Title Page

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Analyzing Inter-organizational Business Processes

Process Mining and Business Performance Analysis using Electronic Data Interchange Messages

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Abstract Companies are increasingly embedded in B2B environments, where they have to collaborate in order to achieve their goals. Such collaborations lead to inter-organizational business processes that may be commonly supported through the exchange of Electronic Data Interchange (EDI) messages (e.g., electronic purchase orders, invoices etc.). Despite the appearance of XML, traditional approaches to EDI, such as EDIFACT and ANSI X.12, still play an overwhelmingly dominant role. However, such traditional EDI standards lack a notion of process. In other words, the exchanged business documents are typically not embedded in the context of other exchanged business documents. This has two shortcomings: (i) the inability to apply proven Business Process Management (BPM) methods, including process mining techniques, in such settings; and (ii) the unavailability of systematic approaches to Business Intelligence (BI) using information from exchanged EDI messages. In this article, we present the EDImine Framework for enabling (i) the application of process mining techniques in the field of EDI-supported inter-organizational business processes, and (ii) for supporting inter-organizational performance evaluation using business information from EDI messages, event logs and process models. As an enabling technology, we present a method for the semantic preprocessing of EDIFACT messages to exploit this potentially rich source of information by applying state-of-the-art BPM and BI techniques. We show the applicability of our approach by means of a case study based on real-world EDI data of a German consumer goods manufacturing company.

Keywords inter-organizational business processes · Electronic Data Interchange · process mining · inter-organizational relationships · Key Performance Indicators

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1 Introduction

Companies and organizations exchange data electronically to perform business transactions (e.g., requests for quotes, purchase orders, etc.). If the interchange of data is carried out in an automated and standardized manner, such processes may be referred to as Electronic Data Interchange (EDI) [33]. Despite the appearance of XML and its proposed employment in business document standards [49], traditional EDI standards like EDIFACT and ANSI X12 still play a dominant role in Business-to-Business (B2B) e-commerce and will presumably continue to be the primary data formats for automated data exchange between companies for years [63,35].

Business Process Management (BPM) [6] has been widely applied in companies for internal business processes for years to leverage benefits such as increased process efficiency/productivity, continuous process improvement, better reporting of process performance, etc. While recent academic research for Web services and business process modeling places lots of emphasis on modeling choreographies of business processes [10], many inter-organizational processes are still realized by means of traditional EDI systems. However, traditional EDI systems lack the explicit notion of a business process. They are solely responsible for sending and receiving messages. Hence, every exchanged document is isolated and the process context is lost. This results in a number of shortcomings.

Shortcoming #1: Unavailability of BPM Methods. An inter-organizational business process comprises one or more message exchanges between companies for conducting an electronic business transaction. When companies intend to analyze their inter-organizational processes they generally have to rely on a-priori models, if models documenting the business processes exist at all. In case there are models, those may describe the business processes as they were planned. Real-world business processes are often different from the hand-made "happy path" models.

Shortcoming #2: Missing Integration of Business and Process Information. The specifics of inter-organizational business processes require not only focusing on the executed activities, but also on the actual exchanged business information. However, information combined from process data and business performance data of the exchanged EDI messages, such as EDIFACT messages, is currently not being exploited in a systematic manner. Despite the potentially valuable input for decision-making there are – to the best of our knowledge – no such approaches for EDI systems.

We address these shortcomings by integrating a set of different technologies and methods, such as traditional EDI, BPM, process mining, Business Intelligence and semantic technologies. To this end, we design a framework that allows for gaining business/economic insights from EDI data. For bridging the gap from the current state of the art to such a framework, we identify the following research questions: (i) "How to use EDI event data for inter-organizational process mining?" and (ii) "How to define and compute KPIs from EDI data?". As a necessary prerequisite for addressing the above two questions, a third question can be identified: (iii) "How to extract event information from EDI data?". Using a Design Science research (DSR) approach [32], we first addressed each of the aforementioned research questions individually by building and evaluating artifacts limited in scope to the corresponding question. These intermediate results of the undertaken DSR process were already published in conference papers [20–26, 40–42, 44]. We were able to validate the practical relevance of the aforementioned shortcomings and research questions with each of three companies with which we conducted specific and focused case studies within the EDImine research project [20, 24, 42]. Moving forward, we combined the individual designed artifacts into an integrated end-to-end approach, the *EDImine Framework*. In order to show the applicability of the overall framework we again used a case study, this time using process descriptions and data from a different company. The data provided were rich in the sense that we were able to cover all the phases and artifacts of the framework. On the other side we limited the evaluation to a case study with one company due to the richness of the framework and since it was hard to find a company providing all these confidential data. The EDImine Framework and said evaluation are presented in this article.

The EDImine Framework presents methods for generating event logs from EDI messages, which in turn allow for mining message choreographies [54] and/or process models of *inter-organizational collaborations* [1]. Moreover, it comprises methods for conducting business performance analyses through the alignment of business information in EDI data to business objectives and KPIs. Finally, the EDImine Framework introduces methods for preprocessing EDIFACT messages using semantic technologies in order to facilitate the extraction of business information as an *enabler* for the former two components.

In the presented approach we build upon state of the art process mining techniques [2, 5], which we extend for inter-organizational systems realized by means of EDI. Thereby, we focus on EDIFACT [11] as it is currently the most prevalent in the EDI standards family. Our approach, however, is independent of the underlying transfer syntax. Hence, it can also be applied to other syntaxes used in EDI, such as XML-based business documents.

In the following section, we discuss the research questions in-depth and elaborate on the relevant state of the art. Then we describe the designed artifacts comprised by the EDImine Framework as well as their prototypical implementations in detail. Next, we present the overarching case study in which we apply our approach end-to-end on a real-world EDI data set. Finally, we discuss conclusions, limitations and future work.

2 Research Questions and State of the Art

In the following, we discuss each of the aforementioned research questions in detail and elaborate on the relevant state of the art.

2.1 Research Question 1: How to Use EDI Event Data for Inter-organizational Process Mining?

Due to the absence of an explicit notion of a *process* in traditional EDI standards, every business document may be provided independently and may be unrelated to the context of a set of document exchanges. This lack of process awareness in traditional EDI systems hinders organizations from applying Business Process Management (BPM) methods in such settings. For example, companies might be interested in identifying factors that promote deviations in the execution of inter-organizational business processes, such as individual line items that are frequently associated with delays in delivery processes [24]. As another example, companies might be interested in learning about performance bottlenecks in just-in-time production processes [20]. In order to gain such and similar insights on EDI-based business processes, we have recently proposed the application of process mining techniques in the context of EDI-based inter-organizational business processes [22]. Because such techniques generally require the availability of event logs, we are faced with the challenge of deriving event logs from EDI messages.

In addressing this challenge, two significant problems need to be solved. Foremost, for generating events from observed EDI messages it is necessary to decide what EDI artifacts[1] constitute events and how to populate the attributes of these events. In order to apply process mining, each event needs to refer to a case, an activity and a point in time. Depending on the objectives of analysis, one may take different approaches to this task. Moreover, depending on the assumed viewpoint with regard to the relationship between messages and events, either messages or events need to be correlated to process instances (cases) in order to allow for the generation of event logs [2, p.113]. This leads us to the following requirements for designing methods for generating event logs from EDI messages:

1. Provide guidelines for mapping *EDI artifacts* in the context of EDI standards to *events* in the context of event logs.
2. Provide guidelines for aligning process-agnostic EDI messages, or events derived therefrom, with process instances *(message correlation / event correlation)*.
3. Account for different objectives of analysis: Analyzing inter-organizational business processes may focus on the exchanged EDI messages (technical analysis) or on the actual business activities carried out (business-level analysis).

State of the Art. Process mining techniques [2,5] extract knowledge about business processes by analyzing event logs and are seen as part of Business Intelligence (i.e., BP Intelligence [31]). Although there is no foundational

[1] An *EDI artifact* can be defined as any structural element or concrete value conveying some piece of business information in an EDI message; hence, their specific manifestation may vary between different EDI standards. For instance, in the case of EDIFACT the term may refer to qualified or non-qualified data elements, segments, segment groups, message types, etc. [11].

reason why process mining cannot be applied across different organizations, most applications of process mining have been conducted inside a particular organization [1,9]. This is reflected in current literature on this topic. The few publications on process mining in an inter-organizational context tend to focus on the area of Web services [4,7,18,50,51,53]. For example, in [4] conformance checking techniques are applied to the message logs of Oracle BPEL. Another example may be found in [7] where process mining techniques are applied in the context of IBM's WebSphere.

In [1], van der Aalst approached the topic of inter-organizational process mining by distinguishing between *vertically* and *horizontally* partitioned inter-organizational business processes. Vertical partitioning refers to work partitioned across organizations by distributing cases over several organizations while the actual *process* is the same for all organizations. Vertical partitioning is often done in order to *exploit commonalities* between different organizations doing similar things. On the contrary, horizontal partitioning denotes the cutting of the process itself into pieces. In other words, different organizations conduct different parts of that process through *inter-organizational collaboration*. In this article, we focus on horizontally partitioned inter-organizational business processes since EDI message exchanges are typically conducted in order to support inter-organizational collaboration rather than to distribute cases of a process over different organizations. In [1], van der Aalst mentions a number of challenges that are associated with process mining of horizontally partitioned inter-organizational business processes, including the following:

> *How to discover a process model when only seeing message exchanges and/or local events?*
> *How to check conformance when only seeing message exchanges and/or local events?*
> *How to identify bottlenecks when only seeing message exchanges and/or local events?*
> *How to correlate messages to process instances? [...]*
> *How to deal with many-to-many relationships across different organizations? [...]*

Related to inter-organizational process mining is *cross-organizational process mining* which denotes the use of process mining techniques for analyzing differences between organizations [2, p291].

2.2 Research Question 2: How to Define and Compute KPIs from EDI Data?

In order to understand the impact of inter-organizational relationships (IORs) on the business performance of collaborating business partners, they need to be evaluated [57]. Recently, we proposed the use of KPIs calculated from EDI data for the evaluation of IORs in order to improve quantifiability and explicitness over previous approaches [40].

Although deriving KPIs from EDI data allows us to have measurements reflecting actual business transactions (i.e., on a transactional level), such measurements do not directly reflect inter-organizational performance on the strategic level. In order to allow for business performance evaluation against business objectives, we argue that *bottom-up* analysis of EDI data for defining/calculating KPIs needs to be connected with *top-down* systems for measuring business performance starting from the strategic level, such as Balanced Scorecards (BSCs) [38].

