Outcome-Based Business Design in IoT-Enabled Digital Supply Chain Transformation

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***Abstract*—In the current economy, we see a shift of focus from delivering products or services to delivering value or outcomes to customers, reflected in the concept of the outcome economy. The concept has been embraced by research and practice but lacks proper operationalization to make it fit for the digital transformation of supply chains. In this paper, we translate the concept into a cybernetic model and accompanying technique and tool that can be used for outcome-based business engineering, leading to structures for Internet-of-Things-enabled, data-driven value delivery in supply chains. Based on a design science research approach, we discuss the development of the Alpha version of this model and tool, the application in business practice, and the use of this experience to develop a Beta version. We provide a bridge from a leading contemporary business concept to structured application in practice, positioning Internet-of-Things and Business Intelligence technologies for data-driven business execution.**

Keywords—outcome economy, outcome business, business engineering, data-driven business, internet of things, business analytics, digital transformation, supply chain.

I. Introduction

In the current economy, we see a major trend towards outcome thinking that is causing a shift of focus for many business organizations. In a traditional business setting, producers deliver products (or services) to their customers. The producers focus on optimizing the quality of their products to their standards and the customers are responsible for using these products to their best advantage. This often causes a mismatch between what is delivered to the customers and what they need to strengthen their own market position. In the new setting known as the *outcome economy*, customers expect producers to deliver their products such that they directly contribute to their success in their market. In other words, producers are expected to create value by delivering solutions to customers that in turn lead to quantifiable results for these customers [1]: their *outcomes*. To quantify these results, i.e., measure and report the outcomes, Internet and Internet-of-Things (IoT) technologies are used to capture data in the customer context and Business Intelligence (BI) technologies are used to transform this data into actionable information in the provider context. Outcome management requires data-driven business management, which gets an increasingly real-time character in modern business settings.

The outcome economy concept has attracted substantial attention from industrial practice and academic research in recent years [1-5]. Examples of this shift from selling products to selling outcomes can be found in many domains. An illustrative example is in the aircraft engine industry, where business models are explored where actual performance of engines is sold instead of the physical product [3]. In the transport and logistics domain, business models are explored where the effects of data analytics services on transport efficiency are sold instead of the services themselves [6]. These applications require real-time data capturing and advanced processing of this data.

The attention to the outcome economy in literature mainly focusses on the business strategy level in a descriptive way [1-3]. Managerial guidelines to set up outcome-based collaboration have been researched [4, 5]. When outcome thinking needs to be translated into actual operational, data-driven business structures, a proper operationalization of the outcome economy concept is still lacking. A guideline for its operational implementation is needed, both in business and in information technology terms. To close this gap, we translate the outcome economy concept into a two-stage cybernetic model that explicitly links the customer-side outcome realization to the producer-side provisioning of products or services. To make the cybernetic model usable in practical, outcome-based business engineering, we map the model to an accompanying usage technique and tool to be used in interactive business design sessions. The model, technique and tool help defining business relations between organizations and positioning data capture and data processing technologies for the data-driven business execution required by the outcome paradigm.

This paper is structured as follows. Section II discusses the methodology underlying our design approach. Section III introduces the conceptual cybernetic model for outcome-based business. Section IV presents the mapping of the conceptual model to a tool for practical, data-driven business design. In Section V, we discuss how we have used this tool in workshops with industry. In Section VI, we show how this model can be further operationalized with IoT and BI technology to arrive at real-time, data-driven business operation. We conclude this paper in Section VII.

II. Methodology and Practical Design Approach

We perform the development of the model, technique and tool in a pragmatic design science research (DSR) setting. In terms of the DSR classification of Gregor and Hevner [7], we map a *construct* (concept) to a *model* (representation), the *model* to a *method* (technique), and the *method* to an *instantiation* (tool as a product). Together, they form an *artifact ensemble* that we refer to as the Structured Outcome Realization Business Engineering Toolbox (SORBET).

Following DSR thinking, we perform four steps containing two iterations, balancing rigor and relevance [7] of our work. In Step 1, we develop a conceptual cybernetic model for outcome business analysis and design (Section III), laying the basis for the rigor in our work. In Step 2, we design a technique and a tool, arriving at the Alpha version of SORBET (Section IV) and laying the basis for the relevance in our work. In Step 3, we apply the Alpha version of SORBET in business practice and learn from this application (Section V), evaluating the relevance of our work. In Step 4, we use the learnings from the Alpha version applications to design a Beta version of SORBET (Section VI), integrating rigor and relevance aspects.

