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Process mining beyond workflows

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ABSTRACT

After two decades of research and development, process mining techniques are now recognized as essential analysis tools, as they have their own Gartner Magic Quadrant. The development of process mining techniques is rooted in process-related research fields such as Business Process Management and fueled by increasing data availability. To cope with the complexity of business processes, the focus of process mining techniques needs to go beyond workflow-like processes, that represent the life-cycle of a single case and enable multiple object types and events. This can only be accomplished by capitalizing on essential concepts from production and logistics domains, such as Bills-of-Materials (BOMs), and Customer Order Decoupling Points (CODPs). Pioneer researchers, e.g. Hans Wortmann contributed to the development of Enterprise Resource Planning, enterprise modeling, product models, and lean manufacturing. Experiences from these fields help to lift the process mining domain from case-based (i.e. workflow mining) to object-centered process mining. These contributions could be realized by conducting insightful case studies at company sites, one of them being discussed in this paper. The evaluation of process mining techniques is elaborated by proposing an "evaluation ladder", and its application is shown in the case study under consideration.

1. Introduction

Since the emergence of the first process discovery methods more than two decades ago, the *process mining* discipline has witnessed remarkable success. Process mining software evolved into a new product category as is reflected by the Gartner Magic Quadrant for Process Mining Platforms (Magic Quadrant for Process Mining Tools, 2023; Magic Quadrant for Process Mining Platforms, 2024). Applications of process mining can be found in retail, logistics, the automotive industry, finance, banking, insurance, transportation, telecom, energy, etc. Reinkemeyer (2020). As the capabilities to record and process event data grow at an unprecedented pace, process mining is increasingly relevant for organizations to scrutinize their processes on a regular basis. In this context, the use of process mining techniques is a must.

Many high quality review papers and books have been published that provide comprehensive overviews about process mining techniques, and the progress of this discipline (see, for instance van der Aalst, 2022; Zerbino et al., 2021; Imran et al., 2022). Process mining was possible to emerge not only due to data availability, but also because existing concepts from disciplines with an established and long history (e.g. statistics, operations research, concurrent theory, formal methods), were combined with more recent ones (machine learning, AI).

The aim of this article is to identify the concepts that originate from production and logistics domains and that have the potential to shape the development of the process mining field. Furthermore, a proposal to set up and report on the evaluation of process mining techniques is offered. The role of practical problems from industry, with high potential for process mining development, is also discussed. Since this Special Issue is dedicated to Hans Wortmann, it makes sense to connect these concepts with his works.

Even in the seventies, scientists such as Sherman Blumenthal came up with the idea of integrating the diverse *flows* in an organization (see Blumenthal, 1969, cited by Wortmann, 2003, p.6). This idea lies at the core of the process-based view, where the focus is "managing the entire chains of events, activities, and decisions that ultimately add value to the organization, and its customers" (Dumas et al., 2018) (p.1). Until 1970, the model-building approach concentrated mainly on solving models, and did not connect much with actual practical problems. In other words, the model-building approach was mainly *prescriptive*, and the practice-oriented approach mainly *descriptive*. After the seventies, the situation changed, and the two streams of research became more integrated (Bertrand et al., 1990) (pp. 1–2).

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Due to the development of Information Systems, in the eighties many models and modeling languages were developed to support these systems, which aimed to model, or mirror, the business processes (Wortmann, 2003) (p.6). A noteworthy transition, facilitated by Enterprise Resource Planning (ERP) systems, started to emerge: from *physical objects* towards *information objects*. In this sense, Hans Wortmann acknowledged the crucial role that the ERP systems play: "...the information system does not only contain a model of the reality, but increasingly it *is* the reality" (Wortmann, 2003) (p.13, translated from Dutch). Furthermore: "an order exists, when it exists in the information system, an activity is executed, when it is executed in the information system, … " (Wortmann, 2003) (p.13). The debate about the nature of reality is actually not new, and has fueled discussions among scholars since antiquity. Hans Wortmann's acknowledgment mentioned above, that was stated in 2003 (Wortmann, 2003), is never more true than today, when digital transformation forces all businesses to change, and to face multiple realities.

In their quest to change and improve, companies need to constantly evaluate their business processes. In this context, process mining becomes the "new normal", and supports in-depth scrutinizing business processes (van der Aalst, 2016b). One of the goals is to identify the discrepancies between the normative (prescribed) processes, and declarative (actual) processes and to facilitate further improvements. The "normative" processes are based on information objects, modeled and implemented in information systems. After process executions, the "declarative", or actual data results are usually recorded in event logs.

Does this data from event logs reveal the *reality* in its complexity? Do the results of process mining methods produce sufficient good insights to achieve efficiency gains and quality improvements? Can the focus of process mining techniques be broadened to go beyond the standard workflow-based approach? And last, but not least, how should proposed process mining techniques be evaluated?