KPI calculation from EDI messages is also challenging on a technical level. In particular, due to the large number of different standards and/or versions used in the EDI realm that need to be dealt with, KPI definitions are required on a semantic level. However, the actual calculation needs to consider concrete syntaxes and potential semantic variability of data elements (data format, data element name, data element position, etc.).

In a nutshell, inter-organizational business performance analysis from EDI data raises challenges including (i) defining KPIs for evaluating IORs based on EDI data, (ii) calculating KPIs from different syntaxes and semantics across heterogeneous EDI data schemas, and (iii) linking KPIs to a business strategy. This leads us to the following set of requirements for developing a performance analysis framework that integrates information from EDI data sources:

1. Enable the definition and calculation of KPIs based on business information and process information extracted from EDI data (*bottom-up* definition of KPIs).
2. Enable the definition of business objectives and success factors that reflect business strategies *(top-down)*. Allow for the alignment of these business objectives and success factors with quantifiable KPIs for lifting the performance evaluation from the operational level to the strategic level.

State of the Art. Most studies concerned with the evaluation of IORs (e.g., [13], [61]) tend to build upon the analysis of *success factors* having an impact on IORs. For example, *trust* [59,68,58], *information sharing* [48,14] and *joint working* [45,36,17] are mentioned as such factors, which are, however, difficult to measure. In order to define KPIs from EDI data for the evaluation of IORs, appropriate success factors and ways of measuring them need to be investigated together with EDI messages and their contained information.

As mentioned above, for analyzing business (process) performance one can distinguish between bottom-up and top-down approaches. As an example for a bottom-up analysis tool, ProM 6 [62], the most prevalent academic tool in process mining, provides several plug-ins supporting analyses based on low-level log data (e.g., ILP Miner [66], α-Miner [8], performance analysis through process mining [34]) as well as business data (e.g., data-aware process mining [47]). Moreover, there are also some commercial process mining tools that have been developed recently such as Disco (by Fluxicon), Celonis, or Perceptive Process Mining, etc.

Results from process mining can also be applied for in-depth analysis of business processes for answering specific business-related questions. For instance, a case study presented in [24] uses the mined model of an inter-organizational purchase order process as well as related business information (e.g., requested delivery date, actual delivery date, ordered quantities, etc.) for answering questions related to operational performance regarding the delivery of items (e.g., “Does the delivery time of line items vary depending on the delivery point?”). However, a drawback of bottom-up approaches is that they usually fall short of accurately reflecting business success on the strategic level.

On the contrary, BSCs are a widely applied top-down measurement system [19]. There are also several works on applying BSCs in inter-organizational contexts such as supply chain management (SCM). For instance, Brewer et al. [12] discuss the interrelationship between BSCs and the SCM field and introduce approaches for supply chain performance analyses based on BSCs. Kleijnen et al. [39] and Chia et al. [15] study examples of KPIs commonly used for measuring supply chain performance following the BSC paradigm. However, top-down approaches are difficult to implement since business objectives and/or strategies are often too broadly defined and, hence, too ambiguous to relate to appropriate KPIs. In addressing this problem, best practice in the BSC framework suggests to align business strategy with KPIs through critical success factors [37].

In [55], the topic of using information from EDI messages for measuring the performance of supply chains has been approached, but best to our knowledge the results have not been formally published. However, some of the findings from this research seem to have found their way into another paper that describes an approach for monitoring and controlling the performance of a supply chain using e-commerce data [56].

2.3 Research Question 3: How to Extract Event Information from EDI Data?

EDI technology is widely used and was developed over several decades. Over time, many different standards have been developed. In addition, individual standards generally comprise multiple different versions. Moreover, EDI standards typically contain large numbers of optional data elements. For instance, names of data elements may be changed as well as data elements added and removed from version to version. On the other hand, data elements with different names may actually refer to the same concept. The correct interpretation of EDI messages is further complicated by the complex way in which semantics of data elements are encoded in traditional EDI standards, including EDIFACT or X12, using so-called *qualifiers* and *qualified data elements* [11]. While current EDI systems typically allow for accurate information extraction from *specific subsets* of such EDI standards only (generally by using hard-coded interpretation logic), the automated and accurate interpretation of *arbitrary* EDI messages still poses a challenge due to the pitfalls of accurately determining the semantics of qualified data elements [23].

Therefore, we identified the following requirements for designing a framework for automated extraction of event information from arbitrary EDI messages:

1. A common formal representation of syntaxes of different EDI standards and releases thereof, as well as of corresponding messages, for alleviating the problem of accessing messages based on multiple different standard releases. By *syntax* we refer to the specific structure of individual EDI message types of different EDI standards and versions. Since in traditional, delimiter-based standards the type of a data element can only be determined by its position in a message, knowledge about the position of data elements in particular message types is crucial for the accurate interpretation of messages. Moreover, since data elements are usually hierarchically structured in EDI messages, knowledge about these hierarchical structures is essential as well (e.g., EDIFACT segments are nested in segment groups).
2. Explicit modeling and storing of qualification relationships between data elements (for an overview of the significance of qualification relationships between data elements, see [23]) in order to allow for a semantically accurate interpretation of qualified data elements in arbitrary EDI messages in an automated manner.
3. A shared ontology of business information concepts that abstracts from specific EDI standards and versions in order to provide a common terminology of business-relevant concepts independent of underlying transfer technology (e.g., revenue, delivery date/time, address, etc.), as well as hierarchical relationships between these concepts (e.g., delivery street address is more specific than delivery address, delivery date/time is more specific than delivery date, etc.).

State of the Art. The need for building ontologies for automating EDI has been observed in various research works such as [27,52,46,16]. In particular, in [46], the authors recognize the problem that standards such as EDIFACT or ANSI X12 are defined in English prose and are thus unavailable for machine processing. The authors of [27,52,16] propose the utilization of ontologies and semantic technologies for overcoming interoperability issues. Nonetheless, best to our knowledge endeavors on providing complete and practically useful ontologies on EDI are only sparsely found in current literature. A notable approach for ontologizing EDI has been conducted in the course of the TripCom project (`http://tripcom.org/ontologies`). The underlying vision of the TripCom project was to enable persistent asynchronous communication for Web services [28] by creating an ontological infrastructure for business processes and business data. Therefore, one aim of the project was to define ontologies for EDI in terms of both syntax and semantics for overcoming heterogeneity problems. As a result, in [29,30] the authors present an approach for ontologizing EDI based on semantic templates. Thereby, the authors utilize manually defined templates serving as a basis for deriving syntax and semantics from EDI standard specifications. One of the major challenges faced when ontologizing EDIFACT is extracting semantics which are defined through textual descriptions as part of the EDIFACT standard specifications. However, the mechanism for dealing with textually defined semantics of data elements remains unclear in these works.

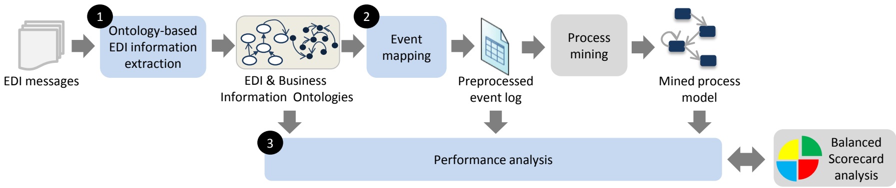


Fig. 1: Overview of the EDImine Framework

The problem of processing qualified data elements semantically accurately is also relevant when mapping EDI standards to other data structures. However, current mapping tools generally do not allow for the generic interpretation of qualification relationships (cf. [23]).

In conclusion, the identified requirements for designing artifacts addressing the above described research questions can be summarized as follows. For Research Question 1 *(How to Use EDI Event Data for Inter-organizational Process Mining?)*, it is required to (i) map EDI artifacts to events, (ii) align process-agnostic EDI messages with process instances, and (iii) allow for different objectives of analysis (technical or business-level analysis). For Research Question 2 *(How to Define and Compute KPIs from EDI Data?)* two requirements were identified: (i) allow for the bottom-up definition and calculation of KPIs from EDI data and (ii) align them with top-down defined business objectives and success factors. For Research Question 3 *(How to Extract Event Information from EDI Data?)* the requirements include (i) a common formal representation of different EDI standards and releases thereof, (ii) modeling and storing of qualification relationships, and (iii) a shared ontology of business information concepts. For addressing these requirements, we developed the EDImine Framework.

3 The *EDImine* Framework

The EDImine Framework consists of (i) a method for ontology-based information extraction from EDI messages (cf. Fig. 1, Mark 1), (ii) methods for enabling message choreography and business process mining from EDI messages (cf. Fig. 1, Mark 2) and (iii) a method for performing business performance analyses on top of data gathered from EDI messages (cf. Fig. 1, Mark 3). In the following, these components are described in detail.

3.1 Ontology-based EDI Information Extraction

In addressing the requirements described in connection with Research Question 3 (cf. Section 2.3), we developed an approach based on semantic technologies to store information about the syntax and semantics of EDI standards in ontologies and knowledge bases. Semantic technologies, such as OWL 2 RL

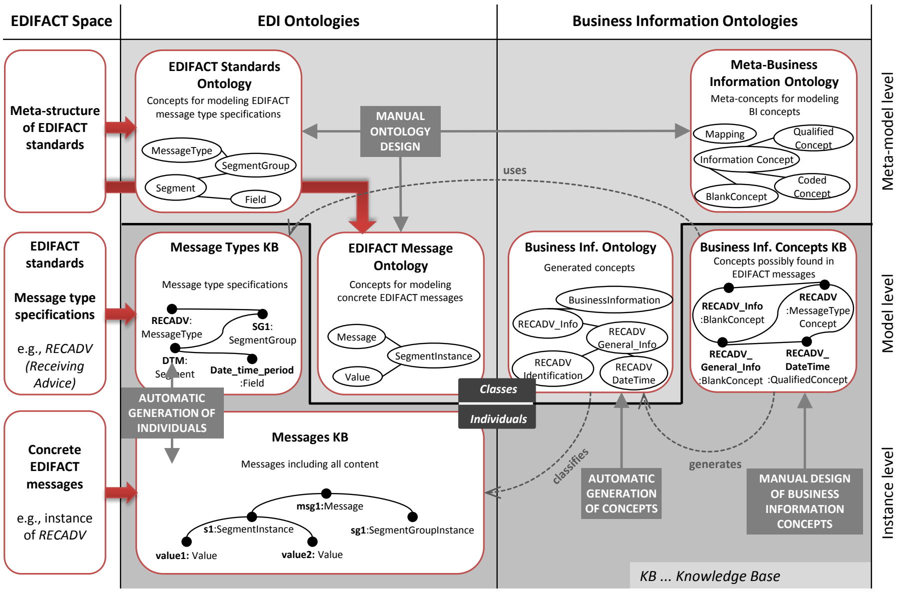


Fig. 2: Architectural overview of the EDI and Business Information Ontologies [23] [41]

[64] which was used in our prototypical implementation, suggest themselves for the given requirements as they (i) allow for a logical representation of hierarchically structured EDI message type definitions (cf. Section 2.3, Requirement 1), (ii) allow for references between entities for capturing semantic relationships between them (Requirement 2), and (iii) allow for the specification of ontologies for business information terminology including hierarchical relationships between these concepts as well as the formulation of logical rules for automatically classifying data into such concepts (Requirement 3). Fig. 2 shows an architectural overview of the proposed ontological framework, which consists of two main building blocks: the *EDI Ontologies* and the *Business Information Ontologies*.

