Chapter 6
Some Future Directions for Business Process Modeling

As observed earlier in this book, both the depth and breadth of interest in business process modeling has increased over the last decades. This increased interest has moved the bar concerning the reasons why people want to use business process modeling approaches, and it has also resulted in increasingly expressive and applicable—and thus complex—modeling languages. We also observe that it is possible to aim for a large number of potential modeling goals. One interesting aspect is that when using models in an industrial setting to obtain long term benefits, the models do not have only one goal. Rather, they aim to be *multivalent*: to provide value toward achieving a number of different potentially conflicting goals, often pushing for even greater expressiveness of the modeling languages to use. On the other hand, practical large scale applications of business process modeling typically use only a pragmatic and often small subset of the standard languages.

In the next section, we will investigate how process modeling in particular has developed given these conflicting requirements and discuss how it might continue to develop in the future as computer systems themselves evolve to support modeling to a greater extent.

6.1 Business Process Modeling Integrated with other Types of Modeling

Modeling languages through the 1980s were primarily mono-perspective (e.g., ER-diagrams for structural modeling and DFD for process modeling); however, methods to more closely integrate the various modeling languages appeared during the 1990s. An early example of such an approach was Tempora (Loucopoulos et al.

J. Krogstie, *Quality in Business Process Modeling*,
DOI 10.1007/978-3-319-42512-2_6

1991), which aimed to create an environment for the development of complex application systems. The underlying idea was that development of a CIS should be viewed as developing the rule base of an organization, which would then be used throughout the development and evolution of the system. However, rules are difficult to visualize; thus, Tempora had three closely interrelated languages for conceptual modeling: ERT, an extension of the ER language; PID, an extension of the DFD; and ERL, a formal language for expressing organizational rules that was also extended to include deontic notions (Krogstie and Sindre 1996). The basic modeling constructs of ERT were entity classes, relationship classes, and value classes. The language also contained most of the usual constructs from semantic data modeling such as generalization and aggregation, derived entities and relationships, and some extensions for temporal aspects that were specific to ERT. The PID language was used to specify processes and their interactions in a formal way. Its basic modeling constructs were processes, ERT views (which were links to a structural ERT model), external agents, flows (both control and data), ports to depict logical groupings of flows as they enter or leave processes, and timers, which could act as either clocks or delays.

A way to combine the models in these languages was developed as a basis for generating prototypes directly from the models (Krogstie et al. 1991; Lindland and Krogstie 1993). In addition to linking PID to ERT models and ERL rules to ERT models and PIDs, there was the possibility of relating rules in rule hierarchies.

As observed in the BPMN evaluation in Sect. 5.3, we find a similar picture here. The process models act as the central artifacts, but often it is desirable to extend the models to cover concepts normally captured through other modeling perspectives. Note that the same pattern occurs in the certification example in Sect. 4.1, where the new language had the processes at its center, but one also wanted to be able to represent relevant rules, data, and organizational entities in an integrated manner. The petroleum industry case in Sect. 4.2 actively pursues a more full-fledged enterprise modeling approach that was not focused solely on the core process models. EEML (Krogstie 2008), which furthered the work from Tempora, also sported a central process modeling language, but with data, actor, and rule modeling as full-fledged perspectives integrated into the process modeling. Enterprise modeling languages such as ArchiMate and 4EM (Sandkuhl et al. 2014) also cover many perspectives in an integrated manner but still preserve the possibility for focusing specifically on business processes. At the same time as these (process) modeling languages were being extended with concepts from other perspectives, we observed in both cases from Chap. 4 that a very limited set of language constructs was chosen for the core models to keep them manageable. This subset has actually been further reduced through use (e.g., removing the possibility of intermediate events in the case presented in Sect. 4.2).

Multiperspective modeling (such as GEMAL (Andersson and Krogstie 2015)) flattens this hierarchy further, treating processes as just one of many perspectives that are all on equal levels, leaving the modeler free to use any modeling perspective as the main one. This type of modeling is believed to be primarily applicable for expert modelers for early sense-making. In contrast, a perspective that leans toward process modeling, where additional aspects are particularly related to the process model, is believed to still be useful (although potentially limiting if used in the wrong way) for extensive use of modeling.