The paper is organized as follows. In Section 2, the role of process mining in manufacturing is determined and the key differences in applications of process mining in finance, services and administration are pointed out. A reflection on how process mining techniques can be evaluated is presented in Section 3. In Section 4, a case study focusing on an E-mail Interaction Mining (EIM) method is discussed, where the evaluation of the proposed method played a major role.

2. Process mining for logistics, production, and information processing

Most organizations first apply *process mining* to their standard administrative or financial processes, e.g., Purchase-to-Pay (P2P) and Order-to-Cash (O2C) (van der Aalst, 2022, 2016a). The reason is that any organization has these processes, and over the last two decades, we have learned how to extract the relevant data from source systems like SAP and gathered a collection of known execution gaps. This way, introducing process mining provides predictable efficiency gains and quality improvements. However, for most organizations, P2P and O2C are not the core processes providing most value. For example, Porsche's core business is to produce beautiful cars, and Maersk's core business is to ship goods. Although there are organizations that only process information, most end-products are physical (food, cars, medicine, phones, etc.). Therefore, production and logistics remain important. Hans Wortmann was one of the pioneers investigating the interplay between information systems, production, and logistics (Wortmann, 2003; Bertrand et al., 1990; Wortmann, 1998). He was an expert when it came to ERP, enterprise modeling, product models, production control, and lean manufacturing. He was also involved in the development of the Dynamic Enterprise Modeling (DEM) approach supported by the Baan ERP system. DEM was introduced in the mid 190-ties to support the implementation of the ERP product using Petri nets (combining workflow modeling and model-driven development).

Note that in the ERP systems of the 1990s the different business functions were already integrated. However, the focus of process mining has been on discovering and improving workflow-like processes. Therefore, in the beginning, process mining was also referred to as "workflow mining" (van der Aalst, 2022, 2016a). To broaden the scope of process mining, it is no longer sufficient to focus on workflow-like processes that describe the lifecycle of a single case. This is the reason for the recent uptake of *Object-Centric Process Mining* (OCPM) (van der Aalst, 2023). To understand this development, we elaborate on the role of process mining in manufacturing and point out key differences with applications of process mining in finance, services, and administration.

2.1. Different types of products

Before elaborating on OCPM, let us first consider some key differences between information processing on the one hand and production and logistics processes on the other hand van der Aalst (1999). If the "product" is information, then

- it is easy to create a copy,
- there are hardly any storage limitations,
- transportation is fast and cheap, and
- products are unique and cannot be exchanged.

For physical products, it takes materials and effort to create a copy (e.g., "copying a car"). Also, moving or storing physical products requires resources. However, production to stock is often possible. One may produce 100 products of a given type (e.g., the latest top-end iPhone model) and these are exchangeable. However, it is impossible to produce 100 insurance claim decisions before the customer actually files an insurance claim. Despite these differences, there are also many commonalities. For example, resources are needed to process products, e.g. humans, robots, machines, etc. and there are common performance indicators such as throughput time, waiting time, service level, and utilization.

As explained, information is mostly "produced to order", i.e., it is impossible to produce "parts" before the demand is there. Physical products are often exchangeable, e.g., the parts of a car. When a customer orders a car with a *specific type* of tires, e.g., "Michelin Pilot Sport 245/35 R20", these tires may be on stock and produced long before the customer places the order. The car needs a specific type of tires, but not four specific tires. All tires of the type "Michelin Pilot Sport 245/35 R20" are exchangeable. Therefore, production planning and control are driven by quantities. For example, *Material Requirement Planning* (MRP I) focuses on quantities of end products and their parts. It assumes that manufacturing and demand are deterministic and there are no capacity limitations. *Manufacturing Resource Planning* (MRP II) determines financial, machine, tool, and personnel requirements in addition to material requirements. *Enterprise Resource Planning* (ERP) extended the reach from core production processes to supply chain management, sales, finance, project management, and staffing. Although process mining is often based on event data extracted from ERP systems it is noteworthy that applications of process mining often focus on financial and administrative processes, such as P2P and O2C, instead of the processes related to MRP I and II. This can be explained by the inability to handle exchangeable products (i.e., tracing individual cases instead of reasoning about quantities) and *Bills-of-Material* (BOMs).

