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A Multi Perspective Framework for Enhanced Supply Chain Analytics

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Abstract. Supply chain analytics, especially in the field of food supply, has become a strategic business function. Monthly executive sales and operations planning meetings utilize supply chain analytics to inform strategic business decisions. Having identified gaps in the strategic management of food supply chains, a multi perspective supply chain analytics framework is developed incorporating process and data attributes to support decision making. Using Design Science as the research methodology, a novel framework with a supporting IT artefact is built and presented with early evaluation results.

The resulting multi perspective beef supply chain analytics framework equips practitioners to identify strategic issues, providing important decision support information. The case study further illustrates the framework has applicability across all integrated food supply chains. This research has highlighted gaps in the application of process science to the supply chain management domain, particularly in the area of simultaneous assessment of process and data. The outcomes contribute to research in this domain providing a framework that will enhance the significant reference modelling and operational management work that has occurred in this field.

Keywords: Multi perspective supply chain analytics, food supply chains, process and data analytics.

1 Introduction

Food supply chain management is a matter of international and national strategic importance, this fact has been reinforced in the wake of the global disruption to food supply chain caused by events such as the Covid-19 pandemic [1]. Supply chain analytics, including data driven insights, allow for the assessment of a food chain’s current state in real time, allowing for decisions to be made regarding alternative routing, sourcing and distribution [2]. It also allows for simulation to support scenario planning, further supporting short- and longer-term decision making [3].

Guided by a design science methodology [4] this research has initially focused on a single, revelatory case study [5], an integrated beef supply chain, to discover the challenges that the industry faces while simultaneously reviewing the adoption of process science methodologies into the supply chain domain. We present a hypothesis that a multi perspective process analytical approach will provide a new level of insight to
managing and improving complex and dynamic supply chains. These supply chain insights are used to drive the most strategic business decisions and are also used in the executive sales and operations planning meetings to drive operations [6]. To test the hypothesis, we have developed a framework, the Multi Perspective Supply Chain Analytics Framework (referred to as MPSCA), together with a supporting IT artefact and have evaluated it with several leading subject matter experts from practice.

The MPSCA framework was built and evaluated in a case study of a large integrated beef supply chain in Australia. The beef business was selected as it is one of the most integrated food supply chains extending from its breeding farms right through to packaged beef products on the retailer’s shelf. This industry is subject to supply chain risk due to environmental factors (for example drought and flood) [7], as well as other factors such as trade tariffs and competition from other protein sources [8], making the ability to rapidly assess the supply chain from multiple perspectives and to evaluate alternative pathways to market, strategically important. The results and learnings are applicable to integrated food supply chain’s globally.

Existing BPM tools and techniques are many and continue to grow [9]. Process mining techniques are proliferating with new approaches to support process discovery, conformance and enhancement. Across these three classes there has been a proliferation of solutions developed, both from an academic as well as commercial base [10]. However, most solutions are siloed into a single class and only few have been integrated for continuum across a process-management lifecycle. The intent of the MPSCA framework is to integrate a number of these technology solutions to support key analytical challenges across the entire end-to-end lifecycle of the food supply chain.

The objective of this research is to develop a data-driven multi perspective framework which will provide a new level of supply chain analytics contributing to the body of knowledge in this domain, while also addressing a real-world problem in managing vertically integrated food supply chains.

2 Related Work

Supply chain management is becoming a strategic focus of business today, supply chain integration is essential to competitive advantage and viewed in some sectors as extended enterprises [11]. Supply chain analysis is currently centered on a process and control flow centric approach, with the Association of Supply Chain Management’s SCOR™ model being one of the most widespread methodologies [12]. Many of the international consultancies have adapted this methodology for their supply chain assessments and leading providers of process modeling solution offer SCOR™ compliant versions of their software. Supply chain researchers have also used the model as a core reference model [13]. The SCOR™ methodology provides hierarchical levels of supply chain from major processes defining the scope of the supply chain to categories describing operations strategy and elements describing the configuration of individual processes. It further describes management practices for producing improved performance and defines the people skills required to perform the processes. The reference
model also provides definitions for standard metrics which are used to describe process performance and define strategic goals.

