomous respectively. It will help the retailers in waste minimisation, streamlining their supply chain, improving its efficiency and making it more consumer centric.

In this study, initially, systematic literature review was conducted to identify the factors influencing the consumers' decision for buying beef products. Then, cluster analysis on consumers' information from Twitter in the form of big data was conducted. It assists in finding how the variables determining the consumers' beef products buying preferences are influenced. Then experts' opinion, ISM and fuzzy MICMAC analysis are used to classify eleven variables into: linkage, dependent, driver and independent variables and their interrelationships are explored. During the study, it was observed that price of the beef product is the most important criteria driving the purchasing decision of consumers. It is followed by nutrition, quality, organic/inorganic, carbon footprint, taste, promotion, colour and advertisement. Based on the findings, recommendations were given for making consumer centric supply chain. Future studies can be performed to develop a theoretical mechanism for sustainable consumer centric supply chain by assimilating some more aspects. Furthermore, confirmatory investigation of variables could be conducted to validate the theoretical framework developed. The proposed model could be validated by using Systems Dynamic Modelling (SDM) and Structural Equation Modelling (SEM). The factors identified to develop consumer centric beef supply chain could be quantified by employing Analytical Network Process (ANP) and Analytical Hierarchical Process (AHP). These factors could be further ranked by utilising Interpretive Ranking Process (IRP) to develop consumer centric beef supply chain.

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Acknowledgement

The authors would like to thank the project 'A cross country examination of supply chain barriers on market access for small and medium firms in India and UK' (Ref no: PM130233) funded by British Academy, UK for supporting this research.

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Ann Oper Res
DOI 10.1007/s10479-016-2303-4

BIG DATA ANALYTICS IN OPERATIONS & SUPPLY CHAIN MANAGEMENT

Use of twitter data for waste minimisation in beef supply chain

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Abstract Approximately one third of the food produced is discarded or lost, which accounts for 1.3 billion tons per annum. The waste is being generated throughout the supply chain viz. farmers, wholesalers/processors, logistics, retailers and consumers. The majority of waste occurs at the interface of retailers and consumers. Many global retailers are making efforts to extract intelligence from customer's complaints left at retail store to backtrack their supply chain to mitigate the waste. However, majority of the customers don't leave the complaints in the store because of various reasons like inconvenience, lack of time, distance, ignorance etc. In current digital world, consumers are active on social media and express their sentiments, thoughts, and opinions about a particular product freely. For example, on an average, 45,000 tweets are tweeted daily related to beef products to express their likes and dislikes. These tweets are large in volume, scattered and unstructured in nature. In this study, twitter data is utilised to develop waste minimization strategies by backtracking the supply chain. The execution process of proposed framework is demonstrated for beef supply chain. The proposed model is generic enough and can be applied to other domains as well.

Keywords Big data · Beef supply chain · Waste minimisation · Twitter analytics

1 Introduction

World population will be around 9 billion by 2050. Huge amount of resources will be needed to feed these enormous amounts of people. There are millions of people losing their lives globally because of hunger on daily basis. On the other hand, one third of the food produced globally is lost within the supply chain or get wasted at the consumer end (Food and Agricul-

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Published online: 28 September 2016

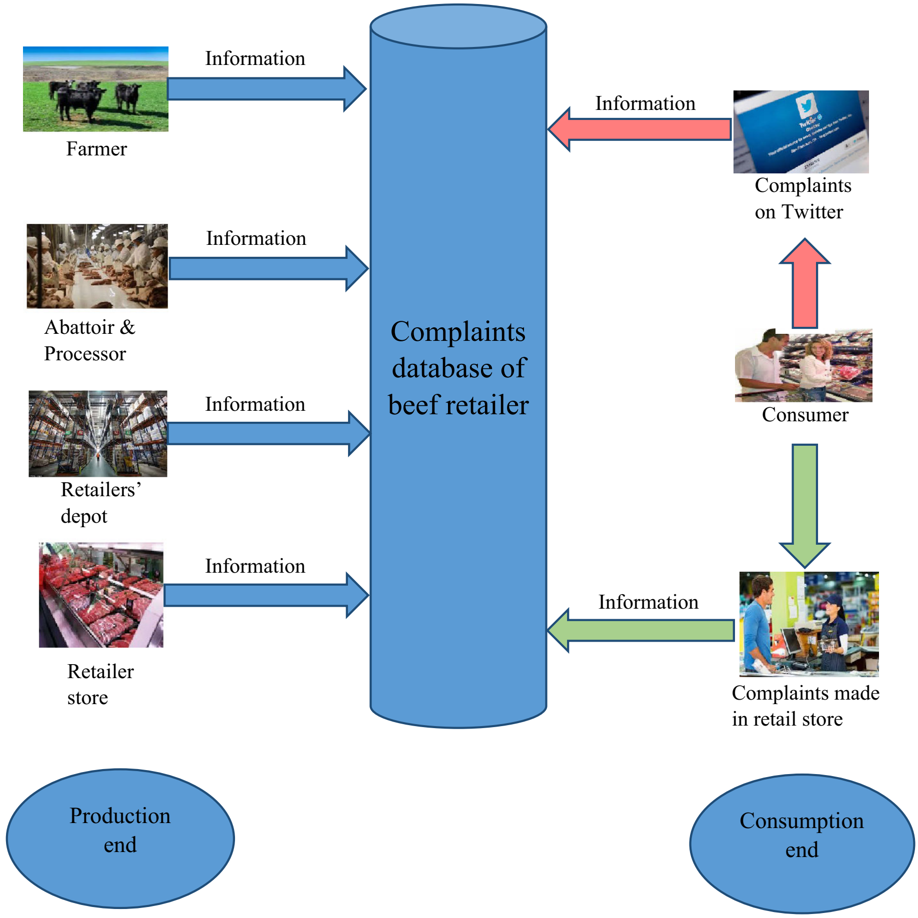

Fig. 1 Various ways of receiving waste related information for beef retailer

ture Organization of the United Nations). This food waste is worth around US $ 680 billion per year in developed countries and approx. US $ 310 billion per year in developing countries (Save Food 2015). All the stakeholders of the food supply chain: farmers, wholesalers, logistics, retailers and consumers have the onus of food waste. Waste might be generated at one end in the supply chain and their root cause might be linked to other segment of the supply chain. For example, if the beef gets discoloured before its sell by date, it may be because of the lack of vitamin E diet fed to the cattle in the beef farms (Liu et al. 1995). Different segments of food supply chain are generating various kinds of waste. Food retailer chains are facing enormous pressure from government legislation, competition from rival brands, sustainable production etc. to minimise the waste in their supply chain. Every day, retailers are collecting enormous amount of data from farmers, abattoir and processors, retailers and consumers as shown in Fig. 1. These data can be utilised to increase the efficiency and minimise the waste. In literature, various methodologies such as six sigma (Nabhani and Shokri 2009), lean principles (Cox and Chicksand 2005), value chain analysis (Taylor 2006), etc. have been developed to address various issues at farmer, processor and retailer end. The maximum amount of waste is being generated at the consumer end. Retailers are trying to utilise the complaints made by consumers in the retail store for waste minimisation. Majority of the customers don't leave the complaints in the store because of various reasons like inconvenience, lack of time, distance, ignorance etc. Therefore, only limited information is available in the retailer stores about the issues faced by consumers, which are leading to food waste. Social media have now become the part and parcel of everyone's life to express their opinions. Many of the customers who are not pleased with food products leave their complaints on the social media every day. These information are enormous and scattered in nature and resembles to the salient features of big data i.e. volume, variety, velocity (Wang et al. 2016; Shuihua et al. 2016; Song et al. 2016; Tayal and Singh 2016) as mentioned below:

1. Volume—Great volume of data, which required big storage or contain large number of records or information. At present, there are 310 million active users on twitter, who are freely expressing their concern (Twitter Usage Statistics 2016).
2. Velocity—Data generate with high frequency. On an average, 500 million tweets related to different topics are tweeted every day (Twitter Usage Statistics 2016).
3. Variety—Data gathered from different sources, format and/or having multidimensional data fields. Consumers express their attitude, sentiments, opinions and thoughts in the form of unstructured data i.e. text, tweets, posts, pictures and videos.

During the study, it was found that on an average, 45,000 tweets are made every day, which are related to beef products. These tweets consist of various quality attributes and problems associated with beef products like flavour, rancidity, discoloration, presence of foreign body, etc. These data can be utilised by retailer to identify the root causes of waste and consequently help in developing waste minimisation in longer term. However, the nature of consumer complaints on social media is quite vague and unstructured. In literature, there was no framework available to link them to root causes of waste in different segments of supply chain. In this article, architecture is proposed to collect and analyse information from twitter and consequently link them to the root causes of food waste in the supply chain.

The organisation of the article is as follows: Sect. 2, consists of literature review of research work done in the domain of big data and food waste in the supply chain. Section 3, consists of beef supply chain and social media data. Section 4, comprises of twitter analytics framework. Section 5, demonstrates the implementation of the framework on beef supply chain. Section 6, includes managerial implications of the framework. Finally, the article is concluded in Sect. 7.

2 Literature review

Food waste is occurring at different stages of the supply chain from farms to the retailer. Various techniques have been employed in the past to address this issue by identifying the root causes of food waste and consequently mitigating them such lean principles (Cox and Chicksand 2005), value chain analysis (Taylor 2006), six sigma (Nabhani and Shokri 2009), and just in time principle. Cicatiello et al. (2016) have explored the waste occurring at retailer end and its environmental, economic and social implications. The data collected from an Italian supermarket project was utilized to develop food waste recovery strategy. In this research both physical and monetary value of food was considered. Mena et al. (2011) have found out the principal causes leading to food waste in the supplier retailer interface. The management practices of UK and Spain have been compared using current reality tree method. Various good practices such as efficient forecasting, shelf life management, promotion management, cold chain management and proper training to employees, etc. have been suggested to mitigate the root causes of waste. Katajajuuri et al. (2014) has quantified the amount of avoidable waste occurring in the food production and consumption chain in Finland. It was found that households were creating 130 million Kg of food waste per year. The waste occurring in food service sector is about 75–85 million kg per year. The whole food industry in Finland was producing waste of 75–140 million kg per annum. It was concluded that overall 335–460 million kg of waste is generated in the finish food chain (excluding farming sector). Francis et al. (2008) have employed value chain analysis technique to evaluate UK beef sector. Waste elimination strategy was developed at producer and processor level in UK beef supply chain by comparing them with Argentine counterparts. Also, good management practices are proposed to minimise the waste.

The majority of waste in beef supply chain is generated at the consumer end. Waste is generated by various issues such as discolouration of beef products prior to expiry of shelf life (Jeyamkondan et al. 2000), lack of tenderness (Goodson et al. 2002; Huffman et al. 1996), presence of extra fat (Brunsø et al. 2005), oxidisation of beef (Brooks 2007), presence of foreign bodies in beef products (FSA 2015) and inefficient cold chain management (Kim et al. 2012; Mena et al. 2011). These root causes are occurring at consumer end because of the issues within the beef supply chain. For instance, discoloration of beef could be due to lack of vitamin E in the diet of cattle (Liu et al. 1995; Houben et al. 2000; Cabedo et al. 1998; O'Grady et al. 1998; Lavelle et al. 1995; Mitsumoto et al. 1993) and temperature abuse of beef products along the supply chain (Rogers et al. 2014; Jakobsen and Bertelsen 2000; Gill and McGinnis 1995; van Laack et al. 1996; Jeremiah and Gibson 2001; Greer and Jones 1991). Lack of tenderness is because of absence or inefficient maturation of carcass from which beef products are derived (Riley et al. 2005; Vitale et al. 2014; Franco et al. 2009; Gruber et al. 2006; Monsón et al. 2004; Sañudo et al. 2004; Troy and Kerry 2010). Presence of extra fat could be due to cattle being not raised as per the weight and conformation specifications of the retailer (Hanset et al. 1987; Herva et al. 2011; Borgogno et al. 2016; AHDB Industry Consulting 2008; Boligon et al. 2011) and inefficient trimming procedures in the boning hall in abattoir (Francis et al. 2008; Mena et al. 2014; Kale et al. 2010; Watson 1994; Cox et al. 2007). The oxidisation of beef could be occurring because of improper packaging at abattoir and processor, damage of packaging along the supply chain and inappropriate packaging technique being followed (Brooks 2007; Lund et al. 2007; Singh et al. 2015). The presence of foreign bodies could be due to improper packaging because of machine error at abattoir and processor, lack of safety checks such as metal detection, physical inspection and lack of renowned food safety process management procedures being followed such as HACCP (Goodwin 2014). The inefficient cold chain management could be because of lack of periodic maintenance of refrigeration equipment (Kim et al. 2012).

In literature, various mechanisms have been developed to analyse big data to mitigate various challenges, bottlenecks in the supply chain. Chae (2015) and Hazen et al. (2016) have suggested a mechanism of twitter analytics for analysis of tweets in the domain of supply chain management. They have attempted to develop an understanding of prospective role of Twitter in the practice of supply chain management and future research. This framework consists of three techniques called descriptive analysis, content analysis and network analysis. It was found that supply chain tweets are being utilised by various professional associations like news services, logistics companies etc. for numerous reasons like recruitment of employees, sharing of information, etc. It was observed that some of the tweets were conveying strong sentiments with regards to risk, environmental impact, sales etc. of certain corporations. Tan et al. (2015) proposed a big data analytic framework for business firms. It is based on deduction graph method. The case study has demonstrated the competitive advantage achieved by business enterprises by analysing big data using the proposed framework. Consequently, the supply chain innovation capabilities of these firms were also being improved. Hazen et al. (2014) identified the issues with data quality in the domain of supply chain management. Innovative techniques for data monitoring and controlling their quality were proposed. The significance of data quality in research and practice of supply chain management has been described. Vera-Baquero et al. (2016) have proposed a cloud-based framework using big data techniques to enhance the performance analysis of businesses efficiently. The capability of the mechanism was demonstrated to deliver business activity monitoring in big data environment in real time with minimal cost of hardware. Frizzo- Barker et al. (2016) have done a literature review of big data associated publications in business journals. The time period of the publications was from year 2009 to year 2014 and 219 peer reviewed research articles from 152 business journals were examined. Quantitative and qualitative analysis was performed using NVivo10 software. The biggest advantages and challenges of implementing big data in domain of business were found out. It remains fragmented and has lots of potential in terms of theoretical, mathematical and empirical research. In literature, it was found that research on big data in domain of business is in preliminary stage. In the past, several researches have been conducted to use social media information in food industry particularly for marketing purposes (Rutsaert et al. 2013; Kaplan and Haenlein 2011; Thackeray et al. 2012). However, big data analytics can be utilised to minimise the waste in food supply chain.

At present, retailers are utilising the big data analytics for waste minimisation by using consumer complaints made in retail store. However, lots of useful information available at social media data, which can be utilised for waste minimisation. Consumer complaints on social media are vague and unstructured in nature. In literature, there was no mechanism available to link social media data with root causes of waste. In this article, architecture has been developed for above-mentioned process. In the upcoming sections, beef supply chain and social media data is explained in detail.

3 Beef supply chain and social media data

The schematic diagram of beef supply chain is shown in Fig. 2. Cattle are raised in the beef farms from age of 3 months to thirty months depending upon breed and demand in the market.

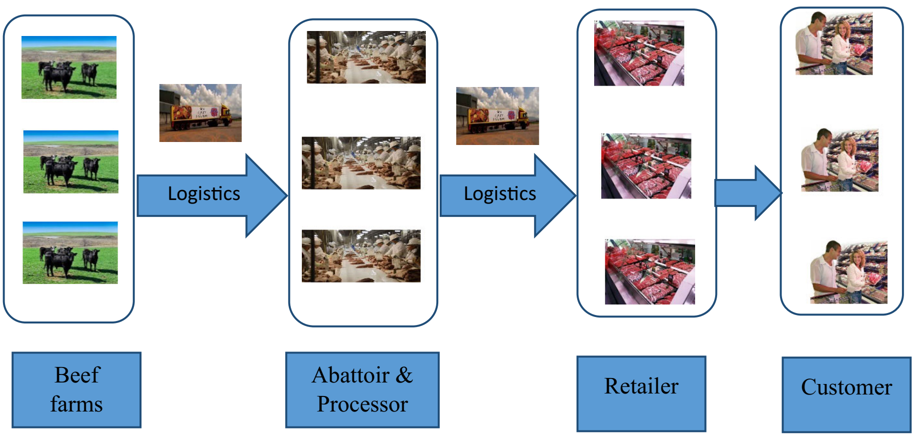

Fig. 2 Product flow in beef supply chain

When they approach their finishing age, they are sent to abattoir and processor. Cattle are butchered, boned and processed into various beef products like mince, steak, burger, joint, dicer/ strifry, etc. Then, the processed products are packed and labelled. The final products are sent to retailer. Consumers expect their beef products to be of high quality in terms of flavour, texture, colour, tenderness, smell, etc. For instance, customers usually desire fresh red colour beef products. If the beef products are not fresh red colour then customers discard them and express these issues on twitter using keywords like beef was having odd colour, beef got discoloured, beef was grey in colour, etc. Similarly, the beef products are expected to be tender when cooked. If they are hard to chew even after cooking, customers gets upset and mention this issue on twitter using phrases like beef was very chewy. Customers don't expect unpleasant smell in their beef products. If bad smell is associated with their beef products, customers discard the beef products and post on twitter comments like the beef was too rancid, beef smells awful, etc. Sometimes, a foreign body like plastic is found in the beef products. In beef industry, various quality assurance and food safety guidelines are available to overcome above mentioned quality and safety issues, which are explained in next subsection.

3.1 Safety checks and quality assurance by regulatory authorities

There are various safety checks and quality assurance procedures followed by regulatory bodies at various stages in beef supply chain. For instance, at beef farms, regular checks are being made to ensure that cattle are being raised as per strict farm assurance schemes, which examines their diet, housing, hygiene, veterinary checks, animal welfare, environmental protection, etc. (Food Standards Agency 2012a). The logistics vehicles used for transportation of cattle are also being monitored by regulatory authorities to ensure if there is ample space allowance provided to each cattle, appropriate ramp angle is maintained for loading/unloading of cattle and the journey time does not exceed from the maximum journey time allowed by government authorities (Red 2011). In the abattoir and processor, application of renowned safety management practice like HACCP is performed at all stages viz. slaughtering, boning and processing into beef products like mince, burger, steak, etc (Meat Industry Guide 2015a). It ensures the food safety, hygiene and quality of beef products made at abattoir and processor (Sofos et al. 1999). The logistics vehicle deployed for transfer of beef products from abattoir and processor to retailer is critically evaluated in terms of hygiene and cold chain efficiency (Meat Industry Guide 2015b). Finally, the quality checks are performed at retailer if they are purchasing beef from an accredited supplier by the regulatory body, random sampling is performed to make sure that the beef products are edible and cold chain management is evaluated (Food Standards Agency 2012b). There are certain quality assurance schemes available, which monitor the meat from farm to fork and ensure that it has gone through the highest standards of food safety and quality assurance. For example, Red tractor scheme in the UK, which maps the whole beef supply chain for quality assurance and food safety (Food Standards Agency 2012a). The beef products produced under this scheme carries red tractor logo so that consumers are assured of their quality attributes. Despite of the aforementioned quality assurance and food safety checks, sometimes, consumers are receiving beef products of substandard quality. It leads to customer dissatisfaction. They also express their concern and issue on social media. This information can be analysed to identify the root causes of waste in the beef supply chain. The next section includes how the customer's tweets have been utilised to develop waste minimisation strategy using twitter framework.

4 Twitter analytics framework

Extracting data from Twitter involves recognition of domain of interest by utilisation of hashtags and keywords. APIs are needed for the data collection. It consists of mining 1 % of publicly available data. Twitter data can also be acquired via data providers or twitter firehoses like GNIP, who can provide access to 100 % of data depending on their guidelines. However this is an expensive approach. API services are available for other social media as well. For instance, Marketing API, Atlas API can be used for Facebook. In this article, we have used publically available data for our analysis purpose.

To access twitter-streaming API, information such as API key, API secret, access token and access token secret is required, which can be obtained from https://apps.twitter.com/. The output from the twitter streaming API is in the JSON (JavaScript Object Notation) format. This format makes it easier to read the social media postings in twitter and it also allows machine to parse it. In this article, the twitter streaming API configurations is used to store/append twitter data in a text file. Then, a parsing method is implemented to extract datasets relevant to this study (e.g. tweets, coordinates, hashtags, urls, retweet count, follower count, screen name and others). The output data of the parsing method was stored in the Comma Separated Values (CSV) file. The collected data were unstructured (like informal expressions), more sophisticated (like URL, hashtags, etc.) as compared to the conventional data (like profit data) stored in database of multinational firms. To extract the useful information from this data, sentiment analysis, descriptive analysis, content analysis are being performed. Thereafter, the result of analysis are linked with the root causes of waste. The detailed description of the proposed framework is depicted in Fig. 3.

4.1 Sentiment analysis

Tweets consist of information as well as sentiments. Therefore, advanced text mining techniques are necessary for opinion gathering. Sentiment analysis could be performed at two levels: to the whole set of tweets collected and to various regions based extracted tweets. The main goal is to classify them as positive, negative and neutral tweets.

Sentiment analysis is defined as a research domain that examines public's appraisals, emotions, attitudes, sentiments, opinions towards numerous aspects, such as corporations, products, problems, subjects and their associated features, services. It represents a wide area of issues. Multiple names are available with slightly distinguished activity like sentiment mining, opinion mining, sentiment analysis, emotion analysis, review mining, opinion extraction, subjectivity analysis and affect analysis. However, all the aforementioned names belong to the broad area of sentiment analysis or opinion mining. While the corporate world employs the term sentiment analysis, the academic world utilises both opining mining and sentiment analysis. Both the terms represents the same research area. Nasukawa and Yi (2003) were the first researcher to mention the term sentiment analysis in literature whereas opinion mining was first cited by Dave et al. (2003). The first research on sentiments and opinions was performed by Das and Chen (2001).