III. Conceptual Cybernetic Model

In this section, we discuss the cybernetic model that is the basis for our approach. First, we discuss a one-stage model for cybernetic control in a single organization. Then, we extend this to a supply chain with outcome-based control.

A. One-stage cybernetic model

In traditional business design, we typically find a one-stage cybernetic model for quality control of produced products or services, shown in Fig. 1. In the model, we see a *business process* that represents the production of goods or services by an organization. It consumes *input*, consisting of combinations of raw materials, parts and possibly input services. It produces *output* in the form of products or services for acquisition by customers. Quality characteristics of the output are measured by a *sensor*. The output of the sensor is processed by a *regulator* to create instructions to the business process whenever the quality level needs to be adjusted. Instructions may be explicit commands or implicit in the form of parameter values for the business process execution.

B. Two-stage cybernetic model

When we use the cybernetic model for a supply chain, we get the model shown in Fig. 2. This model shows a simple chain with two organizations: the focal organization that produces and supplies goods or services and the customer organization that consumes these. The model can be extended to a supply chain of arbitrary length where each predecessor organization provides to its successor organization.

In Fig. 2, each organization has its own feedback loop to control the quality of its own business process. It observes the quality of its own output, but not the quality of the output of its customer. This implies that the focal organization is unaware of the performance of the customer organization in its markets. To implement outcome thinking in this model, we introduce an additional feedback loop across the organizations to create a two-stage cybernetic model with a chain-level feedback mechanism. This model, the *outcome control model*,

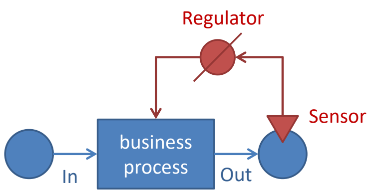

Figure 1: one-stage cybernetic model

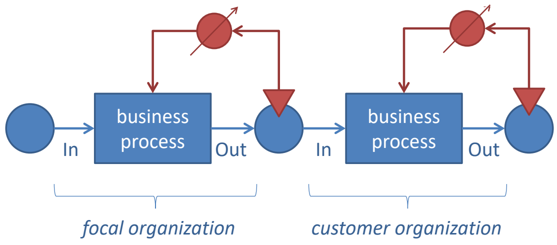

Figure 2: two-stage cybernetic model with local feedback

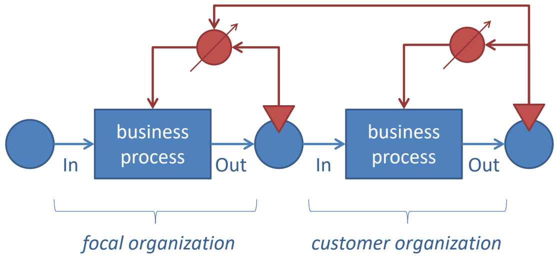

Figure 3: two-stage cybernetic model with chain-level feedback

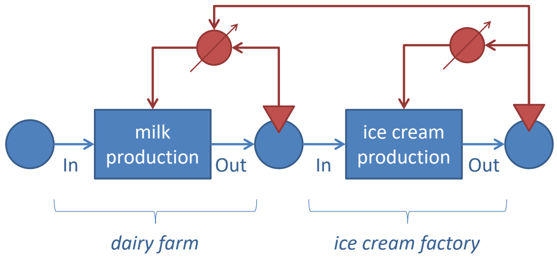

Figure 4: simplified example two-stage cybernetic model

is shown in Fig. 3. The focal organization typically drives the outcome business thinking.

A simple example application of the outcome control model is shown in Fig. 4. The focal organization is a milk producer (dairy farm). Traditionally, the dairy farm is focused on quality control of its output (the milk) according to its own quality criteria, modeled by the short feedback loop in the left of the figure. The customer organization is an ice cream factory with an own short feedback loop. The quality characteristics of the milk influence the quality characteristics of the ice cream, which in turn influence the success of the ice cream factory in its market. By measuring and interpreting effects in this market, the dairy farm can adjust the quality of its milk in a closed two-stage feedback loop to directly contribute to the market success of the ice cream factory.