EDI Ontologies. The objective of the EDI Ontologies is to provide an abstract architecture for formalizing knowledge on how to interpret EDIFACT standards and messages accurately. Successful interpretation of EDIFACT messages requires at least the following bodies of knowledge as an input (cf. Figure 2, *EDIFACT Space*): (i) the messages themselves, (ii) the EDIFACT standards (i.e., message type specifications) and (iii) abstract knowledge on how to read messages and standards (i.e., the meta-structure of the standards). In the EDI Ontologies, these bodies of knowledge are modeled in ontologies and corresponding knowledge bases (cf. Figure 2, *EDI Ontologies*), as described in the following. The meta-structure of the EDIFACT standards with regard to message type specifications is modeled in the *EDIFACT Standards Ontology*. The meta-structure with regard to the generic structure of EDIFACT messages

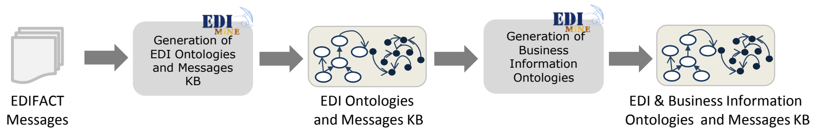


Fig. 3: Ontology-based EDI information extraction

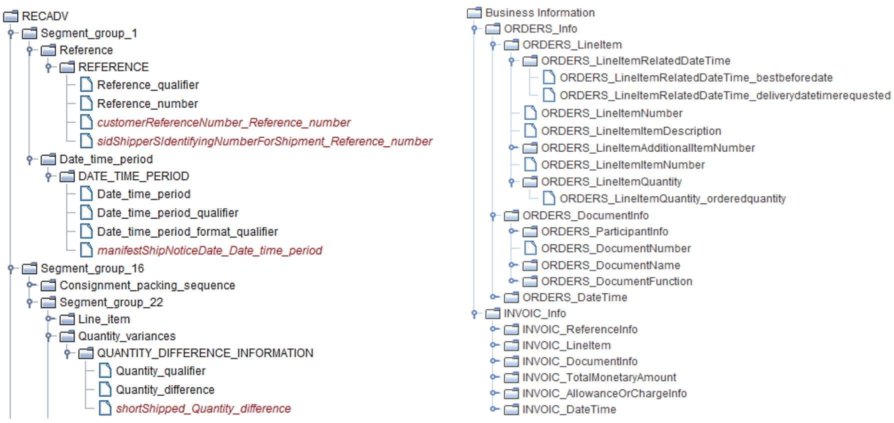
(i.e., regardless of specific message types) is modeled in the *EDIFACT Message Ontology*. Message type specifications and concrete messages are stored in *Message Types KBs*[2] and *Messages KBs*, respectively. The individuals in these knowledge bases can be created automatically from EDIFACT standards specifications and concrete EDIFACT messages by employing custom parsers. In addition to information from the standards, information on qualification relationships between data elements can be modeled and stored in the Message Types KB. When parsing concrete messages into the Messages KB, qualification relationships can be automatically resolved based on this information, and semantic meta data can be added to the values. For details on this mechanism, the reader is referred to [23].

Business Information Ontologies. The Business Information Ontologies [41] allow for mappings of data elements in different EDI standards to common business information concepts. These business information concepts and their mappings are stored in the Business Information Concepts KB (cf. Fig 2, *Business Information Ontologies*), which is manually modeled according to the Meta-Business Information Ontology. From this KB, a concrete Business Information ontology can be automatically generated that maps concrete EDI values in a Messages KB of the EDI Ontologies to business informations concepts by applying reasoning techniques over the ontologies. The resulting ontologies contain the interpreted EDI data classified into business information concepts on a unified semantic level. As mentioned before, in our prototypical implementation we used OWL 2 RL as a formalism and translated the ontologies together with the messages to a Datalog Program for optimizing performance. For details on the reasoning mechanism, the reader is referred to [41].

The Business Information Ontologies allow for flexibility and facilitate automation when dealing with different syntaxes of EDI standards and versions. Additionally, due to the organization of business information concepts in a hierarchical structure, business information may be queried and accessed by referring to business information concepts on different levels of abstraction. For instance, one may query for specific delivery date information in an EDI message by using the *DeliveryDateTime* business information concept. However, one may also query for *any* date/time information which is accessible through the more general *DateTime* business information concept.

Fig. 3 summarizes the process of information extraction from EDI messages in the context of the overall EDImine Framework. EDI messages and

[2] Here, KB is used as an acronym for *Knowledge Base*.



(a) Fragment of a RECADV (Receiving advice) message representation rendered using the EDI Ontologies. Data element references in red/italics display precise data element semantics according to resolved qualification relationships.

(b) Fragments of ORDERS (Purchase Order) and INVOIC (Invoice) message representations rendered using the Business Information Ontologies

Fig. 4: Exemplary EDIFACT message representations rendered using the EDI Ontologies and the Business Information Ontologies

their contained values are parsed and stored in knowledge bases conforming to the EDI Ontologies. Then, the Business Information Ontologies are generated according to the predefined mappings between business information concepts and EDI standards. Fig. 4 shows an example of how this ontological approach can be utilized to visualize the contents of EDI messages in a user-friendly manner.

We evaluated the EDI & Business Information Ontologies against the requirements mentioned in Section 2.3 in two earlier publications. Requirements 1 and 2 were evaluated by comparing the EDI Ontologies with alternative representations of EDI messages [23]. Contrary to alternative representations, the EDI Ontologies allow for modeling of qualified and coded semantics of data elements (Requirement 2) for different releases and versions of EDI standards (Requirement 1). Requirement 3 was evaluated by assessing exemplary cases of accessing business information in EDI data using the Business Information Ontologies. The results showed that the Business Information Ontologies reduce query complexity and improve accessibility of business information as compared to alternative approaches [44].

3.2 From EDI Messages to Event Logs

In addressing the requirements stated in connection with Research Question 2, we propose the following distinct, but complementary methods for generat-

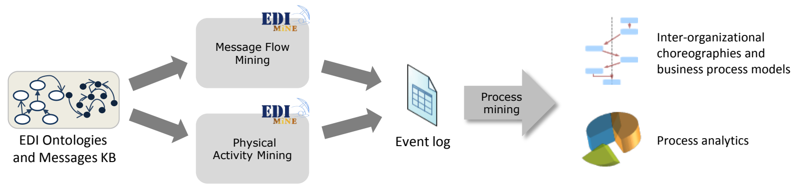


Fig. 5: Workflow for the application of MFM and/or PAM

ing event logs from EDI messages: (i) Message Flow Mining (MFM) and (ii) Physical Activity Mining (PAM), where MFM can be interpreted as a constrained variant of PAM. Fig. 5 depicts a typical flow of processing steps when applying the MFM or PAM methods in the EDImine Framework and starting from EDI Ontologies and Messages KBs as described in Section 3.1.

Message Flow Mining (MFM). Message Flow Mining (MFM) focuses on generating event logs that reflect the message interchanges between collaborating business partners in the course of an inter-organizational business process. In MFM-based event logs, events correspond directly to the receiving or sending of an EDI message. Such a viewpoint can be interesting for both technical and business-oriented analysis of EDI-supported inter-organizational business process. For instance, MFM-based analysis may reveal technical problems related to message interchange, such as repeatedly sent or ignored EDI messages. On the other hand, MFM-based analysis may also be used to analyze a business process with regard to "physical" activities that are performed in a business context if EDI messages are exchanged synchronously with such activities.

For MFM, the *timestamp*, *resource* and *activity* attributes of events are populated according to the corresponding message's interchange timestamp, the name of the interchange-initiating party and the message type, respectively. For example, a *purchase order* message may be interpreted as an activity "Send order" in the corresponding inter-organizational business process. In MFM, the business data inside EDI messages is generally ignored for the purpose of generating event logs, but may be required for *message correlation*, i.e., for the assignment of messages to process instances. In principle, the creation of events using the MFM method can be performed in a highly automated fashion. However, correlation of messages to process instances may require user input from a domain expert.