Dictionary is powerful tool to collect sentiment words as most of them (such as WordNet) offer synonyms and antonyms for each word (Miller et al. 1990). Hence, the basic technique in this method is to use certain sentiment words seeds to bootstrap based on synonyms and antonyms arrangement of the dictionary. Initially, a small set of sentiment words or seeds with well-defined positive and negative orientation is manually collected. Then, the algorithm increases this set via searching for their respective synonyms and antonyms in

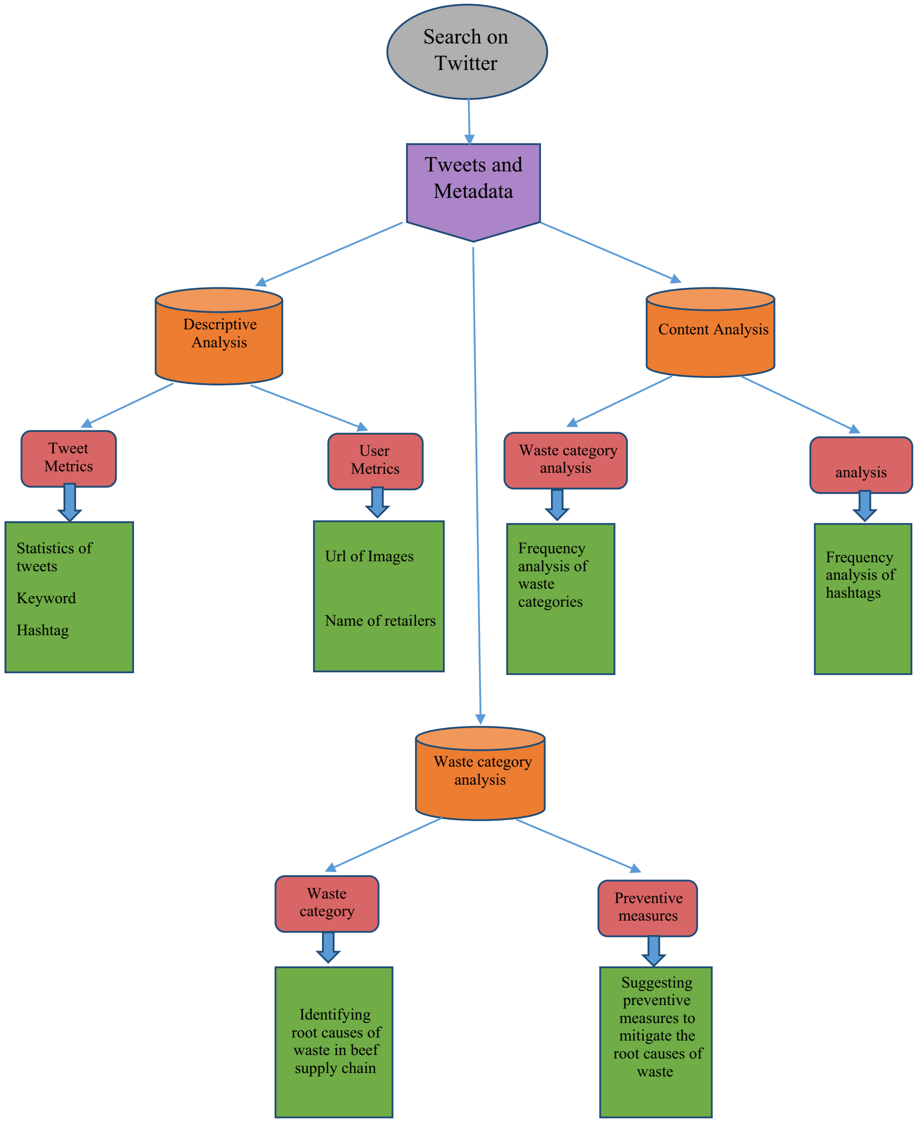

Fig. 3 Twitter analytics framework

the online dictionary like WordNet. The new words searched are combined to the small set. Then, next iteration is initiated. When the search is complete and there no new words being found out, then the iterative process is concluded. This method was followed by Hu and Liu (2004), who suggested a dictionary based algorithm for the sentiment categorisation at aspect level. This technique can calculate sentiment even at the sentence level. It originated from sentiment dictionary developed by using a bootstrapping technique, certain positive and negative sentiment word seeds and the synonym and antonyms relationship in WordNet dictionary. The sentiment scores of all sentiment words present in a sentence or segment of a sentence were summarised to predict the total sentiment of that sentence (Hu and Liu 2004).

In this study, this algorithm is being utilised to extract negative sentiments tweets from the all collected tweets.

4.2 Descriptive analysis (DA)

Twitter data consists of enormous amount of information, primarily tweets and user information (also known as metadata). DA looks after descriptive figures such as total number of tweets, total number of hashtags, and classification of tweets into different types. DA has been mentioned a lot in the research and practice of supply chain management. For instance, researchers describe the DA associated with the survey organized by them. The difference between the DA used by them and the one used in this study is in terms of number of metrics. Survey data has relatively small number of metrics (For example, size of sample, rate of response, etc.) whereas the sophisticated nature of twitter data assists in capturing intelligence via relatively large set of metrics like tweets, users, etc.

Tweet metrics aspires to highlight a basic but crucial idea of data by utilising various metrics (total number of tweets, total number of hashtags, etc.). These led to the evolution of other metrics. The information regarding the users posting tweets, replying to tweets and posting re-tweets is significant for both academic researchers analysing a particular topic and to industrial practitioners aiming to generate value for their trading. In this research, keywords and hashtag analysis are performed to extract the relevant tweet from twitter related to beef products.

Hashtags are an important part of tweets. They have the same role as the topic of interest used to categorise academic research papers. Analysis of hashtag consists of analysis of frequency and association rule mining. Analysis of frequency demonstrates how popular hashtags are. Association rule mining explores the relation between hashtags.

4.3 Content analysis (CA)

The data captured form above method is in the form of unstructured texts. Content Analysis (CA) offers a wide range of text capturing and Natural Language Processing (NLP) techniques for mining intelligence from Web 2.0 (Chau and Xu 2012). A tweet is an informal text and consists of few words, URLs, hashtags and certain other kinds of information. In order to extract intelligence, text cleaning and processing is necessary.

Text capturing and machine learning algorithms are vital ingredients of CA. The unstructured texts could be transformed to structured texts by the utilisation of text capturing techniques such as n-grams, tokenization, etc. (Weiss et al. 2010). The transformed texts can then be utilised for analysis of keyword, summarisation of text, analysis of word frequency, clustering of texts by employing machine learning algorithms, like clustering and association analysis. CA has been mentioned in the literature of supply chain management as a manual or partial manual approach via human interpretations (Seuring and Gold 2012; Vallet-Bellmunt et al. 2011). In this article, CA is performed by automatic text processing methods.

Analysis of word is the first step in CA. It consists of summarization of document, term frequency, analysis of term frequency and clustering. Term frequency has been used a lot for information retrieval. It can be merged with n-gram, which assists in extracting key phrases from the document. They assists in distinguishing topic of interest, which are helpful for analysis at document level, by utilising machine learning algorithms such as clustering. Clustering at document level assists in document categorizing, which aids in thorough analysis of documents as per their categorisation.

4.4 Association of twitter data with waste in the supply chain

The issues occurring at consumer end will be identified using above-mentioned twitter analytics tool. Thereafter, it will be associated with their root causes in the supply chain. The analysis of consumer tweets will assist in finding the issue, which are leading to the maximum amount of waste. Strengthening the coordination among the stakeholders in the supply chain could mitigate these issues.

5 Data collection and analysis

Twitter data is enormous considering about 500 million tweets per day. It is quite difficult to analyse all twitter data. In the literature, usually, analysis is performed over the information collected from twitter for certain time period. Thereafter, a data sampling process based on keyword and hashtag is performed to extract specific intelligence. There are two components of Application Programming Interface (API) to get access to public tweets, which are search API and streaming API. The search API will capture tweets from the past as per the criteria (hashtags, keywords, location, senders, etc.) (Bruns and Liang 2012). This method will only provide access to limited number of tweets. Streaming API can provide access to continuous stream of fresh tweets associated with specific keywords or related to specific location or users. In this research, twitter data related to customer dissatisfaction with beef products were collected using streaming API from January 2015 to January 2016.

5.1 Data collection

Initially, using the keyword ‘beef’ all the tweets related to beef products in the aforementioned period are collected. The sentiment analysis was performed on the collected tweets and only the tweets carrying negative scores were captured. Some examples of the negative tweets captured are shown in Table 1. A filtration criterion was deployed and only the tweets associated with consumers purchasing beef products and cooking them were considered. The tweets related to beef products served in a restaurant to consumers are not considered in this study. For instance, tweets like “When you buy @Tesco beef mince and it goes off before its use by date!!!! No dinner #smellymeat #yuck !!!!!!!!” were considered and tweets such

Table 1 Examples of tweets with negative sentiments

Sentiment Scores	Raw Tweets
−1	*@AsdaServiceTeam why does my rump steak from asda Kingswood taste distinctly of bleach please?*
−1	*The beef lasagne from woolworths smells like sweaty armpits siesðŸ˜· ðŸ˜· ðŸ˜·*
−1	*@Morrisons so you have no comment about the lack of meat in your Family Steak Pie? #morrisons*
−2	*@Tesco just got this from your D’ham Mkt store. It’s supposed to be Men’s Health Beef Jerky...The smell is revolting* https://t.co/vTKVRIARW5
−1	*Buying corned beef from Aldi is an abomination. There are things you cannot and should not buy from Aldi*

as "piece of plastic in my Angus Beef burger. @McDonalds #chokinghazard #mcdonalds #angusbeef #burger #badfood https://t.co/2JHSkElQPH" were discarded.

Collected tweets are divided into five major issues at consumer end. The detailed descriptions of these issues are given in the following subsection.

5.2 Description of issues occurring at consumer end

During the interaction with retailers and consumers, it was found that all the consumer related complaints could be divided into five major subcategories related to discoloration of meat, hard texture, excess of fat, and presence of foreign body, bad smell and flavour. The detailed descriptions of these categories are described below:

1. Losing colour—Customers expect the beef product to be fresh red in colour. If beef products has transformed into grey, brown, etc while cooking or when the packet was opened they get annoyed and disappointed.
2. Hard texture—The beef products are expected to be tender and easy to cut. If the customers find it hard to chew even after cooking, they get dissatisfied. This kind of issues primarily arises in beef products derived from hindquarter of cattle like steak and joint. The softness of beef product plays a crucial role in increasing the customer satisfaction.
3. Excess of fat and gristle—Lean beef with minimum content of gristle is being desired by the customers. It could lead to disappointment if the beef products are not meeting customer expectations. If beef products have surplus of fat and gristle customer perceive that meat is not of high quality and not good for their health.
4. Bad flavour, smell and rotten—Good flavour, smell and fresh outlook are one of the prime selling point of the beef products. If they are bitter in taste or unexpectedly bad, it could lead to the beef products being discarded. Similarly, if their smell is poor and they looks rotten, then customers perceive them as inedible and dump them into the bin.
5. Foreign body—Customers expect only the fresh beef inside the packaging of beef products. In some of the cases, it was observed that some foreign bodies like piece of plastic, piece of metal, insect, mosquito have been identified in them. Customers perceive it as a food safety concern and discard them, which leads to waste.

In order to divide all collected tweets to above-mentioned categories, keywords are identified, which is explained in next subsection.

5.3 Identification of keywords

In order to divide the collected negative tweets into various categories as shown in Table 2, different keywords are identified. Initially, site visit was made to different retailer stores (both main and convenience stores) in the UK to explore the various kinds of complaints filed by customers regarding the beef products. The staff members dealing with customer complaints were interviewed. They provided access to their database of beef products related complaints. It will assist in identifying the keywords used by the customers corresponding to five major issues mentioned above. Few customers were also interviewed regarding the kind of complaints they are facing. The research team of this study also did some research on their own about the kinds of complaints left by customers in the stores. Various keywords used over the twitter are collected and they were discussed with waste minimisation team of retailer and customers. It helped to identify the keywords commonly used by the consumers associated with different types of issues highlighted above. The keywords and hashtags received from all three methods mentioned above are shown in Table 3. Thereafter, with the help of experts these keywords and hashtags are divided corresponding to five major issues

Table 2 Highlighting issues occurring at consumer end and the associated keywords and hashtags

S. no.	Issues occurring at consumer end	Keywords	Hashtags
1.	Losing colour	discoloured, grey colour, odd colour, funny colour, green colour	#odd colour, #discoloured, #greycolour, #funnycolour, #green colour
2.	Hard texture	chewy, hard, not tender	#chewy, #hard, #nottender
3.	Excess of fat and gristle	fatty, gristle, oily, fat	#fatty, #gristle, #oily, #fat
4.	Bad flavour, smell and rotten	awful taste, bad flavour, bitter, foul smell, rancid, oxidised, rotten, stink, taste, flavour, smell	#rotten, #badflavour, #stink, #awfultaste, #rancid, #oxidised, #rotten, #bitter, #foulsmell, #taste, #smell, #flavour
5.	Foreign body	piece of plastic, packaging blown, piece of metal, insect, mosquito, foreign body	#pieceofplastic, #insect, #pieceofmetal, #foreignbody, #packgingblown, #mosquito

Table 3 Keywords and hashtags used for extracting consumer tweets about complaints in beef products

discoloured	#rotten	#rancid	#chewy
#awfultaste	oxidised	#packagingblown	odd colour
#oddcolour	#discoloured	#pieceofplastic	#gristle
grey colour	hard	#oxidised	#taste
#flavour	#smell	#rotten	#funnycolour
fatty	gristle	#hard	chewy
awful taste	rotten	funny colour	rancid
#grey colour	oily	fat	green colour
not tender	#fatty	#green colour	piece of plastic
insect	piece of metal	packaging blown	#stink
#foreignbody	#nottender	#fat	#oily
#pieceofmetal	#insect	bad flavour	bitter
foul smell	stink	taste	flavour
smell	#badflavour	#bitter	#foulsmell
mosquito	foreign body	#mosquito	

as shown in Table 2. Further, tweets corresponding to these keywords are extracted from negative sentiment tweets and are used for further study.

In the tweets capture above, consumers are tweeting about variety of things like complaining, comparing different kinds of beef products like organic, inorganic, mince, burger, steak, joint, etc. Among the tweets, where name of beef products was mentioned, it was found that around 74 % tweets were about steak, 12 % tweets were associated with burger, 7 % tweets were about mince, 4 % tweets were about diced and stir fry products and 3 % tweets were about other beef products such as offal, veal, escalope, etc. The tweets captured consists of various issues such as smell, taste, rotten, lack of tenderness, extra fat, discoloration, presence

Table 4 Example of more than one hashtags used by consumers on Twitter

#rancid#foulsmell	#badsmell#awfulflavour	#discoloration#greycolour
#chewy#unpleasant	#rotten#disappointed	#fatty#gristle
#insect#foreignbody	#browncolour#gutted	#plastic#foodsafety
#packagingblown#piece of plastic	#rancid#flavourless	#oxidised#discoloured
#pieceofmetal#beef	#oddcolour#disappointed	#beef#hard#gutted
#smell#steak#rotten	#beef#awfultaste#chewy	#fatty#gristle#steak
#beef#greencolour#bin	#fatty#beef#gristle	#beef#chewy#smell
#beef#badflavour#stinks	#beef#rotten#packagingblown	#beef#rancid#awfultaste
#steak#discolored #disappointed	#beef#notenderness#gutted	#beef#mince#foulsmell
#beef#burger#gristle	#beef#oddcolour#smell	#steak#fatty#grsitle

of foreign body. The detailed analysis of collected tweets is performed using descriptive and content analysis.

5.4 Descriptive analysis

In the analysis, it was found that there were 88.5 % of original tweets. In few cases, there were some retweets and replies as well. In 3.2 % cases, retweets have occurred. It usually reflects the occurrence of major incidences in beef industry. While, 8.3 % of cases consist of replies. It generally happens when another customer have faced similar situation or a customer in complaint has tagged a name of retailer. Further, analysis was performed to see how many cases hashtags were used. In the study, it was found that in 25 % of cases, hashtags were used to express their concern. The most commonly used hashtags were #disappointment, #complaint, #rotten, #awful, #notimpressed, #inedible, #unhappy, #foodsafety. Sometimes, customers have used more than one hashtags. For example, if customer found grey colour and rancid smell in their beef product. Then, the dissatisfaction is usually expressed by hashtags like #rancidbeef #greycolourbeef. In 16.6 % of cases, more than one hashtags is used to express their dissatisfaction. Some examples of more than one hashtags used are shown in Table 4. Sometimes, customers tag images to their tweets to express their anger and dissatisfaction. In 6.25 % of cases, images were tagged with the tweets. In 51.2 % of tweets, customers have also tagged the name of supermarket in their complaint.

5.5 Content analysis

It is composed of hashtag analysis and frequency analysis. These two analysis are being performed as following:

5.5.1 Hashtag analysis

Hashtags are employed to associate their opinion with a wider community of similar interest. For example, if a customer finds his/hers beef product to be inedible then he/she might use #foodsafety to highlight this issue. They are employed before a keyword to assign the tweets to a certain category. It assists in searching of these tweets when the associated keywords

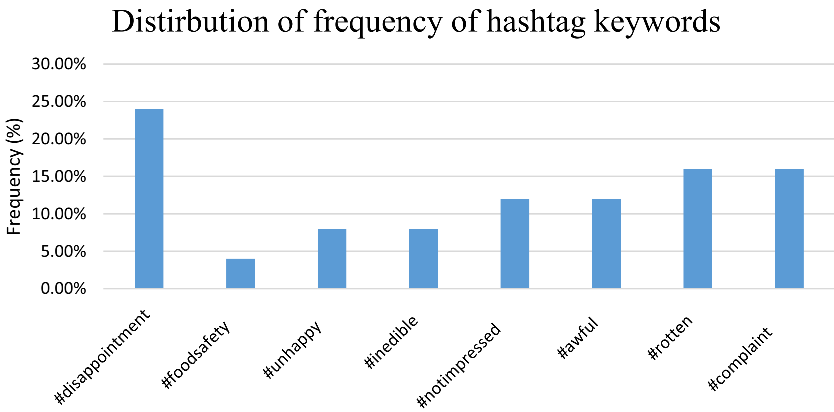

Fig. 4 Frequency distribution of hashtags

are searched in the twitter engine. When the word after hashtag is clicked, all the tweets made in the past consisting of that keyword are shown. Hashtag can be made at any position in the tweets like at the beginning, end or somewhere in the middle. Hashtag analysis was performed on all the collected consumer tweets. In experiment, it was found that 25 % of the tweets were associated with different hashtags. The most widely used hashtags were: #disappointment (24 %), #complaint (16 %), #rotten (16 %), #awful (12 %), #notimpressed (12 %), #inedible (8 %), #unhappy (8 %), #foodsafety (4 %). Their distribution is shown in the bar chart in Fig. 4. Sometimes, more than one hashtags were used in a particular tweet. Most of the hashtags shown in the bar chart below are related to dissatisfaction rather than highlighting any specific issues apart from #rotten, #inedible and #foodsafety. #rotten is primarily related to food expiring prior to the expiry of their shelf life. It may be because of temperature abuse of the beef products or damage in packaging, which might lead to their shorter shelf life. While, #indedible and #foodsafety are very closely related to each other. These kinds of tweets are made when a foreign body like plastic, piece of metal, insect are found in the beef products. During the analysis, it was found that the most commonly used hashtag were #rotten followed by #inedible and #foodsafety.

5.5.2 Frequency analysis of waste categories

All tweets are divided into five major issues using the keywords as shown in Table 2. The amount of customers' tweets corresponding to various issues is: Losing colour (12 %), Hard texture (11.51 %), Excess of fat and gristle (22.7 %), Bad flavour, smell and rotten (18.5 %), Foreign body (35.29 %). This distribution has been depicted in the Fig. 5. It is evident that 'Foreign body in beef products', 'Excess of fat and gristle' and 'Bad flavour, smell and rotten' are contributing to maximum amount of consumer complaints on twitter. These three are the major hotspots of customers' complaints. The preventive measures to minimise the waste is prescribed in next subsection.