The application of the outcome control model in a business scenario is called an *outcome control scenario* in this paper – or just *scenario* for reasons of brevity. The term *scenario* is used in a similar way in a more general e-business context [8]. The two-stage cybernetic model of Fig. 3 is used as the basis for our outcome-based business analysis and design approach. When applied in an agile business setting, it is essential that the focal organization can react fast on changes in the outcomes of the customer organization. To enable this, the feedback mechanism needs to have a (near) real-time character. For this purpose, the mechanism needs to be adequately supported by information technology.

IV. Designing the SORBET Alpha Version

In this section, we show how to use the ingredients of the previous sections in practice for outcome-based business design at the supply chain level. We first describe the developed tool, then the technique of using the tool.

A. The outcome business canvas (OBC)

To support interactive design workshops with business practitioners, we have mapped the outcome model of Fig. 3 to a design canvas. The use of canvases is well accepted for this purpose, e.g., the business model canvas [18] and the business model radar template [19]. We call our canvas the Outcome Business Canvas (OBC). The structure of the OBC is shown in Fig. 5. The middle part of the OBC contains the abstract representation of the model of Fig. 3. The fact that the focal organization and customer organization are not necessarily linked directly in the business chain is emphasized by the 'lightning' connector between the two.

Around the representation of the cybernetic feedback model, five basic questions are positioned that are linked to elements in the model. In the physical form of the OBC, these questions are printed in the boxes shown in Fig. 5. These questions help answering the main design questions for the model. The questions are:

Q1. What is the focal organization in the outcome model? What is its business process?

Q2. What is its customer in the outcome model? Is it a direct/indirect customer? Why is this customer important to the focal organization?

Q3. What is the outcome? Why is it important to the customer? Is it quantifiable?

Q4. How to measure the outcome? Which devices, when, how often, where and by whom?

Q5. How to control the provisioning? How to transform measurements into decision information – and by whom? How can you use this information to improve the outcome? How to link to operations/SCM?

To facilitate reflection in the design process, we have added one additional question that is not linked to a specific element of the model but helps putting the other answers in an innovation perspective: "Q6: What is the greatest challenge? Why aren't you doing it yet?" This sixth question is meant to help designers classify the thresholds to be addressed in realization of an outcome-based model.

B. Use of the OBC in design workshops

Design workshops for outcome-based supply chain design can be organized following the technique described in this subsection. The technique that uses the OBC described above consists of the following steps:

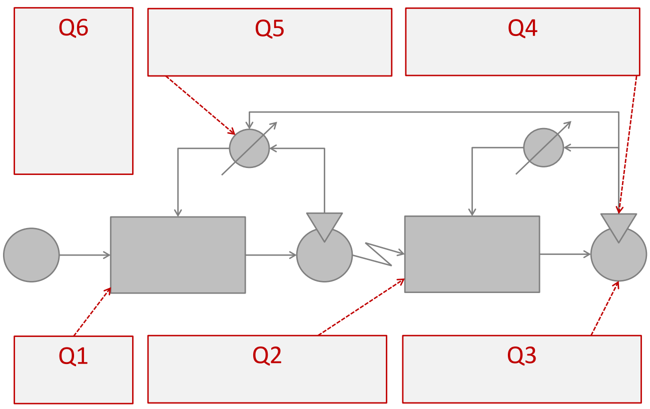

Figure 5: Outcome Business Canvas (OBC) Alpha version

1. Introduction in way of thinking. The participants of the workshop are introduced in the way of thinking of the outcome economy in general and the cybernetic control model we use, illustrated by examples from practice.

2. Introduction of OBC. The OBC as a tool and the technique for using it are introduced as an 'embodiment' of the way of thinking explained before. This can be done as a PowerPoint presentation or by using a physical OBC template.

3. Introduction of design case. The case to be designed in the workshop is introduced in terms of outcome business thinking. Typically, an abstract (graphical) representation of the supply chain at hand is included in the case introduction.

4. Work in groups. The participants are divided into working groups to design outcome control scenarios using an OBC template (either physical or digital).

5. Present and cross-discuss group designs. The scenario designs of the individual working groups are presented in a plenary fashion, discussed and compared.