When generating event logs for process mining from EDI messages, there are generally multiple possible views on events with regard to the process instances they belong to. Consider, for instance, a business process that deals with the ordering and delivery of goods (cf. Fig. 6, upper part). The process starts with the sending of a purchase order by a customer. Subsequently, the supplier ships the ordered goods, sends a despatch advice and sends an invoice. If not all ordered line items can be processed at once, the shipments and despatch advices are partitioned, and invoices are issued accordingly. One

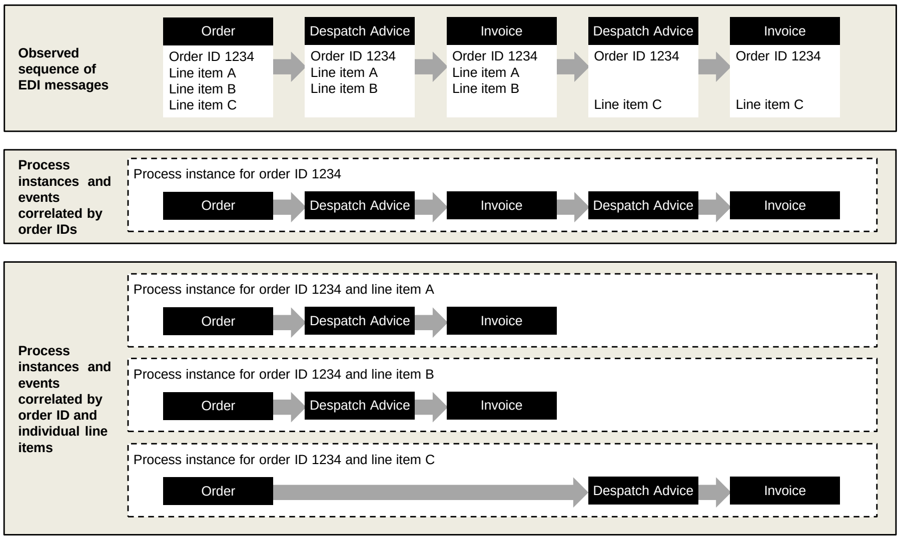


Fig. 6: Example for generated process instances and events using the Message Flow Mining (MFM) method with different correlation criteria, thereby focusing on the lifecycles of different process artifacts

possible approach for examining this business process is to focus on the lifecycle of individual purchase orders. A process model mined from this viewpoint may reflect that an individual order message sent by a customer is generally followed by one or more despatch advices and one or more invoice messages sent by the supplier (cf. Fig. 6, middle part). However, another possibility of examining the same business process is to assume a viewpoint that focuses on the lifecycle of individual line items in the context of the overall procurement process. In this case, one generally observes at most one despatch advice that relates to a particular line item, as well as at most one invoice message (cf. Fig. 6, lower part). In other words, depending on the assumed viewpoint, the involved EDI messages may belong to varying sets of process instances and may trigger the generation of none, one or multiple events. However, individual process instances may contain at most one event per observed EDI message regardless of the assumed viewpoint, since in MFM an event always directly corresponds to the receiving or sending of a message.

Physical Activity Mining (PAM). While in the MFM method business information conveyed in EDI messages is merely used for message correlation, such business information can be used to infer events. For example, an *invoice* message may, in addition to general invoicing information, contain information about a shipping date of invoiced line items. Consequently, from such a particular shipping date one may infer that an activity “Ship goods” has occurred on that date even if no shipping notification has been sent. Events resulting from business information in EDI messages typically reflect activities that represent

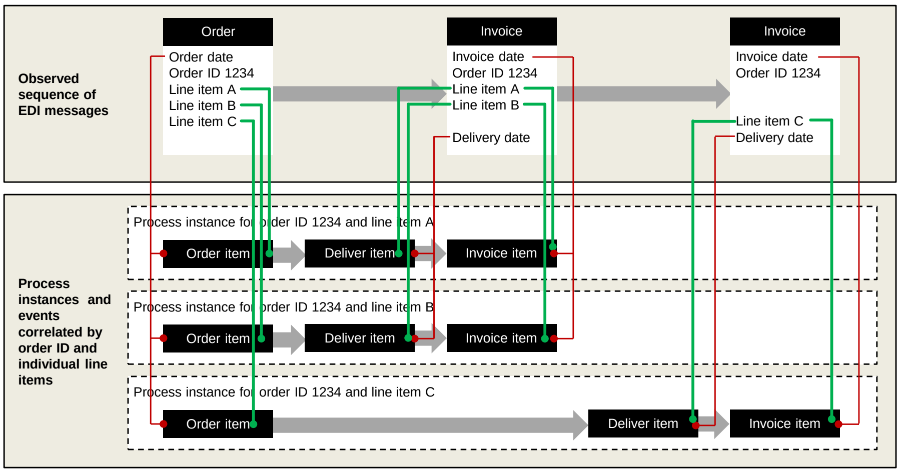


Fig. 7: Example for generated process instances and events using the Physical Activity Mining (PAM) method. Events are correlated to process instances by order ID and line item identifier. Green/thick and red/thin lines indicate event-triggering and timestamp-providing relationships between EDI artifacts and generated events, respectively.

product flows, cash flows or other "physical" activities as opposed to message flows. Hence, we refer to approaches where business information triggers the creation of events as *Physical Activity Mining* (PAM). PAM-based analysis of EDI-supported inter-organizational business processes is more geared towards a business-context oriented viewpoint. The resulting event logs allow for the analysis of "physical" activities even if corresponding EDI messages are exchanged asynchronously. However, PAM typically requires significantly more configuration than MFM.

For PAM, a major challenge is to identify and define appropriate mappings of business information in EDI messages to events and their attributes in event sequences ("EDI/event mappings"). EDI/event mappings specify rules that define (i) what EDI artifacts constitute events ("event-triggering artifacts") and (ii) which EDI artifacts shall be used to populate event attributes ("attribute-populating artifacts"). Attribute-populating artifacts are mapped to event attribute names. In order to improve practical usability, such mappings may as well use default (fixed) values for specific event attributes instead of attribute-populating artifacts. In other words, an EDI/event mapping consists of exactly one event-triggering EDI artifact reference and a map of attribute names and corresponding attribute-populating EDI artifact references or fixed values. Consider, for example, a business process dealing with the ordering and invoicing of goods as shown in Fig. 7. The figure shows how event-triggering and timestamp-providing mappings between EDI arti-

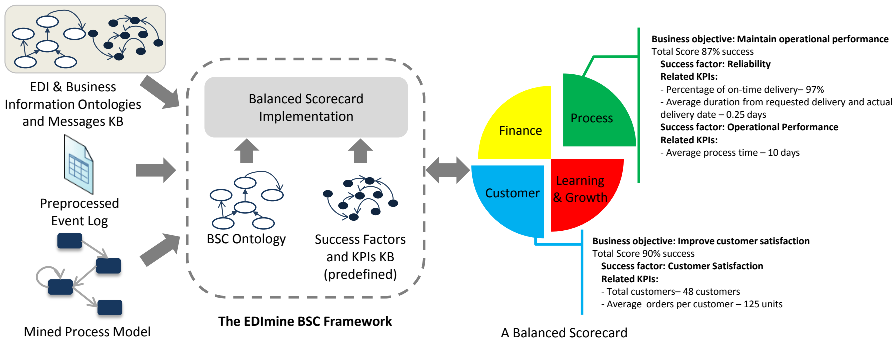


Fig. 8: Overview of the EDImine BSC Framework

facts and events can be used to infer activities from the messages that cannot be discovered using the MFM method (i.e., "Deliver item" events).

We evaluated the MFM and PAM methods against the requirements mentioned in Section 2.1 in two earlier publications. Requirements 1 and 2 were evaluated in a focused case study on MFM and message correlation using EDI data from an automotive supplier company [20]. The case study showed that mining process models from the company's EDI data provided technical insights on their just-in-time supply chain processes. Requirement 3 was evaluated in a focused case study on the PAM method using EDI data from a consumer goods manufacturing company [24]. The results showed that PAM-style EDI/event mappings can be used to answer in-depth questions about the company's inter-organizational business processes from a business-level perspective (e.g., Which products take longest to deliver? What is the average duration between order and invoicing of items?).

3.3 Inter-organizational Performance Analysis

Based on the requirements outlined in Section 2.2 we developed a performance analysis framework, the *EDImine BSC Framework* [42], that integrates both bottom-up and top-down performance analysis approaches. Fig. 8 shows a high-level overview of the framework. Drawing upon (i) EDI & Business Information Ontologies, (ii) event logs, and (iii) process models, the EDImine BSC Framework allows for business performance analysis using BSCs. EDI & Business Information Ontologies and event logs are extracted by applying our business information extraction approach and event mapping approach described above (cf. Sections 3.1 and 3.2), whereas process models can be obtained by employing process mining techniques.

The framework itself consists of (i) the BSC Ontology and (ii) a set of predefined success factors and KPIs. The BSC Ontology conceptually describes BSC elements such as business objectives, success factors, and KPIs. Using the BSC Ontology, KPIs can be modeled and aligned with relevant business

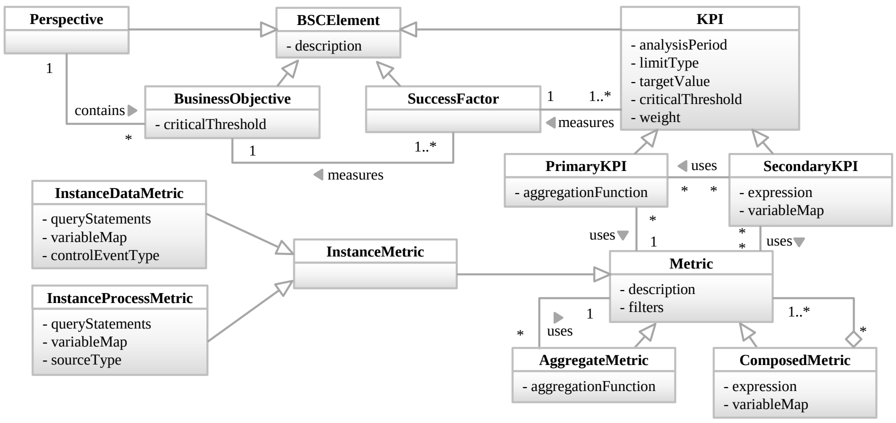


Fig. 9: The BSC Ontology as a UML class diagram (simplified)

objectives. In addition, the framework's predefined set of success factors and KPIs allows for the automated suggestion of potential KPIs with regard to concrete instances of input data. The BSC Ontology and the method that was used for obtaining the set of predefined KPIs are explained in the following.

The BSC Ontology. The BSC Ontology is shown in Fig. 9. As mentioned earlier, the BSC Ontology describes BSC elements. They consist of perspectives *(Perspective)* (e.g., finance, customer, process, learning and growth), business objectives *(BusinessObjective)*, success factors (*SuccessFactor*) and *KPI*s. A perspective contains related business objectives. A business objective can be measured by success factors which are in turn measured by quantifiable KPIs. In other words, success factors are used as mediators to connect business objectives to KPIs. We categorized KPI into two types: primary KPIs and secondary KPIs. A primary KPI is calculated by applying an aggregation function (i.e., sum, average, count, etc.) on a metric, whereas a secondary KPI is calculated based on several metrics and other KPIs by using an algebraic calculation expression. *Metric* is not a BSC element but it is required as a basis for calculating KPIs: metrics are calculated on individual events of a process instance, whereas KPIs aggregate one or more metrics over a specific period of time.