5.6 Root cause identification and waste mitigation strategy

In the beef supply chain, highest amount of waste is generated at consumer end. It is caused due to various issues in the supply chain as shown in Fig. 6. The consumer tweets regarding

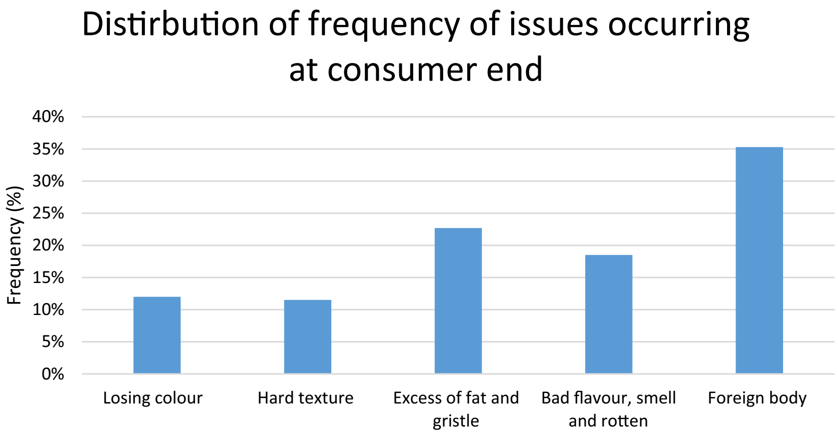

Fig. 5 Frequency distribution of issues occurring at consumer end

issues in beef products are vague in nature. They are not as accurate as the complaints made in the retail store, which consists of details like bar code, date of purchase, shelf life expiry, etc. The rich information available for specific complains made in retail store could be employed to find its exact root cause in the supply chain. However, this process could not be performed with that precision using social media data to pinpoint the exact issue in the supply chain as they are written in a very casual and short form and also they have a limit of 140 characters per tweet. Hence, using social media data only probable root causes of waste could be identified within the supply chain. These probable root causes of the waste (issues) and their preventive measure are being explained below:

a. *Losing colour*—Sometimes, beef products loses their colour before their shelf life is expired (Jeyamkondan et al. 2000; Renerre 1990). Consumers think that these products have gone past their shelf life and do not buy them, which is ultimately dumped as waste. The primary reason for this issue is that the cattle were not fed with fresh grass, which is rich in Vitamin E and helps to maintain fresh red colour for longer duration (Liu et al. 1995; Houben et al. 2000; Cabedo et al. 1998; Formanek et al. 1998; O'Grady et al. 1998; Lavelle et al. 1995; Mitsumoto et al. 1993). There could be other reasons contributing to discolouration of meat as well. The beef products might have been subjected to temperature abuse (Rogers et al. 2014; Jakobsen and Bertelsen 2000; Gill and McGinnis 1995; Eriksson et al. 2016). If they have been exposed to a temperature of more than three degree Celsius, they loses their fresh red colour prior to expiry of their shelf life (Rogers et al. 2014; van Laack et al. 1996; Jeremiah and Gibson 2001; Greer and Jones 1991). Therefore, to avoid the issue of discolouration of meat at consumer end, the cattle should be fed with fresh grass at beef farms and after getting processed into beef products, they should be kept at chilled temperature throughout the supply chain.

b. *Hard texture*—The tenderness of the beef products plays a crucial role in deciding their quality (Goodson et al. 2002). If the beef purchased by customers doesn't have enough tenderness and is not easy to chew while eating, it could disappoint the customers and would be discarded by them (Huffman et al. 1996). Usually, this issue occurs in steak and joint, which are derived from hindquarter of the cattle. The main root cause of this issue is that the carcass is not being matured properly after the cattle were slaughtered (Riley et al. 2005; Vitale et al. 2014; Franco et al. 2009; Gruber et al. 2006; Monsón et al. 2004; Sañudo et al. 2004; Troy and Kerry 2010). Maturation process refers to carcass being kept at chilled temperature for

7–21 days depending on age, gender and breed of the cattle (Riley et al. 2005). Therefore, the beef should be matured properly in order to improve their tenderness.

c. *Excess of fat and gristle*—It was observed that beef products were having excess of fat instead of lean beef desired by customers. Hence, they get discarded as waste (Brunsø et al. 2005; Byers et al. 1993; Unnevehr and Bard 1993). The root cause of this issue lies in both beef farms and slaughterhouse. If the cattle are not raised to the weight and conformation specifications of the retailer, then the meat derived from them might be having excessive fat on them (Hanset et al. 1987; Herva et al. 2011; Borgogno et al. 2016; AHDB Industry Consulting 2008; Boligon et al. 2011). In the boning hall of slaughterhouse, if appropriate trimming procedures are not being followed then beef products are left with extra layer of fat (Francis et al. 2008; Mena et al. 2014; Kale et al. 2010; Watson 1994; Cox et al. 2007). The cattle should be raised in an optimum way to meet the weight and conformation specifications of retailer and proper trimming of primals should be performed in the boning hall. Customers often complain about too much gristle in beef products. The beef products derived from shoulder, chuck and legs should be processed through optimum butchering and boning techniques so that minimum amount of gristle is left in the meat cuts (Cobiac et al. 2003).

d. *Bad flavour, smell and rotten*—One of the major reason of bad flavour, smell and beef products becoming rotten is their oxidisation i.e. their exposure to air resulting in oxidisation of lipids and proteins (Brooks 2007; Campo et al. 2006; Utrera and Estévez 2013; Wang and Xiong 2005). Consumers perceive these products as inedible and dump them into the bin. The root cause of this issue lies in the packaging of beef products. They might not be packed properly at abattoir and processor, the packaging might be damaged at some stage in the supply chain and inappropriate packaging method might be used causing premature oxidisation of the beef products (Barbosa-Pereira et al. 2014; Brooks 2007). Regular maintenance of packaging machines, random sampling of beef products and use of modern packaging technology, which delays oxidisation of beef products like Vacuum Skin Packaging (Cunningham 2008) could assist in mitigating this issue at abattoir and processor end. The staff in the retailer store must be properly trained so that the mishandling of beef products does not damage the packaging. Another significant issue leading to bad smell, flavour and making beef products rotten is failure of cold chain (James and James 2002, 2010; Raab et al. 2011). It is very important to maintain a chilled temperature of 1–3 degree Celsius for beef products throughout the supply chain whether it is at abattoir, processor, logistics or retailer (Kim et al. 2012; Mena et al. 2011). The inefficient cold chain management could be due to lack of periodic maintenance of refrigeration equipment (Kim et al. 2012). Therefore, efficient cold chain management must be maintained for the whole beef supply chain to avoid the wastage of beef products. There should be periodic temperature checks performed at various stages in the supply chain to ensure that appropriate temperature is being maintained for the efficient product flow of the beef products.

e. *Foreign bodies*—In some of the rare cases, foreign bodies like plastic, piece of metal, insect have been found on the beef products or damaged packaging (FSA 2015). Customers perceive these beef products as inedible and dump them into the bin. The root cause of this issue lies in the inefficiency of machines doing the packaging at abattoir and processor, lack of safety checks like metal detection, physical inspection, lack of renowned process management technique for food safety such has HACCP, etc (Goodwin 2014; Lund et al. 2007; Jensen et al. 1998; Piggott and Marsh 2004). There should be regular maintenance of the packaging machines and random sampling of beef products performed at their premises. Appropriate

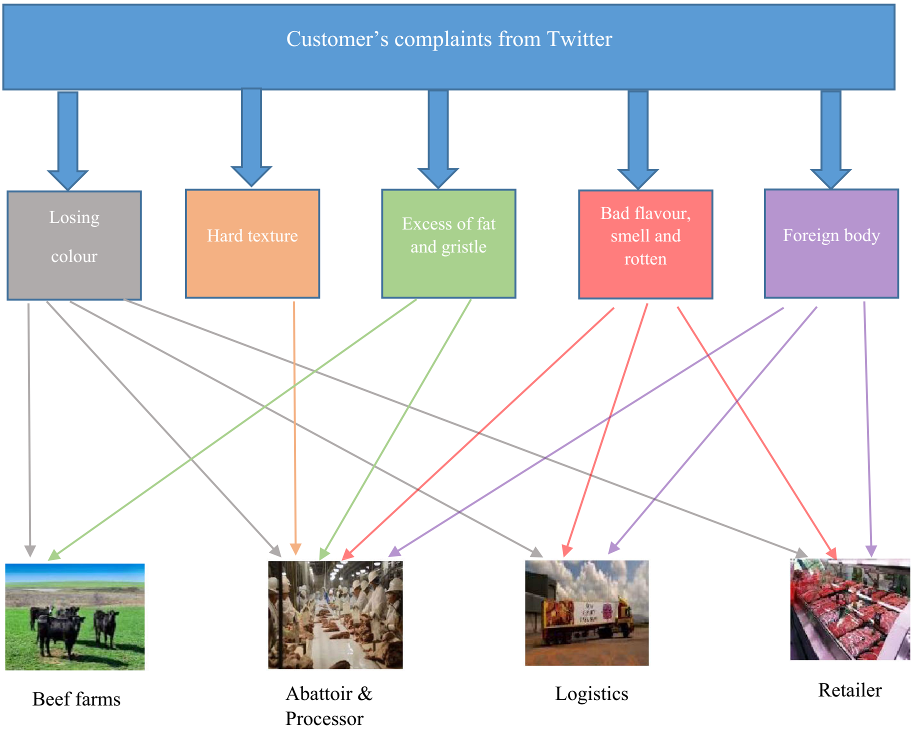

Fig. 6 Association of issues occurring at consumer end with various stakeholders of beef supply chain

safety checks like metal detection, physical inspection, should also be performed at various stages in abattoir and processor and a well-established food safety process management procedures like HACCP, GMP, must be followed address to this issue (Bolton et al. 2001; Goodwin 2014; Roberts et al. 1996). The beef products also damage by mishandling within the supply chain (Goodwin 2014; Singh et al. 2015). The workforce working at premises of all the stakeholders must be appropriately trained and supervised to address this issue. There should be quality checks performed at various stages in the supply chain so that beef products consisting of foreign bodies like piece of metal and insects are discarded prior to being sold to the consumers.

In the next section, managerial implications of proposed framework has been described in detail.

6 Managerial implications

Complaints associated with the food products are a critical issue for major retailers both because of loss of revenue and also it affects their reputation. It might also lead to loss of customers. Complaints in the food products lead to food waste, which raises a moral question considering there are millions of people losing their lives because of scarcity of food, across the world. Food waste and the complaints associated with them are a cause of concern for the whole world. Various retailers are employing different strategies to mitigate the food waste and reduce the amount of complaints being received from customers. They have given the opportunity to customers to make complaints about food products if they are not satisfied with them. However, all unhappy customers didn't make complaints in the retail store. Instead, majority of them express their dissatisfaction on social media like twitter. Often, they tag the name of the retailer while tweeting their complaints. Hence, the long-term reputation of retailers is at stake. The complaints made by consumers on social media are vague and unstructured in nature. In the past, there was no mechanism available to link them with the root causes of waste in various segments of supply chain. The proposed methodology will assist the manager of food retailers to extract all the complaints posted on twitter. It will help them to identify the root causes of these complaints within their supply chain, which can be mitigated and consequently lead to waste minimisation of food products. The proposed methodology in this study will help them to extract more useful data with respect to customer complaints and help them to make their supply chain more robust.

The major issues revealed by customer's tweets helps to identify their root causes in supply chain. It can be at the premises of a stakeholder, at the interface of two stakeholders or at multiple places in the supply chain. The proposed framework in this study will help the policy makers of the retailer to prioritize the mitigation of various issues as per their impact on food waste. Normally, all the stakeholders in a beef supply chain work independently. If a common issue is identified in the whole supply chain leading to the waste in the customer end then the retailer can assist all the stakeholders to improve their coordination (in terms of information sharing) and collectively address this issue. The improved coordination among stakeholders will not just help in waste minimisation but assist in improved product flow, efficiency and sustainability of the supply chain. These aspects would be beneficial for both the retailer firms and the society.

7 Conclusion

Rising population is a cause of concern globally as there are limited resources (land, water, etc.) to produce food for them. Millions of people are dying worldwide because of being deprived from food. These complications cannot be mitigated alone by development of innovative technologies to extract more harvest from the limited natural resources. Waste minimisation must be made a priority throughout the food supply chain including their consumption at consumers' end. Food waste financially affects all the stakeholders of food supply chain viz. farmers, food processors, wholesalers, retailers, and consumers. Majority of waste is being generated at consumer end. Often, consumers are not happy with the food products and discard them. Apart from food waste, retailers are losing their customers because of their dissatisfaction. Although, major retailers have made a provision for the customers to make a complaint in the store, still, customers are not doing so. They are using social media like twitter to express their disappointment. Consumers usually tag the name of the retailer while making their complaints on social media, which is affecting the reputation of the retailers. There is plenty of useful information available on twitter, which can be used by food retailers for developing their waste minimisation strategy. This information is big in size considering its volume, variety and velocity. However, the consumer complaints posted on twitter (social media) are vague and unstructured in nature. In literature, there was no framework available to link them with root causes of waste at different segments in food supply chain. In the proposed methodology, customers' tweets associated with complaints of beef products are being extracted and sorted into five categories. These individual issues occurring at customer's end were then linked to their respective root causes in the beef supply chain. The root causes can be mitigated to reduce the food waste, improve the satisfaction of customers and their loyalty, and improve brand value of retailer and consequently financial revenue of the retailer. In future, an enhanced list of keywords could be used for further analysis of the issue. Twitter analytics could be employed for longer time duration and could be applied to other domains of food supply chain like lamb supply chain or any other food supply chain.

Acknowledgments The authors would like to thank the project '*A cross country examination of supply chain barriers on market access for small and medium firms in India and UK*' (Ref no: PM130233) funded by British Academy, UK for supporting this research.

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Transportation Research Part E xxx (2017) xxx–xxx

Contents lists available at ScienceDirect

Transportation Research Part E

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

Social media data analytics to improve supply chain management in food industries

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A R T I C L E I N F O

Article history:
Received 31 May 2016
Received in revised form 1 April 2017
Accepted 16 May 2017
Available online xxxx

Keywords:
Beef supply chain
Twitter data
Sentiment analysis

A B S T R A C T

This paper proposes a big-data analytics-based approach that considers social media (Twitter) data for the identification of supply chain management issues in food industries. In particular, the proposed approach includes text analysis using a support vector machine (SVM) and hierarchical clustering with multiscale bootstrap resampling. The result of this approach included a cluster of words which could inform supply-chain (SC) decision makers about customer feedback and issues in the flow/quality of food products. A case study in the beef supply chain was analysed using the proposed approach, where three weeks of data from Twitter were used.

1. Introduction

In the modern era, food is a crucial commodity for consumers, as it has a direct impact on their health (Caplan, 2013; Swaminathan, 2015; Tarasuk et al., 2015). The food supply chain is more complicated than the manufacturing and other conventional supply chains, owing to the perishable nature of food products (La Scalia et al., 2015; Handayati et al., 2015). Food retailers aim to adjust their supply chain to become consumer centric (a supply chain designed as per the requirements of end consumers by addressing organisational, strategic, technology, process, and metrics factors) by taking into account various methods, including market surveys, market research, interviews, and offering the opportunity to consumers to provide feedback within the retailer store. However, food retailers are not able to attract large audiences by following these procedures; thus, their data sample is small. Any decisions made based on a smaller sample of customer feedback are prone to be ineffective. With the advent of online social media, there is substantial amount of consumer information available on Twitter, which reflects the true opinion of customers (Liang and Dai, 2013; Katal et al., 2013). Effective analysis of this information can provide interesting insight into consumer sentiments and behaviours with respect to one or more specific issues. Using social media data, a retailer can capture a real-time overview of consumer reactions regarding an episodic event. Social media data are relatively inexpensive, and can be very effective in gathering the opinions of large and diverse audiences (Liang and Dai, 2013; Katal et al., 2013). Using different information techniques, business organisations can collect social media data in real time, and can use it for the development of future strategies. However, social media data are qualitative and unstructured in nature, and are often large in volume, variety, and velocity (He et al., 2013; Hashem et al., 2015; Zikopoulos and Eaton, 2011). At times, it is difficult to handle them using the traditional operation and management tools and techniques for business purposes. In the past, social media analytics have been implemented in various supply chain

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http://dx.doi.org/10.1016/j.tre.2017.05.008
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problems, predominantly in manufacturing supply chains. The research on the application of social media analytics in the domain of the food supply chain is in its primitive stage. In the present work, an attempt has been made to use social media data in the domain of the food supply chain to transform it into a consumer-centric supply chain. The results from the analysis have been linked with all the segments of the supply chain to improve customer satisfaction. For instance, the issues faced by consumers of beef products, such as discoloration, presence of foreign bodies, extra fat, and hard texture, have been linked to their root causes in the upstream of the supply chain. First, data were extracted from Twitter (via the Twitter streaming application programming interface (API)) using relevant keywords related to consumer opinion on different food products. Thereafter, pre-processing and text mining was performed to investigate the positive and negative sentiments of tweets, using a support vector machine (SVM). Hierarchical clustering of tweets from different geographical locations (world, UK, Australia, and the USA) using multiscale bootstrap resampling was performed. Furthermore, root causes of issues affecting consumer satisfaction were identified and linked with various segments of the supply chain to render it more efficient. Finally, recommendations for a consumer-centric supply chain were prescribed.

The organisation of the paper is as follows: Section 2 explores various issues associated with big-data applications, including Twitter and other social media platforms. In Section 3, a new framework of social-media data analytics adopted in this study is described in detail. Section 4 provides an implementation of the proposed framework on a case study in the beef supply chain. It also details the comparison of several sentiment-mining techniques, as well as their results. Section 5 comprises the identification of issues affecting consumer satisfaction and their respective means of mitigation within the supply chain. Section 6 explains the managerial implications on the supply chain decisions. Finally, the paper is concluded in Section 7.

2. Related work

In literature, distinct frameworks have been proposed for the investigation of big-data problems and issues associated with the supply chain. Hazen et al. (2014) have determined the problems associated with the quality of data in the field of supply chain management. Novel procedures for the monitoring and the managing of data quality have been suggested. The importance of the quality of data in the application and further research in the field of supply chain management has been mentioned. Vera-Baquero et al. (2016) have recommended a cloud-based mechanism, utilising big-data procedures to efficiently improve the performance analysis of corporations. The competence of the framework was revealed in terms of delivering the monitoring of business activity comprising big data in real time with minimum hardware expenses. Frizzo-Barker et al. (2016) have performed a thorough analysis of the big-data literature available in reputed business journals. They considered 219 peer reviewed research papers, published in 152 business journals from 2009 to 2014. Both quantitative and qualitative investigation of the literature was performed by utilising the NVivo 10 software. Their investigation revealed that the research work conducted in the domain of big data is fragmented and primitive in terms of empirical analysis, variation in methodology, and theoretical grounding.

Twitter information has emerged as one of the most widely used data source for research in academia and practical applications. In the literature, there are various available examples associated with practical applications of Twitter information, such as brand management (Malhotra et al., 2012), stock forecasting (Arias et al., 2013) and crisis management (Wyatt, 2013). It is anticipated that there will be a swift expansion in the utilisation of Twitter information for numerous other purposes, such as market prediction, public safety, and humanitarian relief and assistance (Dataminr, 2014). In the past, Twitter data-based studies have been conducted in various domains. Most research work is conducted in the area of computer science for various purposes, such as sentiment analysis (Schumaker et al., 2016; Mostafa, 2013; Kontopoulos et al., 2013; Rui et al., 2013; Ghiassi et al., 2013; Hodeghatta and Sahney, 2016; Pak and Paroubek, 2010), topic detection (Cigarrán et al., 2016), gathering market intelligence (Li and Li, 2013; Lu et al., 2014; Neethu and Rajasree, 2013), and gaining insight of stock market (Bollen et al., 2011). There are various works which have been conducted in the domain of disaster management (Beigi et al., 2016), such as studies on dispatching resources in a natural disaster by monitoring real-time tweets (Chen et al., 2016) and on exploring the application of social media by non-profit organisations and media firms during natural disasters (Muralidharan et al., 2011). Analysis of Twitter data has also been conducted by researchers in the domain of operation management; such analyses include capturing big data in the form of tweets to improve the supply-chain innovation capabilities (Tan et al., 2015), investigating the state of logistics-related customer service which is provided by e-retailers on Twitter (Bhattacharjya et al., 2016), examining the process of service recovery in the context of operations management (Fan et al., 2016), developing a framework for assimilating social media into the supply chain management (Sianipar and Yudoko, 2014; Chae, 2015), determining the ranking of knowledge-creation modes by using extended fuzzy analytic hierarchy process (Tyagi et al., 2016), exploring the amalgamation of conventional knowledge management and the insights derived from social media (O'leary, 2011), improving the efficiency of the knowledge-creation process by developing a set of lean thinking tools (Tyagi et al., 2015a), and optimising the configuration of a platform via the coupling of product generations (Tyagi , 2015b).

Researchers have employed numerous methods for the extraction of intelligence from tweets, which are listed in detail in Table 1. For instance, Ghiassi et al. (2013) used n-gram analysis and artificial neural networks for determining sentiments of brand-related tweets. Their methodology offered improved precision in the classification of sentiments, and minimised the complexity of modelling as compared to conventional sentiment lexicons. However, their study was conducted by offsetting

Table 1
Studies based on social media analytics in the literature.

Area	Method	References
Sentiment analysis, topic detection and gathering market intelligence	Formal Concept Analysis (FCA), Descriptive statistics, ANOVA and *t*-tests, *n*-gram analysis and dynamic artificial neural network, numeric opinion summarisation framework, Naive Bayesian classifier and support vector machine, lexicon-based Sentiment analysis, Granger causality analysis and a Self-Organizing Fuzzy Neural Network, Crowdsourced sentiment analysis	Schumaker et al. (2016), Mostafa (2013), Kontopoulos et al. (2013), Rui et al. (2013), Ghiassi et al. (2013), Hodeghatta and Sahney (2016), Cigarrán et al., 2016, Li and Li (2013), Bollen et al. (2011), Lu et al. (2014), Neethu and Rajasree (2013), Pak and Paroubek (2010)
Disaster management	Implementation of a real-time tweet-based geodatabase, Content analysis	Chen et al. (2016), Muralidharan et al. (2011)
Operation and Supply chain management	Descriptive analysis, Content analysis, Network analysis, Grounded theory approach, Inductive coding, sentiment analysis, Extended Fuzzy- AHP approach, Lean thinking, knowledge creation, DNA- based framework	Chae (2015), Tan et al., 2015, Fan et al. (2016), Tyagi et al. (2016), Bhattacharjya et al. (2016), Sianipar and Yudoko (2014), O'leary (2011), Tyagi et al. (2015a), Tyagi (2015b)

the false positives, and was performed on one single brand. Hence, the efficacy of the framework needs to be verified on other brands. Bollen et al. (2011) have utilised the Granger causality analysis and a self-organizing fuzzy neural network to analyse tweets for the measurement of the mood of people associated with the stock market. Their framework was sufficiently capable of measuring the mood of people along six distinct dimensions (such as calm, alert, sure, vital, kind, and happy) with an accuracy of 86.7%. Li and Li (2013) have developed a numeric opinion-summarisation framework for the extraction of market intelligence. The aggregated scores generated by the framework assisted the decision maker in effectively gaining insight into market trends through following the fluctuation in tweet sentiments. However, their study did not consider the synonymous terms while classifying the tweets into thematic topics, as different users might have used distinct terms in their tweets. For instance, a dictionary-based approach could be applied to incorporate all possible synonyms. Lu et al. (2014) proposed a visual analytics toolkit to gather data from Bitly and Twitter for the prediction of the ratings and revenue generated by feature films. The advantages of the interactive environment for predictive analysis were demonstrated through statistical modelling methods, using results from the visual analytics science and technology (VAST) box-office challenge in 2013. The proposed framework was flexible to be used in other social media platforms for the analysis of advertisement and the forecasting of sales. However, the data-cleaning and sentiment analysis process employed was considerably challenging and became complicated for larger data sets. Mostafa (2013) applied lexicon-based sentiment analysis to explore the consumer opinion towards certain cosmopolitan brands. The text-mining techniques utilised were capable of exploring the hidden patterns of consumer opinions. However, their framework was quite oversimplified, and was not designed to perform some of the most prevalent analysis, such as topic detection. Tan et al. (2015) developed a deduction graph model for the extraction of big data to improve the capabilities for supply chain innovation. This model extracted and developed inter-relations among distinct competence sets, thereby generating opportunity for extensive strategic analysis of the capabilities of a firm. The mathematical methodology that was followed to achieve the optimum results was quite sophisticated and monotonous, considering that it was not autonomous. Chae (2015) developed a Twitter analytics framework for the evaluation of Twitter information in the field of the supply chain management. An attempt was made by them to fathom the potential engagement of Twitter in the application of supply chain management, as well as in further research and development. This mechanism was composed of three procedures, which are known as descriptive analysis, network analysis, and content analysis. The shortcoming of this research was that data collection was performed using '#supply chain' instead of keywords. Therefore, the data collected may not be the large enough for sentiment analysis. Bhattacharjya et al. (2016) implemented inductive coding to examine the efficiency of e-retailer logistics-specific customer service communications on social media (Twitter). Their approach illustrated informative interactions, and was able to distinguish with precision the beginning and conclusion of interactions among e-retailers and consumers. However, the data-mining mechanism which was utilised might have overlooked certain types of exchanges, which were relatively low in frequency. Kontopoulos et al. (2013) used formal concept analysis (FCA) to develop an ontology-based model for sentiment analysis. Their framework performed efficient sentiment analysis of tweets by differentiating the features of the domain and by allocating a respective sentiment grade to it. However, their framework was not sufficiently robust to deal with advertisement tweets. It was either considered as positive tweets or rejected by their mechanism, thereby reducing the precision of sentiment analysis. Similarly, Cigarrán et al. (2016) also utilised the FCA approach for the analysis of tweets for topic detection. Although the FCA approach was quite efficient, it was not sufficiently robust to deal with tweets that presented lack of clarity; therefore, it created uncertainty on its ability to offer precise sentiment grades. Rui et al. (2013) used an amalgamation of the naive Bayes classifier and the SVM to explore the impact of pre-consumer opinion and post-consumer opinion on feature film sales data. The algorithms utilised by the researchers for sentiment analysis of tweets effectively classified sentiments into positive, negative, and neutral. The only limitation in their work is that the naive Bayes classifier is considered to be an oversimplified method; therefore, the accuracy of its results is not as appreciable compared to those of some of the more sophisticated tools which are currently available for sentiment analysis. Pak and Paroubek (2010) developed a Twitter corpus by gathering tweets via the Twitter API. The corpus was utilised to create a sentiment classifier derived from multinomial naive Bayes classifier (using n-grams and part-of-speech (POS) tags as features). This framework leaves room for error because only the polarity of emoticons was employed to label the tweet emotions in the training data set. Only the tweets with emoticons were available in the training data set, which rendered it fairly inefficient. Neethu and Rajasree (2013) utilised a machine-learning approach to investigate tweets on electronic products, such as laptops and mobile phones. A new feature vector was proposed for sentiment analysis, and it gathered intelligence on these products from the viewpoint of people. During the study, the researchers found that the SVM classifier yields results of higher accuracy than the naive Bayes classifier.