6. Agree on follow-up. Based on the plenary discussion, the scenario designs for further elaboration are selected (or constructed by combining several designs). Agreements are made about the process for further elaboration.

V. Application in Practice

We have applied the presented cybernetic outcome model and the OBC in practical workshops for business practitioners from diverse business domains: supply chain management, agri-food and digital transformation consultancy services. Below, we describe two of the executed workshops to illustrate the application of our approach. To paint a complete picture, we have selected one workshop with business users and one workshop with IT consultants. The workshops were moderated by authors of this paper. After the discussion of the workshop, we provide an overview of our generalized learnings from the workshop.

A. Business user workshop in supply chain management

The business user workshop was organized for members of the European Supply Chain Forum (ESCF). ESCF is a non-profit organization that helps supply chain professionals creating value by generating, exchanging and integrating knowledge across industries and academia. ESCF currently has more than 50 business organizations as members. The workshop was physically executed in a conference center. About 15 business practitioners from about 10 companies registered for the workshop, with a few participants dropping out as a consequence of harsh winter weather at the day of the workshop.

For this workshop, we selected the case of the production and use of semi-autonomous, electric trucks. The case is inspired by current developments in the automotive market, driven by a focus on customer values and great attention for self-driving technology and electric propulsion, both enabled by real-time IT. We presented the abstract supply chain of Fig. 6 (only the five solid-colored organizations) to the participants of the workshop, with the remark that they were free to modify or extend the supply chain. The focal company is the Truck Producer. The assignment was to design an outcome-based feedback model that enhances the outcome for a direct or indirect customer in the supply chain, such that it would benefit the market position of the truck producer. The participants were split into two groups. In their scenario designs, both groups interpreted the value of semi-autonomous electric trucks primarily in the context of last mile

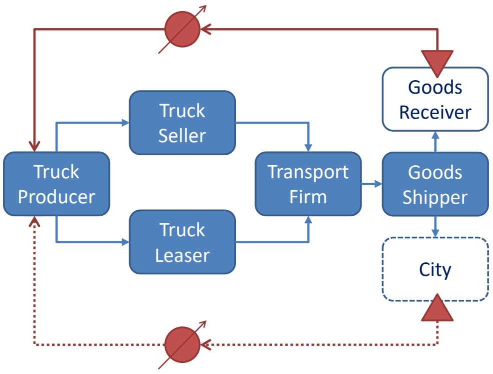

Figure 6: outcome model from business user workshop

logistics to inner-city delivery addresses, such as retail outlets. This interpretation led to different scenario designs by the two teams, as illustrated in Fig. 6.

The first group added the Goods Receiver to the supply chain and selected this party as the customer in the outcome control scenario (the feedback loop in Fig. 6 with solid lines). The outcome in this scenario is timely delivery of retail goods. Measurements of this outcome can be used by the Truck Producer to configure its trucks such that they meet inner-city delivery circumstances best. The main measurements of the outcome are produced by the operational information systems of the Goods Receiver that record the actual deliveries. The measurements are combined with other data and manually processed to derive improved truck configurations.

The second group went even one step further in their analysis: they added the City to the chain and selected this party as customer in the outcome control scenario (illustrated in Fig. 6 with dashed lines). The reason for this choice is the powerful position of cities in inner-city logistics. The outcome in this scenario is the appreciation of trucks of the Truck Manufacturer's brand by the City. Like in the first case, the Truck Producer can use measurements of the outcome to configure its trucks. The sensor in the outcome mechanism is of an external kind: a system from which sentiment data can be pulled (such as political news sites in this case). As the data is diverse and complex, only simple automated analytics are possible in this case.

B. Consultant workshop in IT services

The second workshop is a business design workshop conducted for Atos, a leading, global IT services provider. The audience consisted of 6 consultants working in the digital transformation consulting domain, most with a technical background. Given COVID circumstances, the workshop was conducted online. This allowed for gaining experience with a digital setting for our technique and tool. For this workshop, we used a business case in the pharmaceutical industry for animal health with an extended supply chain, shown in Fig. 7 (without the feedback loops). The focal company is a producer of pharmaceutical animal health products (Pharma Producer). These products are delivered to farms, either directly or through a veterinary service supplier (Vet) and used on animals for (in this case) meat production. From the farm, the supply chain includes five intermediate organizations to reach the final consumer of the meat.