6.2 Beyond the Activity—Business Process Modeling across Organizational Levels

Another primary observation is that the type of process modeling language used varies across organizational levels. The way to model the top-level processes (the process maps) in the oil and gas case in Sect 4.2 is different than the way to represent the intermediate level models, which are different from the workflow models in the BPMN variant. Malinova and Mendling (2015) comes to a similar result. They found that BPMN is neither complete nor clear for modeling process maps. Thus, if organizations use BPMN to design their process maps, they will encounter multiple BPMN elements that embody the same semantics as one process map concept and vice versa: One BPMN element may be used to represent multiple process map concepts. These findings illustrate that many concepts are specializations of others. An underlying reason is that BPMN models and process maps have differing purposes; that is, while the purpose of a BPMN model is to show the details of a process, the purpose of a process map is to depict an abstract overview of all the processes for an entire company; hence, process maps show how BPMN models fit together while excluding their details.

Going back to the differentiation of the "as-is," "to-be," and "ought-to-be" models from Chap. 1, this concept can also be used to illustrate how it can be beneficial to use different modeling approaches at different levels of abstraction.

Process modeling at a company level often starts with the company vision and business value. It is also important to develop both corporate future goals and target architecture in the form of a "Future Operating Model" (an ought-to-be model), as well as detailed workflows that include both as-is and to-be activities.

To achieve this, one needs a combined top-down and bottom-up approach. The Future Operating Model is a top-down model that describes best practices for the way the organization wants to operate in the future (ought-to-be). In contrast, the workflow model is a bottom-up model that shows how the enterprise operates with today's (as-is) systems and organization and how it will operate with tomorrow's (to-be) systems and organization.

The Future Operating Model describes best practices derived from previous experience, technological development, regulatory requirements, and so on and shows ambitions and plans on a general level: It models how the enterprise should operate in the future. This model is used for both understanding and planning programs and projects.

The model is used to perform basic analyses and to help answer questions such as:

- "What is our enterprise doing?"
- "Are we doing the right things?"
- "How are our main processes and value chain operations being performed?"
- "Could we redesign our basic processes?"

The preceding questions lead to analysis that should be conducted before going into the details such as:

- "Who/what does which tasks?" (Humans/machines).
- "Which IT systems are used for what tasks?"

Only after these basic analyses have been conducted and decisions made can one move forward to create detailed workflow models. A unifying overall process model such as this makes it possible for people with varied backgrounds—who come from different organizational units and disciplines and have worked in different ways in the past—to agree on common work processes and value chains. A unifying model contributes to common terminology for processes, concepts, information objects, and so on. A generic overall model also contributes to process modeling standardization so that work processes can be described the same way across different departments and disciplines, which is important for communication and reuse. The process hierarchy provides a total overview of the enterprise and agreements about best practices. Experience shows that it is the transitions in the value chain that often slips, and this becomes explicitly evident in this type of overall end-to-end model. In this model, it is also important to keep customer/client relationships in focus and to ensure that customer interactions with the company are explicitly modeled.

As illustrated in Fig. 6.1, the Future Operating Model is a top-down planning model that shows value chains, but also value shop and value networks if relevant, whereas the workflow model is a bottom-up implementation model that shows the detailed workflow for defined parts of the value chain. The left side of Fig. 6.1 shows a top-down process breakdown structure, from an "overall view" that proceeds over several levels down to "processes/activities." The right side shows a bottom-up workflow model built up in levels from Applications and Roles to IT Services and Procedures for Implementation (Orchestration).