2.2. Structuring products using bills-of-material

Bills-of-Material (BOMs) play a key role in manufacturing, but are typically abstracted away in process management and mining. Most end-products are composed of different parts. For example, a car is composed of thousands of components. A traditional BOM is a hierarchical structure (i.e., a rooted tree) where the root describes the end-product (e.g., a car), the leaf nodes describe the input of the production (e.g., the parts delivered to the car company), and all

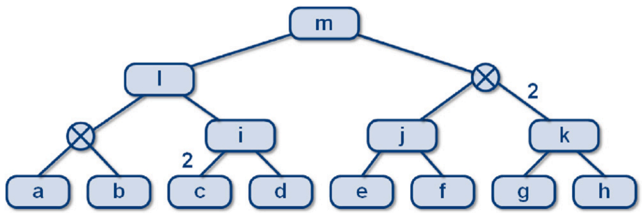

Fig. 1. A generative Bill-of-Material(BOM) with two configuration options.

other nodes are intermediate products also called sub-assemblies. Such a BOM describes one product type. However, often there is a lot of variability possible through so-called *configuration options*. For example, a customer can choose color, engine, add a navigation system, etc. This leads to an exponential increase in the number of possible types of cars. Hence, so-called *generative BOMs* were proposed (Hegge and Wortmann, 1991; van Veen and Wortmann, 1992).

Fig. 1 shows an example of such a generative BOM. The numbers on the arcs denote quantities, and the circular nodes with a cross describe configuration choices. In the abstract example, end-product m is composed of sub-assembly l and a choice between sub-assembly j and two times sub-assembly k. Sub-assembly l is composed of sub-assembly i and either part a or part b. Since there are two binary configuration choices, $2 \times 2 = 4$ BOMs can be generated from this generative BOM. The nodes in Fig. 1 are at the type level, i.e. a, b, c, etc. refer to product *types* and not to concrete products (i.e. product instances). Fig. 2 shows four concrete end-products of type m: $m234$, $m222$, $m235$, and $m773$. Note that, for example, node $a234$ refers to a concrete product of type a, and node $b344$ refers to a concrete product of type b.

Generative BOMs are a natural way to deal with product variability. However, even for a specific BOM there may be many ways of executing the process. In Vanderfeesten et al. (2010), we developed techniques for the automated generation of process models based on a BOM (also modeling services and information using BOMs). The process mining tool *ProM* was extended with the ability to create process models based on BOMs using different strategies, e.g., to optimize flow times (Vanderfeesten et al., 2010). This approach is one of the few attempts to incorporate principles from production and logistics in information processing (see Fig. 2). Most process mining tools do not support the notion of a (generative) BOM due to the focus on workflow-like processes (workflow nets, process trees, directly-follows graphs, and BPMN). This is unsurprising because the mainstream modeling notations, like the industry standard BPMN (Business Process Modeling Notation), are case-centric. Therefore, it is natural to take these notations as the target language of discovery algorithms. In a BPMN model of an order handling process, all activities refer to precisely one order. This keeps things simple, but also disconnected from reality. Real-world activities often involve multiple objects, e.g., customers, orders, products, shipments, containers, machines, suppliers, workers, etc. Looking at a BOM, it is evident that assembly steps also involve multiple objects. Object-Centric Process Mining (OCPM) addresses the limitations of traditional process modeling and process mining by allowing any number of objects to be involved in an activity. The so-called Event-to-Object (E2O) and Object-to-Object (O2O) relations, discussed later, are essential to capture ERP concepts such as the BOM.

2.3. Customer order decoupling points

A key concept in production and logistics is the *Customer Order Decoupling Point* (CODP). The CODP is the point in the material flow where the product is tied to a specific customer order. Different positions of the CODP are visualized in Fig. 3. For the sake of simplicity, the figure assumes a linear manufacturing process using four steps.

In a *Make-to-Order* (M2O) scenario, the CODP is located deep in the production process. The product is manufactured almost from scratch into a finished product based on a customer order. M2O may also involve purchasing parts or materials based on customer orders. If the majority of parts and materials is purchased based on customer orders we can also use the term *Purchase-to-Order* (P2O). In an *Assemble-to-Order* (A2O) scenario, the different parts are kept in stock, but finished products are assembled based on concrete customer orders. In a *Make-to-Stock* (M2S) scenario, finished products are assembled based on anticipated demand, i.e. end-products are kept in stock to ship goods the moment the customer places an order. In an *On-Stock* (OS) scenario, the customer does not need to order, because the supplier ensures that there are enough products at the customer's site.

Customer Order Decoupling Points (CODPs) are rarely considered in process mining. The reason is that in traditional process mining, only end-to-end process instances with a single case identifier are considered. When products are put in stock, supply and demand get decoupled making it impossible to use a single case identifier. Therefore, processes such as shown in Fig. 3 are divided into sub-processes where each process centers around a specific case notion.

2.4. Implications for process mining

Using a single notion (i.e., each event refers to one process identifier) makes it impossible to cover BOMs and COPDs. Classical process modeling and process mining make this implicit assumption. *Object-Centric Process Mining* (OCPM) (van der Aalst, 2023) aims to address such limitations by allowing for *multiple object types* and events that may involve *any number of objects*.