Supply chain management is still a young discipline and research in this field has largely focused on operational management areas [14]. The gap in the above methodology is that it approaches supply chain analytics from a single perspective which is the reference model and as a “static” methodology as opposed to a dynamic analytical process capable of interrogating event data; event data is execution data, produced as a side product when a task is executed. Supply chain by its very definition is a series of interconnected events. Analyzing the control flow aspects of a supply chain is one perspective, being able to co-currently analyze performance data will provide a new dimension of analytics not currently deployed in this domain. It is hypothesized that such a multi-perspective approach to supply chain analytics will enhance supply chain performance and can also further leverage the knowledge embedded in the SCOR™ model through advanced conformance checking.

[15] reinforces that supply chain are critical to market strategy, while [16] note that logistics can greatly benefit from process mining as the identification and tracking of goods involves many IT systems. Their work also focused on an area important to the meat and livestock value chain, namely, documentation. They focused on automated mining for process documentation by adding context information including frequency of occurrence of process and the cycle time of processes. With documentation such as cattle movement advices, a regulatory requirement along the meat and livestock value chain, this extraction feature will be examined during the research.

3 Method

This study applies a Design Science approach [4]. Below we present the methods applied for framework building and early evaluation outcomes presented herein.

3.1 Building the Framework

The framework building has three forms of input; insights from a literature analysis, case study data (from interviews and documents) and subject matter expert insights (collected in the form of interviews). The resultant framework is presented in Section 4 below.

Our earlier work [i.e.17] in this domain provided a foundational basis. We also reviewed process mining literature to identify algorithms and solutions relevant to supply chain analytics and the beef supply chain [18]. Our earlier research work exposed us to several beef cattle businesses as well as indications that there were gaps in the analytics and insights available across the supply chain. Further literature research validated the gap, with lack of supply chain integration and data sharing identified as strategic risks [19]. Research in other industries such as automotive component supply noted that logistics can greatly benefit from process mining approaches [20]. It was with this background that the concept of a supply chain analytics framework for food supply chain was created.
The case study chosen (Case A\(^1\)) for this research is the largest vertically integrated beef supply chain in Australia. The case study is revelatory since other businesses are less vertically integrated with a focus either on the cattle farming side, either breeding or backgrounding, the feedlotting or the processing component.

As depicted in Table 1, respondents from the case study and other selected subject matter experts from practice were identified to contribute to the design (and evaluation) of the framework. The interviewees were specifically selected in order to ensure a cross section of managers from C-suite Executives, in order to understand the strategic management requirements to Farm Managers, to understand the tactical management requirements. In addition to operations management, data managers and IT managers were selected to get insights into challenges in collection of data and accuracy. To obtain a broader industry perspective industry researcher from Meat and Livestock Australia\(^2\) were also consulted. Each interview took 30–45 minutes.

### Table 1: Interviewees and their contributions

| Interviewee | Contribution to Framework                                                                 | Evaluation Focus                                           |
|-------------|-------------------------------------------------------------------------------------------|------------------------------------------------------------|
| C Suite Executive | Business value of improved decision making.                                                  | Summative: High-level review of Case Study Data             |
| Cattle Business owner (small & medium) | Decisions required across the supply chain for improving business outcomes, current decision support solutions and their value. | Formative: Initial review based on artificial data and digital twin simulation |
| Farm Manager | Factors influencing on farm decision making, current sources and availability of data.     | Summative: High-level review of Case Study Data             |
| Data Manager | Current availability of data for decision making, data accuracy, accessibility of data, users of data. | Summative: High-level review of Case Study Data             |
| IT Manager | Current systems for data capture, connectivity issues.                                       | Summative: High-level review of Case Study Data             |
| Industry Researcher x 2 | Best practice in beef supply chains, adoption of best practice.                            | Selected for Phase 2 Evaluation on different Case Study     |
| Solution Developer x 2 | Technical advantages of their process analytics solution, specific questioning for a combined process and data perspective. | Both Formative and Summative focused on their specific solutions |

#### 3.2 Framework Evaluation

[21]’s FEDS framework was used for evaluation design. The FEDS framework covers both the functional purpose of evaluation as well as the type of evaluation. Our’s was a summative approach with naturalistic criteria [21], and this required ‘real’ industrial data and an IT Artefact to evaluate the MPSCA framework, where the case study provided an opportunity to analyze data more readily across the supply chain. The IT Artefact consists of several process mining algorithms hosted on the open-source framework, ProM\(^3\) with supporting data analytics solutions such as Power BI\(^4\). With the design risk of being technically orientated a Technical Risk and Efficacy Evaluation strategy was selected, allowing for an initial formative approach based on artificial data and simulations advancing through to a summative approach with naturalistic criteria.