Our employed ontology of metrics builds upon the work of Wetzstein et al. [67]. Their KPI and metric ontology focuses on states of process instances since it is designed for real-time monitoring of process-related KPIs. In other words, their ontology was designed for KPIs that can be only calculated based on the runtime data of process executions. Hence, other KPIs such as revenue, profit, ordered quantities are not considered in their work. In contrast, we focus on calculating KPIs related to both process-related and non-process related perspectives, in a determined analysis period. Therefore, in our BSC ontology metrics are categorized for supporting the calculation of both process-related and non-process related KPIs, as explained in the following. Metrics are divided into instance metrics *(InstanceMetric)*, aggregate metrics *(AggregateMetric)*, and composed metrics *(ComposedMetric)*. Instance metrics are based on query statements and can be further divided into (i) instance data metrics *(InstanceDataMetric)* and (ii) instance process metrics *(InstanceProcessMetric)*. Instance data metrics use queries on the EDI and Business Information Ontologies. As described in Section 3.1, we conceptualize raw data elements from EDI standards into generic business information concepts in these ontologies. These business information concepts can be used in query statements of instance data metric for querying data on a conceptual level (e.g., ordered quantity, invoiced amount, etc.). Instance data metrics may be employed primarily for metrics focusing on business performance that are calculated from business information in EDI messages (e.g., ordered quantity).

Instance process metrics use query statements that reference time-related information gathered from event logs and process models. As a consequence, instance process metrics may be used primarily for metrics focusing on process performance that are calculated from event data, such as event sequence patterns or event timestamps (e.g., order date/time). It may be non-trivial to specify corresponding queries on event sequence patterns when there are multiple different patterns of sequences of some events. By replaying an event log according to a specified event sequence pattern in a query, relevant process metrics can be calculated accurately (i.e., transition times between activities). Mined process models may help domain experts to identify event sequence patterns (i.e., activity sequence patterns) to formulate appropriate queries.

Aggregate metrics aggregate values of metrics by using aggregation functions such as sum, average, count, etc. Composed metrics allow for the use of algebraic expressions on several metrics in order to further aggregate metrics (e.g., duration between ordering and invoicing).

Predefined Success Factors and KPIs. For addressing the challenge of defining concrete KPIs for evaluating IORs from EDI messages, we performed two main tasks: (i) identification of inter-organizational success factors as well as their related measurements by conducting a literature review and (ii) definition of KPIs from EDIFACT messages based on the success factors obtained from the review.

For identifying inter-organizational success factors we conducted a systematic literature review. The selection of relevant studies was based on search criteria covering the topics of inter-organizational success factors, inter-organizational performance evaluation, and business partner selection. We considered only studies published in the period from 2000 to 2012. Using Google Scholar[3] with these search criteria pointed us to 177 qualified published works. We mainly extracted success factors related to IORs along with their measurement metrics used for evaluating them. More than 80 success factors have been found in the literature review. We simplified success factors by grouping them and assigning a hierarchical structure. In particular, success factors sharing similar definitions as well as similar measurement metrics were grouped. The total

[3] http://scholar.google.com

Table 1: Examples of KPIs that can be derived from EDIFACT data [40]

KPI	**Mapping to EDI data**
Success Factor: Satisfaction	
Ordered quantity^{s,a,p}	Ordered quantity (*Quantity* in QTY segments qualified by value 21) from ORDERS, INVOIC, ORDCHG, RECADV or RETANN messages
Returned quantity^{s,a,p}	Returned quantity (*Quantity* in QTY segments qualified by value 61) from INVOIC, RETANN, INVRPT, RETINS or SLSRPT messages
Success Factor: Reliability	
Lost goods quantity^{s,a,p}	Lost goods (*Quantity* in QTY segments qualified by value 126) from INVOIC messages
On-time delivery^{p,c}	i) The delivery which the arrival is before or on the day of the expected delivery date/time ii) Expected delivery date/time is shipment, requested delivery and expected delivery date/time (*Date/time* in DTM segments qualified by value 10, 2 and 191 respectively) from DELFOR, DESADV, DELJIT, ORDERS or ORDCHG messages iii) Actual delivery date/time is despatch, received and good receipt date/time (*Date/time* in DTM segments qualified by value 11, 310 and 50 respectively) from DESADV or RECADV messages

The superscripts ^{s},^{a},^{p},^{c} on KPI names indicate applicable aggregation functions: sum, average, percentage, count. In this table, message types are represented as code only (e.g., ORDERS corresponds to *Purchase order* messages). The full description of segments and message types in EDIFACT release D10A is provided in `http://www.unece.org/trade/untdid/d10a/trsd/trsdi1.htm` and `http://www.unece.org/trade/untdid/d10a/timd/timdi1.htm` respectively.

result yielded 56 inter-organizational success factors. Details on the literature review can be found in [43].

Based on these success factors, we identified a set of KPIs that can be calculated from information in EDIFACT messages, as well as concrete guidelines for their calculation, by studying a sample of EDIFACT message type specifications in various releases of the EDIFACT standards (ranging from D96A to D10A) and real-world industry Message Implementation Guidelines (MIGs). Thereby, we considered the frequencies of data elements as well as the semantics of both data elements and message types. Furthermore, we presented aggregations of these KPIs in order to define quantitative measurements for inter-organizational success factors. Examples of so-derived KPIs are shown in Table 1. Details on the conducted study for identifying KPIs from EDIFACT standards can be found in [40].

The set of success factors and their related KPIs derived from EDI messages are part of a knowledge base supporting KPI identification in the EDImine BSC Framework. These KPIs focus on measuring performance from a non-process perspective, such as ordered quantities, revenue, etc. However, in addition to these pre-defined KPIs, the EDImine BSC Framework allows for the definition and calculation of additional KPIs related to the process perspective (e.g., process time, duration between orders and deliveries, etc.) depending on the available inputs (i.e., event log and process model).

In an earlier publication [42], we evaluated the EDImine BSC Framework against the set of requirements put forward in Section 2.2 and conducted a focused case study using real EDI data from a beverage manufacturing company. The case study demonstrated that the EDImine BSC Framework enables both bottom-up definition and calculation of KPIs (Requirement 1) and top-down definition of business objectives and success factors (Requirement 2) for evaluating the company's inter-organizational performance.

3.4 Implementation of the EDImine Framework

For supporting the MFM and PAM methods, we developed *EDIminer* [26], a toolset that allows for (i) visualization of the contents of EDI messages using the approach for ontologizing EDI described in Section 3.1, (ii) MFM-based (automatic) or PAM-based (manual) definition of mappings of EDI artifacts to events as described in Section 3.2, (iii) generation of events from such mappings, (iv) semi-automatic correlation of events to process instances and (v) generation of industry-standard XES event logs for subsequent application of conventional process mining techniques. Since EDIminer is concerned with the generation of event logs, we consider it a *preprocessing* toolset for subsequent process mining analyses. Hence, the toolset was implemented as a stand-alone application instead as a plug-in for a process mining suite such as a ProM.

In order to provide tool support for the EDImine BSC Framework, we developed the EDImine BSC Plug-In for ProM 6 [42]. Based on an event log and EDI & Business Information Ontologies derived from EDI messages as well as a corresponding mined process model, the plug-in allows for the modeling of KPIs and related metrics. Fig. 10 shows a screenshot of the KPI and metrics configuration panel. In particular, in the metric configuration panel business information contained in the EDI messages and the process model are shown simultaneously. Related business information is displayed specifically for each activity in the process model in order to facilitate the definition of metrics for the user. The plug-in also allows for the definition of KPIs based on such metrics, including the definition of their attributes (i.e., thresholds, analysis periods, weights, etc.) required for BSC calculation. In addition to bottom-up KPI definition, the plug-in allows for the top-down modeling of BSC models where business objectives are aligned with KPIs through success factors. In the business objective configuration panel, different BSC perspectives, business objectives, and success factors can be modeled and corresponding attributes can be specified (e.g., thresholds, weights, etc.).

4 Case Study

In the following, we present a case study with the objective of evaluating the applicability and usefulness of the EDImine Framework. The issue is, given the data from the company as input, are we able to "reproduce" the respective processes and business indicators. Thus, we show that all steps of the framework could be performed, and that the results obtained on both the process as well as the business level can be "mapped" to the company's real performance data. As input we had a sample of of EDI data reflecting transactions of a German consumer goods manufacturing company with its retail business

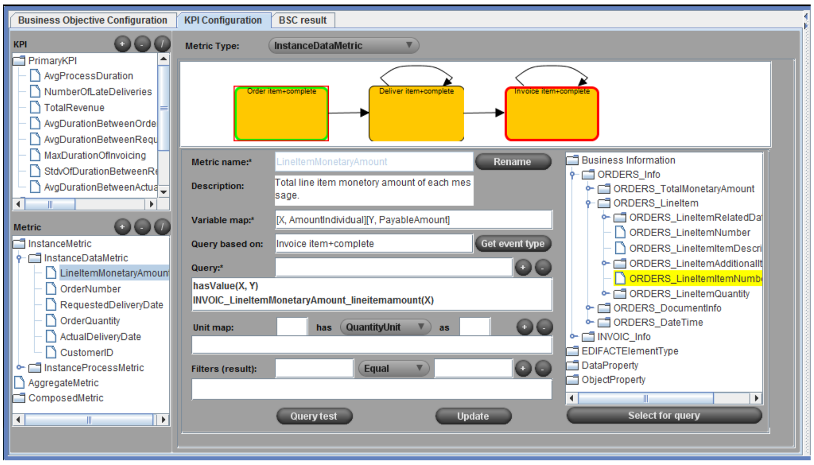


Fig. 10: Screenshot of the KPI and metrics panel of the EDImine BSC Plug-In

partners. For the sake of confidentiality, we cannot reveal this organization and simply refer to it as SellerCo. In addition, all monetary and quantitative figures have been multiplied by an undisclosed constant factor.

Firstly, we establish some basic facts and assumptions on SellerCo and its business processes that are relevant for the design of the case study. SellerCo declares its primary mission to be the provision of highest quality products and services. Moreover, since SellerCo delivers to a large number of individual supermarket branches, SellerCo's process of ordering, invoicing and delivery of goods to individual customers is of particular importance to the business' success and, thus, receives particular attention in this case study. This process starts when a customer sends an order to SellerCo. In such an order, the customer usually specifies a requested delivery date for the ordered goods. Subsequently, SellerCo despatches the goods. This is generally done in due time to meet the requested delivery date of the customer. If an order cannot be fulfilled at once, the ordered items may be shipped in partitions. After goods have been shipped, SellerCo sends invoices for the corresponding line items. Again, line items that were ordered in a single purchase order may be scattered over different invoices.