The application of social media data in the food supply chain is at a primitive stage. This study addresses the gap in the literature by analysing social media data to identify issues in the food supply chain and by investigating how these issues can be mitigated to achieve a consumer-centric supply chain. The consumer tweets regarding beef products were analysed through SVM and hierarchal clustering using multiscale bootstrap resampling to explore the major issues faced by consumers. For the accumulation of ultimate opinions, the subjectivity and polarity associated with the opinions were identified and merged into the form of a numeric semantic score (SS). The identified issues from the consumer tweets were linked to their root causes, in different segments of the supply chain. For instance, issues such as bad flavour, unpleasant smell, discoloration of meat, and presence of foreign bodies were linked to their root causes in the upstream of the supply chain, namely the beef farms, abattoir, processor, and retailer. The corresponding mitigation of these issues will be also provided in detail. The next section describes the Twitter data analysis process employed in the present work.

3. Twitter data analysis process

In terms of social media data analysis, three major issues are considered: data harvesting/capturing, data storage, and data analysis. In the case of Twitter, data capturing starts with finding the topic of interest by using an appropriate keywords list (including texts and hashtags). This keywords list is used along with the Twitter streaming APIs to gather publicly available datasets from twitter postings. Twitter streaming APIs allow data analysts to collect 1% of the available Twitter datasets. There are other third-party commercial data providers, such as Firehose, which offer full historical twitter datasets.

Morstatter et al. (2013) demonstrated that the comparison between the data sample collected by Twitter streaming API and the full data stored by Firehose presented good agreement. This comparison was performed to test whether the data obtained by the streaming API is a good/sufficient representation of user activity on Twitter. Their study suggested that there are various ways of setting up the API to increase the representativeness of the data collected. One of the ways was to create more specific parameter sets through the use of bounding boxes and keywords. This approach can be used to extract more data from the API. Another key issue highlighted in their study was that the representation accuracy (in terms of topics) increased when the volume of data collected from the streaming API was large. Following these suggestions, we used set of specific keywords and regions to extract data from the streaming API in such a manner that data coverage, and consequently the representation accuracy, may be increased.

The Twitter streaming API allowed us to store/append twitter data in a text file. Then, a parsing method was implemented to extract datasets relevant to the present study (e.g. tweets, coordinates, hashtags, URLs, retweet count, follower count, screen name, favourites, location, etc.). Please refer to Fig. 1 for details on the overall approach. The analysis of the gathered Twitter data is generally complex owing to the presence of unstructured textual information, which typically requires natural language processing (NLP) algorithms. To investigate the extracted Twitter data, we proposed two main types of content

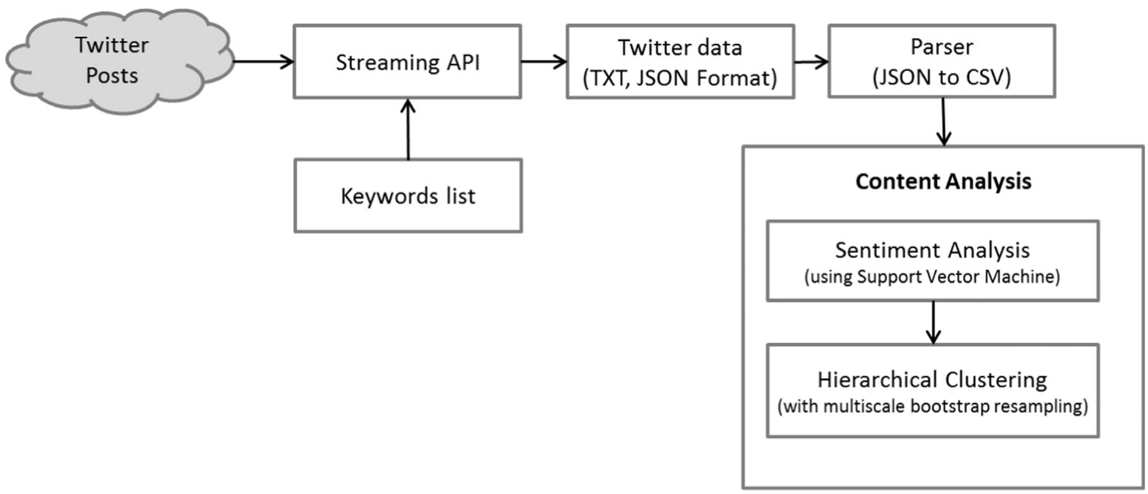

Fig. 1. Overall approach for social media data analysis.

analysis techniques—sentiment mining and clustering analysis. More information on the proposed sentiment-mining method and hierarchical-clustering method will be presented in detail in the following subsections.

3.1. Content analysis

The information available on social media is predominantly in the unstructured textual format. Therefore, it is essential to employ content analysis (CA) approaches, which includes a wide array of text mining and NLP methods to accumulate knowledge from Web 2.0 (Chau and Xu, 2012). A tweet (with a maximum of 140 characters) comprises a small set of words, URLs, hashtags, numbers, and emoticons. Appropriate cleaning of the text and further processing is required for effective knowledge gathering. There is no optimal way to perform data cleaning, and several applications have used their own heuristics to clean the data. A text cleaning exercise, which included the removal of extra spaces, punctuation, numbers, symbols, and html links were used. Then, a list of major food retailers in the world (including their names and Twitter handles) was used to filter and select a subset of tweets, which are used for analysis.

3.1.1. Sentiment analysis based on SVM

Tweets contain sentiments as well as information about the topic. Thus, sophisticated text-mining procedures, such as sentiment analysis, are vital for extracting true customer opinion. In the present work, the objective is to categorise each tweet as a one expressing either a positive or a negative sentiment.

Sentiment analysis, which is also widely known as opinion mining, is defined as the domain of research that evaluates public sentiments, appraisals, attitudes, emotions, evaluations, and opinions on various commodities, such as services, corporations, products, problems, situations, subjects, and their characteristics. It represents a broad area of issues. Several names exist to accommodate this concept, with minor differences, such as opinion mining, sentiment mining, sentiment analysis, opinion extraction, affect analysis, emotion analysis, subjectivity analysis, and review mining. Nonetheless, all these names are covered under the broad domain of opinion mining or sentiment analysis. In the literature, both terms, namely 'opinion mining' and 'sentiment analysis', are intermittently utilised.

In the proposed sentiment-mining approach, an opinion is elicited in the form of numeric values from a microblog (in text format). This approach identifies the subjectivity and polarity associated with the opinions, and merges them in the form of a numeric semantic score (SS) for the accumulation of ultimate opinions. The steps involved in this approach are the following:

Identifying subjectivity from the text: Although posts on microblogging websites are quite short in length, there are certain posts that comprise multiple sentences highlighting numerous subjects or views. The subjectivity of an opinion is investigated by determining the strength of an opinion for a topic. Bai (2011) and Duan et al. (2008) have classified opinions into subjective and objective opinions. Objective opinions reveal the basic information associated with an entity, and do not present subjective and emotional perspectives. On the other hand, subjective opinions represent personal viewpoints. As the purpose of this framework is to analyse Twitter user perspective on food products, subjective opinions are more crucial. People mostly utilise emotional words when describing their opinions, rather than objective information. Therefore, the opinion subjectivity (OS) of a post is defined as the average sentimental and emotional word density in every sentence of microblog m, which describes a topic t (in this study, we are examining words that are related to *beef/steak*).

The subjectivity level of opinions can be evaluated by developing a subjective word set which comprises sentimental and emotional words, and by expanding the word set through the use of WordNet. WordNet is a web-based semantics lexicon, and is the database of word synonyms and antonyms. In the present approach, a small set of seeds or sentiment words with defined positive and negative inclination was initially gathered manually. Then, the algorithm expanded this set by exploring an online dictionary, such as WordNet, for their respective synonyms and antonyms. The fresh words found were then transferred to the small set. Thereafter, the next iteration was initialised. This iterative procedure concluded when the search was complete, and no new words could be found. This approach was followed in the work of Hu and Liu (2004). Following this procedure, a subjective word set ϕ was identified. The opinion subjectivity associated with a post m as per the topic t, denoted as $OS_{m,t}$, can be expressed as

$$OS_{m,t} = \frac{\left(\sum_{s\in S_t^m} \frac{|U_s\cap\phi|}{U_s}\right)}{|S_t^m|} \tag{1}$$

where U_s denotes the set of unigrams contained in the sentence and S_t^m represents the set of sentences in tweet m which has the topic t.

Sentiment classification module: The identification of the polarity mentioned in the opinion is crucial for transforming the format of the opinion from text to numeric value. The performance of data-mining methods such as SVM is excellent for sentiment classification (Popescu and Etzioni, 2007). In the present approach, the SVM model was employed for the division of the polarity of opinions. The prerequisites for SVM are threefold. Initially, the features of the data must be chosen. Then, the data set utilised in training process needs to be marked with its true classes. Finally, the optimum combination of model settings and constraints needs to be calculated. The unigrams and bigrams are the tokens of one-word and two-word posts identified from the microblog, respectively. While there is a constraint on the length of the microblogging post, the probability of iterative occurrence of a characteristic in the same post is quite low. As such, this study uses binary values $\{0,1\}$ to represent the presence of these features in the microblog. The appearance of a feature in a message is denoted by '1', whereas the absence of a feature is denoted by '0'.

SVM is a technique for supervised machine learning, which requires a training data set to identify the best maximum-margin hyperplane (MMH). In the past, researchers have used approach where they have manually analysed and marked data prior to their use as training data set. Posts on a microblogging website are short; therefore, the number of features associated with them is also limited. In this case, we examined the use of emoticons to identify sentiments of opinions. In this study, Twitter data were pre-processed based on emoticons to create a training dataset for SVM. Microblogs with ':)' were marked as '+1', representing a positive polarity, whereas messages with ':(' were marked as '−1', representing negative polarity. It was observed that more than 89% messages (using a small sample of 1000 tweets) were manually marked with precision by following this procedure. Thus, the training data set was collected using this approach for SVM training. More specific details on the parameter values and associated details are provided in Section 4 where a case study is discussed. Then, a grid search (Hsu et al., 2003) was employed for the identification of the optimum combination of variables γ and c to carry out SVM with a Radial Basis Function kernel. The polarity ($Pol_m \in \{+1, -1\}$), representing positive and negative sentiment of a microblog m, respectively, can be predicted using a trained SVM. Thus, the semantic score, SS, can be calculated by using the resultant subjectivity and opinion polarity on for a topic t via following equation:

$$SS_{m,t} = Pol_m \times OS_{m,t} \tag{2}$$

where $SS_{m,t} \in [-1, 1]$.

In real life, when consumers buy beef products, they leave their true opinion (feedback) on Twitter. In this article, the SVM classifier was utilised to classify these sentiments into positive and negative, and consequently gather intelligence from these tweets.

3.1.2. Word and Hashtag analysis

Another type of content analysis that was conducted in the present work is word analysis. This type of analysis includes term frequency identification, summarisation of document, and word clustering. Term frequency is commonly utilised in text data retrieval and identification of word clusters and word clouds. These analyses can help to identify various issues under discussion in the tweets, as well as their relevance to the food supply chain management practices. Term frequency can help to extract popular hashtags and Twitter handles, which may offer information on the features and relevance of a tweet. Other types of analysis include machine-learning-based clustering and association rules mining. The association rules mining can help to identify associations of different terms that frequently occur in the tweets.

3.1.3. Hierarchical clustering with p-values using multiscale bootstrap resampling

Once the semantic score is identified through the SVM and subjectivity identification, then hierarchical clustering method is applied individually to the tweets, which are positively and negatively scored. In this research, we employed a hierarchical clustering with p-values via multiscale bootstrap resampling (Suzuki and Shimodaira, 2006). The clustering method creates hierarchical clusters of words; moreover, it computes their significance using p-values (obtained after the multiscale bootstrap resampling). This enables to easily identify significant clusters in the datasets and their hierarchy. The agglomerative method used was the ward.D2 (Murtagh and Legendre, 2014). The pseudocode for the hierarchical clustering algorithm is presented in Fig 2.

Fig. 2 illustrates how the hierarchical clustering generates a dendrogram which contains clusters. However, the support of the data for these clusters was not determined using the method presented in Fig 2. One way to determine the support of data for these clusters is by adopting multiscale bootstrap resampling. In this approach, the dataset is replicated by resam-

$d_{i,j}$: distance between cluster i and j
C: set of all clusters
$\boldsymbol{D}$: set of all $d_{i,j}$
n_i: number of data points in cluster i

Step 1: Find smallest element $d_{i,j}$ in $\boldsymbol{D}$
Step 2: Create new cluster k by merging cluster i and j (where $i, j \in C$)
Step 3: Compute new distances $d_{k,l}$ (where $l \in C$ and $l \neq k$) as

$$d_{k,l} = \alpha_i d_{i,l} + \alpha_j d_{j,l} + \beta d_{i,j}$$

Compute number of data points in cluster k as n_k as

$$n_k = n_i + n_j$$

where, $\alpha_i = \frac{n_i+n_l}{n_k+n_l}$, $\alpha_j = \frac{n_j+n_l}{n_k+n_l}$, $\beta = \frac{-n_l}{n_k+n_l}$ (Ward's minimum variance method)

Step 4: Repeat steps 1 to 3 until $\boldsymbol{D}$ contains a single group made of all data points.

Fig. 2. Hierarchical clustering algorithm.

pling several times, and then the hierarchical clustering is applied (see Fig. 2). We conducted hierarchical cluster analysis with multiscale bootstrap with number of bootstrap equal to 1000. During resampling, the replicating of sample sizes was changed to multiple values including smaller, larger, and equal to the original sample size. Then, bootstrap probabilities are determined by counting the number of dendrograms which contain a particular cluster and by dividing it by the number of bootstrap samples. This procedure is performed for all the clusters and sample sizes. Then, these bootstrap probabilities are used for the estimation of the *p*-value, which is also known as approximately unbiased (AU) value.

The result from the hierarchical clustering with multiscale bootstrap resampling is a cluster dendrogram. At every stage, the two clusters which bear the highest resemblance are combined to form one new cluster, as presented in Fig. 2. The distance or dissimilarity between the clusters is denoted by the vertical axis of dendrogram. The various items and clusters are represented on horizontal axis, which also illustrates several values at the branches, such as the AU *p*-values (left), the bootstrap probability (BP) values (right), and the cluster labels (bottom). Clusters with an AU $\geq$ 95% are usually enclosed in red rectangles, which represent significant clusters (as depicted in Fig. 4).

4. Case study and Twitter data analysis

The proposed Twitter data analysis approach was used to understand issues related to the beef/steak supply chain based on consumer feedback on Twitter. This analysis can help to analyse the reasons behind positive and negative sentiments, to identify communication patterns, prevalent topics and content, and characteristics of Twitter users discussing about beef and steak. Based on the result of the proposed analysis, a set of recommendations were prescribed for the development of a customer-centric supply chain.

The total number of tweets extracted for this research was 1,338,638 (as per the procedure discussed in Section 3). They were captured from 23/03/2016 to 13/04/2016 using the keywords ‘beef’ and ‘steak’. Only tweets written in the English language were considered, with no geographic constraint. Fig. 3 illustrates the location of tweets, and presents the geolocation data on the world map. Then, keywords were selected to capture the tweets relevant to this study. In order to select the keywords, on-site visits were carried out to various main and convenience retail stores in the UK, to discover the different negative and positive feedback left by the consumers with respect to beef products. We conducted interviews with the retail-store staff members dealing with consumer complaints, who provided access to databases of consumer complaints regarding beef products. Interviews of certain consumers were also conducted to explore the type of keywords used by them to express their view. The research team involved in this article also investigated the various complaints made by consumers to the store, worldwide. Different keywords employed on Twitter for beef products were captured and discussed with retailers and consumers. Consequently, a comprehensive list of the keywords (as listed in Table 2) was composed to explore issues that related to beef products, and that were highlighted by consumers on Twitter. The overall tweets were then filtered using this list of keywords, so that only the relevant tweets (26,269) would be retrieved. Then, country-wise classification of tweets was performed by using the name of the supermarket corresponding to each country. It was observed that tweets from the USA, the UK, Australia, and the world were 1605, 822, 338, and 15,214, respectively. Several hashtags were observed in the collected tweets. The most frequently used hashtags (more than 1000) are highlighted in Table 3. Top Twitter handles (that

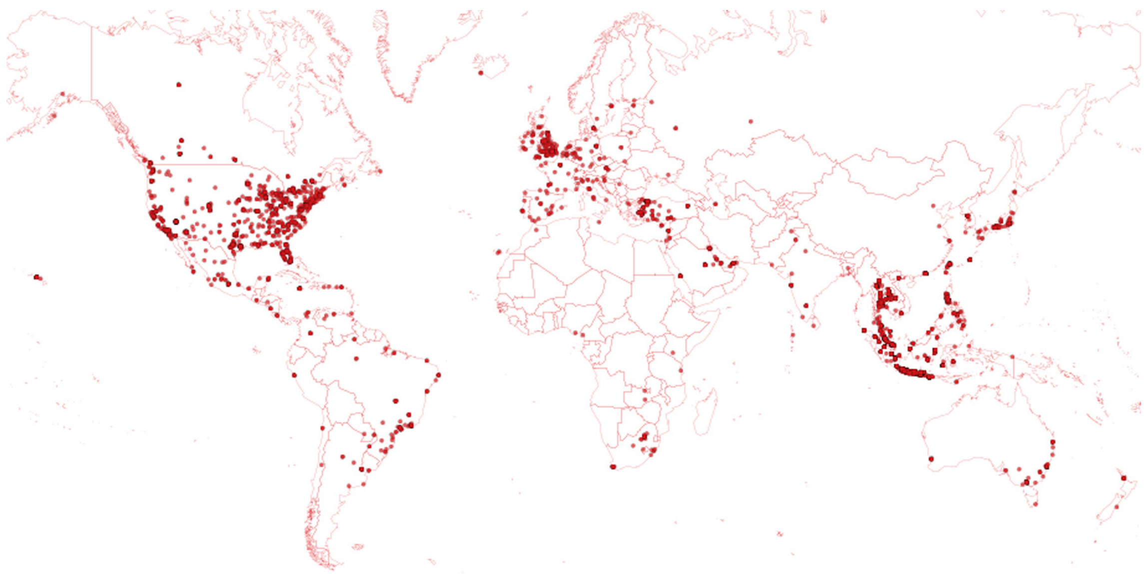

Fig. 3. Visualisation of tweets with geolocation data (23,422 out of 1,338,638 tweets containing ‘beef’ and/or ‘steak’).

Please cite this article in press as: Singh, A., et al. Social media data analytics to improve supply chain management in food industries. Transport. Res. Part E (2017), http://dx.doi.org/10.1016/j.tre.2017.05.008

Table 2
Keywords used for extracting consumer tweets.

Beef#disappointment	Beef#rotten	Beef# rancid	Beef#was very chewy
Beef#taste awful	Beef#unhappy	Beef#packaging blown	Beef#was very fatty
Beef#odd colour beef	Beef#discoloured	Beef#plastic in beef	Beef#gristle in beef
Beef#complaint	Beef#grey colour	Beef#oxidised beef	Beef#taste
Beef#flavour	Beef#smell	Beef#rotten	Beef#funny colour
Beef#horsemeat	Beef#customer support	Beef#bone	Beef#inedible
Beef#mushy	Beef#skimpy	Beef#use by date	Beef#stingy
Beef#grey colour	Beef#packaging	Beef#oxidised	Beef#odd colour
Beef#gristle	Beef#fatty	Beef#green colour	Beef#lack of meat
Beef#rubbery	Beef#suet	Beef#receipt	Beef#stop selling
Beef#deal	Beef#bargain	Beef#discoloured	Beef#dish
Beef#stink	Beef#bin	Beef#goes off	Beef#rubbish
Beef#delivery	Beef#scrummy	Beef#advertisement	Beef#promotion
Beef#traceability	Beef#carbon footprint	Beef#nutrition	Beef#labelling
Beef#price	Beef#organic/inorganic	Beef#MAP packaging	Beef#tenderness

Table 3
Top hashtags used.