Fig. 4 shows a meta-model for *Object-Centric Event Data* (OCED). *Events* are *typed* and these types are often referred to as *activities*. Next to a type events have a timestamp, attributes, and may refer to any number of objects. Also, *objects* are *typed* and the same object may be involved in multiple events. Objects do not have a timestamp, but can have time-stamped attributes (e.g., quality, wear, price, or weight). Objects may be related (e.g. a "part-of" relation). Both the *Event-to-Object* (E2O) relations and *Object-to-Object* (O2O) relations may be qualified, i.e., describe a named property. For example, the O2O relations may express the "part-of" relations in a BOM.

The various process mining techniques need to be "reinvented" to deal with OCED. For example, process discovery techniques need to return models describing the dynamic relations between objects. We have implemented several multi-object process discovery and conformance checking techniques. See van der Aalst (2023) for some pointers. OCPM algorithms developed in open-source tools such as ProM, pm4Py, OCPM, OCPA, and OCπ and standardization efforts such as OCEL 2.0 (www.ocel-standard.org) served as an example for commercial tools such as Celonis. The new Celonis platform is completely object-centric. Fig. 5(a) shows an object-centric process model discovered for an order management process using inductive mining. The model in combination with the OCED for the four object types can also be used to analyze (b) performance and (c) conformance.

OCED and OCPM provide several advantages compared to traditional process mining approaches:

- Using OCED, it is possible to create a system-agnostic, single source of truth. Process mining is no longer driven by the data that happened to be in the source system and the initial questions at hand. Instead, using multiple object types, it is possible to create a more holistic and yet more accurate starting point.
- An organization needs to manage one data set, thus avoiding data fragmentation and redundancy. In the classical situation there is one data set for every view on a process. These may be overlapping, e.g., multiple data sets may refer to products, suppliers, etc. This leads to duplication and inconsistencies. Using OCED and OCPM, views can be created on demand without going back to the source systems.

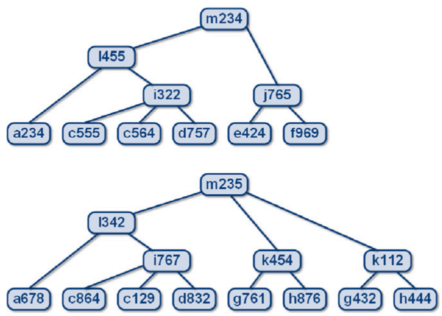

Fig. 2. Four concrete instances of the generative BOM in Fig. 1.

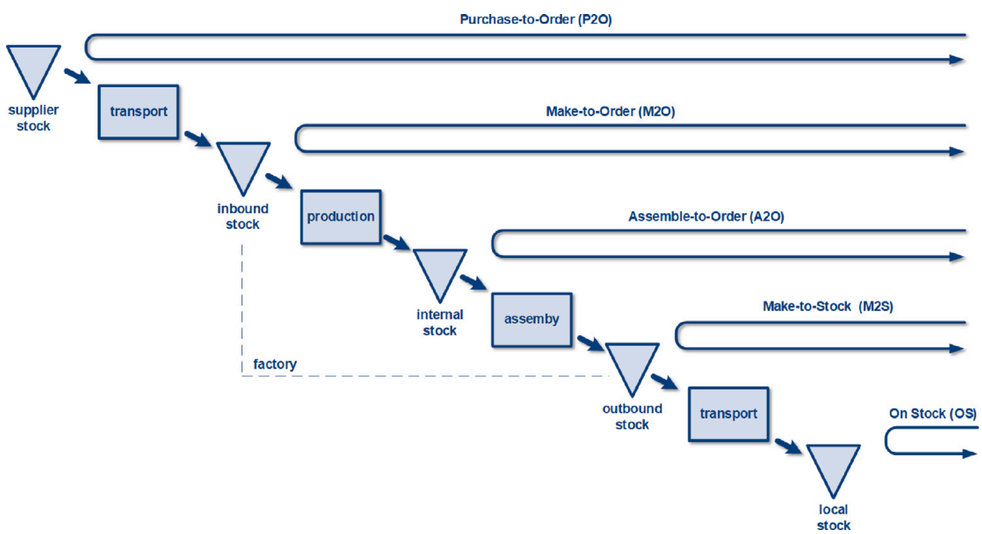

Fig. 3. Possible Customer Order Decoupling Points (CODPs), based on (Wortmann, 2003).

