Technological Forecasting & Social Change 172 (2021) 121021

Contents lists available at ScienceDirect

Technological Forecasting & Social Change

journal homepage: www.elsevier.com/locate/techfore

Process Science in Action: A Literature Review on Process Mining in Business Management

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ARTICLE INFO

Keywords:
Process mining
Business intelligence and analytics
Business process management
Industry 4.0
Machine learning
Data science

ABSTRACT

Process Mining is a new kind of Business Analytics and has emerged as a powerful family of Process Science techniques for analysing and improving business processes. Although Process Mining has managerial benefits, such as better decision making, the scientific literature has investigated it mainly from a computer science standpoint and appears to have overlooked various possible applications. We reviewed management-orientated literature on Process Mining and Business Management to assess the state of the art and to pave the way for further research. We built a seven-dimension framework to develop and guide the review. We selected and analysed 145 papers and identified eleven research gaps sorted into four categories. Our findings were formalised in a structured research agenda suggesting twenty-five research questions. We believe that these questions may stimulate the application of Process Mining in promising, albeit little explored, business contexts and in mostly unaddressed managerial areas.

1. Introduction

The importance of Information Systems (ISs) lies in digitalisation and in the overlap between the information and the physical flows in business processes (Li, 2020; van der Aalst, 2016). Within this context, the capability of recording and gathering *events*, the most elementary unit of a business process, has gained new momentum in terms of deeper granularity and wider scope (van der Aalst, 2017).

Process Mining (PM) has emerged as a novel approach in exploiting these advancements. PM is a set of data-driven techniques for diagnosing and enhancing business processes by combining Machine Learning and Business Process Management (BPM). PM leverages the event data from ISs to identify process deviations and inefficiencies and to compare the resulting process flow to how the IS should perform. PM thus bridges the gap between the extant model-driven approach and current data-driven BPM techniques. Indeed, model-driven techniques often overlook the hidden evidence that can be extracted from the data, while data-driven methods "*tend to be process agnostic*" (van der Aalst, 2016, p. 15). PM overcomes these limitations by harnessing the event data in order to improve end-to-end business processes.

The formalisation of the PM Manifesto (van der Aalst et al., 2012) led to a considerable increase in the body of PM-related literature Augusto et al., (2019a); Rojas et al., (2016). Given the strong link between PM and Business Management for purposes ranging from performance analysis (Khanna et al., 2017) to auditing (Jans et al., 2011a; Zerbino et al., 2018) or to acquiring process intelligence (Wang et al., 2014b), PM has also attracted interest from practitioners (Gartner., 2020). However, PM conference papers outnumber PM journal papers,[1] despite their lower scientific impact (Usée et al., 2008). This may mean that PM is still a burgeoning area of literature and thus has room for improvement.

The scientific community has investigated PM mostly from a Computer Science standpoint mainly by developing new algorithms (Günther and van der Aalst, 2007; Leemans et al., 2014), improving the existing algorithms (Li et al., 2007; Weijters and Ribeiro, 2011) or checking for their scalability (Leemans et al., 2018) and focusing on pre-processing steps (Günther and van der Aalst, 2006; Song et al., 2009). From a Business Management point of view, PM appears to support decision making (*e.g.* Satyal et al., 2019). Nonetheless, the exploitation of PM for making better operational, tactical, and strategic decisions has been moved into the background. The potential of PM from a managerial perspective has yet to be fully clarified. Furthermore, Business Management-orientated PM studies often fail to propose

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[1] The search was carried out on Scopus on September 2020. The search string was "process mining" in the title of the paper. It returned 858 conference papers and 365 journal papers.

https://doi.org/10.1016/j.techfore.2021.121021
Received 7 January 2021; Received in revised form 5 July 2021; Accepted 10 July 2021
Available online 22 July 2021
0040-1625/

holistic and systematic advancements in knowledge because of two potential shortcomings:

- To the best of our knowledge, the scientific literature does not propose any up-to-date research agenda defining specific business contexts and managerial areas in which PM may be fruitful. Moreover, it lacks an exhaustive summary of the state-of-the-art of PM, which could include all the most relevant types, purposes, and analytical perspectives of PM.
- Although a few reviews deal with PM, they have a narrow scope. For example, Rojas et al. (2016) and Ghasemi and Amyot (2016) are limited to healthcare. Thiede et al. (2018) adopted an exclusive perspective on the empirical applications of PM in organisations. Williams et al. (2018) focused only on primary care. Verenich et al. (2019) restricted their review to time prediction methods, whereas Garcia et al. (2019) proposed an extensive mapping study, but they did not develop a research agenda.

Accordingly, by focusing on the contributions mostly related to the management research field, this manuscript aims to answer the following research questions (RQs):

RQ1: "*Which are the most used PM types, perspectives, and algorithms in the Business Management field?*"

RQ2: "*In which business sectors, business functions, and decision-making levels has PM been mostly exploited?*"

In line with the Business Management scope of these RQs, in this paper we adopt the process view of organisations as proposed by Porter (1985), in which the management of a firm is conceived according to the firm's Value Chain. This is consistent with the business process orientation on which PM and BPM are based.