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\(^{1}\) We use the pseudo-name ‘Case A’, in line with the anonymity and research ethics agreements.  
\(^{2}\) See [https://www.mla.com.au](https://www.mla.com.au) for further details.  
\(^{3}\) [http://www.processmining.org/tools](http://www.processmining.org/tools)  
\(^{4}\) [https://powerbi.microsoft.com](https://powerbi.microsoft.com)
The integrated beef supply chain extends from breeding farms through to the retailer as shown in Figure 1. In analyzing the beef supply chain of Case A, the MPSCA Framework was followed and various process analytical solutions tested on the data. Interviewees were approached again at this stage (See Table 1). The IT Artefact was built focusing on the questions of interest that the interviewees had posed, as well as the cattle data that was made available to the researchers. The core focus of the case study was to validate the framework, with a key design principle being that the various data and process algorithms as well as visualization and simulation solutions used can be interchanged. The resulting (MPSCA) framework is presented in detail next.

![Figure 1: The Integrated Beef Supply Chain](image)

4 Multi Perspective Supply Chain Analytics Framework

A conceptual framework from a synthesis of multiple data from the study was derived first, and this was then applied to Case A (as explained in Section 5).

The Multi Perspective Supply Chain Analytics Framework (referred to as MPSCA) combines process and data analytics while also factoring in the importance of effective visualization, simulation as well as an effective means of interaction with the user for decision support. At its core the framework is data driven. The key focus on a data driven approach resulted from both information received from the interviewees that the businesses were data rich, but information poor, as well as research that indicates much data is collected along a supply chain [22].

The MPSCA Framework consists of six stages, five of which we refer to as “views” to reflect the visualization that is provided to the processes and data:

- Define Analysis Questions of Interest Stage
- Process Analytics Supply Chain View
- Data Analytics Performance View
- Multi Perspective Decisions View
- Simulation Analytics Scenario View
- Orchestration Prediction and Prescription View

The view all interact with the Data Extraction and Analysis Core as illustrated in Figure 2 below.
5 Applying the Framework to the Use Case

5.1 Define Analysis Questions of Interest

The key question of interest for the case study, as determined from the interviews is weight gain of the cattle through each stage of the supply chain. As cattle pass through the various stages of maturity: calf, weaner, backgrounder and feeder [23] they increasingly gain weight and it is farm management’s role to ensure the cattle remain “on a rising plane of nutrition”\(^5\). While the key objective is to ensure that cattle always have enough edible pasture, this is not always the case with environmental factors playing a significant role, for example drought. Farmers must also carefully manage their stocking rates to ensure that pastures are not overgrazed, overgrazing can cause long term damage to pasture and in extreme cases render them unsuitable for animals. With cattle weight the key criteria for determination of payment to farmers, the analysis questions of interest were posed as follows: “When do you move animals to the next stage of the supply chain?” Supporting questions being: “How much weight did each cow gain at each stage of the supply chain?” “How much did each cow weigh when it was transferred to the next stage of the supply chain?”

\(^5\) interview note from C Suite Executive large cattle business
5.2 Core Data Analysis and Extraction

The business which participated in the case study made its cattle database available to the researchers for the purposes of building and evaluating the framework. The business began collecting and centralising individual cattle data since October 2018. In order to do this the business had to install RFID\(^6\) readers and weighing systems together with cattle yard information gathering systems that are able to capture the data, on ruggedized laptops and later transmit the data to the headquarters central database, once the team conducting the cattle management process returned to an area with connectivity, which is normally the main farm house/office.

Due to the cost of installing the physical cattle management infrastructure and the sheer scale of operations, this process has been systematically rolled out over the past 18 months. The complete set of data since the beginning of the roll out was provided for the purposes of this research. The data set includes original testing data, this data was identified and excluded which reduced the data set to 390,834 records. New data attributes have been added to the cattle management system over the months as additional information requirements are identified. Currently the cattle management system captures 69 data attributes per animal all referenced to the animal RFID.

To understand the data attributes in more detail a summary data model was developed, see Table 2 below.

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\(^6\) Radio Frequency Identification

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![Data Model Diagram](image)

**Table 2:** High level data model

The data model shows that key animal data is collected as well as location and supply chain history.