Hashtag	Freq (>1000)	Freq (%)	Hashtag	Freq (>1000)	Freq (%)	Hashtag	Freq (>1000)	Freq (%)
#beef	17708	16.24%	#aodafail	1908	1.75%	#bmg	1255	1.15%
#steak	14496	13.29%	#earls	1859	1.70%	#delicious	1243	1.14%
#food	7418	6.80%	#votemainefpp	1795	1.65%	#soundcloud	1169	1.07%
#foodporn	5028	4.61%	#win	1761	1.62%	#vegan	1131	1.04%
#whcd	5001	4.59%	#ad	1754	1.61%	#rt	1128	1.03%
#foodie	4219	3.87%	#cooking	1688	1.55%	#mrpoints	1116	1.02%
#recipe	4106	3.77%	#mplusplaces	1686	1.55%	#staydc	1116	1.02%
#boycottearls	3356	3.08%	#meat	1607	1.47%	#wine	1072	0.98%
#gbbw	3354	3.08%	#lunch	1577	1.45%	#np	1069	0.98%
#kca	2898	2.66%	#bbq	1557	1.43%	#yelp	1052	0.96%
#dinner	2724	2.50%	#yum	1424	1.31%	#ufc196	1048	0.96%
#recipes	2159	1.98%	#yummy	1257	1.15%	#britishbeefweek	1045	0.96%
#accessibility	1999	1.83%	#bdg	1255	1.15%			

is, users who are mentioned very frequently) were identified among the extracted tweets. The Twitter users who have been mentioned more than 2000 times were considered as top Twitter handles, and they are presented in Table 4.

As described in Section 3.1.1, the collection of training data for the SVM was performed automatically, based on emoticons. The training data were developed by collecting 10,664 (from all the tweets with 'beef' and 'steak') messages from the Twitter data captured with emoticons ':)' and ':('. The microblogs/tweets consisting of ':)' were marked as '+1', whereas messages comprising ':(' were marked as a '−1'. The tweets containing both ':)' and ':(' were removed. The automatic marking process was concluded by generating 8560 positive, 2104 negative, and 143 discarded messages. Positive and negative messages were then randomly classified into five categories. The 8531 messages in the first four categories were utilised as the training data set and the rest of the 2133 messages were utilised as the test data set. The values $\gamma = 2.3$, $c = 2.85$ (for positive class) and $c = 11.4$ (for negative class) was used for radial basis function in SVM. We used differential costs for positive and negative class to account for class imbalance present in the dataset, *i.e.*, 8560 positive and 2104 negative tweets, i.e., the misclassification penalty for the minority class is chosen to be larger than that of the majority class.

Numerous pre-processing steps were employed to minimise the number of features prior to the implementation of the SVM training. Initially, the target query and terms related to the topic (beef/steak-related words) were deleted to prevent the

Table 4
Top Twitter users.

Twitter handle	Freq (>2 k)	Freq (%)	Twitter Handle	Freq (>2 k)	Freq (%)	Twitter Handle	Freq (>2 k)	Freq (%)
@historyflick	10903	9.16%	@chipotletweets	3701	3.11%	@shukzldn	2203	1.85%
@metrroboomin	10725	9.01%	@globalgrind	3626	3.05%	@zacefron	2201	1.85%
@jackgilinsky	8814	7.40%	@trapicalgod	3499	2.94%	@foodpornsx	2190	1.84%
@itsfoodporn	8691	7.30%	@viralbuzznewss	2964	2.49%	@redtractorfood	2166	1.82%
@kanyewset	7452	6.26%	@crazyfightz	2798	2.35%	@sza	2155	1.81%
@youtube	6593	5.54%	@soioucity	2795	2.35%	@therock	2131	1.79%
@earlsrestaurant	5822	4.89%	@kardashianreact	2765	2.32%	@tmzupdates	2093	1.76%
@hotfreestyle	3794	3.19%	@sexualgif	2564	2.15%	@ayookd	2031	1.71%
@audiesamuels	3775	3.17%	@cnn	2504	2.10%	@mcjuggernuggets	2015	1.69%
@freddyamazin	3758	3.16%	@euphonik	2335	1.96%			

classifier from categorising sentiments based on certain queries or topics. Then, the numeric values in the messages were replaced with a unique token 'NUMBER'. A prefix 'NOT_' was added to the words followed by negative word (such as 'never', 'not', and words ending with 'n't') in each sentence. Finally, the Porter stemming algorithm was utilised to stem the rest of the words (Van Rijsbergen et al., 1980).

Various feature sets were collected and their accuracy level was examined. Tweets with ':)' and ':(' are assumed to be the true classes representing positive and negative sentiments. These true classes were used for comparing the NB and SVM techniques. Unigrams and bigrams representing one-word and two-word tokens were extracted from the microblog posts. In terms of performance of the classifier, we used two types of indicators: (i) the five-fold cross validation (CV) accuracy and (ii) the accuracy level obtained when the trained SVM is used to predict sentiment in the test data set. We also implemented a naive Bayes classifier to be compared with the performance of the SVM classifier.

Table 5 lists the performance of the naive Bayes- (NB) and SVM-based classifiers on the collected microblogs. The best performance is provided when using the unigram feature set in both SVM and NB classifiers. It can be seen that the performance of the SVM is always superior to the NB classifier in terms of sentiment classification. The unigram feature set yields better result than the other feature sets. This occurs because additional casual and new terms are utilised to express the emotions. It negatively affects the precision of the subjective word set characteristic, as it is based on a dictionary. Furthermore, the binary representation scheme produced comparable results, except for the case of unigrams, with those produced by the term frequency (TF) based representation schemes. As the length of micro-blogging posts are quite short, the binary representation scheme and the TF representation scheme are similar to each other, and present almost matching performance levels. Therefore, the SVM-based classifier with unigrams as feature set represented in binary scheme was used for the estimation of the sentiment score of the microblog.

The sentiment analysis based on the SVM was performed on the country-wise classification of tweets. Table 6 lists certain example tweets and their sentiment scores.

To identify meaningful topics and their content in the collected tweets, initially, we performed sentiment analysis to identify sentiments of each of the tweets. To gain more insight, the sentiment scores and country type were then used to perform content analysis. The next section explains the results by sub-setting the captured data based on sentiment scores and the country type.

4.1. Content analysis based on the country type

4.1.1. Analysis of all the tweets from the world

The collected tweets were examined to identify the most frequently used words by consumers to express their views. 'Beef' and 'steak' were the most frequently used words, followed by 'fresh', 'taste', and 'smell'. Then, on these tweets, association rule mining was performed to discover which words are mostly used in conjunction with 'beef' and 'steak'. It was found that the words 'celebrate' and 'redtractorfood' were the most widely used, and that words such as 'smell' and 'roast' were scarcely used with 'beef'. For instance, tweets such as '*Celebrate St. Patrick's Day with dinner at the Brickstone! Irish Corned Beef and Cabbage tops the menu! https://t.co/vRnewdKZYd*' present considerably higher frequency compared to the tweets similar to '*@Tesco just got this from your D'ham Mkt store. It's supposed to be Men's Health Beef Jerky…The smell is revolting https://t.co/vTKVRIARW5*'.

Furthermore, cluster analysis was carried out to classify tweets into certain groups (or clusters) as per the similarities between them. The proposed clustering approach involves hierarchical cluster analysis (HCA) with uncertainty assessment. For each cluster in hierarchical clustering, the *p*-values were calculated using multiscale bootstrap resampling. The *p*-value of a cluster indicates its strength (i.e. how well it is supported by data). A parallel-computing-based HCA with *p*-values was implemented to quickly analyse the high number of tweets. The cluster which presents high *p*-values (approximately unbiased) were strongly supported by the capture tweets. These clusters can help us to explain user opinion on beef and steak across the globe. The two predominant clusters identified (with a significance level of >0.95) are represented in Fig. 4 as red coloured rectangles. The first cluster consists of certain closely related words, such as *gbbw*, *win*, *celebrate*, *hamper*, *redtractorfood*, and *dish*. It primarily highlights an event called *Great British Beef Week* in the UK, where an organisation associated

Table 5
Performance of the SVM- and NB-based classifier on selected feature sets; CV: 5-fold cross validation, NB: naive Bayes.

Representation scheme	Feature type	Number of features	SVM		NB
			CV (%)	Test data (%)	Test data (%)
Binary	Unigram	12,257	91.75	90.80	70.68
	Bigram	44,485	76.80	74.46	63.60
	Unigram + bigram	56,438	87.12	83.28	63.48
	Subjective word set (ϕ)	6789	66.58	65.52	41.10
Term Frequency	Unigram	12,257	88.78	86.27	72.35
	Bigram	44,485	77.49	71.68	65.90
	Unigram + bigram	56,438	84.81	80.97	59.24
	Subjective word set (ϕ)	6789	68.21	62.25	39.71

Please cite this article in press as: Singh, A., et al. Social media data analytics to improve supply chain management in food industries. Transport. Res. Part E (2017), http://dx.doi.org/10.1016/j.tre.2017.05.008

Table 6
Raw Tweets with sentiment polarity.

Sentiment polarity	Raw Tweets
Negative	*@Tesco just got this from your D'ham Mkt store. It's supposed to be Men's Health Beef Jerky...The smell is revolting https://t.co/vTKVRIARW5*
Negative	*@Morrisons so you have no comment about the lack of meat in your Family Steak Pie? #morrisons*
Negative	*@AsdaServiceTeam why does my rump steak from asda Kingswood taste distinctly of bleach please?*
Positive	*Wonderful @marksandspencer are now selling #glutenfree steak pies and they are delicious and perfect! Superb stuff.*
Positive	*Ive got one of your tesco finest* beef Chianti's in the microwave oven right now and im pretty pleased about it if im honest*
Positive	*@AldiUK beef chilli con carne! always a fav that goes down well in our house! of course with lots of added cheese on top! #WIN*

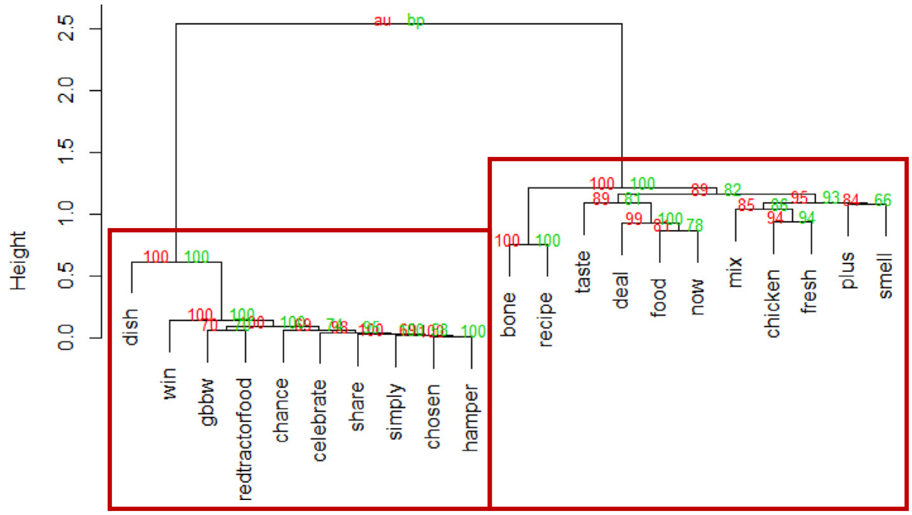

Fig. 4. Hierarchical cluster analysis of the all tweets originating in the world; approximately unbiased p-value (AU, in red), bootstrap probability value (BP, in green). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

with farm assurance schemes, called Red Tractor, has asked customers to share their dish to win a beef hamper for the celebration of this event. The second cluster consists of words such as *bone*, and highlights the presence of bone fragments in the beef and the steak of the customers. In their tweets, customers both appreciate or complain about the *taste*, *smell*, *freshness* and various *recipes* of the beef products. The details on the deals and promotions associated with food products, particularly with beef, have been described by the aforementioned customers.

During the analysis, it was found that Twitter data can be broadly classified in two clusters: tweets associated with episodic events and tweets associated with the opinion of consumers on beef products. The intelligence gathered from the episodic event cluster can help retailers to pursue effective marketing campaigns of their new products. Retailers can also identify the factors which have high influence within the network and on their association with other related products. They can also use this medium to address consumer concerns. The second cluster will provide insight into the likes and dislikes of consumers. Certain tweets in this cluster were positive and others were negative; this ambivalence will be explained in next subsections.

4.1.2. Analysis of negative tweets from the world

The collected tweets were divided into positive- and negative-sentiment tweets. In the negative sentiment tweets, the most frequently used words associated with 'beef' and 'steak', were 'smell', 'recipe', 'deal', 'colour', 'spicy', 'taste', and 'bone.'

Cluster analysis was performed for the negative tweets from the world, to divide them into clusters in terms of resemblance among their tweets. The three predominant clusters identified (with a significance level of >0.95) are represented in Fig. 5 as red-coloured rectangles. The first cluster consists of *bone* and *broth*, which highlights the excess of bone fragments in the broth. The second cluster is composed of *jerky* and *smell*. The customers have expressed their annoyance with the bad smell associated with jerky. The third cluster consists of tweets comprising *taste* and *deal*. Customers have often complained to the supermarket about the bad flavour of the beef products bought within the promotion (deal). The rest of the words highlighted in Fig. 5 do not lead to any conclusive remarks.

This cluster analysis will help global supermarkets to identify the major issues faced by customers. It will provide them the opportunity to mitigate these problems and raise customer satisfaction, as well as their consequent revenue.

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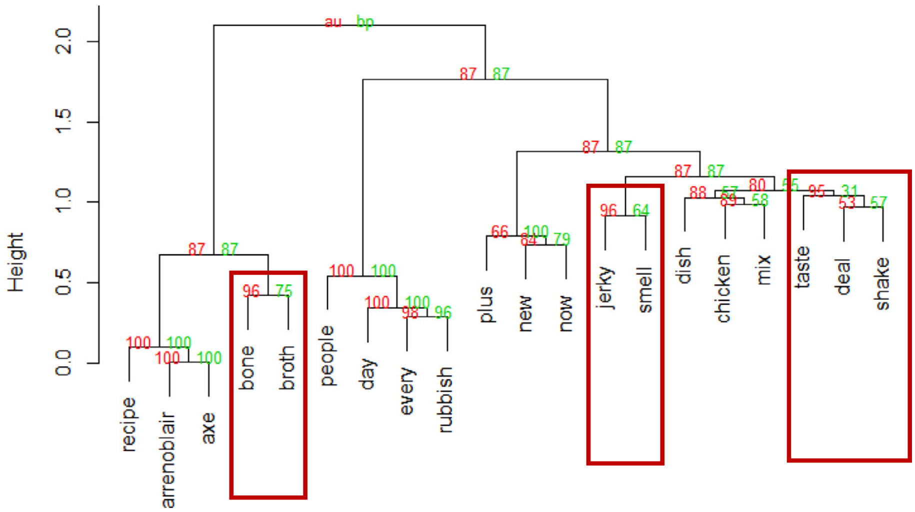

Fig. 5. Hierarchical cluster analysis of the negative tweets originating in the world.

4.1.3. Analysis of positive tweets from the world

The positive tweets from the world were analysed, and the most frequently used words after 'beef' and 'steak' were 'fresh', 'dish', and 'taste'.

The association rule mining evaluation of the positive tweets from around the world was performed. It was found that 'beef' was closely associated with words such as 'celebrate' and 'redtractorfood', and was rarely used with words such as 'months' and 'ways'. The word 'steak' was frequently used with words such as 'awards' and 'kca', whereas it was sparsely used with 'chew' and 'night'.

The positive tweets from the world were classified into two clusters based on the similarity of their tweets. They were divided into two clusters, as shown in Fig. 6. The first cluster was composed of words such as '*dish*', '*win*', '*gbbw*', '*celebrate*', '*redrtractorfood*', '*share*', and '*hamper*'. These tweets are associated with the celebration of the Great British beef week in the UK. Red Tractor has asked customers to share their dish in order to win a beef hamper. The findings from this cluster do not contribute to the objective of this study, which is the development of a consumer-centric supply chain. However, retailers may utilise it to develop a strategy to introduce appropriate promotional deals to capture a larger market share than their rivals during events such as the great British beef week. The second cluster is composed of words such as '*love*', '*taste*', '*best roast*', and '*delicious food*', where customers have praised the taste and the overall quality (such as smell and tenderness) of

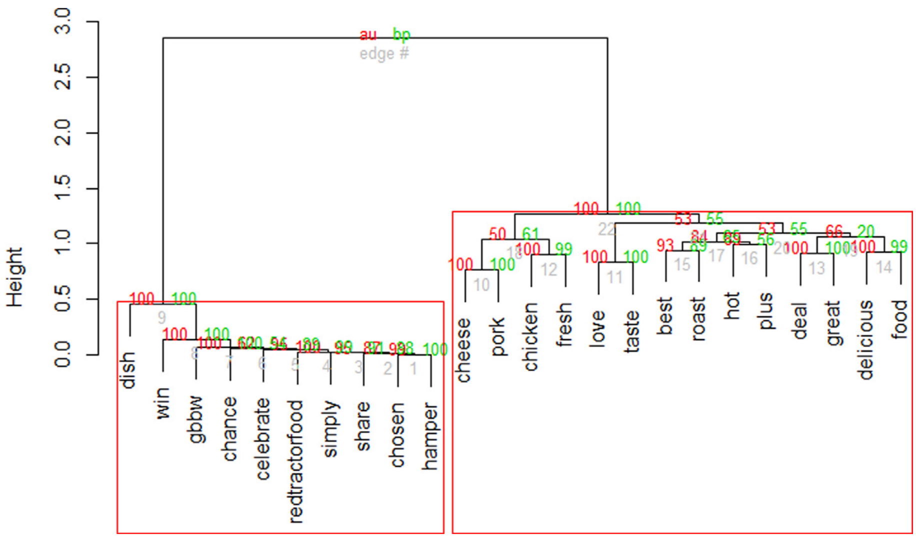

Fig. 6. Hierarchical cluster analysis of the positive tweets originating from the world.

the beef products. The words like '*deal*' and '*great*' highlight the promotions, which were very popular among customers while purchasing beef products.

This cluster analysis will help global supermarkets to present their best-performing beef products and their strengths such as taste and promotions. Moreover, the analysis can help supermarkets to introduce new products and promotions.

4.1.4. Analysis of positive tweets from the UK

The positive tweets from the UK were analysed; the most widely used words after 'beef' and 'steak' were 'adliuk, 'morrisons', 'waitrose' and 'tesco'. The association rule mining of tweets from the UK with positive sentiment was conducted, and the word 'beef' was most closely associated with terms such as 'roast britishbeef' and 'Sunday', whereas it was least used with words such as 'type' and 'tell'. The term 'steak' was most frequently used with words such as 'days', 'date', and 'free', whereas it was rarely used with terms such as 'supper', 'quick', and 'happy'.

The positive tweets from the UK were classified into three clusters based on the similarity to their tweets. The first cluster consists of words such as '*leeds*' and '*nfunortheast*', and highlights an event that took place in Leeds, UK, where supermarket Asda joined the National Farmers Union (NFU) Northeast in selling Red Tractor (farm assurance) approved beef products. The second cluster consists of words such as '*delicious*', '*roast*' and '*lunch, Sunday*', where customers talk about cooking roast beef products on Sunday, which turn out to be delicious. The third cluster is composed of words such as '*thanks*',' '*love*', '*made*' and '*meal*', where customers are grateful for the good quality of beef products after cooking them.

The cluster analysis will help UK supermarkets to discover customer preferences. For instance, they prefer the beef originating from the farms approved by farm assurance schemes (Red Tractor). Supermarkets may also monitor their best performing beef products, which will assist them in launching their new products. This will help retailers to develop a strategy to align their products with the preference of the consumers.

4.1.5. Analysis of negative tweets from the UK

The most widely used words after 'beef' and 'steak' were 'tesco', 'coffee', 'asda', 'aldi'. The association rule mining indicated that the word 'beef' was most closely associated with terms such as '*brisket*', '*rosemary*', and '*cooker*'. It was least used with terms such as '*tesco*', '*stock*' and '*bit*'. The word '*steak*' was highly associated with '*absolute*', '*back*' and '*flat*', and was rarely associated with words such as '*stealing*', '*locked*' and '*drug*'.

The four predominant clusters were identified (with a significance level of >0.95). The first cluster contained words, such as '*man*', '*coffee*', '*dunfermline*', '*stealing*', '*locked*', '*addict*' and '*drug*'. When this cluster was analysed together with raw tweets, it was found that this cluster represents an event where a man was caught stealing coffee and steak from a major food store in Dunfermline. The finding from this cluster was not linked to our study. However, it could assist retailers in various purposes, such as developing strategy for an efficient security system in stores to address shoplifting. Cluster 2 was related to the tweets discussing high prices of steak meal deals. Cluster 3 represented the concerns of users on the use of horsemeat in many beef products offered by major superstores. This revealed that consumers are concerned about the traceability of beef products. Cluster 4 comprised tweets which discuss the lack of locally produced British sliced beef in major stores (with *#BackBritishFarming*). This reflects that consumers prefer the beef produced from British cattle instead of from imported beef. The rest of the clusters, when analysed together with raw tweets, did not highlight any conclusive remarks, and users mainly discussed one-off problems with cooking and cutting slices of beef.

The proposed HCA can help to identify (in an automated manner) root causes of the issues with the currently sold beef and steak products. This may help major superstores to monitor and respond quickly to the customer issues raised in social media platforms.

4.1.6. Analysis of negative tweets from Australia

The tweets reflecting negative sentiment from Australia were analysed, and the most frequently used words after 'beef' and 'steak' were '*aldi*' and '*safeway*'. The association analysis revealed that the term 'beef' was most closely associated with words such as '*safeway*', and '*corned*' and was least associated with '*grass, 'gross'* and *packaged*'. The word '*steak*' was mostly used in conjunction with terms such as '*woolworths*', *'breast*' and '*complain*', and was rarely used with terms such as '*waste*', '*wine*' and '*tough*'.

Cluster analysis was performed on the negative tweets from Australia; the results were classified into two clusters based on tweet similarity. The first cluster consisted of words such as '*feel*', '*eat*' *and* '*complain*', which reflects customer complaints on the quality of beef products, particularly in terms of tenderness and flavour. The second cluster comprised words such as '*disappointed*', '*cuts*', '*cook*', '*sold*' and '*dinner*', which illustrated the annoyance of customers regarding beef products cooked for dinner, particularly in terms of smell, cooking time, and overall quality.

This analysis will assist Australian supermarkets in exploring the issues faced by customers. It may help them backtrack their supply chain and mitigate these issues in order to improve customer satisfaction and consequent revenue.

4.1.7. Analysis of positive tweets from Australia

The tweets from Australia which resonated positive sentiment were analysed, and the most frequently used words after 'beef' and 'steak' were 'aldi', 'woolworths', 'flemings' and 'roast'. The association analysis indicated that the word 'beef' was most closely associated with terms such as 'roast', 'safeway' and 'sandwich', whereas it was least used with terms such as 'see', 'slow' and 'far'. The word steak was commonly used with terms such as 'flemings' and 'plate', and was rarely used with words such as 'spent', 'prime' and house'.