Modeling a top-down generic model can be accomplished using different notations. A case from the hospital sector presented in Fossland and Krogstie

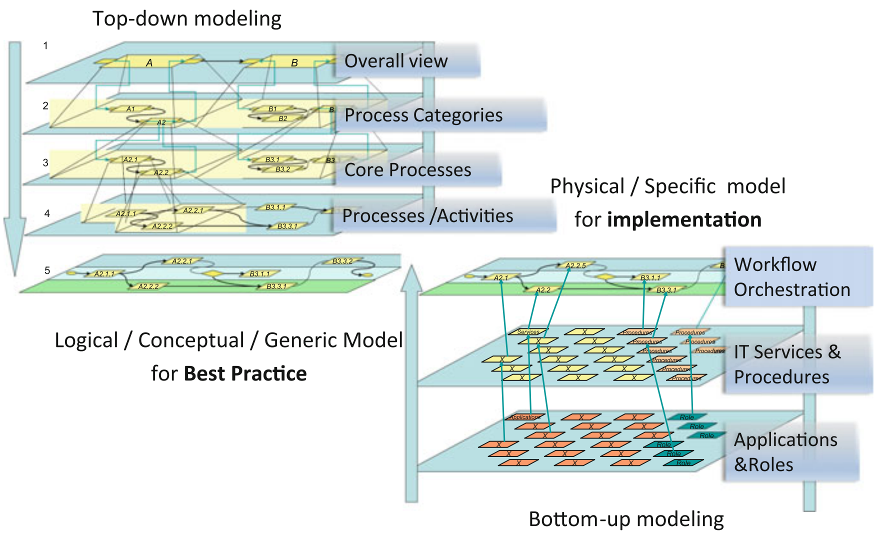

Fig. 6.1 The interplay between top-down and bottom-up modeling (Fossland and Krogstie 2015)

(2015) used IDEF0, which is regarded as a best practice for building logical/generic/conceptual process models with a "process breakdown structure."

The ought-to-be model should be made independent of specific applications or organization structure, making it viable for use even when technological innovations and organizational changes such as mergers or divisions occur. The workflow model is a bottom-up implementation model (e.g., in BPMN as in the case presented in Fossland and Krogstie (2015)) that shows detailed workflows for defined parts of the value chain. Based on the level of dynamicity of the process (cf. Fig. 1.10), other less rigid modeling languages than BPMN (e.g., languages supporting interactive process modeling (Krogstie and Jørgensen 2004; Lillehagen and Krogstie 2008)) can be more beneficial. Additionally, work on combining imperative process modeling such as BPMN and declarative process modeling is being pursued in so-called hybrid models (Maggi et al. 2014).

6.3 Welcome to the Machine—Tools from Interpreters to Modelers as Part of Big Data Ecosystems

Whereas modeling has traditionally been conducted by humans, with the availability of large amounts of data, machine learning algorithms, and tool support, tools are now being given more active modeling roles. For process modeling, this increase is most obvious based on the collection of event data in the field of process mining, but in connection with big data developments, there is a need to model on the type level based on models on the instance level (data) (Conti et al. 2012; Lukyanenko and Parsons 2013).

Process mining is described in the process mining manifesto (van der Aalst et al. 2011) in the following way:

> Process mining techniques are able to extract knowledge from event logs commonly available in today's information systems. These techniques provide new means to discover, monitor, and improve processes in a variety of application domains. There are two main drivers for the growing interest in process mining. On the one hand, more and more events are being recorded, thus, providing detailed information about the history of processes. On the other hand, there is a need to improve and support business processes in competitive and rapidly changing environments.

Thus, in process mining, data—in particular event data—are regarded as essential. Five levels of event data quality are described in the process mining manifesto (van der Aalst et al. 2011):

1. Event logs are of poor quality. Recorded events may not correspond to reality, and events may be missing.
2. Events are recorded automatically, often as a by-product of some information system. Coverage varies. No systematic approach is followed to decide which events are recorded. Moreover, it is possible to bypass the information system. Hence, events may be missing or not recorded properly.
3. Events are recorded automatically, but no systematic approach is followed to record events. However, unlike the logs at level 2, there is some level of guarantee that the events recorded are trustworthy (but not necessarily complete). Consider, for example, the events recorded by an ERP system. Although events need to be extracted from a variety of tables, the information can be assumed to be correct (e.g., it is safe to assume that a payment recorded by the ERP actually exists).
4. Events are recorded automatically and in a systematic and reliable manner; logs are trustworthy and complete. Unlike the systems operating at level 3, notions such as process instance and activity are supported in an explicit manner.
5. The event log is of excellent quality, both trustworthy and complete according to the needs, and events are well defined. Events are recorded in an automatic, systematic, reliable manner. Privacy and security considerations are addressed adequately. Moreover, the events recorded (and all their attributes) have clear semantics. This implies the existence of one or more ontologies. Events and their attributes point to this ontology.