After a plenary introduction and case explanation, the participants were divided into two groups. The groups were asked to select a customer party in the chain (and modify the chain if needed) and identify the outcome for this customer.

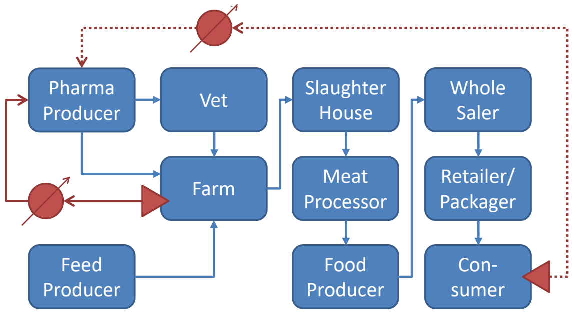

Figure 7: outcome models from business consultant workshop

The two groups designed two radically different scenarios (illustrated in Fig. 7): one with a short feedback loop (represented by the solid feedback links) and one with a very long feedback loop (represented by the dashed links).

The first group chose the Farm as the customer, with optimal observed animal health during animal growth as the outcome. Measurements of this outcome allow the Pharma Producer to tune its products to obtain the optimal effect on animal health as observed by the farmer. The outcome sensor in this case is embodied by smart farming IoT equipment [20] that measures characteristics of animals and their living environment. Data about these characteristics is pushed by the measuring equipment to the regulator element. The regulator supports the establishment of causal relations between pharma product characteristics and observed animal health.

The second group chose the Consumer as customer, with perceived meat quality as the outcome. The line of thinking here is the fact that consumers become increasingly aware of the quality of meat and its dependence on the treatment of the animals. Consequently, it is of prime importance for the Pharma Producer to produce its products such, that they do not negatively influence the opinion of consumers about meat from animals treated with these products. Sentiment analysis of consumers [21] can help the Pharma Producer in making choices for its products and hence not negatively influence its market position. In this case, the outcome sensor element is a social media system. As changes in sentiment are not so easy to predict, a data push mechanism can be used that sends data to the regulator elements when thresholds are crossed. A regulator is used to make market predictions: changing pharma products characteristics takes a long time and is costly, so it is desirable to be able to predict its consequences on perceived meat quality.

C. Learnings from the workshops

The results from this workshop show that in practical settings, very different designs can be made for outcome business feedback mechanisms, depending on the chosen customer and outcome. The first described workshop shows that the customer may not be part of the 'trivial' supply chain. The second workshop shows that short and long loops in the cybernetic feedback mechanism can be chosen, which implement radically different business concepts in terms of outcome thinking and hence very different outcome control scenarios. The use of SORBET helped workshop participants in exploring and designing outcome models in a structured way. The created models, however, lack precision in two main aspects: the precise use of IT in data capturing and processing and the way sets of customers are handled. We discuss these aspects in the next section as a basis for the second iteration of our SORBET design process.

VI. DESIGNING THE SORBET BETA VERSION

In the practical application workshops discussed in the previous section, we learnt that the Alpha version of SORBET is well applicable for designing outcome scenarios. In the workshops, we have observed two shortcomings of the Alpha version, though. Firstly, the created models are rather abstract and lack the detail to be used as a basis for the design of IT-based embodiment of these scenarios. In the current time frame of digital transformation, however, we should focus on possibilities for automated feedback loops that cater for real-time, data-driven outcome management across a business chain, including IoT for data capturing and BI for data processing. Secondly, the outcome business model implicitly suggests that there is a single customer in the scenario. In many scenarios, however, there is a set of customers that are served in a single scenario. This confuses participants in the workshops. Apart from this, combining raw outcome data from multiple customers is often not possible because of competition between these customers. To handle this, additional technology is required to eliminate the transmission of raw IoT data for central BI application.