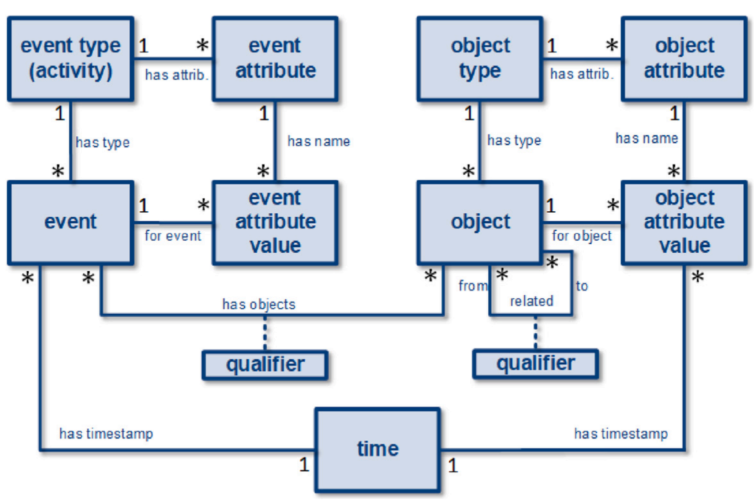

Fig. 4. Meta-model describing Object-Centric Event Data (OCED) (van der Aalst, 2023).

- OCED are closer to reality, allowing organizations to find problems that exist at the intersection points of processes and organizational units. For example, a customer order may be delayed due to procurement and production problems. These causes remain invisible when considering only the handling of customer orders.

Although Fig. 4 does not explicitly mention BOMs and COPDs the extensions provide the "hooks" to better capture such mechanisms and process patterns. Although process mining is often based on data originating from ERP systems much of the data specific to production and logistics (the original core of such systems) remain unused. Therefore, it is worthwhile to apply OCPM to the principles described by Hans Wortmann and colleagues (Wortmann, 2003; Bertrand et al., 1990; Wortmann, 1998; Hegge and Wortmann, 1991; van Veen and Wortmann, 1992). There are many opportunities to combine recent developments in process mining with concepts from logistics and production.

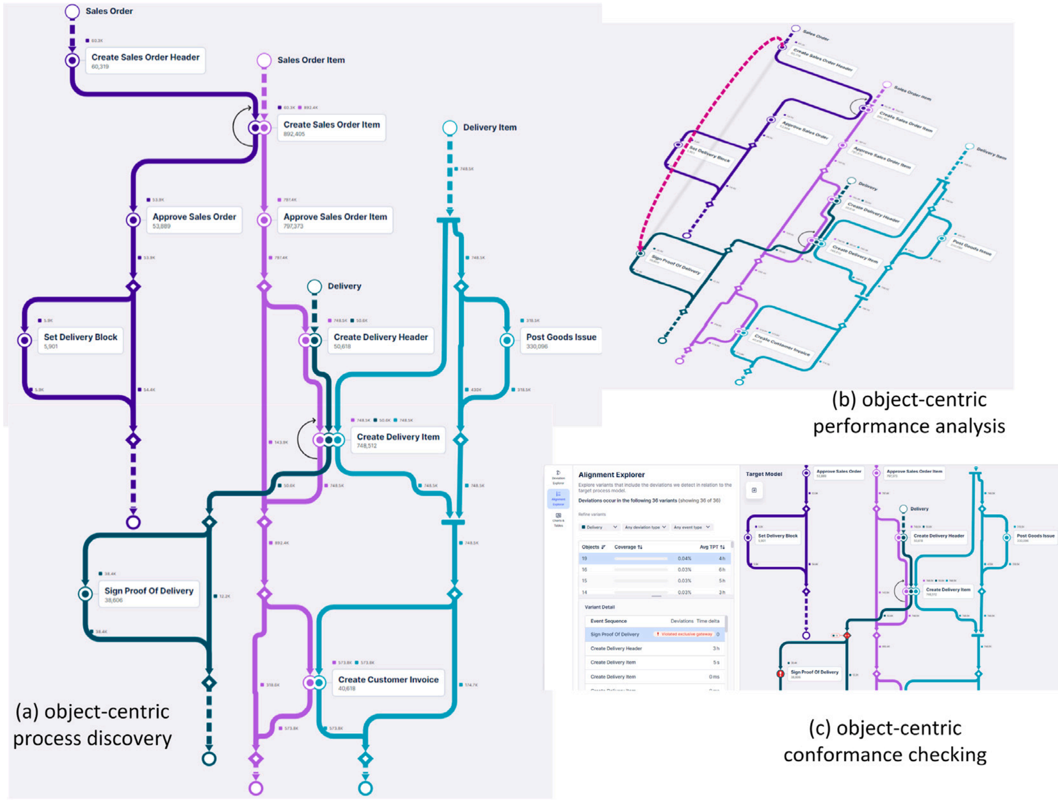

Fig. 5. An object-centric process model automatically discovered using the Celonis Process Adherence Manager using OCED related to four object types: sales orders, sales order items, deliveries, and delivery items.

3. Evaluation of process mining techniques

Since the advent of process mining, an impressive number of techniques have been developed to better understand processes. Techniques have been proposed for process discovery, conformance checking, process prediction, causal inference, and many other purposes. Anybody who proposes a new process mining technique should reflect at some point what its added value is in comparison to the state of the art. Evaluation is the activity of doing so in a methodological, transparent, and fair way.