Event data are as other data clearly models and can be viewed from the perspective of model quality. The above description of quality levels of event data primarily relates to physical, syntactic, and semantic quality (in an objectivistic sense). Process mining can be looked upon relative to the so-called BPM life cycle (van der Aalst 2016). The life cycle describes the different phases of managing a particular business process.

- In the design phase, business processes are modeled.

- In the configuration/implementation phase, the model is activated by being transformed into an executable system. If the model is already in executable form, this phase may be very short (automatic activation). However, if the model is informal, it only acts as the context of change for a traditional development project.
- After the system supports the modeled processes, the enactment/monitoring phase starts. In this phase, the process is instantiated, and the process instances are running while being monitored.
- The diagnosis/requirements phase evaluates the process instances and monitors emerging requirements due to changes in the environment of the process (e.g., changing laws, policies, or environmental factors).

Poor performance or new demands from the environment may trigger a new iteration of the BPM life cycle starting with the redesign phase. According to van der Aalst (2016) until recently, there were few connections between the data produced while executing the process instances and the business process modeling. Process mining offers the possibility to close the BPM life cycle. Data, in particular event data recorded by the system, can be used to provide a better view of the actual processes, i.e., deviations can be analyzed and the quality of models to be closer to the actual situation can be improved although one should be aware of the risk of premature closure (Krogstie 2012).

The focus on event data in process mining points to that this area is part of the larger area of data science (van der Aalst 2016). As discussed also in Chap. 2, data in general can also be looked upon as models (Krogstie 2013). There is no "true," objective data, and data are always captured under some presumption of what is relevant. We will look at the area of quality of big data relative to the possibility of automatic development of (process) models, extending the presentation given in Krogstie and Gao (2015), also taking into account that event data from future process mining will not come from individual systems in one company, but from a multitude of systems in a number of different more or less uncoordinated organizations as discussed in Sect. 1.3.

Big data have been "conceptualized" by using a number of "V" words similar to the 6-V framework described below. Big data aspects are found in a number of domains (Chen et al. 2012):

- *Volume* refers to the large amounts of data that can be exploited. The database field has always had to cope with increasing volumes—as exemplified by the fact that one of the main conferences in the field already established in the 1970s is called VLDB, which stands for very large databases. Still, the exponentially increasing volumes provide new challenges when datasets are too large to be stored and analyzed using traditional database technologies. Modern big data tools use distributed systems to store and analyze data across databases that are potentially spread around the world using different cloud computing solutions. On the other hand, more data as such do not necessarily mean better results (Boyd and Crawford 2012).

- *Velocity* refers to the speed at which new, relevant data are generated and distributed, which can potentially occur at any time. Technology now allows us to analyze data while it is being generated, without ever storing it in traditional databases.
- *Veracity* refers to the messiness or trustworthiness of the data. With many forms of big data, data quality and accuracy are less controllable than it was discussed in Chap. 2 (consider Twitter posts with hash tags, abbreviations, typos, and colloquial speech as well as the questionable reliability and accuracy of the content).
- *Variety* refers to the different types of data that one might want to look at in concert. In the past, efforts focused mainly on structured data that fit into tables or relational databases. However, a large percentage of the world's data are unstructured (text, images, video, voice, etc.). Other relevant data might come from human interaction with systems. With big data technology, one can now analyze and bring together data of different types such as messages, social media conversations, photographs, clickstreams, sensor data, video, and voice recordings. Note that the variety aspect is not specific to big data; the same issues are found within large organizations as they attempt to address data integration (Krogstie 2013; Martin et al. 2012) internally or in collaboration with business partners, where the data stem from data warehouses or from less structured, ad hoc sources. On the other hand, in big data ecosystems, data by definition reside in and are controlled and evolved by many different organizations. This limits the possibilities for standardizing on one representational format for the typically secondary use of data found in big data ecosystems used by many different consumers.
- *Visualization*. To be able to obtain value from the data, it must be abstracted and visualized in a manner that makes the data useful for the end user, applying and extending techniques in the area of information visualization (Ware 2000). In our context, visualization relative to process models is of particular interest (van der Aalst 2016).
- *Value*. Having access to big data provides no advantage unless it can be turned into some value. Another term used in this regard is *viability*.