The abstract nature of the results of the workshops is caused by the fact that the Outcome Business Canvas is of a conceptual nature, i.e., it contains no information about its embodiment. The designed chain-level feedback loop can in principle be of any kind, either manual or automated. This holds for the embodiment of both the sensor element and the regulator element. The confusion about the customer 'fan-out' is caused by the nature of the conceptual model and by the fact that this fan-out is not an element in the OBC. The problem with data abstraction is not dealt with because the Alpha version of SORBET does not provide any handles for this. To overcome these shortcomings of our approach, we design the Beta version of SORBET, based on three updates addressing the above discussed problems. Firstly, we add support for classification of automated sensor embodiment, taking into account Internet and IoT technologies. Secondly, we add support for classification of automated regulator embodiment, taking into account BI technologies with various levels of ambition and related complexity. Thirdly, we add support for explicit modeling and specification of customer fan-out in outcome management loops, as well as technical support for outcome data abstraction. We address these updates in the following three subsections. We present the resulting Beta version of SORBET in the fourth subsection and a preliminary application of this beta version in the last subsection.

A. Sensor embodiment classification in SORBET

The way the sensor function can be embodied depends heavily on the nature of the variables that describe the outcomes to be measured. From a systems point of view, these variables can be divided into three main classes, with corresponding sensor elements. Firstly, there are variables of which the values are recorded in an existing information system of the customer (such as the number of sales transactions). In this case, the sensor is a software interface to the information system of the customer. Secondly, there are physical variables that can be measured directly in the customer's domain (such as the speed of a vehicle). In this case, the sensor is a physical measuring (IoT) device in the field of operation of the customer with a software data interchange interface. Thirdly, there are non-physical variables that cannot be measured directly (such as customer satisfaction). In this case, the variables are measured by and stored in a system external to the cybernetic feedback system, such as a social media system. To the cybernetic feedback system, such external systems are black boxes. Hence, the external system *is* the sensor.

The data provisioning mechanism from sensor to regulator can be organized in either a push or a pull fashion. In the push fashion, the sensor element automatically provides the values to the regulator component on a periodic basis. In real-time feedback mechanisms, the period is short and the data takes the form of a continuous data stream. In the pull fashion, the regulator element explicitly requests the values from the sensor element. In case of a real-time, continuous data stream, this may imply substantial overhead. In more 'sparse' circumstances, this can avoid unnecessary data transfer.

When we combine these two dimensions of the feedback mechanism, we obtain the six classes of sensor elements shown in Table 1. We briefly discuss the six classes below.

Table 1: types of sensor elements

	Push	Pull
Recorded data	(i) data provisioning software module	(ii) data query interface
Physical data	(iii) active IoT device or CPS	(iv) passive IoT device or CPS
External data	(v) external with data stream subscription mechanism	(vi) external system with data query interface

(i) Pushed recorded data is provided by a software module in an information system that retrieves the data from the data store of that system and sends it on its own initiative to the regulator element of our framework. Data can be pushed on a periodic basis (such as once per minute) or on the basis of specific events (such as observed threshold values). The provisioning module can either be a standard module of the system or a plug-in for monitoring purposes.

(ii) Pulled recorded data is explicitly requested by the regulator element of our framework. To enable this, the information system managing the recorded data needs to publish a query interface. The regulator element determines the moments that data is pulled and the exact nature of the data. The source system and the regulator typically belong to different organizations, so the query interface needs to be subject to an access control mechanism.

(iii) Pushed physical data is provided by an active IoT device containing a measuring instrument or by a cyber-physical system (CPS) containing such an instrument. An example is a digital temperature sensor or a GPS location sensor. It is 'wrapped' by the IoT device or CPS that transmits the data resulting from measurements. The IoT or CPS determines when data is sent and may perform basic data processing, such as averaging measurements.

(iv) Pulled physical data is provided by an IoT device or CPS like in Class iii, but in this class the device or CPS are passive: they only provide data upon request by the regulator element. Like in Class ii, explicit access control is important in this class. An advanced CPS may have a query interface like the systems in Class ii. A simple IoT device typically has a simpler polling interface.

(v) Pushed external data originates from active external systems that monitor the environment of the customer, which function as a sensor in the feedback loop. Examples of such systems are social media systems and traffic monitoring systems. Subscriptions are required to a data stream provided by these systems, where the subscription parameters specify the precise kind of data streamed.

(vi) Pulled external data originates from active external systems that function as a sensor, like in Class v. To allow data pulling from the sensor, these systems provide external query interfaces. These query interfaces are often made available in the form of Web Services or public APIs. To use them, a subscription may be required.