We set three research objectives: (1) to present a holistic overview pertaining to the Business Management-orientated PM literature; (2) to review the literature from a multi-dimensional perspective; (3) to provide clear indications for guiding further research. We hope that achieving these objectives may stimulate academics to probe less explored and more promising directions regarding PM and to increase the awareness and effectiveness of PM initiatives in the Business Management field.

To fulfil the objectives, we developed a systematic literature review based on the review protocol by Pittaway et al. (2004). We built a multi-dimensional framework to guide the selection and the arrangement of the papers and to analyse them in a structured way. Starting from over 3600 papers, we selected a final set of 145 manuscripts. We then pinpointed eleven literature gaps that led to the definition of a structured research agenda.

The remainder of this work is structured as follows. Section 2 explains the research design, Section 3 describes the results from the literature review, Section 4 discusses the results, and Section 5 concludes the paper, drawing up the research agenda.

2. Research design

The research design consisted of two steps. First, we identified a set of dimensions of analysis to carry out the literature review and to classify and interpret the results so as to gain new insights (Webster and Watson, 2002). Second, we conducted the review according to the methodology by Pittaway et al. (2004), which is consistent with other well-acknowledged review methodologies (*e.g.* Petticrew and Roberts, 2006; *cf.* Easterby-Smith et al., 2013) and which has been used widely by other academics (*e.g.* Savino et al., 2017; Kauppi et al., 2018). The following sections outline the dimensions of analysis (2.1) and detail the review methodology (2.2).

2.1. Dimensions of analysis

To steer the selection and the arrangement of the papers, we considered seven dimensions of analysis structured as follows:

1 *Type of contribution*, to distinguish the nature of the papers between *conceptual* and *empirical*;
2 *Type of Process Mining algorithm*, to specify the algorithm(s) exploited in the paper;
3 *Type of Process Mining*, to detail the aim(s) of the PM application, where present;
4 *Process Mining perspective*, to identify the unit(s) of analysis of the PM application;
5 *Sector*, to delimit the industry sector which PM was used in;
6 *Business function*, to single out the business function(s) which PM was applied in;
7 *Managerial focus*, to identify the decision-making level(s) the paper aimed at impacting.

Dimensions 2, 5, 6, and 7 were considered for the empirical papers only. Sections 2.1.1 – 2.1.7 delve into the seven dimensions.

2.1.1. Type of contribution

The scientific literature has proposed both *conceptual* and *empirical* contributions. Conceptual contributions develop analysis frameworks or refine PM techniques and algorithms without a structured case study. Empirical contributions apply PM to specific event logs for a range of purposes within a structured case study. Empirical contributions were further differentiated into applications using *real datasets* and applications with *synthetic datasets*. PM applications in real-life settings with real datasets usually reveal intrinsic complexity of a real context. On the other hand, simulated/synthetic datasets provide a useful operational input for applying PM, but they may be unable to reproduce such complexity because they may rely on a simplified version of reality. Given the managerial perspective of this manuscript, works using datasets purely for experimental evaluations, for example, validations of an algorithm, were classified as conceptual.

2.1.2. Type of process mining algorithm

The development and application of new PM algorithms, *e.g.* Weijters and Ribeiro (2011), Leemans et al. (2014), Augusto et al. (2019b), have been conditioned by the limitations of the early PM algorithms and by some operational needs, *e.g.* to improve the understandability of the outcomes from process discovery activities (Günther and van der Aalst, 2007). Thus, this dimension of analysis identifies which families of algorithms have been exploited so far and provides an overview of the academic interest in them. Algorithms used only for supporting PM activities (*e.g.* clustering activities) were not considered because they are not PM-specific.

2.1.3. Type of process mining

PM may be used for different objectives and be grouped into three PM types (Partington et al., 2015). The first is process *discovery*, which extracts the blueprint of a business process, referred to as *de facto* model, from an IS event log. The second is process *conformance*, assessing the extent to which the *de facto* model conforms to a reference process model, *i.e. de jure* model, which describes how the business process should be carried out. The third type is process *enhancement* which, based on additional information contained in the event log (*e.g.* frequencies, time performances), is aimed at extending or improving an existing process model to improve the fit with the *de facto* model. This is done by dealing with process bottlenecks, deadlocks, or frequencies or throughput times of specific activities.

2.1.4. Process mining perspective

The scientific literature proposes four main perspectives that can be adopted in PM analyses, either alone or combined (van der Aalst, 2016):

Table 1
Definition of the instances and attributes for the PM perspectives.

PM perspective	Set of instances	Minimum set of attributes
Process perspective	A set of instances assuring that the outcoming control flow is representative of the whole business process; ideally, all the complete instances should be considered.	The set of attributes necessary and sufficient to identify the ordering of the activities.
Time perspective	A set of instances that assures to obtain a reliable and comprehensive overview of the time and frequency performances; possibly, all the complete process instances should be considered.	The set of attributes needed in the process perspective, enriched with the time attributes (*e.g.* timestamp).
Organisational perspective	A set of instances that assures reliability and completeness of the resource network in output; possibly, all the complete process instances should be considered.	The set of attributes needed in the process perspective, enriched with the resource attributes (*e.g.* roles).
Case perspective	The set of instances that fulfils the specific purposes of analysis and of case characterisation (from one to a small number of instances); the selection of the instances depends on which case attributes/properties and event attributes the analyst is interested in and on their values.	The set of attributes necessary and sufficient to meet the requirements of the scope of analysis and to characterise the groups of cases; potentially, all the attributes might be considered.