We can position the big data characteristics (considering data sources as part of the digital ecosystems described in Chap. 1) in relation to the quality levels of SEQUAL in the following way:

Deontic quality: It is closely related to the description of the point *value* in the list above: Are we able to utilize the data for our particular purpose? *Viability* is a subarea of this that can be related to the discussion of feasible quality in SEQUAL. Although one might achieve value through additional processing, the cost of such processing might be regarded as higher than the benefit. Based on the goal of the data use, and also partly dependent on the data sources to be matched and aggregated, different weights might be assigned to the different quality levels described below. From the point of view of data-enabled digital ecosystems, the use of data from many sources is secondary: The data were not originally created to fit the purpose of use in the ecosystem setting. Additionally, there might be many secondary users who would like to use the data in different ways to achieve different goals. A framework for personalization of big data quality deliberations is found in Embury et al.'s study (2009) which investigates some of these issues. Note that traditional models within an organization might also need to fulfill many different goals, as discussed earlier in this book based on Heggset et al. (2014) and Krogstie et al. (2008), but because those situations are within a well-defined organizational setting, they might be easier to tackle.

Social quality: Provenance issues relating to the trustworthiness of the data source as part of *veracity* are central at this level. In combination with *variety* (which includes data from a number of different sources evolving in an uncoordinated fashion by autonomous actors constituting parts of a digital ecosystem), new issues potentially arise compared to traditional data and model quality discussions because some sources might be more trustworthy than others. Variety might also be an issue internally in organizations, for example, matching personal data held in local spreadsheets with data from enterprise systems such as ERP or PLM system (Krogstie 2013). However, because these sources lie within the same organization, the possibility for enforcing compliance is larger than in a big data ecosystem setting. Due to *velocity* aspects, one might need to quickly and automatically deduce a source trust level using a trust model (Artz and Gil 2007) based on existing metadata for the data source, which thus would also need to be available.

Pragmatic quality: This type of quality is related both to machine understanding of data sources and to human understanding of the results. From a machine-understanding standpoint, the issues here are very different for different types of data (e.g., between structured and unstructured data). In particular, *velocity* drives the increased need to devise tool understanding techniques. When using automated means to structure data, one must use some preconceived model for interpreting the different data sources; this model should also be made available as metadata for human consumers of the end result. Conversely, from the standpoint of a human understanding the results (e.g., visualized as process models), this must also be supported by taking empirical quality into account when devising the *visualizations*. Another approach that can be used is to provide personalized output —a personalized view of data—in which case it might be important to make the user model used in the personalization controllable and scrutable by the user (Asif and Krogstie 2014). Given the expanding types of stakeholders typically involved, personalization is of increasing importance. Different techniques can be used for different types of stakeholders, supporting multiple views for different stakeholder types using the same model to enhance individual comprehension. On the other hand, as discussed earlier, personalization can be at odds with the goal of using the generated model as a framework for building common understanding.

Semantic quality: Whereas traditional quality aspects such as completeness, accuracy, and consistency are not discussed specifically in the big data literature, the area *veracity* points more generally toward a focus on data and model quality. One reason for the *variety* of sources used in many big data scenarios and applications is to achieve improved completeness: Not all relevant data can be found in one data source. On the other hand, *variety* is accompanied by the traditional challenges in data integration quality (Martin et al. 2012), requiring data matching on different levels of abstraction and precision. When data are produced by sensor networks, there may be redundancy issues (e.g., reporting location every second even from an object that is not moving). Such redundancies should be filtered out, as should erroneous readings due to noise, for example, an indication that an object suddenly moved a large distance in a short time. Moreover, this filtering must be performed in the correct sequence. To avoid issues of poor physical quality (see below), it is often possible to abstract the data, in which case it is important that the abstracted dataset maintains the important characteristics of the original dataset (Wad 2008). This illustrates an interesting side of big data not typically experienced in traditional modeling and data representations, namely that the modeling (i.e., abstraction) is partly performed by algorithms rather than solely by humans. From the digital ecosystem point of view, the federated approach will bring new challenges concerning how we regard the semantic quality of the overall model. Whereas semantic quality in smaller domains can be followed up much as is typically proposed in traditional data quality literature (i.e., looking at the feasible (perceived) completeness and validity), one would to a larger degree need to be able to live with inconsistencies across federations (Krogstie 2012). Consequently, it would be important to be able to identify those aspects of the models across domains that need to be consistent for integration purposes and equally important to identify the inconsistencies we can live with given the current need to utilize the different data sources.