Since recording and reporting the location of a specific animal is a mandatory regulatory requirement [24] it was hypothesised that this event data could well be used to extract the journey of the animal through its lifecycle using process analytics techniques. The location of the animal through each stage of its lifecycle...
together with its weight gain at each stage and location would provide good insights into how to improve the cattle supply chain for optimum yield such as weight gain.

5.3 Applying the Process Analytics Supply Chain View

Having assessed the cattle data next step in the MPSCA framework is to apply process analytics to extract the supply chain view. As the extracted data set of 390834 records with 69 data attributes was considered too large for initial trial of process analytics techniques, it was decided to reduce the data attributes initially to weight only, aligning to the analysis question of interest. The key event data was classified as follows:

Case/Unique identifier: Individual animal RFID
Event name: CurrentPIC (Current Property/Farm Identification Code)
Date and Time/Completion Time: Session Date
Data Attribute: Animal Weight

An initial process discovery analysis was conducted using the Inductive Visual Miner (IVM) algorithm [25]. The fitness of this model was checked and found to be unsatisfactory. A more suitable process mining algorithm was sought and after referencing Leemans et al [26] the Directly Follows Visual Miner (DFVM), produced a better fit than the Inductive Visual Miner as due to nature of the cattle event logs. The sequential nature of supply chain is more suited to the type of algorithms deployed in the DFVM compared to the more complex algorithms of the IVM.

The discovered process model is shown in Figure 3.

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Figure 3: Process Analytics Supply Chain View

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7 Interview with Sander Leemans, developer of the IVM and DFVM algorithms
This view has discovered the individual supply chain of each animal as well as revealing several supply chain management issues which are discussed in Section 6.

5.4 Applying the Data Analytics Performance View

The Process Analytics Supply Chain View has highlighted several supply chain movements that do not appear to be optimal in order to satisfy the Analysis Question of Interest. Animals are shown to be moved along the supply chain in paths that are not optimal. This observation led to the Process Analytics Supply Chain stage to be rerun focusing on Babbiloora, Dungowan, Redford and Niella (BDRN) supply chain in more detail.

After repeating the Process Analytics Supply Chain cycle several times on the BDRN supply chain and filtering out intra farm movements the Process Analytics Supply Chain View was able to detect that several animals were been returned to farms where they were being bred as well as directly to the finishing farm (Niella) bypassing the backgrounding farms. It was suspected that unusual environmental factors were the root cause and a check was made of rainfall and historical rainfall records\(^8\). These records showed that the region in which the BDRN farms were located had experienced extreme drought conditions over the period in which the cattle data was recorded.

The weight distributions on each farm were also extracted via Power BI, this data mining exercise shown in Figure 4, further validated the observations from the Process Analytics Supply Chain View that extraordinary management practices were being applied. The holding of heavier animals on the breeding farm Babbiloora being an example.

Figure 4: Cattle weight distributions on BDRN farms

\(^{8}\) http://www.bom.gov.au/qld
5.5 Applying Multi Perspective Decisions View

This view was included in the MPSCA Framework as the ability to create a data aware overlay to the supply chain perspective is of value, particularly in determining the impact of data driven decision making along the supply chain. This perspective was tested on the case study data as follows.

Further literature research was conducted which led to the data-aware process mining work of de Leoni and van der Aalst [27]. Their work has focused on using conformance checking techniques to align an event log with data and a process model with decision points. Further development of this work has led to the development of the Multi-perspective process explorer [28]. This new algorithm factors in decisions that are not fully deterministic allowing for the discovery of overlapping decision rules. Due to the anomalies in the supply chain already discovered by the Process Analytics Supply Chain view as well as the lack of data across the cattle supply chain the decision making is clearly not deterministic and therefore the multi-perspective process explorer was selected to explore the data perspective.

Data attributes attached to events are used to analyse processes from other perspectives. With the significant amount of animal data now collected this perspective is most important in the analysis of the cattle supply chain. To discover this perspective the BDRN event log set was selected together with the BDRN petri net model and run through the multi-perspective process explorer. The results of the input model are shown in Figure 5 below.