For the case study we followed the workflow of the EDImine Framework shown in Fig. 1. We start from a real-world sample of SellerCo's EDI interchange data and generate an event log reflecting the actual delivery process execution of SellerCo. Thereby, we use the PAM method since we are interested in the delivery process from a business-oriented viewpoint (i.e., we are more interested in the "physical" business process than in technical aspects of the EDI message exchanges). Then we mine a process model from the event log and employ the EDImine BSC Framework in order to lift the gathered information to the strategic level and derive additional business intelligence. The gathered results were discussed with representatives of SellerCo.

4.1 Data Set and Data Preprocessing

The above described business process of SellerCo is supported by EDI messages that are interchanged between the IT systems of SellerCo and its customers. The data set consists of 1389 received EDIFACT ORDERS (Purchase order) messages, 1289 sent DESADV (Despatch advice) and 1840 sent INVOIC (Invoice) messages collected between March 1 and June 5, 2013 (dates refer to interchange timestamps). ORDERS messages received by SellerCo were all encoded according to the D96A[4] EDIFACT release, while DESADV and INVOIC messages were sent both in D96A and D01B[5] releases of EDIFACT.

We used the EDIminer toolset to parse the EDI messages into EDI Ontologies and corresponding Message KBs. Furthermore, we generated Business Information Ontologies based on manually defined mappings of business information concepts to actual data elements of EDI messages. These mappings were defined in a way such that semantically equivalent data elements of different EDIFACT standards releases were unified in common business information concepts and the hierarchical structure of these concepts reflects aggregations and/or compositions of these business information concepts (for examples of such mappings, see [41] and Section 3.1/Fig. 4a).

4.2 Definition of EDI/Event Mappings

In order to generate an event log from the EDI data set, we start by defining a set of EDI/event mappings using the EDIminer toolset. The employed mapping definitions are shown in detail in Table 2. Since we used the EDIminer toolset for defining EDI/event mappings, these mappings are based on the above described ontological data model of EDIFACT messages and allow for direct access to the concrete semantics of qualified data elements.

We consider the ordering, delivery and invoicing of goods as the crucial activities for our analysis since they are directly related to the performance of the delivery process. Hence, we define EDI/event mappings for "Order item", "Deliver item" and "Invoice item" activities. Furthermore, since we intend to investigate delivery performance with regard to individual line items, we focus on the lifecycles of individual line items in the defined mappings as well. Consequently, we use individual line items in the EDI messages as event triggers for all of the three aforementioned activities.

Firstly, for the "Order item" activity we define a mapping that uses individual line items in ORDERS messages as event triggers and populate their timestamp attributes with the document dates of the messages (i.e., *Document/message date/time*). Secondly, for the "Deliver item" activity, one may consider using individual line items in DESADV messages as event triggers. However, since the DESADV messages in our data set only contain document dates as well as estimated delivery dates, this would only allow us to generate

[4] `http://www.unece.org/trade/untdid/d96a/content.htm`
[5] `http://www.unece.org/trade/untdid/d01b/content.htm`

Table 2: EDI/event mappings used for the case study

Activity	**Event attribute**	**Msg.type**	**Associated EDI artifact**			
			Segment group	**Segment**	**Composite data element**	**Data element**
Order item	*(Event trigger)*	ORDERS (D96A)	25	LIN	Item number identification (C212)	Item number (7140)
	time: timestamp		-	DTM	Date/time/period (C507)	*Document/message date/time* (2380 [2005='137'])
	org:resource				(Interchange sender)	
	itemID		25	LIN	Item number identification (C212)	Item number (7140)
	orderID		-	BGM	-	Document/message number (1004)
Deliver item	*(Event trigger)*	INVOIC (D96A/D01B)	25 (D96A) 26 (D01B)	LIN	Item number identification (C212)	Item number (7140) (D96A) Item identifier (7140) (D01B)
	time: timestamp		-	DTM	Date/time/period (C507)	*Delivery date/time, actual* (2380 [2005='35'])
	org:resource				(Interchange sender)	
	itemID		25 (D96A) 26 (D01B)	LIN	Item number identification (C212)	Item number (7140) (D96A) Item identifier (7140) (D01B)
	orderID		1	RFF	Reference (C506)	*Order number (purchase)* (1154 [1153='ON'])
Invoice item	*(Event trigger)*	INVOIC (D96A/D01B)	25 (D96A) 26 (D01B)	LIN	Item number identification (C212)	Item number (7140) (D96A) Item identifier (7140) (D01B)
	time: timestamp		-	DTM	Date/time/period (C507)	*Document/message date/time* (2380 [2005='137'])
	org:resource				(Interchange sender)	
	itemID		25 (D96A) 26 (D01B)	LIN	Item number identification (C212)	Item number (7140) (D96A) Item identifier (7140) (D01B)
	orderID		1	RFF	Reference (C506)	*Order number (purchase)* (1154 [1153='ON'])

Note: The data set under consideration contains messages based on both the D96A and D01B releases of EDIFACT for both of which we define mappings. Since these releases overlap in many cases, most mapped EDI artifacts are identical in both kinds of mappings; the cases in which the mappings differ are explicitly highlighted.
Note: Qualified data elements are shown in italics. For example, for EDIFACT release D96A, label *Document/message date/time* refers to the value of data element 2380 (Date/time/period) qualified by value '137' (code for "Document/message date/time") in data element 2005 (Date/time/period qualifier). This qualification relationship is specified as "(2380 [2005='137'])".

events that reflect the shipment of goods or the estimated delivery of goods, respectively. However, in this case study we are more interested in the actual deliveries of the goods at the customer's site. Hence, we exploit that the INVOIC messages in our data set contain actual delivery dates for the invoiced line items and define a mapping for the "Deliver item" activity that uses individual line items in INVOIC messages to create events and corresponding values of *Delivery date/time, actual* as their timestamps. Consequently, we do not further consider the observed DESADV messages for our case study. Thirdly, for the "Invoice item" activity we define a mapping that uses individual line items in INVOIC messages as event trigger and the invoice's document date (i.e., *Document/message date/time*) as a timestamp. Finally, we add common attributes *itemID* and *orderID* to all three of the aforementioned mappings and map them to the corresponding EDIFACT data elements in order to allow for subsequent correlation of generated events to process instances by means of *(itemID, orderID)* tuples. The organizational resource *(org:resource)* associated with generated events is set to the interchange senders from the message envelopes (i.e.,EDIFACTs UNB segments) for all mappings.

4.3 Event Log Generation and Process Mining

Using the above described event mappings, the data set under consideration corresponds to an event log containing 52622 events (14026 “Order item” events, 19318 “Deliver item” events and 19318 “Invoice item” events). As mentioned earlier, we intend to investigate the performance of the delivery process from a line-item centric perspective in the context of individual orders. In the aforementioned set of 52622 events, *orderID*s are unique for “Order item” events; as a consequence, they can be assumed to be generally unique. Hence, we correlate events to process instances by grouping them according to *(orderID, itemID)* tuples. This results in 21215 process instances (cases). We store the generated events and process instances in an XES log and use the LTL Checker Plug-In of the ProM process mining suite to filter the results for cases which contain complete traces (i.e., having at least one activity instance of all three defined activity types). Filtering for complete traces allows us to look only at customers of SellerCo who implement the whole order and delivery process by means of EDI (see also [24] for a discussion on the implications of filtering for complete cases). This reduces the log size to 4751 compliant cases and 14779 events (4751 “Order item”, 5014 “Deliver item” and 5014 “Invoice item” events). Further removal of 16 cases with apparent anomalies in associated date/time information results in a log of 4735 cases which serves as the basis for our subsequent analysis.

An analysis of the sender/receiver information in the EDIFACT interchange headers of the messages reveals that in this dataset SellerCo receives ORDERS messages from 13 different customers and sends INVOIC messages to six different customers. Three of these customers are overlapping, i.e., they handle both orders and invoices electronically via EDI. These three customers account for 1574 (3̃3%) of the 4751 complete cases. The remaining 3177 (6̃7%) complete cases originate from a fourth customer where ORDERs are sent from a subsidiary company having a different GLN than the headquarters receiving the INVOICes. In other words, we use the EDI data of four different customers for our subsequent analyses.

The resulting event log is further mined for a process model using the *Heuristics Miner* algorithms [65] (cf. Fig. 11).

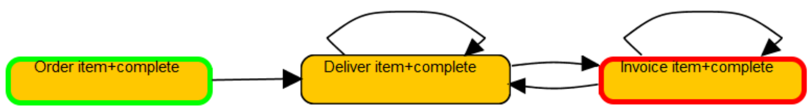


Fig. 11: Process model discovered by *Heuristics Miner* [65] as a *flexible model*

Table 3: The BSC (strategy part) - business objectives and success factors

Perspective	Business Objective	Success Factor
Financial	Increase revenue	Financial performance
Customer	Maintain customer satisfaction	Satisfaction
Process	Improve product and service quality	Reliability
	Improve operational performance	Operational Performance

4.4 BSC Modeling and Calculation

For modeling and calculating the BSC, we define business objectives as well as corresponding success factors and KPIs and apply them on the input data.

Business Objectives and Success Factors. In order to evaluate business performance against business objectives by using the EDImine BSC Framework, we firstly define business objectives and related success factors to be used in the BSC for this case study. We considered SellerCo's primary mission statement – which is the provision of products and services of the highest quality – and translated it into business objectives which reflect this focus, as shown in Table 3. The "Improve product and service quality" business objective focuses on the quality of the manufactured goods as well as on related services such as delivery, after-sale services, etc. "Maintain customer satisfaction" reflects the organization's intention to retain existing customers as well as to attract new customers as an indirect indicator of product and service quality. Furthermore, "Increase revenue" and "Improve operational performance" have been included as business objectives for SellerCo, as these represent typical goals of profit-oriented companies. Note that in real-world applications of the EDImine BSC Framework, business objectives may be derived from an already existing BSC of the company under analysis. As also shown in Table 3, for each of the business objectives we select success factors which relate to that objective (cf. Section 3.3).