Cluster analysis was performed on the positive tweets from Australia. Two significant clusters were identified. The first cluster consisted of words such as '*new*', '*sandwich*', '*best*' and '*try*', where customers were praising the new beef sandwich they tried in different supermarkets. The second cluster included words such as '*delicious*', '*Sunday*', '*well*', '*roast*' and '*best*', in which customers were appreciative of the flavour of the roast beef that was cooked on Sunday, and bought form different supermarkets.

The cluster analysis of positive tweets may help Australian supermarkets to see the best performing beef products among their brands and their rival brands. Moreover, cluster analysis may help them to identify the most popular beef products among customers, as well as to launch new beef products and to strengthen their position in the market against their rivals.

4.1.8. Analysis of negative tweets from the USA

The tweets from the USA resonating negative sentiments were analysed, and the most frequently used words were 'beef', 'carnival', 'steak', 'walmart', 'sum' and 'yall'. Association rule mining was performed, and the results indicated that the term 'beef' was most closely associated with words such as '*carnival', 'yall'* and *dietz*', and was least associated with terms such as '*cake', 'sum', 'ride'* and *'grow'*. The word 'steak' was most frequently used with terms such as *'shake', 'walmart'* and *'stolen'*, and was least frequently used with words such as *'show', 'minutes'* and *'fries'*.

Cluster analysis was performed on the negative tweets from the USA, and they have been classified into two clusters based on tweet similarity. The first cluster included words such as '*mars', 'corned', 'beef', 'cream', 'really', 'eggs', 'trending', 'bars'* and *'personally*'. There was a tweet which was retweeted several times, which expressed the annoyance of a customer regarding the price of corned beef, comparing it to Mars bars and Cream eggs. The second cluster was composed of terms such as *'jerky', 'eat'* and *'went*', where customers have visited the supermarket to buy steak or joint, however, they could only find beef jerky on the shelves.

The negative cluster analysis may help the US supermarkets to understand the issues faced by customers. For instance, the high price of corned beef and the unavailability of steak and joint were the major issues highlighted. The supermarkets may liaise with their suppliers and develop appropriate strategies to satisfy their customers, and thereby generate more revenue.

4.1.9. Analysis of positive tweets from the USA

The positive tweets from USA were analysed, and the most frequently used words were 'beef', 'lamb', 'lbs', 'steak', 'tops' and 'walmart.' The association rule mining of tweets from the USA was performed, and the results indicated that term 'beef' was most closely associated with words such as *'lamb', 'pork', 'lbs'* and *'generate*', and was least associated with terms such as '*tops', 'cheese'* and '*equivalents*'. The word 'steak' was most frequently used with terms such as 'butter' and 'affordable', and was rarely used with terms such as '*truffles', 'sea'* and *'honey'*.

Two significant clusters were identified. The first cluster consisted of words such as '*tops', 'equivalents', 'cheese', 'greenhouse', 'gases', 'generate', 'pork', 'every', 'list', 'lamb'* and *'lbs*'. Customers have compared the greenhouse gases generated by the production of beef to that of lamb and cheese. They have suggested that beef production generates lower emissions than lamb. The second cluster comprises terms such as '*top', 'new', 'publix', 'better'* and *'best*', where customers appreciated the beef products sold by Publix compared to that of other supermarkets, in terms of quality and price.

The cluster analysis of positive tweets may help US supermarkets to find out the qualities preferred by consumers. For instance, supermarkets were conscious of the carbon footprint generated in the production of beef, lamb, and cheese. They also sought for high-quality beef products at a reasonable price. This analysis may help the US supermarket to develop their strategy for introduction of new products.

In the next section, we will describe how content analysis of Twitter data could help retailers in terms of waste minimisation, quality control, and efficiency improvement by linking them to the upstream segments of the supply chain.

5. Identification of issues affecting consumer satisfaction and their mitigation within the supply chain

During the analysis of consumer tweets, it was revealed that there were numerous issues affecting customer satisfaction, such as bad flavour, hard texture, extra fat, discoloration of beef products, and presence of horsemeat in beef products, as listed in Table 7. The root causes of these issues are located within various segments of the supply chain, as depicted in Fig. 7, and are often interrelated. Usually, retailers struggle to establish the relationship between customer dissatisfaction and their root causes. The major issues faced by consumers, their root cause, and the actions for their respective mitigation are described below:

1. Bad flavour and unpleasant smell—One of the major reasons for bad flavour and unpleasant smell is the oxidisation of beef products, which refers to the oxidisation of their proteins and lipids when exposed to air (Brooks, 2007). The beef products associated with issues of bad flavour and unpleasant smell leads to consumer disappointment, and often become discarded. Inefficient packaging methods employed by the abattoir and the processor, and the mishandling of beef products in logistics and other stages of beef products leads to their oxidisation (Barbosa-Pereira et al., 2014). Reg-

Table 7
Summary of issues identified from consumer tweets, and actions for their mitigation.

S. No.	Issues identified from consumer tweets	Mitigation of issues
1	Bad flavour and unpleasant smell	Periodic maintenance of packaging machines at abattoir and processor, efficient cold chain management, appropriate training of workforce in logistics and throughout the supply chain so that mishandling of beef products is avoided
2	Traceability issues in beef products	Supply chain mapping, strong vertical and horizontal coordination, use of ICT
3	Extra fat	Raising of cattle as per the weight and conformation specifications of retailer, and appropriate trimming of primals at abattoir and processor
4	Discoloration of beef products	Raising cattle on fresh grass at beef farms and maintaining efficient cold chain management throughout the supply chain
5	Hard texture	Appropriate maturation of carcass after slaughtering
6	Presence of foreign body	Following renowned food safety process management techniques such as Good manufacturing practices (GMP), Hazard analysis and critical control points (HACCP). Appropriate safety checks, such as physical inspection, metal detection, and random sampling. Periodic maintenance of machines at abattoir and processor

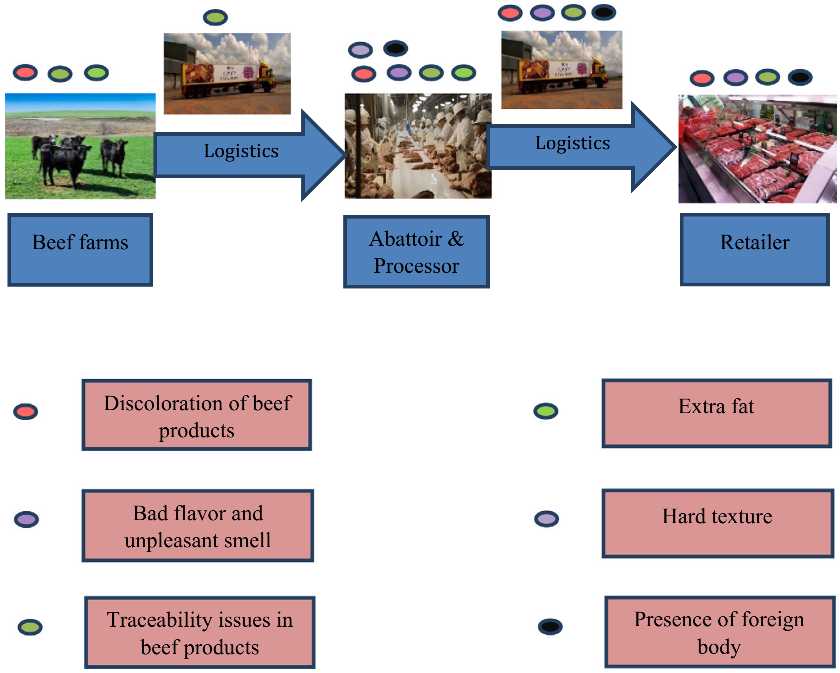

Fig. 7. Highlighting the location of root causes of issues faced by consumers in the beef supply chain.

ular maintenance of packaging machines and random sampling of beef products could assist in addressing this issue (Cunningham, 2008). Appropriate training should be provided to the staff of logistics, as well as to all segments of the supply chains, to avoid product mishandling. Inefficiency of the cold chain also leads to unpleasant smell and bad flavour (Raab et al., 2011). Maintenance of chilled temperature at the premises of the abattoir and the processor, the retailer, and in the logistics vehicle is vital to mitigate this problem (Kim et al., 2011). Periodic maintenance of refrigeration equipment and regular temperature checks are necessary for the improvement of the efficiency of the cold chain management.

2. Traceability issues in beef products—The analysis of consumer tweets reveal their concern about the traceability of beef products, particularly regarding horsemeat since the scandal in the European market in 2013. The scandal undermined consumer confidence in the quality of beef products and on the audits performed by retailers on their suppliers (Barnett et al., 2016). These kinds of issues could be avoided in the future by following a strict traceability regime in the beef supply chain, and by mapping all stakeholders, viz. farms, abattoirs, as well as processors and retailers (Sarpong, 2014). This regime should be sufficiently robust so that each beef cut presented on retailer shelf could be traced back to the animal from which it derived, as well as to its associated farm, breed, diet, and gender. All stakeholders of the beef supply chain should store product flow information locally, and share it with other stakeholders in the supply chain. This would improve consumer confidence and assist audit authorities in identifying any potential adulteration.

Please cite this article in press as: Singh, A., et al. Social media data analytics to improve supply chain management in food industries. Transport. Res. Part E (2017), http://dx.doi.org/10.1016/j.tre.2017.05.008

3. Extra fat—Presence of extra fat on beef products leads to customer dissatisfaction (Brunsø et al., 2005). The yield of cattle that have not been raised as per the weight and conformation specifications of the retailer is often associated with excess of fat (Borgogno et al., 2016). Similarly, inefficient trimming procedures at abattoirs and at the processor affect the leanness of beef products (Mena et al., 2014). This issue could be mitigated by implementing appropriate guidelines of animal welfare in beef farms, so that cattle are raised as per weight and conformation specifications of the retailer, and by adopting appropriate trimming procedures at the abattoir and the processor.
4. Discoloration of beef products—The phenomenon of discoloration of beef products prior to the expiry of their shelf life was reported by certain consumers on Twitter. It adds up to the annoyance of consumers, as they perceive these products as inedible. Deficiency of vitamin E in cattle diet is the primary root cause, which indicates that cattle are not raised on fresh grass (Houben et al., 2000). Moreover, the failure of the cold chain also results in beef products losing their fresh red colour. The discoloration of beef products could be avoided by raising the cattle on fresh grass and by maintaining an efficient cold chain throughout the supply chain.
5. Hard texture—Consumers become disappointed if it is inconvenient to chew beef products owing to lack of tenderness (Mishra and Singh, 2016; Huffman et al., 1996). The insufficient maturation of carcass of beef products leads to beef products of low tenderness (Vitale et al., 2014). Carcass is preserved in chilled temperatures from 7 to 21 days depending on the age, gender, and breed of the animal (Riley et al., 2005). Appropriate maturation of carcass could improve the tenderness of beef products.
6. Presence of foreign body—In certain instances, foreign bodies, such as insects, pieces of plastic, and metal, were found in beef products. Consumers perceive them as inedible, and these instances add up to their discontent. This issue is generated by the errors caused by packaging machines of the abattoir and the processor, the deficiency of food safety management procedures, such as Hazard Analysis and Critical Control Point (HACCP), and lack of safety checks, such as metal detection, damage of packaging due to mishandling of beef products (Goodwin, 2014; Lund et al., 2007). Regular maintenance of packaging machines; performing systematic safety checks, such as random sampling, physical inspection, and metal detection; implementing appropriate food safety process management techniques, such as Good Manufacturing Practices (GMP) and HACCP; and providing training to the workforce of all stakeholders of the beef supply chain could assist in addressing these issues.

6. Managerial implications

The findings of this study will assist beef retailers in developing a consumer-centric supply chain. During the analysis, it was found that sometimes, consumers were unhappy because of the high price of steak products, lack of local meat, bad smell, presence of bone fragments, lack of tenderness, cooking time, and overall quality. In a study, Wrap (2008) estimated that 161,000 t of meat waste occurred because of customer dissatisfaction. The majority of food waste was attributed to discolouration, bad flavour, smell, packaging issues, and the presence of a foreign body. Discolouration can be solved by using new packaging technologies and by incorporating natural antioxidants in diet of cattle. If the cattle consume fresh grass before slaughtering, it may help to increase vitamin E in the meat, and have a huge impact on delaying the oxidation of colour and lipids. The issues related to bad smell and flavour can be attributed to temperature abuse of beef products. The efficient cold chain management throughout the supply chain, raising awareness and proper coordination among different stakeholders, may assist retailers in overcoming this issue. The packaging of beef products can be affected by mishandling during the product flow in the supply chain or by implementing inefficient packaging techniques at the abattoir and the processor, which can also lead to presence of foreign bodies within beef products. Inefficient packaging affects the quality, colour, taste, and smell. Periodic maintenance of packaging machines and using more advanced packaging techniques, such as modified atmosphere packaging and vacuum skin packaging, will assist retailers in addressing the above-mentioned issues. The high price of beef products can be mitigated by improving the vertical coordination within the beef supply chain. The lack of coordination in the supply chain leads to waste, which results in the high prices of beef products. Therefore, a strategic planning and its implementation may assist food retailers in reducing the price of their beef products more efficiently than their rivals.

During the analysis, it was found that products made from the forequarter and the hindquarter of cattle has different patterns of demand in the market, which leads to carcass imbalance (Simons et al., 2003; Cox and Chicksand, 2005). This imbalance leads to retailers suffering huge losses, and contributes to food waste. Sometimes, consumers think that meat derived from different cuts, such as the forequarter and hindquarter, possess different attributes, such as flavour, tenderness, and cooking time, as well as price. The hindquarter products, such as steak and joint, are tenderer, require less time for cooking, and are more expensive, whereas forequarter products, such as mince and burger, are less tender, require more cooking time, and are relatively less expensive. Consumers think that beef products derived from the forequarter and hindquarter have different taste, and this affects their buying behaviour. In the present study, it was found that slow-cooking methods, such as casseroling, stewing, pot-roasting, and braising, can improve the flavour and the tenderness of forequarter products (Guide to Shopping for Rare Breed Beef). Through the help of proper marketing, and advertisement, retailers can raise awareness between the consumers, and can increase the demand of less favourable beef products, which will further assist in waste minimisation, and reform the supply chain to become more customer-centric.

The analysis of consumer tweets revealed that consumers, particularly the ones from the UK, were interested in consuming local beef products. Their main concerns were quality and food safety. Particularly after the horsemeat scandal, customers are prone towards the traceability of information, i.e. information related to animal breed, slaughtering method, animal welfare, use of pesticides, hormones, and other veterinary drugs in beef farms. Retailers can win consumer confidence by following the strict traceability regime within the supply chain.

The analysis of positive sentiments of tweets revealed that good promotional deals usually motivate consumers to buy the product from a particular retailer store. As food products have direct impact on the health, consumers assign more importance to the quality, food safety, and brand image than to the price of beef products. There were several positive tweets associated to the Red Tractor farm assurance scheme. By proper labelling, retailers will be able to capture maximum market share compared to their competitor. There were numerous discussions on consumers appreciating the combination of roast beef products along with different kinds of wine; this may assist retailers to develop marketing and promotional strategies.

There are few limitations associated with the approach discussed in this paper. First, Twitter API based data collection was performed only for limited time period. Larger samples of data can be collected over longer time periods to increase the representativeness of the collected sample. Second, keyword (using food retailer names) based approach involves time and resources to conduct appropriate review of the case study. More automated approach can be developed or employed to quickly and reliably extract topic-relevant tweets from the dataset. Third, twitter users may use different terms for the same topic and a comprehensive analysis and inclusion of synonyms could result in better visualisation of hierarchically clustered data. Fourth, accurate analysis of real opinion expressing users can prevent malicious spamming. Our approach does not take into account user's profile or basic information to increase the credibility of the analysis. Additional work can be conducted to rank customers on different products offered by companies and use these rankings to better manage and plan business strategies.

7. Conclusions

Consumers have started expressing their views on social media. Using social media data, a company may gain insight into the perception of their existing or potential consumers about their product offerings. Social media data are one of the cheapest and fastest methods to capture the viewpoint of larger audiences on a particular topic. Food is one of the most significant necessities of human life, and greatly impacts human health. In the current competitive market, consumers are searching for high-quality safe products at a minimum cost. Both positive and negative sentiments related to a particular product are crucial components for the development of a customer-centric supply chain. In this study, Twitter data were used to investigate consumer sentiments. More than one million tweets with 'beef' and/or 'steak' were collected using different keywords. Sentiment mining based on SVM and HCA with multiscale bootstrap sampling techniques was proposed for the investigation of positive and negative sentiments of the consumers, as well as for the identification of their issues/concerns regarding food products. The collected tweets were analysed to identify the main issues affecting consumer satisfaction. The root causes of these identified issues were linked to their root causes in different segments of the supply chain. As the focus of this work was to illustrate the use of the text-mining approach for social media analysis, it was therefore assumed that data from Twitter would be representative of real opinions. During the analysis of the collected tweets, it was found that the main concerns related to beef products among consumers were colour, food safety, smell, flavour, as well as the presence of foreign particles in beef products. These issues generate great disappointment among consumers. A significant number of tweets related to positive sentiments; the consumers had discovered and shared their experience about promotions, deals, and a particular combination of food and drinks with beef products. Based on these findings, a set of recommendations were prescribed for the development of a consumer-centric supply chain. However, there are certain limitations in the proposed approach. During the hierarchical clustering analysis, it was found that some of the results were not linked to the beef supply chain. These findings do not contribute towards the objective of the study, which is to develop a consumer-centric supply chain, and were therefore not described in detail. However, these results could be used for different purposes, and are a topic for future research. Moreover, other algorithms such as the latent Dirichlet algorithm may be used for the better understanding of consumer behaviours. A larger volume of tweets could be captured using Twitter Firehose instead of the streaming API, which may better represent the data. In the future, the proposed analysis could also be performed on other food supply chains, such as the lamb or pork food supply chains.

Acknowledgement

The authors would like to thank the project 'A cross country examination of supply chain barriers on market access for small and medium firms in India and UK' (Ref no: PM130233) funded by British Academy, UK for supporting this research.

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Int. J. Production Economics 164 (2015) 462–471

Contents lists available at ScienceDirect

Int. J. Production Economics

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

Cloud computing technology: Reducing carbon footprint in beef supply chain

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ARTICLE INFO

Article history:
Received 30 April 2014
Accepted 11 September 2014
Available online 19 September 2014

Keywords:
Carbon footprint
Beef supply chain
Cloud computing technology (CCT)

ABSTRACT

Global warming is an alarming issue for the whole humanity. The manufacturing and food supply chains are contributing significantly to the large-scale carbon emissions. Beef supply chain is one of the segments of food industry having considerable carbon footprint throughout its supply chain. The major emissions are occurring at beef farms in the form of methane and nitrous oxide gases. The other carbon hotspots in beef supply chain are abattoir, processor, logistics and retailer. There is a huge amount of pressure from government authorities to all the business firms to cut down carbon emissions. The different stakeholders of beef supply chain especially small and medium-sized stakeholders, lack in technical and financial resources to optimize and measure carbon emissions at their end. There is no integrated system which can address this issue for the entire beef supply chain. Keeping the same in mind, in this paper, an integrated system is proposed using Cloud Computing Technology (CCT) where all stakeholders of beef supply chain can minimize and measure carbon emission at their end within reasonable expenses and infrastructure. The integrated approach of mapping the entire beef supply chain by a single cloud will also improve the coordination among its stakeholders. The system boundary of this study will be from beef farms to the retailer involving logistics, abattoir and processor in between. The efficacy of the proposed system is demonstrated in a simulated case study.

1. Introduction

Carbon emission in the environment is becoming a crucial issue and has a wide range of consequences for both society and climate. Climate change and global warming are drawing the attention of all stakeholders of supply chains from various industries (Shaw et al., 2013). The UK government has decided to curtail carbon emission upto 80% by 2050 (Barker and Davey, 2014). All major industries and organizations are looking for ways to cut down carbon emissions in their supply chain and have fewer burdens on the environment. There is a considerable uncertainty in terms of methods followed for measuring the carbon footprint in both future and existing businesses. Most of the businesses are currently working on minimizing carbon footprint at segment level in a supply chain. Carbon emission occurring in one segment of the supply chain affects the emission in other segments as well. No emphasis is given on an integrated approach of reducing carbon footprint of the whole supply chain.

The term carbon footprint is getting a wide range of attention from academic personnel and practitioners. The widely used definition of carbon footprint is "A carbon footprint measures the total greenhouse gas emissions caused directly and indirectly by a person, organization, event or product" (Carbon Trust, 2012).

Beef is a vital source of protein and is widely consumed across the globe. It accounts for almost 24% of global meat production (Boucher et al., 2012). According to Environmental Protection Agency (2012), livestock is responsible for approximately 3.4% of the global greenhouse gas emissions. The whole supply chain of beef is associated with carbon emission. However, major carbon emission is occurring at beef farms alone (EBLEX, 2012). The main reason behind it is the emission of methane from the cattle because of the process called enteric fermentation. Methane is a greenhouse gas, which is 25 times more potent than carbon (Forster et al., 2007). Abattoir, processor, retailer and logistics are also emitting significant amounts of carbon at their end. The primary reason behind this is the energy used in their premises like electricity, diesel, etc. and the fuel used for logistics.

Conventionally, carbon footprint measurement in the beef industry is also done in a segregated way, i.e., at farm, abattoir, retailer and logistics level. The availability of an integrated model for measuring carbon footprint in the beef industry as a whole is very rare. However, in this study, the principles of Life Cycle Assessment (LCA) are proposed to be used. This approach considers the carbon emission in the product flow of beef from cradle to grave. The LCA model for

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http://dx.doi.org/10.1016/j.ijpe.2014.09.019
0925-5273/

beef supply chain is depicted in Fig. 1. The system boundary of this study is from farm to retailer.

In the past, Cloud Computing Technology (CCT) was used to integrate the segregated segments of a particular industry using minimum resources. It has given excellent results and has a wide range of applications in various industries like banking, manufacturing, IT, etc. It makes the information visible to all segments of an industry by deploying its service delivery models like Software as a Service (SaaS), Platform as a Service (PaaS) and Infrastructure as s Service (IaaS). Keeping these attributes in mind, CCT is deployed here to minimize the carbon footprint of the entire beef supply chain. The retailer, being a key stakeholder is going to maintain a private cloud, which will map the entire beef supply chain. The information related to carbon footprint associated with every stakeholder will be available on the cloud. This information will be accessible to all of them by using basic computing and Internet equipment.