Hans Wortmann was involved in the development of one of the first techniques to discover and analyze e-mail-driven business processes, which he and his co-author referred to as E-Mail Interaction Mining (EIM) (Stuit and Wortmann, 2012). One of the key aspects of the paper in which EIM was introduced is the significant attention that was paid to the evaluation of this technique. This is characteristic of the scientific mentality of Hans Wortmann, for whom real-world utility was always a prime concern.

In this part of the present paper, a brief reflection on how process mining techniques can be evaluated is provided, which can serve as a guideline for setting up and reporting on such an evaluation. We will illustrate this reflection on the evaluation of a number of well-known process mining techniques and that of EIM in particular.

3.1. The evaluation ladder

An evaluation that is too shallow or is misaligned with the purported benefits of an artifact will not convince anyone, let alone that it will get published as an academic achievement. To support a claim, effort is required. However, the angles to critically look at the strengths and weaknesses of a complex artifact and the conditions under which these manifest themselves are endless. Somehow a balance must be struck. Evaluation, therefore, is an activity that needs to be proportional to the claims that are made with respect to the artifact and the insights that its developers wish to develop about its functioning.

It may be useful to think of evaluation in terms of choosing the right step for standing on a ladder. Consider Fig. 6, in which – from left to right – four ascending purposes can be seen for an evaluation. To convince a stakeholder, in particular a reviewer of the manuscript in which a new technique is introduced one can attempt to make that person perceive a proposal as *imaginable*, *feasible*, *effective*, or *competitive*. Often, it may even be beneficial to select multiple steps of the ladder to stand on.[1]

To discuss which step of the ladder is appropriate to aim for the first question to answer is whether the technique that is being proposed is *new* in its kind or should be seen as an *alternative* to existing techniques (see the top of the figure). When the α algorithm was introduced in van der Aalst et al. (2004) slightly comparable approaches existed, but none of these could provide any guarantees with respect to the class of process structures that could be discovered. This is arguably a good reason to consider the merits of such a technique on its own and evaluate it as a new technique. In such a situation, the first three evaluation steps are the viable options.

Shortly after the introduction of the α algorithm, a follow-up paper was published (Alves de Medeiros et al., 2004) that addressed the problem of a pattern the original algorithm could not recognize, i.e. so-called short loops. In this situation, given the incremental nature of the so-called α+ algorithm, the evaluation purpose must be – at the very least – to show how competitive it is to the existing solution, as indeed it did.

[1] Since most people have two legs, this is generally unproblematic.

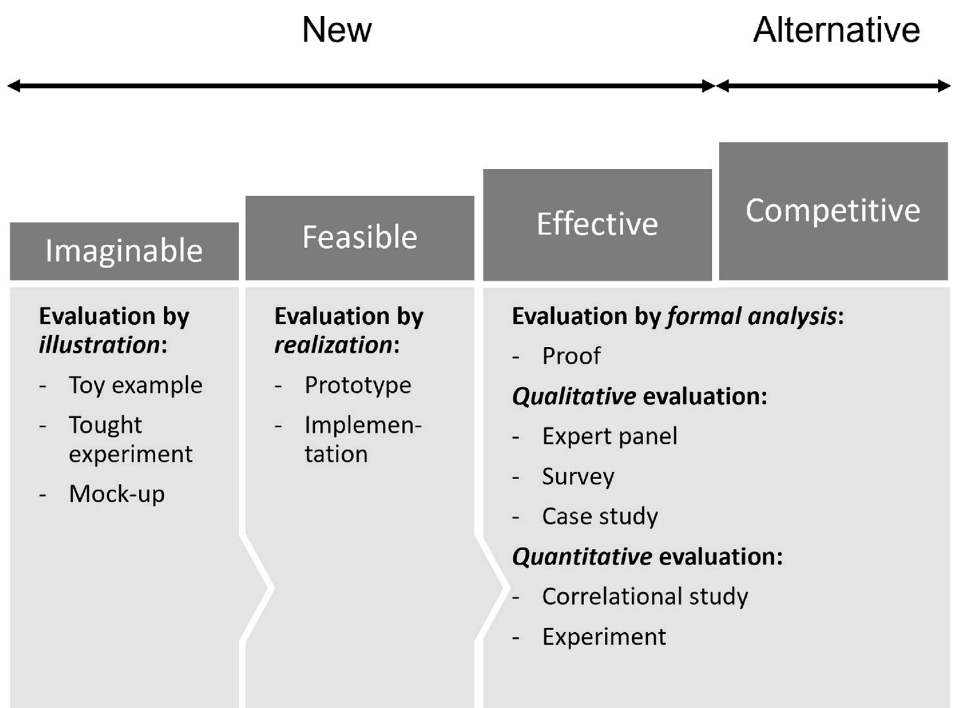

Fig. 6. The evaluation ladder.