Definition of KPIs. Based on the available data from SellerCo, we identified concrete KPIs for measuring each of the success factors as shown in Table 4. Target values and critical thresholds were agreed upon and validated by representatives of the company. The KPI "Total revenue" is defined to reflect the success factor "Financial performance" whereas the KPI "Average revenue per customer" and "Average ordered quantities per customer" are used to evaluate customer satisfaction. We set the target value of revenue to 600,000[6]. We consider a total revenue of less than 300,000 as critical. The

[6] We refrain from specifying units since all monetary figures and quantity figures have been altered in this article.

Table 4: The complete Balanced Scorecard

Business Objective	Success Factor	KPI
Increase revenue	Financial performance	**Name:** Total revenue **Weight:** 100% **Limit type:** More is better **Target value:** 600,000 **Critical threshold$_{\Delta}$:** 300,000 **Calculation:** SUM(invoiced amount of line item in INVOIC)
Maintain customer satisfaction	Satisfaction	**Name:** Average revenue per customer **Weight:** 50% **Limit type:** More is better **Target value:** 150,000 **Critical threshold$_{\Delta}$:** 60,000 **Calculation:** SUM(invoiced amount of line item in INVOIC) / COUNTDIS(interchange sender in ORDERS) *Note: Counting distinct senders of ORDERS messages yields the total number of customers.*
		Name: Average ordered quantities per customer **Weight:** 50% **Limit type:** More is better **Target value:** 18,000 **Critical threshold$_{\Delta}$:** 6,000 **Calculation:** SUM(ordered quantities of line item in ORDERS) / COUNTDIS(interchange sender in ORDERS)
Improve product and service quality	Reliability	**Name:** Number of late deliveries **Weight:** 50% **Limit type:** Less is better **Target value:** 0 **Critical threshold$_{\Delta}$:** 5 **Calculation:** COUNT if (actual delivery date in INVOIC − requested delivery date in ORDERS) greater than or equal 1
		Name: Pct. of just-in-time deliveries **Weight:** 30% **Limit type:** More is better **Target value:** 100 **Critical threshold$_{\Delta}$:** 20 **Calculation:** COUNT if (actual delivery date in INVOIC − requested delivery date in ORDERS) between 1 and -3 / COUNT(actual delivery date in INVOIC − requested delivery date in ORDERS) × 100
		Name: Standard deviation of duration between requested delivery date and actual delivery date **Weight:** 10% **Limit type:** Two-side **Target value:** 0 **Critical threshold$_{\Delta}$:** 2 **Calculation:** STDV(actual delivery date in INVOIC − requested delivery date in ORDERS)
		Name: Average duration between requested delivery date and actual delivery date **Weight:** 10% **Limit type:** Two-side **Target value:** -1 **Critical threshold$_{\Delta}$:** 2 **Calculation:** AVG(actual delivery date in INVOIC − requested delivery date in ORDERS)
Improve operational performance	Operational performance	**Name:** Maximum duration of invoicing **Weight:** 50% **Limit type:** Less is better **Target value:** 1 **Critical threshold$_{\Delta}$:** 7 **Calculation:** MAX(timestamp of Invoice-item event − timestamp of Deliver-item event)
		Name: Average duration of invoicing **Weight:** 50% **Limit type:** Less is better **Target value:** 1 **Critical threshold$_{\Delta}$:** 2 **Calculation:** AVG(timestamp of Invoice-item event − timestamp of Deliver-item event)

The weight of KPIs must total to 100% for each business objective. The calculation of KPI scores is inspired by ADOscore (`http://www.boc-group.com/products/adoscore`). The *limit type* influences the calculation of scores as follows:

1. "More is better" indicates that actual values higher than the target value are preferred:

$$Score_{KPI} = \frac{actual - (target - criticalThreshold)}{target - (target - criticalThreshold)} \times 100 \tag{1}$$

2. "Less is better" indicates that actual values lower than the target value are preferred:

$$Score_{KPI} = \frac{actual - (target + criticalThreshold)}{target - (target + criticalThreshold)} \times 100 \tag{2}$$

3. "Two-side" indicates that actual values equal to the target value are preferred. If the actual value is less than the target value, then Equation (1) applies, otherwise Equation (2) applies.

KPI calculation formulas are described as aggregation functions applied over sets of results calculated from algebraic expressions. These algebraic expressions are applied on each of the process instances which start in the given analysis period.

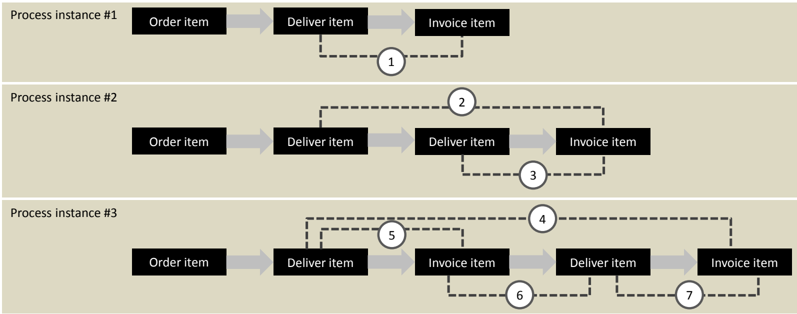


Fig. 12: Examples of event sequences that conform to the model in Fig. 11

target value of “Average revenue per customer” is one fourth of the target value of total revenue since SellerCo has four main customers (cf. Section 4.3). Beside average revenues per customer, customer satisfaction is also reflected by ordered quantities which we model by means of a KPI “Average ordered quantities per customer”.

In the process perspective, we focus on the performance of the delivery and invoicing processes. We define four KPIs related to delivery performance to reflect the success factor “Reliability”: “Number of late deliveries”, “Pct. of just-in-time deliveries”, “Standard deviation of duration between requested delivery date and actual delivery date”, and “Average duration between requested delivery data and actual delivery date”. “Number of late deliveries” can influence customer satisfaction and trust since late deliveries may harm the reputation of organizations. Since we want to emphasize the penalty on late deliveries, we give it a 50% weight which is half of the total score of the business objective “Improve product and service quality”. The optimal case is not to have any late deliveries, therefore we set the target value to zero and set the critical threshold$_\Delta$[7] to five late deliveries. Similarly, the KPI “Pct. of just-in-time deliveries” reflects the reliability of SellerCo’s delivery service. The KPI “Average duration between requested delivery date and actual delivery date” is also used to evaluate overall delivery performance. The duration between requested delivery date and actual delivery date should be as little as possible. We set the target value to -1 (i.e., delivery at most one day in advance) and the critical threshold$_\Delta$ to two days with the limit type as two-sided (i.e., more than three days early or one day late is considered critical).

For evaluating the operational performance, we focus on invoicing times and the duration between ordered date and actual delivery date. The KPI “Maximum duration of invoicing” is used to indicate the longest invoicing period after some delivery completed. We focus on the duration between “Deliver item” events and subsequent “Invoice item” events. However, the calculation mechanism of timestamps needs to ensure the correctness of underlying event

[7] We specify critical thresholds as relative values (i.e., threshold$_\Delta$) with respect to target values in order to allow for the simple definition of thresholds for two-sided KPIs.

sequences. There are several possible event sequences that conform to the mined process model, as illustrated in Fig. 12. In the case of process instance #1, it is obvious that the duration of invoicing is the time period between a "Deliver item" event and its consecutive "Invoice item" event (cf. Fig. 12, Mark 1). However, in the case of process instance #2 and #3, the definition of what constitutes the actual duration becomes ambiguous. In particular, there are two "Deliver item" events followed by one "Invoice item" event in process instance #2. This yields two possible pairs of "Deliver item" event and "Invoice item" event (i.e., Fig. 12, Mark 2 and 3). The ambiguity of acquiring the correct information becomes clearer in the example of process instance #3 where there are two "Deliver item" events and each of them is followed by its corresponding"Invoice item" event. This results in four possible pairs (i.e., Fig. 12, Mark 4, 5, 6 and 7). For calculating the duration of invoicing, we focus on the duration between "Deliver item" events and consecutive "Invoice item" events. Since we want to measure time of invoice response after delivery finished. Therefore, the calculation is required to be limited to the pattern of interest. In this case, by considering the mined process model (cf. Fig. 11) we define the activity sequence pattern such that in each process instance the timestamps of "Deliver item" events and the timestamps of subsequent "Invoice item" events are retrieved. Based on this pattern, our calculation mechanism leverages the concept of *log replay* (cf. [3]) to step through the event log and retrieve corresponding activity timestamps accurately. Following this pattern with respect to the examples shown in Fig. 12, durations between event pairs of 1, 3, 5, and 7 are retrieved. Normally, SellerCo's invoices should be issued 1-2 days after the delivery date. Hence, the target value is set to one day. However, invoicing later than one week is considered unusual. Hence, we set the critical threshold$_\Delta$ to seven days. In order to evaluate the overall performance of invoicing, the KPI "Average duration of invoicing" is applied. The calculation of invoicing duration of the previous mentioned KPI is also applied for this KPI. The majority of invoicing processes is expected to last around 1-2 days. Therefore, the average duration of invoicing should be one day (i.e., one day after some delivery).

BSC Calculation. According to the above described BSC model and definition of KPIs, we calculate the scores for each of the KPIs. In turn, the achievement scores of the business objectives can be calculated as the weighted sum of the related KPIs' scores. In this case study, we consider business objectives having achievement scores less than 50% to be critical. The BSC is calculated monthly, hence, the scores of business objectives (and corresponding KPIs) are calculated month by month. We limit maximum and minimum scores to 100% and 0% respectively.