![Figure 5: Multi Perspective View BRDN Supply Chain](image)

The data aware discovery algorithm was run on this input model based on the weight data attribute. Followed by the decision tree data discovery based on the

While the average fitness of the decision is relatively low at 59% the event logs are based on actual historical animal movements which we now know were determined by the drought. The output of this algorithm does however demonstrate that the influence of a key attribute such as animal weight can be discovered over a process model that represents the lifecycle of an animal. This result is most significant as it indicates that the proposed digital twin could utilise this functionality.
5.6 Applying the Simulation Analytics Scenario View

The analysis in Section 5.3 has shown that while significant data is been captured per animal, it is not captured adequately across the supply chain. The hypothesis that a digital twin of both supply chain as well as a typical cow will be required to fill the data gaps therefore holds true. In order to create the Simulation Analytics view of the BDRN supply chain the discovered BDRN model was edited to exclude all edges that were as a result of abnormal factors. For the case study the simulation view requires the simulation of a cow with respect to its growth through its various stages of maturity. We have named the simulation the Digital Cow. In order to create a digital cow research had to be undertaken on typical growth patterns of a cow through the various lifecycle stages. Based on [29] an initial algorithm was developed to calculate the weight gain of a cow during the stages, calf, weaner, backgrounder and feeder. The initial algorithm considers weight gain when there is normal feed available to the animal. With further research the algorithm will be extended to account for weight gain in poor and good pasture conditions, ultimately linking to the available biomass modelling and measurements.

The output of the Digital Cow algorithm is shown in Figure 6 below:

The Digital Cow algorithm was then used to develop synthetic event logs for the BDRN Digital Supply Chain which were then run through the multi perspective process explorer. The output further validates the MPSCA model as the data driven (weight) split of animals between Dungowan and Redford was 100% verifiable with the synthetic event logs.

Having proven that the combination of the digital twin of a supply chain as well as a digital cow can generate meaningful business data in circumstances where there or gaps in the actual supply chain data, our future research plan is to extend the digital
supply chain to the entire integrated supply chain, using the digital cow to simulate data currently not available from the major breeding farms.

5.7 Orchestrated Prediction and Prescription View

While each of the stages of the MPSCA Framework has shown to provide insights into management challenges and decisions along the supply chain, to be of value to business the framework must be able integrate and consolidate the insights for enhanced decision support. To identify an appropriate process orchestration engine several solutions were investigated. Camunda\(^9\) has been rated by several studies [30], [31] as high in execution and operation criteria. While Camunda is a robust, BPMN 2.0 compliant workflow engine most suitable for commercial applications, the work of van der Aalst et al [32] in developing RapidProM, an extension of the scientific workflow management solution RapidMiner\(^10\), provides a solution specifically focused on process analytics. With RapidProM process mining analysis is repeatable and data and process mining combined, these features are considered core to the MPSCA Framework and has been used in this final stage.

The Orchestration Prediction and Prescription View was configured in RapidProM with several scientific workflows as follows:

1) Discover the cattle supply chain workflow: import supply chain event data > run visual miner > run conformance checker.
2) Run the multi-perspective process explorer workflow: import supply chain event data including special data attributes > run visual miner > run multi-perspective inductive miner.
3) Run the simulation analytics workflow digital twin - supply chain: import supply chain event data > import digital twin – supply chain petri net > run visual miner > run conformance checking.
4) Run the simulation analytics workflow digital twin – cow: import supply chain data generated by digital twin - cow > import actual supply chain petri net > run visual miner > run conformance checking.

6 Summary Discussion

As highlighted in the data model (Table 2) and the discovered process analytics supply chain view of Figure 3, it is possible to discover and extract the complete supply chain of an individual animal. This ability is most significant, not only for the deeper analytics that occur with this information (for example what were the environmental factors such as weather when the animal was on a farm), but also for provenance, a growing consumer requirement. By adjusting parameters in the ‘directly follows visual miner’ of the complete business cattle data, a group of farms (the BDRN group, as introduced in

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\(^9\) https://camunda.com
\(^10\) https://rapidminer.com
Section 5.5) was identified for deeper analysis. This group formed their own complete supply chain, illustrating that the MPSCA framework can “zoom-in” to areas of interest identified in the overall supply chain view.

Further focus on the BDRN group through filtering out of their intra – farm movements and focusing only on their inter-farm movements, highlighted several bi-directional animal transfers. Animals were returned to their previous property which is not best practice. Having observed in the data model (Table 2) that environmental data was not captured in the cattle data base, it was assumed that environmental factors were contributing to this supply chain behaviour. The framework’s Data Analytics Performance view seeks to gain additional data to describe a supply chain action. Manual extraction of weather data for these farms was able to confirm that the farms were in severe drought during the observed supply chain events and animals had to be transferred between farms to ensure the animals had enough edible pasture.