3.2. Evaluating a new technique

Let us now consider the first three evaluation steps all of which can be used for the evaluation of a new process mining technique. The lowest step is to evaluate by *illustration*. A new technique always needs to be motivated and specified as part of the contribution. A *toy example*, using a simple setting and a small set of exemplary data, can be used to explain the technique, but can also be seen as a first attempt to let someone envision the application and effects of the proposed technique. Similarly, a *thought experiment* can achieve that effect. To make someone imagine the look and feel of an implemented technique, in particular with respect to its input/output behavior, a *mock-up* can be built.

It should be noted that all of these options are seen as very weak forms of evaluation. There are only two situations where it may make sense to go for these and not aim for a higher step of evaluation. The first is that the new idea is so strong, so innovative, that the publication of that idea is meritorious in itself. The second is that the setting in which the technique is proposed is actually welcoming early, immature ideas, as, for example, could be the case in a scientific workshop.

The second step is to evaluate by *realization*. This is a slightly underestimated means of evaluation, but by realizing the technique in the form of a working code a strong signal is given that it is feasible to execute it. Indirectly, the realization of a technique in the form of a *prototype* or even full *implementation* shows reviewers that the proposers themselves have already encountered any obvious weaknesses they might have overlooked in their conceptual design. Furthermore, by making the code publicly available, others will be provided with an opportunity to play with the artifact and evaluate the technique themselves.

The third step consists of three classes of evaluation, all of these are aimed at showing that the technique does what it is supposed to do, i.e. that it is effective. The first of these is evaluation by *formal analysis*. This entails that one or more properties of the proposed process mining techniques are mathematically proven. In the case of the α miner that was mentioned earlier a proof was provided that it could correctly mine sound SWF-nets without short loops.

Qualitative evaluation relates to approaches that involve a subjective component as to the claims that are on the table; *quantitative* evaluations, by contrast, are based on the assumption that there is a measurable property (or properties) of the technique that can be expected to change (cf. Kitchenham, 1996). Typical ways of executing a *qualitative* analysis are by means of:

an expert panel The idea is that a group of experts is brought together to study the characteristics or behavior of a technique to form a consensus opinion on that artifact;

a survey Surveys can take the form of *interview studies*, where researchers ask participants in a one-on-one fashion open-ended questions about the artifact. Surveys can also be carried out by means of *questionnaires*, where a sample of participants receive predefined, mostly close-ended questions, usually in an online setting or on paper;

a case study This is an empirical inquiry that studies the application of a technique in a real-world setting. This evaluation approach may also include other approaches, such as observation and interviews.

A *quantitative evaluation* is usually aimed at gathering numerical data by applying a process mining technique under different circumstances. A way to distinguish between different kinds of quantitative evaluations is to look at the way the data collection is organized. If systematic variation of factors that can influence the results are applied, for example the level of noise in an event log, then this is an *experiment*. If systematic control is not being applied, a quantitative evaluation can – at best – be considered as a *correlation study*, in which the statistical relation between the property of interest and other factors is studied.

3.3. Evaluating an alternative technique

In the previous section, the first three levels of the evaluation ladder were discussed. The one step on the ladder that is left is *comparison*. As stated before, in the situation where a technique is proposed that can be seen *as an incremental improvement* of an existing technique it is crucial to show how the newer technique compares to and, hopefully, improves it.

It is important to note the following: Even if a technique is not technically an extension of something that already exists, but aims *at generating the same insights or benefits* of state-of-the-art techniques, comparison is also the way to proceed. While it may be technically impressive that similar results can be obtained in a different way, there is always the fair question that needs to be answered: Why is there a need for this new technique?

A good case in point that illustrates both of these considerations is the work on the Inductive Miner - Infrequent (IMI) (Leemans et al., 2013), which is compared in the same paper with the Inductive Miner it extends, as well as three other process mining techniques in terms of its performance and the quality of the models it is able to discover. This is a very appropriate and balanced set-up for an evaluation.

As can be seen from Fig. 6 the approach to evaluation for the comparison is the same as for the effectiveness level, i.e. evaluation by formal analysis, qualitative evaluation, and quantitative evaluation. In principle, each of these can be used to compare a new process mining technique to the state of the art. For example, a new technique can be proven to be superior to an existing technique (formal analysis) or people can be asked to compare different process mining techniques in interviews (qualitative analysis). In practice, comparison of process mining techniques mostly takes place through quantitative evaluation. A very usual and attractive setting is that benchmark data is used for the sake of comparison.

4. The E-mail interaction mining (EIM) case study

In Stuit and Wortmann (2012) a method to extract e-mail message threads, and to construct an interaction-centric process model is proposed. The method described here shows that a process can be discovered from data (e-mail messages), even when there is no explicit workflow reference in the e-mail subject. Furthermore, the evaluation ladder proposed in the previous section is applied to the EIM case study from (Stuit and Wortmann, 2012).