4.5 Results and Discussion

The EDI messages were collected between March 2013 and the beginning of June 2013. KPI scores and business objective scores were calculated for the

Table 5: The BSC calculated from March 2013 to May 2013

Business Objective / KPI	March 2013		April 2013		May 2013	
	Score (%)	Actual Value	Score (%)	Actual Value	Score (%)	Actual Value
Financial perspective						
Increase revenue	100	n/a	58.61	n/a	2.74	n/a
Total revenue	100	682,088	58.61	475,832	2.74	308,209
Customer perspective						
Maintain customer satisfaction	100	n/a	36.58	n/a	0	n/a
Average revenue per customer	100	170,522	48.26	118,958	0	77,052
Average ordered quantities per customer	100	19,359	24.89	13,493	0	9,148
Process perspective						
Improve product and service quality	25.72	n/a	56.44	n/a	50.61	n/a
Number of late deliveries	20	4 times	100	0 times	80	1 times
Pct. of just-in-time deliveries	23.18	84.64%	0	78.45%	11.69	82.34%
Standard deviation of duration between requested and actual delivery date	33.84	1.32 days	28.89	1.42 days	28.54	1.43 days
Average duration between requested and actual delivery date	53.78	-1.92 days	35.52	-2.29 days	42.53	-2.15 days
Improve operational performance	64.59	n/a	57.15	n/a	57.15	n/a
Maximum duration of invoicing	29.17	5.96 days	14.29	7 days	14.29	7 days
Average duration of invoicing	100	0.25 days	100	0.28 days	100	0.27 days

The performance results highlighted in light-gray are *poor but acceptable* according to their critical thresholds, whereas the performance results highlighted in dark-gray are *critical*.

first three months in this period. There are no results for the period of June 2013 because the EDI messages sent/received in this period belong to the process instances that start in the previous months (i.e., there are no *Order item* events in June). Table 5 shows the calculated BSC for these three months.

In the period of March 2013, SellerCo perfectly achieves its business objectives in both the financial and customer perspectives. The business objectives "Increase revenue" and "Maintain customer satisfaction" are successfully met with a score of 100% since all of their related KPIs score 100% as well. However, the KPIs of the process perspective exhibit less desirable scores. Delivery performance – reflecting the business objective "Improve product and service quality" – is much lower than targeted. There are four late deliveries in this month, which is only slightly below the critical threshold$_{\Delta}$ of five late deliveries per month. Similarly, the percentage of just-in-time deliveries and the standard deviation of duration between requested delivery date and actual delivery date are also achieved lower than the expectation. Although none of the KPIs for "Improve product and service quality" is critical, the business objective itself is in a critical status since the overall achievement score is lower than 50%. However, the business objective "Improve operational performance", focusing on invoicing processes, is still acceptable.

In April and May 2013, the performance indicators of the financial and customer perspectives drop significantly (cf. Table 5).

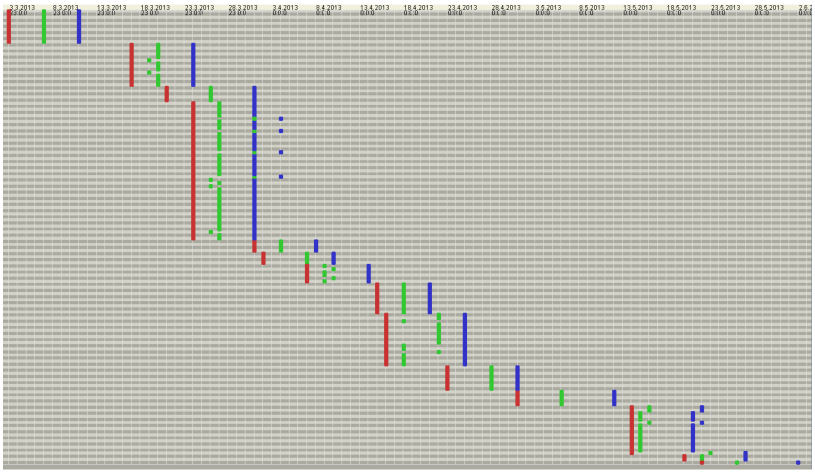


Fig. 13: Dotted chart showing the time frame of the 148 cases of late invoices. The red, green and blue dots represent *Order item* events, *Deliver item* events, and *Invoice item* events, respectively.

In summary, the scores of the business objectives in the financial and customer perspectives keep falling in each of the examined months. The averages of ordered quantities per customer drop around 30% each month. Consequently, the total revenue also keeps declining. This might be the result of poor operational performance since all related business objectives score low. This may reduce customer satisfaction which in turn leads to declining revenues. However, this cannot be concluded with certainty from the results since the analysis period of three months is too short. Nevertheless, the results suggest that SellerCo may investigate the underlying cause for the low scores of KPIs related to customer satisfaction as well as put additional efforts into the improvement of operations performance.

In addition to these results, we further investigated the cases of late deliveries and late invoices for deriving clues for such anomalies. In doing so, other analysis techniques can be applied for answering in-depth questions, such as "What are factors affecting delivery performance?", "How much does customer satisfaction depend on operational performance?", etc. (cf. [24]). With regard to cases with late deliveries, we found that two of the five late-delivery cases feature ordered quantities more than 100 (i.e., 460.8 and 194.4) and another two of them feature ordered quantities between 51-100 (i.e., 64.8 and 97.2), whereas the majority of all cases (74%) features ordered quantities up to 50. In other words, late deliveries may be related to large quantity orders.

With regard to late invoices, there are 148 cases in which invoices are issued more than two days after corresponding deliveries. We analyzed the time periods between "Delivery item" events and "Invoice item" events of these cases using dotted chart analysis [60] as shown in Fig. 13. The analysis showed that 82.43% of late-invoices cases featured time periods ranging over weekends.

Therefore, we subtracted two days from the duration of these cases in order to obtain the accurate total working days for invoicing. In total, we found 108 cases which took more than two working days for invoicing. Among these cases, 73% belong to one particular customer. From these in-depth investigations, three main insights can be derived. *First, the analysis of late deliveries shows that ordered quantities may be the cause of the delays. Second, most of late-invoice cases occurred during weekends. Finally, late invoices usually belong to the cases of one particular customer.* According to our findings, the company should further analyze their manufacturing or delivering process especially in the cases of large ordered quantities for finding the root cause of the delivery performance. Furthermore, they should pay attention to invoicing cases that span over weekends and further inspect the reason of the late invoices related to the aforementioned particular customer.

When comparing SellerCo's *real* revenue figures (as disclosed to us by a company representative) with the revenue figures from our results based on EDI data, it turns out that only a fraction (between 5% and 50%) of the actual revenue of the company gets reflected in our analysis. This implies that a significant portion of real-world business transactions of SellerCo is actually not reflected in the sample of EDI messages used in this case study, which is expectable considering that heavily cleaned data was used. Moreover, some business transactions of SellerCo may not get reflected in EDI data at all. Hence, the results of the case study need to be interpreted with care with regard to their capability of adequately reflecting the overall performance of SellerCo. Furthermore, information in EDI messages is limited to certain kinds and, hence, some KPIs of interest may not be derived from EDI data at all. For instance, in this case study KPIs related to the *learning and growth* perspectives of BSCs (e.g., number of new products, employee turnover rate, etc.) as well as some KPIs which may directly reflect SellerCo's business objectives (e.g., profit, number of customer complaints, etc.) could not be derived.

Overall, this case study shows the applicability of the approach to real-world situations where all steps of the framework could be performed and its usefulness for gathering business intelligence in the form of process models, KPIs linked to business objectives and the related BSC. These final results can be mapped to the real situation of the company. More concretely, the following conclusions can be drawn: Firstly, the employed PAM approach proved useful for preparing an event log that serves for discovering a model that reflects actual "physical" activities (i.e., decoupled from asynchronously interchanged EDI messages) of the inter-organizational business process under examination (cf. Research Question 1, Section 2.3). Secondly, the EDImine BSC Framework allowed for the bottom-up definition and calculation of KPIs in line with business objectives defined in a top-down fashion (Research Question 2). Thirdly, the EDI & Business Information Ontologies allowed for the unified handling of EDI messages of different EDIFACT releases varying in syntax and semantics, and for their consolidation in overarching process models and KPIs (Research Question 3). Finally, the combined application of these contributions led to concrete insights in a business context, such as factors that promote delays in the examined business process. However, the results from the case study also indicate that there is significant room for improvement with regard to the congruency of EDI-based KPIs with the actual business situation of the organization under analysis. In particular, information from non-EDI data sources is required for the calculation of some types of KPIs.

In this article, we identified two shortcomings associated with current usage of EDI technology in industry. In addressing these shortcomings, we proposed using EDI messages directly as a data source for inter-organizational process mining as well as for business performance analysis. We formulated three related research questions and discussed the corresponding state of the art. Subsequently, we introduced the *EDImine Framework* which comprises (i) a method for extracting business information from EDI messages using semantic technologies, (ii) methods for identifying events and process instances from EDI artifacts and (iii) a framework for calculating KPIs from events and business information originating from EDI data. For evaluating the presented approach, we developed the *EDIminer* toolset as well as the *EDImine BSC Plug-In for ProM 6* and conducted a case study in the context of a real-world company.

Our results show that mining EDI messages can provide organizations with business intelligence for investigating inter-organizational business processes as they are executed *in reality*, not as they were merely planned and/or modeled. Together with related business information from exchanged EDI messages which is transformed to scores of KPIs and business objectives, organizations are able to evaluate their inter-organizational business performance. This is in line with the idea of BPM, which aims at the continuous improvement of business processes by stepping through the BPM life cycle [6]. By means of the EDImine Framework, companies are not only able to visualize and document their EDI-based processes, but also monitor and audit them from both process and business performance perspectives and based on both historic and real-time data (e.g., through online process mining; cf. [2, p.241]). According to the BPM life cycle, the insights gained in the monitoring phase may serve as input to the next phase covering process optimization. The task of process optimization and continuous improvement can be considered of special interest for the field of EDI, where legacy systems are commonly in use.

Our future research will concentrate on tackling three current limitations of the EDImine Framework. Firstly, the current implementation of the EDImine Framework as well as the case study presented in this article focus on EDIFACT. As mentioned earlier, the framework can be adapted to support other interchange standards (e.g., XML-based business documents formats). However, the specific benefits of applying our approach in other settings than traditional EDI need yet to be investigated. Secondly, the EDImine Framework is currently only evaluated by one case study. More cases in different context would provide additional insights and learnings. Thirdly, our approach is currently limited to business transactions supported by and reflected in electronic business documents. However, as discussed in the case study, business transactions of an organization may be enacted as well by different means than EDI.

We intend to investigate how insights gained from EDI data may be integrated with other data sources, such as operational databases, for fully reflecting an organization's performance. Moreover, deriving KPIs solely from EDI data is also insufficient to cover the measurement of all inter-organizational success factors. This is because some success factors (i) require KPIs that are not related to business transactions (e.g., number of new products, employee turn-over rate, etc.) and (ii) are difficult to measure quantitatively. Therefore, including different data sources other than usual business operational data is necessary for extending performance analysis coverage to additional perspectives. In addition, an extension of the framework towards the integration of inter- and intra-organizational business processes may facilitate analyses of an organization's business performance in its entirety.

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