Syntactic quality: *Variety* comes into play here because not all data sources have a strictly defined meta-model with a predefined syntax. Therefore, to match the different data sources, certain presumptions must be made about the structure and contents of data, meaning one needs to instill structure if it is not there and in some cases assign meaning (as discussed under semantic quality) to data based on statistics and qualified guesses. As data usage and terminology evolves, the underlying data model may evolve as well. Thus, even if a match between the languages used for federated sources was established at a certain point in time, it might cease to be valid at a future point in time.

Empirical quality: Support for empirical quality will be increasingly incorporated into tools that build up models from raw data using techniques such as process mining (van der Aalst et al. 2011) to integrate information visualization tools and modeling tools. Note that guidelines for aesthetics are partly incompatible; therefore, one must make choices based on usage and interpretations of the representation. In connection with maps for example, (Shekhar and Xiong 2008) states that "different combinations, amounts of application, and different orderings of these techniques can produce different yet aesthetically acceptable solutions." Because data visualizations must often be auto generated (to address issues of *velocity*), aspects described under this level are even more important for pragmatic quality than for traditional models developed mostly manually by human modelers, where a model that is not empirically ideal might work just fine because the original modelers are familiar with the overall model structure.

Physical quality: *Volume* is particularly relevant on this level because it can be difficult to have access to all the relevant data at the same time. Rather than being based on central repositories, available data storage must be distributed and federated, utilizing standard interchange formats and supporting mash-ups using data from different sources stored at different places. This brings up a new issue: Determining what part of the total model must be available for each data reuse. This is complicated because the accessibility of the right (most current) data is influenced by the *velocity* of data changes. To support provenance, it might also be necessary to store the full chain of the data revisions (the data movement effect plan (D'Andria et al. 2015)), not only the last version. In general, provenance metadata should be represented independently of the technologies used for data storage. One area that is underdiscussed in current big data literature is the security aspects, even though the use of big data-oriented techniques on personal data is rife with privacy challenges. People's growing awareness of such issues may potentially make it more difficult for those working with big data techniques to access all the data that is of interest; for example, users may adopt anonymous surfing methods. This notes a need to be open about how big data (e.g., location data) will be used (Biczok et al. 2014), both for its primary usage area and for secondary usage areas.

6.4 Summary

Although modeling is only one of many aspects of BPM, it is an important area both directly and indirectly. For instance, van der Aalst 2013 lists the following as key concerns in BPM.

- Process modeling languages,
- Process enactment infrastructure,
- Process model analysis,
- Process mining,
- Process flexibility,
- Process reuse.

All of these areas to some extent involve the manual or automatic development or use of business process models.

As we have attempted to illustrate in this book, quality in business process modeling can be achieved by appropriately balancing the purposes of modeling, the people involved, the tools, modeling languages, and techniques used.

In this book, we have looked at different aspects of this problem area, both theoretically and through in-depth investigations of cases where process models are used on a large scale in business organizations. In the main cases of this book, we have focused on process models being mainly manually activated, noting that there are other works that go in more detail on interactive activation (e.g., Lillehagen and Krogstie 2008) and automatic activation (e.g., ter Hofstede et al. 2010).

In this final chapter, we have indicated some of the directions in which process modeling approaches are headed. Even though we ended by describing visions of more automatic modeling, parts of the use of business process modeling will continue to be an activity intended to support human thinking, communication, and knowledge development.

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