The outputs from the process analytics on the BDRN group are significant, firstly, demonstrating that supply chain anomalies can be discovered with the ‘directly follows visual miner’ and reinforcing the need for scientific workflow as described in Section 5.7 within the framework. The scientific workflow should be extended to collect additional supply chain performance data, not captured in the event log for additional processing, for example in a decision model. The multi perspective process explorer was able to effectively detect the influence of the key data attribute, animal weight, on the decision to send animals to a farm. While the analysis question of interest for the case study, “When do you move animals to the next stage of the supply chain?” is dependent on more factors than animal weight alone, the fact that the animal weight dimension can be simultaneously analyzed with the control flow perspective adds significant value to the supply chain analytics.

Creation of the digital twin – farm was simplified through the ability to edit out unrequired “arcs” or supply chain connections from the discovered supply chain. The resultant petri net was then saved for later import into the ‘directly follows visual miner’ together with the real cattle event logs for compliance checking and highlighting of variations to the best practice supply chain. While the analysis shows that the BDRN supply chain had complete data, showing animals moving through their lifecycle and gaining weight through the various stages, the supply chain view of the farms (Figure 3), shows that this is not the case for all. In discussing this observation with the business, it was noted that the large breeding properties supplying the cattle to these properties have not yet installed the cattle yard data capture systems. The first capture of all the historical data occurs when an animal reaches the backgrounding farm.

The above observation highlights the importance of the digital twin - cow in the Simulation Analytics view. Not only can the digital twin – cow algorithm produce event logs which can test various supply chain scenarios, it can also be used to produce event data, for example the typical weight gain of a calf and a weaner while it is on the breeding properties and close a key data gap. The digital twin - cow algorithm combined with the digital twin - supply chain can highlight where current cattle practices are deviating from best practice and alert cattle business owners especially those with large integrated cattle supply chains as to where the potential problem areas are. This information could be used to improve decision making regarding when to move animals to the next stage
of the cattle supply chain in order to maximize weight gain and ultimately profit per animal.

The key challenge in this research has been the combination of process and data mining in order to solve the supply chain analytics gap, so critical to strategic management. Placing data extraction and analysis as the core of the framework has proven well suited, as a significant amount of data filtering and analysis occurred through the applied stages of the process. Testing the framework on significant amounts of real data has been most insightful, both in terms of the sorting and cleansing requirements when dealing with large quantities of industrial data as well as the gaps in data.

7 Conclusion

The study commenced with the hypothesis that, gaps in the strategic management of food supply chains could be addressed by a multi perspective supply chain analytics framework. A Multi Perspective Supply Chain Analytics (MPSCA) Framework was presented with empirical support, highlighting its ability to uniquely combine previously fragmented data and process mining methodologies to enable effective analysis of an integrated food supply chain. An IT Artefact was created and applied within the integrated beef supply chain of a revelatory case study (Case A), to demonstrate the applicability of the MPSCA Framework. This enabled evaluators to assess the framework from both formative and summative [21] perspectives. The core focus has been the development and evaluation of the framework and its design principles, while being agnostic to the various solutions used in each stage of the framework, as such an approach allows for a broader adoption of the framework. There has been a constant cycle of evaluation and feedback from domain specialists both within and external to the case study (Table 1) across the study phases, enabling the framework and its IT Artefact to be continuously improved.

While the research has focused on a single integrated food supply chain, the size and scale of the case study as well as similarity to other food supply chains would suggest that there is an opportunity to apply the framework more broadly. We argue that the results and learnings from this integrated supply chain case study are applicable to integrated food supply chain’s globally.

Having established the core scientific workflow for the MPSCA Framework, the next phase of research is to provide a workflow that will combine the decision support information. Learnings from this research can later be applied to beef supply chains with multiple business owners where the additional challenges of data ownership and transparency will need to be addressed. The researchers intend to validate the MPSCA in other areas (e.g. a horticulture business) in the next phase of evaluation. In combining event data as well as performance data in the MPSCA Framework, the opportunity to integrate the SCOR™ framework into MPSCA is also possible, both from a best practice reference perspective when conformance checking as well as from a performance data perspective. Such an inclusion will further drive adoption across food supply chains.
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