The organization of the article is as follows: Section 2 includes the literature review. Section 3 consists of explanation of Cloud Computing Technology (CCT). Section 4 comprises of explanation of beef supply chain and utilization of cloud in measuring its associated carbon footprint. A case study on application of cloud computing in the measurement of carbon footprint of the entire beef supply chain is incorporated in Section 5. Section 6 embodies managerial implications, which is followed by conclusion in Section 7.

2. Literature review

Peters et al. (2012) have assessed the carbon footprint of red meat supply chains in Australia and compared them with that of international studies on red meat production. They considered three supply chains (sheep, beef and premium export beef) in different parts of Australia and used Life Cycle Assessment (LCA) technique to measure their carbon footprint. Consequently, it was found out that carbon footprints of Australian red meat supply chains are either average or below average when compared to International studies on red meat supply chain. They also emphasized that feedlot based cattle have lower carbon emissions than grassland based cattle. Desjardins et al. (2012) have reported the carbon footprint for beef in Canada, European Union, USA, Brazil and Australia. The decline of carbon emission associated with beef industries was reported in the past 30 years in the above-mentioned countries along with the

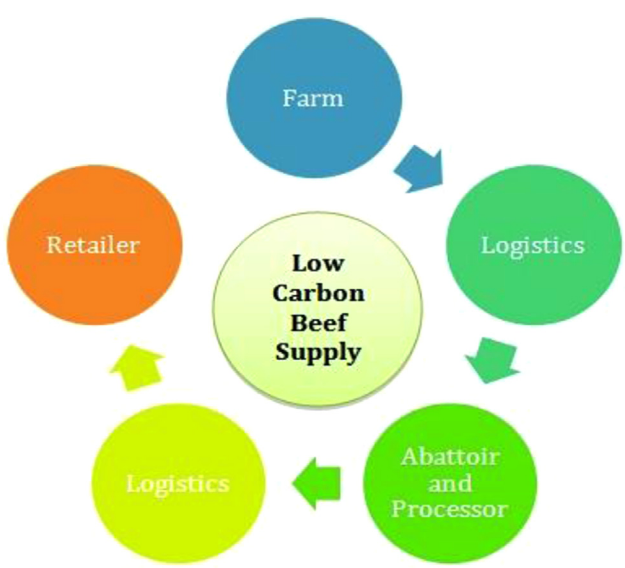

Fig. 1. LCA of beef supply chain.

reasons. It was also suggested to allocate carbon emission to the by-products obtained from beef like hide, offal, fat and bones. Therefore, they have expressed carbon emission for beef as CO_2 eq./kg of beef. Kythreotou et al. (2011) proposed a method to calculate the greenhouse gas emissions caused due to energy usage (electricity, LPG, diesel, etc.) in breeding of cattle, pig and poultry in Cyprus. The greenhouse gas emission of each energy source and the corresponding consumption by livestock species mentioned were calculated to obtain the aggregate results. This study has excluded the greenhouse gas emission due to transport and the impact of anaerobic digestion. The results obtained were compared to the major emissions in breeding of livestock, which are manure management and enteric fermentation. Bustamante et al. (2012) have determined the Greenhouse Gas (GHG) emission from the cattle farming from year 2003 to 2008. The root causes for the GHG emissions were identified. Their study showed that GHG emissions associated with cattle raising account for almost half of the aggregate GHG emissions done by Brazil. Some policies for public and private sectors were proposed to mitigate the GHG emissions associated with cattle farming. Schroeder et al. (2012) calculated the carbon footprint of three beef supply chains, two from UK and one from Brazil. They have used Life Cycle Assessment (LCA) methodology for their calculations and taken the phenomenon of carbon sequestration into account. It was found out that maximum emission is at farm end as compared to slaughterhouse, logistics, etc. Some suggestive measures were given like increasing the weaning rate and reducing the age of slaughter from 30 to 24 months for reduction of carbon footprint associated with beef supply chain. Bellarby et al. (2013) have investigated the GHG emission associated with the livestock supply chain (from production to consumption and wastage) in EU27 in the year 2007. Their analysis showed that the main reasons of emissions were livestock farms, Land Use and Land Use Change (LULUC) and food waste. The reduction in waste, consumption and consequent production to reduce GHG emissions was emphasized. They have also given some recommendations for mitigation of GHG emission like use of grassland based farms instead of intensive grain production for raising cattle. Ogino et al. (2007) have assessed the environmental consequences of the beef cow calf system in Japan. The system boundary of this study was the processes involved in the cow calf system like feed production and transportation, animal welfare, etc., and the method used for the analysis was LCA. Their study showed the impact of one calf in its whole lifetime on environment in terms of greenhouse gas emission, eutrophication, acidification and energy consumption. It was also found out that reducing the calving interval by 1 month and increasing the weaning rate can reduce the impact of cow calf system on the environment in all above-mentioned categories. The next section consists of description of Cloud Computing Technology (CCT).

3. Cloud computing technology (CCT)

Cloud computing is an easy-to-adopt technology with simple and latest architecture (Hutchinson et al., 2009). This architecture presents information technology (IT) as a paid service in terms of deployment and maintenance (Sean et al., 2011). Cloud computing technology is not a new concept for most of the sectors like banks, automobile, retail, health care, education and logistics (Al-Hudhaif and Alkubeyyer, 2011). Various deployment models of cloud computing make the adoption easy for any type of sector, depending on the need of usage. This innovative technology makes the collaboration easier among companies by the use of cloud (Xuan, 2012). Some of the main benefits of cloud computing are hardware and software cost reduction, better information visibility, computing resources being managed through software as a service and faster deployment.

CCT have three service delivery models, which are Software as a Service (SaaS), Platform as a Service (PaaS) and Infrastructure as a Service (IaaS). These services are delivered through industry standards such as service-oriented architecture (SOA). SaaS is an application that is hosted as a service and provided to customers by using Internet. Service providers look after the software maintenance and support associated with the application. For example, CRM, Google Office, Salesforce, Netsuite, etc. PaaS provides a computing platform, i.e., networks, servers, storage and other services. The consumer creates the software and also controls software deployment and configuration settings. Examples are Facebook F8, Salesforge App Exchange, Google App Engine, Joyent, Azure, etc. IaaS provides storage, network capacity, and other computing resources on rent basis. The customer uses the infrastructure to deploy their service and software. They can manage or control the OS, storage, apps and network components. Examples of IaaS are OpSource, Blizzard, terremark, Gogrid, etc.

There are three types of cloud deployment models, i.e., public, private and hybrid cloud, which are shown in Fig. 2. Public cloud is a cloud that is provided by third party service provider, e.g., Google, Amazon via the Internet. It is an easy and cost effective way to deploy IT solution by the pay-as-you-go concept. Google Apps is an example of a public cloud that is used by many organizations of all sizes (Sean et al., 2011). A private cloud offers many of the benefits of a public cloud-computing environment. It provides greater control over the cloud infrastructure, and is often suitable for larger installations. It is also manageable by third-party provider (Sean et al., 2011). A hybrid cloud is a combination of a public and private cloud, i.e., non-critical information is outsourced to the public cloud, while business, confidential, mission critical services and data are kept within the control of the organization (Sean et al., 2011).

The above-mentioned model in Fig. 2 makes cloud computing an ideal choice for any industry irrespective of its scale. Big companies that already have their big IT infrastructure and cannot go immediately towards expansion because of agile environment of business can buy services from third party companies like Google and Amazon and go over the cloud to meet the ever changing demand of technology. Companies having offices or branches across the globe can use cloud as a means of connectivity and put their generalized applications over the cloud through SaaS (software as a service). CCT appears to small and medium-sized firms as an easy startup. Small firms that are going to start their business straight away and do not have resources to invest on IT infrastructure can make use of services provided by third party service providers like Google and Amazon. They adopt the approach of pay-as-you-go and get benefits of IT services with their existence over the cloud. These firms also use SaaS to create their profile over the cloud and make themselves available to the global competitive environment of business.

The use of CCT is very less in food sector especially in the measurement of carbon footprint. In this article, cloud-computing architecture, as shown in Fig. 3, has been designed to minimize the carbon footprint of the entire beef supply chain. In the proposed architecture, all stakeholders of beef supply chain, viz., farm, processor and retailer are mapped. All stakeholders of beef supply chain can utilize the benefit of different software available on the cloud using SaaS concept.

4. Cloud-based beef supply chain and associated carbon footprint

This section briefly describes the different stakeholders of beef supply chain and the corresponding sources of carbon emission. A schematic diagram of beef supply chain is shown in Fig. 4. In the beef farms, farmers raise the cattle till the age of 3 months to 30 months depending upon the breed and demand of cattle in the market. When cattle reach their finishing age, they are transferred to abattoir and processor using logistics. Cattle are slaughtered in the abattoir and cut into primals. These primals are then processed into products like steak, mince, joint, dicer/stir-fry, burger/meatball, etc. These products are then packed and labeled. The packed beef products are then sent to retailer using logistics.

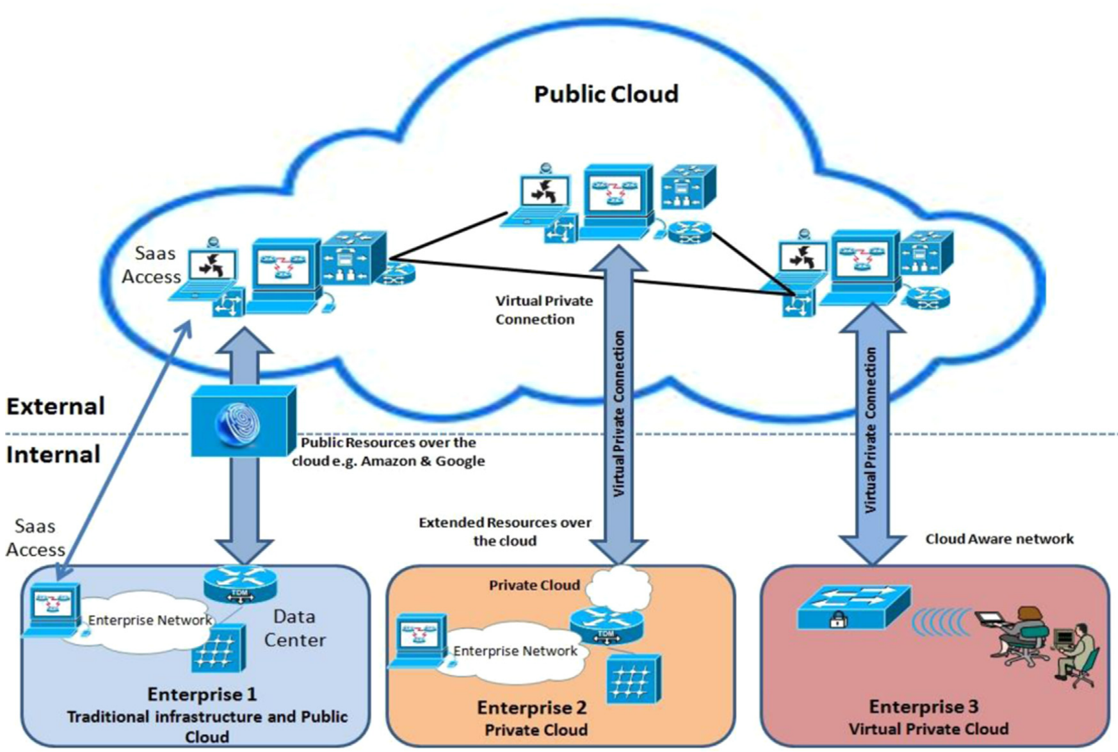

Fig. 2. The CCT deployment model.

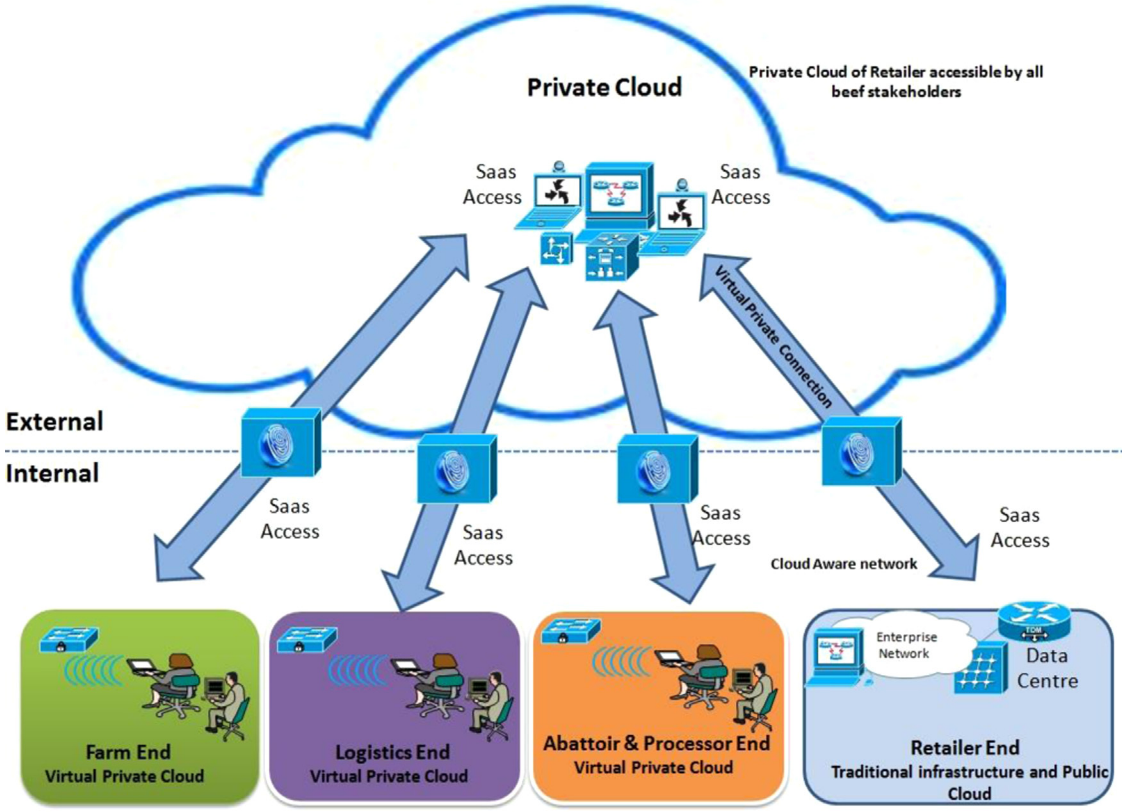

Fig. 3. The cloud-based conceptual model for beef supply chain.

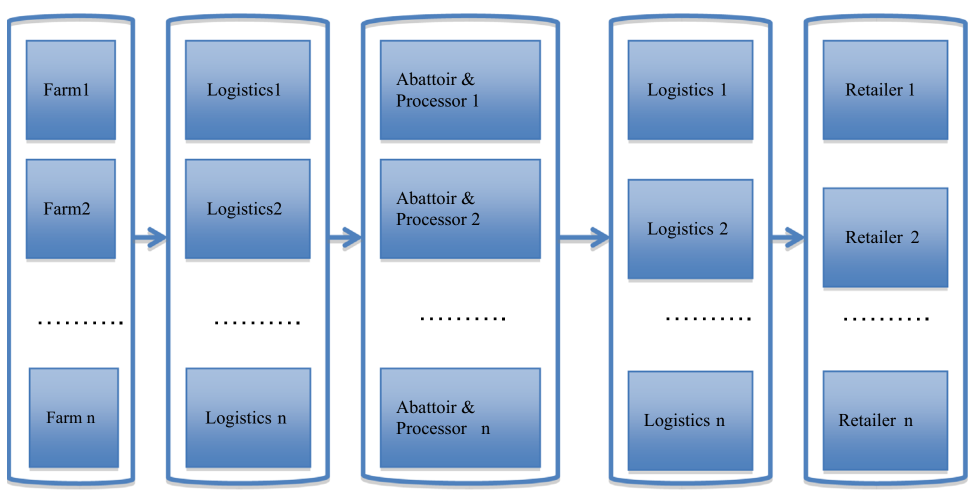

Fig. 4. Showing beef supply chain.

There are various sources of carbon emission in the entire beef supply chain. These are known as carbon hotspots, which are discussed for all the stakeholders as follows. -

4.1. Farm

The beef farms are responsible for the maximum amount of carbon emission occurring in the whole beef supply chain (EBLEX, 2012). The major factors responsible for this emission (carbon hotspots) are described as follows: -

1. Enteric fermentation – It is a process occurring in the digestive system of cattle where they convert the feed into methane gas and release it into the environment. Methane gas is a very hazardous greenhouse gas (GHG). It is 25 times more potent than carbon dioxide for causing global warming. The process of enteric fermentation is the major reason of carbon footprint in the beef supply chain. It is dependent on the breed of cattle. For example, bull beef releases less methane than dairy cows. Moreover, the number of cattle in a farm also affects the impact of this phenomenon.
2. Manure – The manure of cattle releases various GHGs like methane, nitrous oxide, ammonia and other oxides of nitrogen. Therefore, efficient manure handling plays a significant role in reducing the carbon footprint at farm end.
3. Fertilizer used for feed – The fertilizer applied to the grasslands or to the crops grown for feed of cattle release various GHGs, predominantly nitrous oxide. The potency of nitrous oxide

is 298 times more than carbon dioxide (Forster et al., 2007). Therefore, the rate of application of fertilizer (in kg/ha of grassland) should be optimum as it has a significant carbon footprint associated with it. Beef farmers, especially those who are growing feed for the cattle on their own might not be aware of it. They must be informed about the hazards associated with excess application of fertilizer as it can also penetrate into the meat derived from the cattle as well.

4. Energy used – The energy (electricity, diesel, etc.) used at beef farms and at the farms where feed for cattle are grown is also responsible for carbon footprint. However, their impact is much less as compared to methane and nitrous oxide generated from the above-mentioned sources. Moreover, there is a variation in the carbon footprint depending upon the source of energy used. For example, renewable energy has zero carbon footprint and electricity has lower carbon footprint than diesel or other fossil fuels.

The above-mentioned factors (carbon hotspots) highlight the potential sources of carbon emission at farm end in beef supply chain. The primary reasons for carbon emission are enteric fermentation and the fertilizers used for the feed. There are various carbon calculators available in the market for measuring carbon footprint at beef farms having their respective advantages and disadvantages. These calculators are often very expensive. Usually, small beef farmers are lacking in financial and technical awareness. They get confused in selecting a particular calculator for their farms to obtain more precise results. In the proposed architecture, the retailer will select an appropriate and user-friendly calculator for their farms and will upload it on the private cloud. The farmers can use these calculators to minimize the carbon footprint using Software as a Service (SaaS) concept. They will feed relevant information about their farms in the carbon calculator and obtain current emission results and suggestions for reducing carbon footprint. More information about the input and output to/from these calculators is presented in the case study (Section 5). This phenomenon is depicted in Fig. 5. The calculator will further give feedback to reduce their carbon footprint. It will help the farmers to take appropriate decisions and bring necessary changes in their practice. Finally, the farmers will estimate carbon emission at their end and this information will be visible to all stakeholders of beef supply chain. It will further boost the coordination among the stakeholders in improving the product flow and reducing the carbon footprint.

4.2. Logistics

The logistics of beef supply chain are very complex as compared to that of other industries. It has to take various factors into consideration; such as the vehicles used for carrying beef products are temperature sensitive. There is a restriction in terms of maximum number of cattle which can be carried in a vehicle and the maximum journey they can travel. They have to also take into account the stress factor in the cattle, which can degrade the meat quality and its associated shelf life. For example, they have to take certain precautions like keeping sexually active animals of opposite sex separately, keeping familiar animals together, keeping animals with horns separately from animal without horns, etc. Usually, the logistics associated with small and medium beef farms are only concerned about these major factors. They were not able to address the carbon emission associated with logistics processes. However, the carbon calculator proposed in this study will equip them appropriately to cope with these issues. There are numerous sources of direct and indirect carbon emissions among which the major emission is because of the GHGs released from exhaust of the vehicles used for transportation of cattle or beef products. These sources of carbon emission in logistics are described as follows:

1. Distance – The carbon footprint generated from logistics is directly proportional to the distance traveled by them. However, farm enterprise has to keep in mind the government regulations associated with the maximum journey time of cattle. For example, in UK, after a journey of 14 h, they must be given a rest of 1 h (DEFRA, UK, 2014). During the rest, they are provided with liquid

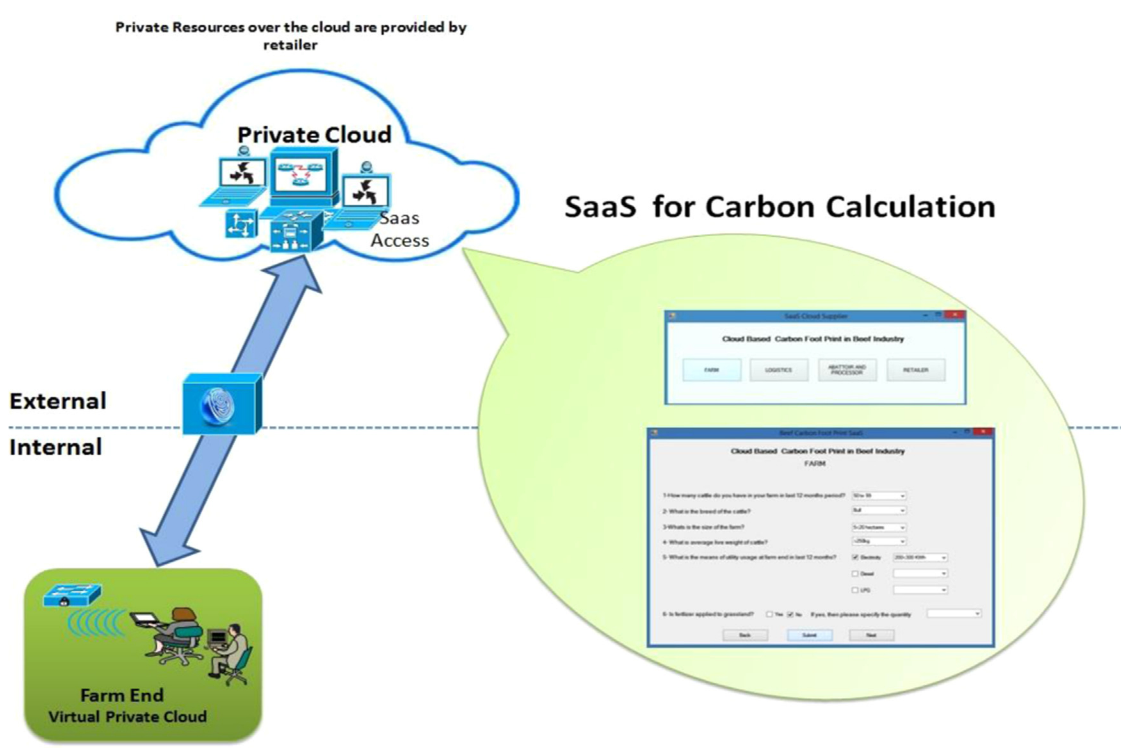

Fig. 5. Software as a Service at the farm end.

and could be fed as well. Thereafter, they can go for another 14-h journey. If they have not reached the destination yet, then the cattle need to be unloaded and given rest at a EU-approved control post where they are appropriately fed and watered. Therefore, the mechanism of CCT in this study will suggest the shortest and less busy route within the government regulations by the logistics firm to reduce their carbon footprint.
2. Number of Cattle – The number of cattle allowed in a vehicle should be as per the space allowance mentioned in the government regulations (DEFRA, UK, 2014). These space allowances are based on the weight of the cattle. If they are not followed, cattle get stressed and have a huge impact on meat quality and its shelf life. The product, which will be lost due to these reasons, will be replaced by another similar product with the same amount of carbon footprint associated with it. Hence, it leads to additional burden on the environment.
3. Temperature-sensitive vehicle – The temperature guidelines from government authorities should be taken into consideration by the logistics firms. For example, in UK, while transporting cattle, the temperature should not fall below zero degrees Celsius. Similarly, for transporting fresh beef products, the temperature of $+3\,^{\circ}\mathrm{C}$ must be maintained in the carrier vehicle. Keeping these requirements in mind, appropriate decision must be made in selecting a vehicle which meets these requirements and has minimum emission in its category. Moreover, these vehicles should be fitted with best quality catalytic converter so that they can reduce the intensity of the carbon emissions.
4. Load optimization – There might be inefficient load optimization procedures followed by the logistics firms. They should be addressed and it should be ensured that minimum number of vehicles are used for the delivery of beef products thereby reducing the carbon footprint associated with them.
5. Means of transport – The selection of means of transport should be done wisely so as to reduce the carbon emission from it. For example, rail freight transport can be used if possible instead of lorries as it runs on electricity instead of fossil fuel and hence less carbon footprint is associated with it.
6. Use of alternative fuel – An effort must be made to adulterate the fuel used in the vehicles with biodiesel or other alternative fuel to reduce the carbon footprint associated with them.