The case study described by Stuit & Wortmann in Stuit and Wortmann (2012) was executed at Gasunie Transport Services Inc. (GTS), which is the operator of the national gas transmission grid in the Netherlands. The case study focused on an infrastructural process at GTS, which depended heavily on e-mail communication. GTS was interested to apply the EIM method, to expose collaboration problems, and to identify improvement opportunities for future infrastructural projects.

While it is common to execute process mining research based on data originating from ERP and workflow management systems, the EIM method shows that in the case of Human Collaboration Processes (HCP), another approach is needed. Namely, in HCPs collaboration and interaction are essential: “the workflow-based process modeling languages are appropriate for modeling business processes that display complex tasks flows (i.e. workflow processes), but are less appropriate for modeling business processes that involve the interaction of a multitude of actors (i.e. HCPs)” (Stuit and Wortmann, 2012, p.144). Other research, for example (van der Aalst and Nikolov, 2008), makes assumptions on how the case and activity concepts of process mining are mapped onto elements of e-mails such as subject, sender, receiver, etc. In this way, a direct connection between email messages and event data can be established.

The EIM case study illustrates how an innovative method, that went beyond the established process mining techniques focusing on tasks execution, could add both scientific and business value. The current developments to “reinvent” process mining aiming to deal with OCED confirm the continuous innovating trend in this field (van der Aalst, 2023).

By reflecting on the paper proposing EIM it becomes apparent that Hans Wortmann and his co-author devote considerable attention to the evaluation of the process mining technique. In fact, four out of the nine sections of the paper are directly related to this topic and the interpretation of the evaluation.

In the description of their related work, they explain different connections to existing techniques, and focus on discussing one technique (see Stuit and Wortmann (2012)) in depth since it resembles EIM the most. They argue that EIM is different since “the focus is not on the structure of tasks [...] in a workflow process but on the structure of interactions”. The authors clearly use this insight to justify their evaluation approach from the angle of EIM being a *new* artifact: it stems from a different angle on business operations.

The evaluation approach is then based on two steps of the evaluation ladder:

- an evaluation by *realization* through the *implementation* of EIM as a tool, and
- a *qualitative* evaluation of the use of EIM in a *case study*.

It is interesting to note that the implementation of EIM as a tool is explicitly positioned as a way to demonstrate “the feasibility of the method and its design decisions”. The tool is also made available to others, via a public link, which further enhances the notion that the ideas are realizable. In its turn, the case study, which involved the application of EIM in the setting of GTS,[2] is explicitly framed as a way to assure research relevance through addressing a business need. The application of EIM indeed leads to the generation of specific enterprise design suggestions, thus clearly illustrating the relevance of this work.

All in all, the paper on EIM is a beautiful illustration of a multi-faceted and in-depth evaluation of a process mining technique, which can still inspire all those who are considering how to set-up and communicate the evaluation of an artifact.

5. Conclusions

Hans Wortmann was one of the pioneers investigating the interplay between information systems, production, and logistics. Many process mining developments originate from these domains, and they continue to represent a rich potential to the growth of the process mining field, such as Bills-of-Materials (BOMs), and Customer Order Decoupling Points (CODPs). In the shape of an evaluation ladder a proposal to setup and report on the evaluation of process mining techniques is submitted.

One of Wortmann’s research papers was selected (Stuit and Wortmann, 2012), in which a discovery and analysis method was developed based on e-mail archive data, collected from a Dutch gas transport company. The evaluation of the case application shows that the method uncovers the e-mail-driven business process and realizes business value. In terms of the evaluation ladder, the case from (Stuit and Wortmann, 2012) accomplishes the evaluation by realization through method implementation, and a qualitative evaluation in a case study.

Hans Wortmann was a visionary scientist, with a deep understanding of manufacturing processes. Due to his involvement and close contact with industry, he realized the great potential of data-driven research in the context of business processes. He set up and conducted research projects in many companies, which provided the context and the necessary ingredients for business value-adding research, with real impact.

[2] Between 2008–2009, more research projects took place at GTS under the coordination of Hans Wortmann. Another example is the gas booking process, which had to be redesigned due to the liberalization of the European gas market. A redesign approach using simulation and process mining techniques was proposed in Maruster and van Beest (2009).

CRediT authorship contribution statement

Wil M.P. van der Aalst: Conceptualization, Formal analysis, Investigation, Methodology, Validation, Visualization, Writing – original draft, Writing – review & editing. **Hajo A. Reijers:** Conceptualization, Formal analysis, Investigation, Methodology, Validation, Visualization, Writing – original draft, Writing – review & editing. **Laura Maruster:** Conceptualization, Formal analysis, Investigation, Methodology, Project administration, Validation, Visualization, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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