B. Regulator embodiment classification in SORBET

Like for the embodiment of the sensor element in the cybernetic feedback mechanism, we can classify the types of embodiment of the regulator element. Here, we focus on classifying the functionality of the data processing by the regulator, based on Gartner's ambition levels for data analytics [9]. Going from low to high ambition level, we have the following classes of regulators (summarized in Table 2):

(a) A **descriptive regulator** interprets data from the sensor element in the customer environment and produces descriptions of this data, i.e., summarizes what happened in the market environment of the customer. Interpretation of this information is performed completely manually by the focal organization. A descriptive regulator typically requires rather simple analytics technology. The level of automation in the feedback mechanism is low in this case. In production environments, this class of regulator can be referred to as a digital shadow [10] of the customer outcome.

(b) A **diagnostic regulator** interprets data from the sensor element in the customer environment and produces diagnoses for the events that happened in the market environment of the customer in terms of the business process of the focal organization. It typically also requires measurements from the sensor element local to the customer. This provides the focal organization with input for reactively tuning its business process to optimize the outcome for its customer. This class of regulator is a digital twin [11] with simple analytical power.

(c) A **predictive regulator** interprets data from the sensor element in the customer environment (and the local sensor of the focal organization) to generate predictions of the effects of changes to the business process of the focal organization on the outcome for the customer organization. This enables the focal organization to perform what-if analyses and to tune its business processes proactively to optimize the outcome for its customer. This class of regulator corresponds to a digital twin [11] with advanced analytical power.

(d) A **prescriptive regulator** interprets data from the sensor element in the customer environment (and the local sensor of the focal organization) to generate models that prescribe the parameters for the business process of the focal organization to optimize the outcome of its customer. Prescriptive analytics is the most advanced class of analytics, but it is considered in industry [12]. It can be used in a supply chain that requires a high level of automation where human involvement can be avoided. If the prescriptive regulator can also autonomously control the business process of the focal organization (e.g., by linking it to a process management system [13]), we obtain a fully automated control loop.

Table 2: types of regulator elements

Type	Level of Complexity	Level of Automation
(a) Descriptive	Low	Low
(b) Diagnostic	Low-Medium	Medium
(c) Predictive	Medium-High	Medium
(d) Prescriptive	High	High

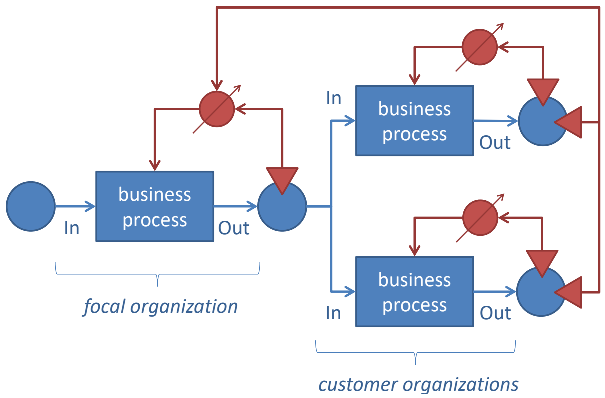

Figure 8: cybernetic model with multiple customer organizations

C. Customer fan-out and data hiding support in SORBET

In our discussion so far, we have assumed that the focal organization serves a single customer in a cybernetic feedback mechanism. Obviously, if there are several customers with different characteristics, the focal organization can engage with each of these in a 'private' outcome management feedback loop. The situation is different, however, if there are multiple similar customer organizations that each produce only part of the data required for tuning the business process of the focal organization – like in Fig. 7. This leads to the situation shown in Fig. 8 as an extension of Fig. 3. We show only two customer organizations for reasons of simplicity, but this can be trivially extended to an arbitrary number.

From a technical perspective, we can apply the same mechanisms as discussed so far. But from a business perspective, there is an issue: in most practical business situations, customer organizations don't allow their sensitive outcome business data to be used in a multi-customer setting for reasons of competitiveness. To address this issue, we propose the use of federated learning [14, 15] in distributed business settings [16, 17]. In federated learning, part of the analytics mechanism is not kept central, but 'pushed' to the data sources. Consequently, the processing of sensitive data can take place locally at these data sources and only abstract model vectors are sent to the central analytics mechanism, which combines these vectors to integrate the local learnings into an analytics model for the entire federation.