The aforementioned factors (carbon hotspots) describe the root causes of carbon emission at logistics end. The major concerns for logistic firms are increasing profit and expanding their business. There is considerable pressure from government authorities to reduce the carbon footprint. Sometimes, SMEs logistic firms do not have technical expertise and financial resources to select an appropriate calculator to measure the carbon footprint. Keeping these criteria in mind, retailers select an appropriate carbon calculator for their logistic firms and uploaded it on the private cloud. Logistic firms can use these calculators to measure carbon emission using SaaS concept. The calculator will also give them feedback to reduce their carbon footprint. This will help logistics managers to take optimal decisions and can bring corresponding changes in their operation. The information entered by logistics in the calculator and the results obtained will be visible to all the stakeholders of beef supply chain. This process will help to improve the coordination between logistics and other stakeholders. For example, it will suggest the beef farms when to stop feeding cattle so that they can be collected by logistics firms for transporting them to abattoir.

4.3. Abattoir and processor

The major emission from abattoir and processor is because of the utility used at their premises and fractionally from animal byproducts produced during processing of beef. The major factors responsible for carbon footprint at abattoir and processor are described as follows:

1. Energy – The abattoir and processor plant consume huge amounts of energy for their operations. Therefore, it is crucial to use cleaner energy sources like renewable source of energy. For example, wind energy, solar or electricity derived from hydroelectric power plants.
2. Animal byproducts – The animal byproducts, apart from specified risk material (brain, spinal cord, etc.), when disposed to landfill lead to emission of methane. They could be used in composting and generation of biogas, hence reducing the resultant carbon footprint associated with them.
3. Packaging – The manufacturing of fresh packaging of beef consumes huge amounts of resources and energy and is therefore a potential source of carbon emission. Emphasis should be laid on blending fresh packaging with the recycled content. Moreover, bigger packaging materials like pallets and big trays should be reused and 100% recycled.
4. Forecasting – The amount of beef products processed in the abattoir and processor might not be proportionate to the forecasted demand of the retailer. Therefore, modern techniques and personnel should be deployed for better forecasting. This process can reduce significant amounts of beef products going waste, thereby saving the carbon footprint involved in manufacturing of equivalent fresh products.
5. Maturation of carcass – It is a process occurring after slaughtering the cattle. The carcass is kept in a freezing temperature of $1\,^{\circ}\mathrm{C}$ from 7 to 21 days in Maturation Park depending upon age, gender and breed of cattle. Strong provision must be made so that the carcasses do not get over matured, as there is huge consumption of energy in maintaining the freezing temperature in the Maturation Park. Hence, it is a potential source of carbon emission, which could be reduced by efficient management.

At abattoir and processor, the major carbon emission is from the energy utilized for their operations. The retailer has closely inspected their operations and selected a carbon calculator for them. The retailer is maintaining a private cloud for the entire beef supply chain and has uploaded this calculator on it. It has further provided to the abattoir and processor personnel access to the private cloud and the appropriate training to use it. Now, the abattoir and processor personnel can access the carbon calculator using basic computing and Internet equipment in the form of SaaS. They will enter the required information in the calculator and obtain the results for their emission. The calculator will also give them feedback to reduce their carbon footprint. The policy makers at abattoir and processor will do the optimal decision-making and bring corresponding changes in their operation. Finally, they will deploy the calculator again and measure their carbon footprint. The information entered by them to the calculator and the results obtained will be visible to all the stakeholders.

4.4. Retailer

The major carbon footprint associated with retailer is because of the energy consumption and the beef products getting waste because of inefficient management. These factors are described as follows:

1. Energy usage – The retailer stores consume huge amounts of energy for their operations like refrigeration, air conditioning, etc. Therefore, it is crucial to use cleaner energy sources like renewable source of energy such as wind, solar or electricity derived from hydroelectric power plants.

2. Forecasting – The amount of beef products ordered by the retailer might not be proportional to the forecasted demand of the customers. Moreover, some retailers order more products to make their shelf look full and often these products remain unsold and run out of their shelf life. The transportation of waste products to anaerobic digestion plant or landfill again creates an unnecessary carbon footprint. Therefore, modern techniques and personnel should be deployed for better forecasting considering all the factors like weather, promotions, etc. This process can reduce significant amounts of beef products going waste thereby saving the carbon footprint involved in the manufacturing of equivalent fresh products.
3. Lack of coordination – There might be lack of coordination between the retailer and abattoir and processor in terms of quantity of beef products being ordered and sent, respectively. Sometimes, more beef products are delivered to the retailer than have been ordered. Then, the excess products are sent back to the abattoir and processor via reverse logistics and an unnecessary carbon footprint is generated. Moreover, the shelf life of fresh beef products is very short and a crucial amount of that is wasted in this process.
4. Efficient and skilled labor – The labor employed in the retailer store might not be perfectly trained so that beef products go waste because of mishandling or not following the procedures of stacking and shelving.

The above-mentioned factors highlight the major factors (carbon hotspots) responsible for carbon emission at the retailer end. Carbon emission occurring at the retailer end is the cumulative of individual emissions of all retailer stores operating. The retailer has taken the initiative to cut down the carbon emission of the entire beef supply chain. Therefore, they are maintaining a private cloud for all the stakeholders of beef supply chain. They have selected a particular carbon calculator for retailer stores and uploaded it on the private cloud. These stores will access this calculator in the form of SaaS via basic computing and Internet equipment and enter the relevant information. The calculator will generate results for their carbon emission and it will further give the feedback to reduce their carbon footprint. The retailer stores will do the optimal decision-making and bring relevant changes in their operation. Finally, they will deploy the carbon calculator again and measure their carbon footprint. The information entered by a particular retailer store to the calculator and the results obtained will be visible to all the other retailer stores and the stakeholders of the beef supply chain.

5. Case study: application of CCT in beef supply chain

This section describes the execution of the framework described in Section 3. It involves a retailer of beef products operating at various stores across the country. The cattle for these beef products are grown in different beef farms. An abattoir and processor firm, that has several branches nationwide, then processes these cattle. The processed beef products are then brought into stores of the retailer for selling to the consumers. The retailer wanted to cut down the carbon emission of its entire supply chain because of government's pressure. The targeted goal could not be achieved by optimizing the operation and management practices of the retailer stores alone. The retailer took an initiative to involve other stakeholders of beef supply chain in this process. When the policy-makers of the retailer interacted with beef farmers about carbon footprint generated in their farms, they observed that farmers lack in technical and financial resources to address it. The carbon calculators available in market are complicated having their respective advantages and shortcomings. It was really hard for the farmers to select and use an appropriate calculator for their business. The same issues were identified for the remaining stakeholders, viz., logistics and abattoir and processor as well. Logistics personnel reported that they are trying their best to reduce carbon footprint at their end by taking certain measures like taking the shortest possible route, etc. However, it was not sufficient enough to meet the target. During the discussion, it was revealed that a significant amount of avoidable carbon footprint is generated because of lack of coordination among stakeholders. As a result, the retailer realized that there is need of a mechanism which can help all stakeholders to minimize the carbon footprint and make this information visible to all stakeholders. The retailer has selected the services of Cloud Computing Technology (CCT) to achieve this goal with minimum expenses. This private cloud will map all the stakeholders of beef supply chain. Then, the retailer will select the most effective, precise and user-friendly carbon calculator for all the stakeholders of beef supply chain and upload it on the private cloud. All stakeholders can access it in the form of Software as a Service (SaaS) via basic Internet and computing equipment at their premises. The retailer will also provide appropriate training and user manuals regarding the use of CCT to all the stakeholders. This CCT interface will consist of a carbon emission calculator and feedback in the form of a list of suggestive measures for mitigating carbon footprint corresponding to each stakeholder. Fig. 6 shows SaaS at the farm end.

Farmers will access the CCT interface via basic computing and Internet equipment. A window will pop up asking for the required information for the calculation of carbon footprint at farm end, as shown in Fig. 6. The farmer will feed the required information and a new window will pop up, which will give the carbon footprint results and feedback to mitigate them. This phenomenon is shown in Fig. 7.

The current carbon footprint is calculated using the information entered by a farmer as 16 kg CO_2 eq. The feedback is generated in the form of a list of suggestive measures corresponding to the information entered by the farmer. For example, it will suggest to the farmers which breed and feed will generate minimum carbon emission. It also shows the net reduction (2 kg CO_2 eq.) in carbon footprint, which could be achieved as compared to the current carbon footprint. The farmers will take optimal decisions and will bring relevant changes in their farming practices. Finally, they will utilize this calculator again and measure their carbon footprint. The information entered by the farmers and the results obtained at farm end will be visible to all the stakeholders via the private cloud. This information can be used by other stakeholders to reduce their carbon footprint at their end by mitigating the dependent factors or carbon hotspots. For example, logistics providers will identify if some delay or inefficiency in operation at their end is leading to unnecessary carbon emission at the farms. They will coordinate with farmers and address that issue. The CCT interface for logistics is generic in nature. Any logistics firm can deploy it, which can be either logistics firm operating between the farm and abattoir and processor or between abattoir and processor and the retailer. These firms will individually deploy their respective CCT interface and a new window will open. They will enter the relevant information and obtain results regarding carbon emission. The calculator will also give them feedback to reduce their carbon footprint. For example, it will give suggestion in terms of using alternative fuel or cleaner mode of transport like rail freight. Finally, they will use the calculator again and measure their carbon footprint. The information entered by logistics and corresponding results will be visible to all stakeholders. This phenomenon will generate opportunities for other stakeholders to help logistics in reducing their carbon footprint in terms of dependent factors. For example, logistics will receive the information from beef farmers like the number of cattle, date and venue of collection of cattle, etc. via the private cloud. They will also receive the information in advance about the weight, sex, etc. of the cattle so that logistics can make proper arrangements for their

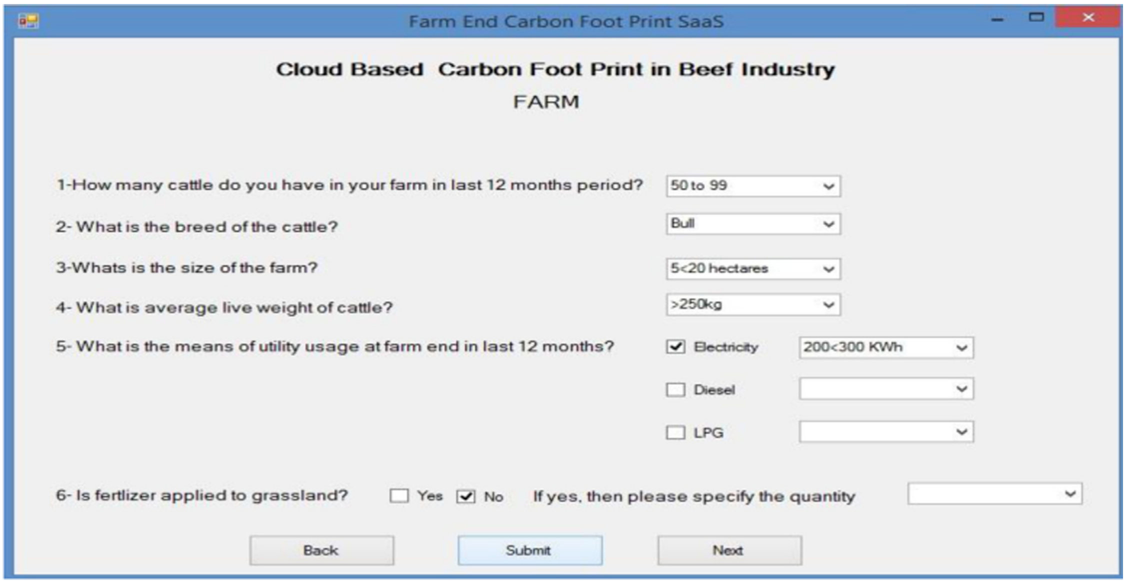

Fig. 6. CCT interface at the farm end.

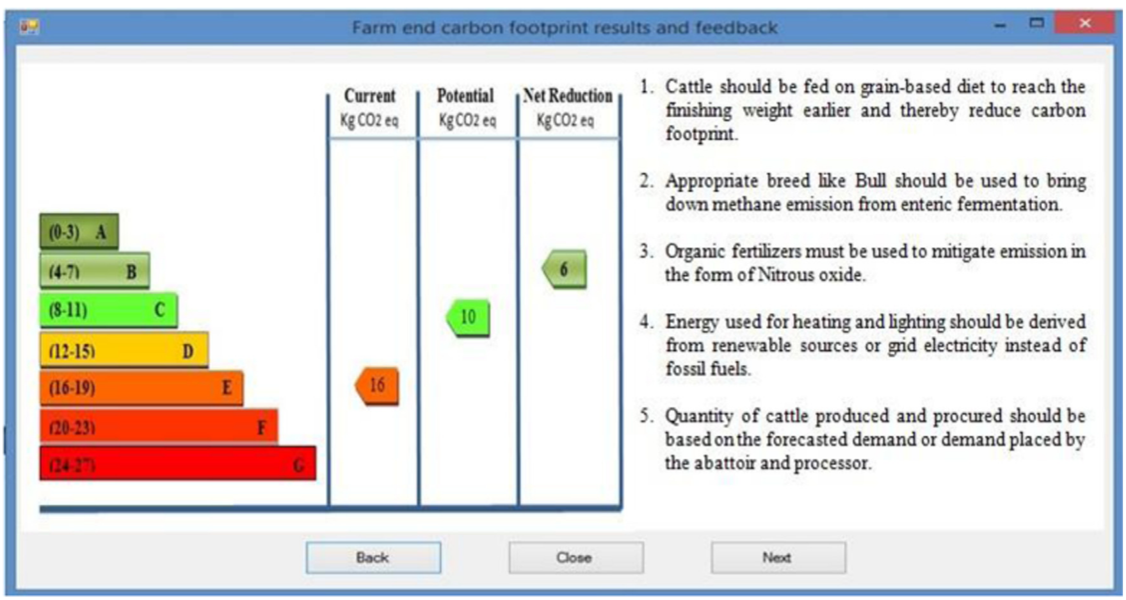

Fig. 7. Result of carbon footprint and feedback at the farm end.

transport keeping the space allowance and other government guidelines in mind in terms of animal handling while in transportation. This phenomenon will improve the coordination of logistics with the other stakeholders. The calculator will also suggest the best possible route by which the journey can be completed within the maximum journey time permitted by the government regulations, taking into account the carbon emission. Since the emission results of all stakeholders are visible on the private cloud, one logistics firm can observe the operations and procedures of other logistics firms to improve and modify their process. The logistics between abattoir and processor and retailer are much complex, as their vehicles are temperature sensitive. Still, these firms can learn from the good practices of each other as well as identify bad practices being followed at their end. This will further help them to optimize their carbon emissions. Similarly, the branches of abattoir and processor will enter the required information and obtain the results of the carbon footprint associated with them. These calculators will also give them feedback to reduce their carbon footprint. Abattoir and processor will also deploy the finding on the private cloud and this information will be visible to all stakeholders. Similarly, retailer stores, which are located at different geographical locations, will individually deploy the CCT interface for themselves. They will enter the mandatory information in it and obtain the results corresponding to their carbon emission. The calculator will also give them feedback to reduce their carbon footprint. For example, it will suggest the use of clean energy derived from renewables rather than the one derived from fossil fuels. It will also suggest the good practices to be followed in a particular store in comparison to other stores like following appropriate stacking and shelving procedures and extra caution in handling the product, etc. It will also emphasize the fact that store managers must use modern techniques for forecasting the demand of the consumers. Consequently, the retailer stores will take optimal decisions and will bring relevant changes in their operation. When all the retailer stores implement these procedures at their respective premises then the overall carbon footprint at the retailer end will be reduced. The proposed cloud will also help retailer stores to reduce their carbon footprint by mitigating their dependent factors and carbon hotspots.

In this way, the initiative taken by the retailer to minimize carbon footprint will bring rewards to all stakeholders without disturbing their financial budget. It is particularly beneficial to small-scale stakeholders whether it is a beef farmer or logistics firm as they are not able to purchase a carbon calculator on their own. The most appropriate, user-friendly carbon calculators are made available to all stakeholders at minimum cost. The carbon footprint of the entire beef supply chain will be optimized using an integrated approach.

6. Managerial implications

This paper suggests an integrated system to measure and minimize carbon footprint of the entire beef supply chain by utilizing the services of CCT. The proposed system will be particularly useful for managers of small and medium-sized stakeholders involved in beef supply chain as these firms lack in resources, infrastructure and awareness of carbon emission from their operations. This approach will save them from individually purchasing carbon calculators as they can access them in the form of SaaS from a private cloud.

All stakeholders will access the private cloud provided by the retailer and enter the relevant information in the carbon calculator uploaded on it in the form of SaaS and obtain the carbon footprint results. These results and information will be accessible by managers and policymakers of all stakeholders. The calculator will also give them feedback to reduce their carbon footprint. This phenomenon will help the managers of various stakeholders in appropriate decision-making and thereby increase their productivity and curb their carbon emission. For example, it will suggest the farmers which breed of beef is having the least carbon emission. This study will help the managers to identify which segment is weak in terms of product flow and carbon emission and it can be rectified with the suggestive measures provided by the carbon calculators.

As the cloud is mapping the entire beef supply chain, it will also help in mitigating carbon emission of a particular stakeholder caused due to its dependency on other stakeholders. For example, it will highlight the feasible options available to managers of logistics to reduce carbon footprint by mitigating their carbon hotspots, which are dependent on the retailer. It will also help to identify the good practices and bad practices followed by a particular stakeholder in terms of carbon emission. For example, there might be different logistics firms deployed from the farm to abattoir and processor and from abattoir and processor to the retailer. The managers of these firms can utilize the carbon emission information associated with each other to identify the bad practices followed by them and thereby follow the better approach. This study can remarkably influence the conventional method of measurement of carbon footprint at one end (stakeholder) of beef supply chain. It will further help in improving the coordination of the managers of all stakeholders in terms of efficient and eco-friendly product flow. For example, it will boost the coordination of managers of logistics and farmers in planning in advance the transportation of cattle and the special needs to be taken into account like space allowance, maximum journey time of cattle, etc.

Customers, nowadays, have become very selective about the traceability of beef especially after the horsemeat scandal in the UK. The information visibility aspect of CCT utilized in this study will promptly address this issue. Therefore, it will help the managers of the retailer to charge the premium price to consumers in facilitating traceability for them. Similarly, the customers are also gradually getting curious about the carbon footprint associated with the products they purchase. This issue can be addressed by this study and could be capitalized by the retailer in their promotion of transparency to customers or in terms of selling sustainable products. Finally, it will help the managers and policymakers of retailers to identify the segments of its supply chain which need to be modified to achieve the government's target of reduced carbon budget.

In this way, carbon hotspots for the entire beef supply chain can be identified, quantified and then prioritized while optimizing them. Moreover, all the managers associated with beef supply chain can continuously monitor their progress in reducing their carbon footprint, as their past records will be stored in the database of the private cloud.

7. Conclusion

Carbon emission is occurring at different stages in the beef supply chain. In the past, stakeholders were only bothered about their profit and productivity. However, nowadays, they are also concerned about the carbon footprint generated from their operations as well because of the pressure from government authorities. Some of the stakeholders, especially small and medium-sized stakeholders, of beef supply chain are not capable of addressing this issue because of scarcity of financial resources and knowledge. There is also lack of coordination among the stakeholders as there is no single platform where they can reveal their respective carbon emission details. Keeping these crucial discrepancies in mind, this article proposes a collaborative, integrated and centric approach of optimizing and measuring carbon footprint of the entire beef supply chain by using Cloud Computing Technology (CCT). Initially, carbon hotpots are identified for all stakeholders, viz., farm, logistics, abattoir & processor and retailer. Thereafter, the retailer develops a private cloud, to map the entire beef supply chain regardless of their geographical locations. Carbon footprint associated with the product flow of beef, from farm to the retailer will be optimized and measured. It will also boost the coordination among the stakeholders thereby making their operations more efficient and environment friendly. Step-by-step execution process of the proposed system has been described in the case study section. This paper has a further scope of being a pilot study with real time data from all the stakeholders.

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