In our outcome mechanism as shown in Fig. 8, using federated learning implies that part of the functionality of the regulator element is pushed into the sensor elements. The sensor elements become 'smart' as they perform part of the data analytics. The analytical task of the regulator element is reduced to federation-level integration of local results. Making sensors 'smart' is possible for those classes of sensor types that are under the control of the participants in the federation, i.e., *Class i* to *Class iv*. This is not possible for *Class v* and *Class vi*, because these rely on external sensors. But the outcome data here is already external, so data privacy issues are between the customer organizations and the owner of the external systems. Consequently, there is no need to change the sensor in this case.

D. SORBET Beta Version

The three discussed extensions to the Alpha version of SORBET lead to the design of the Beta version of SORBET, containing an extended version of the OBC with classification guidelines to fill in the canvas and an extended usage guideline. The Beta version of the OBC is presented in Fig. 9.

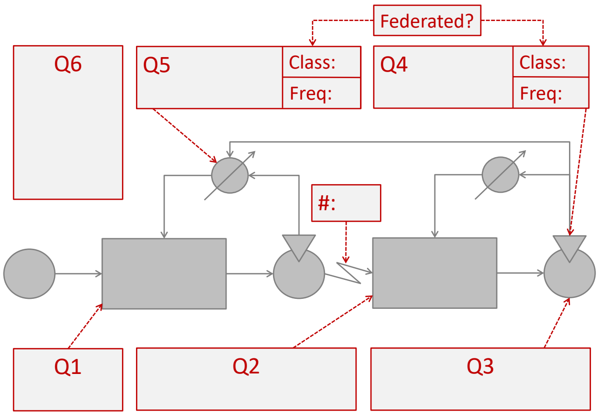

Figure 9: Outcome Business Canvas Beta version

with respect to the Alpha version: a field to indicate the customer fan-out in the outcome model (#); an explicit classification of the sensor element (based on Table 1) and an indication of the data acquisition frequency of the sensor; an explicit classification of the regulator element (based on Table 2) and an indication of the data processing frequency of the regulator; an explicit indicator whether federated data processing is used for sensor and regulator.

The Beta usage guideline is an extension of the Alpha version presented in Section IV.A, with three added elements. In Q2, we add "*Is this a single customer or a set of customers? If a set, how large is this set?*" In Q4, we add "*Which class of sensor element is applicable (see Table 1)? Is federated data processing required?*" In Q5, we add "*Which class of regulator element is applicable (see Table 2)?*"

E. Preliminary application of SORBET Beta version

Even though a classification of the scenario designs in terms of Table 1 and Table 2 was not performed during the workshops discussed in Section V, we can classify the four workshop scenarios in hindsight as a first desk research application of the Beta version of the OBC. A classification based on the descriptions of the designed outcome scenarios in Sections V.A and V.B is shown in Table 3. By varying design parameters, different choices can be made. The table shows a broad variety of scenario classes. For reasons of brevity, we omit the OBC representations of these scenarios.

Table 3: possible classification of cases

Focal Company	Customer	Sensor Class	Regulator Class	Feder-ated?
Truck Producer	Receiver	(i)	(a)	Yes
	City	(vi)	(a)	No
Pharma Producer	Farm	(iii)	(b)	Yes
	Consumer	(v)	(c)	No

VII. Conclusion and Future Work

In this paper, we present an engineering approach to the design of IT-enabled outcome control scenarios, called SORBET. The approach is based on a two-stage cybernetic feedback model and was developed in two versions. The Alpha version of SORBET is used for high-level design of outcome control scenarios. Using the Beta version of SORBET, a scenario can be mapped to technology classes for data collection and processing. With the presented approach, we bridge the gap between the outcome economy as a rather abstract, strategic concept and the practical embodiment of this concept in real-world, data-driven supply chains using Internet, IoT and BI technologies. Though the approach is engineering-based in its design, the executed workshops have shown that it is close to the world of business thinkers.

In future work, the Beta version of SORBET needs to be evaluated in a more formal focus group setting, using industrial practitioners like we have done for the Alpha version. An interesting future refinement of our work is to explicitly use the scenario classifications of Table 1 and Table 2 to further sharpen the discussion during a scenario design workshop. This discussion can be further sharpened by taking the desired frequency of the feedback mechanism explicitly into account. An extension of the presented technique is to compare the classification of a scenario with the available data sources and data processing infrastructure.

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