- *Process perspective*, which elicits the control flow – *i.e.* the ordering of the activities of a business process;
- *Time perspective*, which extracts and deepens the time and frequency metrics of the process events;
- *Organisational perspective*, which analyses the business process through the lens of the process resources, *i.e.* of the actors (*e.g.* people, departments, roles, equipment, machines) involved in the process and of the network of relationships;
- *Case perspective*, which analyse cases characterised by specific attributes or values.

Although these perspectives are quite common in the literature, the term "perspective" has not been clearly defined within the PM context. Consequently, there is ambiguity in delimiting the four PM perspectives. To dispel this ambiguity, we clarified the four abovementioned PM perspectives by specifying the elements that define their unit of analysis.

The typical PM unit of analysis is the process instance, also known as a "case", structured into a set of attributes. While some attributes are needed to identify a case unequivocally, additional attributes further characterise the case in order to perform more advanced inquiries. We thus define a PM perspective as *the focus of the PM analysis in terms of the selected set of instances and of the chosen instance attributes and event attributes*. In line with this definition, Table 1 details the four perspectives.

2.1.5. Sector

The domain in which PM is applied is critical to each investigation. Different contexts have different business process characteristics (*e.g.* heterogeneity and number of process instances and activities) that affect the selection and application of PM techniques, and the interpretability and usefulness of their outcomes. For instance, healthcare processes often present several process variants as compared to how the process should be carried out (Rebuge and Ferreira, 2012). This entails greater difficulty in conducting PM analyses, but also higher process improvement potential. On the other hand, other contexts may include more linear business processes with a low number of variants. This context is less difficult to analyse and has less room for PM-enabled improvements (*cf.* van der Aalst, 2016).

Hence, the analysis of the scope of the PM application can identify which contexts have attracted more attention and may provide possible hints as to why some contexts may have been overlooked. Therefore, we classified the empirical PM applications into eight clusters corresponding to eight industry sectors: Energy & Materials, Industrials, Consumer Goods, Consumer Services, Healthcare, Utilities, Financial, and Technology. These sectors emerged by matching and re-arranging the industry clusters defined by three International Industry Classification taxonomies: *Industry Classification Benchmark*,[2] *Global Industry Classification Standard*,[3] and *Thomson Reuters Business Classification*.[4] Further details regarding the eight sectors are reported in Table A1 in Appendix A.

2.1.6. Business function

In addition to analysing the sector viewpoint, we added a functional perspective based on the Value Chain by Porter (1985) because a firm's business functions have different levels of formalisation that affect the underpinning business processes. This functional perspective consists of the following eight functions of the Value Chain: Operations, Marketing & Sales, Logistics, Service, Procurement, Research and Development (R&D), Human Resource Management (HRM) and Infrastructure. The Outbound Logistics and Inbound Logistics functions in the Value Chain were merged into a single Logistics function because this distinction is not relevant to PM.

2.1.7. Managerial focus

To clarify the decision-making level of abstraction that the PM contributions aim to support, we used the Management Triangle (Anthony, 1965), which classifies the decision-making planning and control into three hierarchical layers: *strategic, tactical*, and *operational*. Within the context of this work, strategic contributions regard how PM evidence may help in making long-term decisions on the firm's strategic directions, *e.g.* organisational structure redesign or allocation of multi-year resources. Tactical contributions concern how PM applications support medium-term decision making, *e.g.* variations in the exploitation of the production capacity, build-up of seasonal inventories. Operational contributions address short-term decision making, for example human resources scheduling, *i.e.* operational control to ensure that process tasks are performed effectively and efficiently.

2.2. Review methodology

Table 2 details the steps of the literature review. The application of the inclusion/exclusion criteria (Table B1 in Appendix B) led to a first set of 1795 Scopus papers and 1029 ISI papers (Phase 6, first skimming step). The analysis of title, abstract, and keywords of these works restricted the number of papers to 376 (Phase 6, second skimming step). By examining the references of the 376 papers and by applying the same criterion used in the second skimming step, we identified twenty additional conference papers (Phase 7). The 396 manuscripts were sifted by means of quality criteria (Table B2 in Appendix B) adapted from Pittaway et al. (2004). This quality assessment (Phase 8) was carried out according to specific evaluation rules (Table B3 in Appendix B) and led to dropping those papers which, despite being relevant to PM, did not show a good fit with the management research field. The resulting 145 papers formed the final set on which a thorough content analysis was conducted (Phase 9).

Independently of each other, the authors indexed the papers according to the seven dimensions of analysis. The results were compared

[2] See https://www.ftserussell.com/data/industry-classification-benchmark-icb

[3] See https://www.msci.com/gics

[4] See https://www.refinitiv.com/en/financial-data/indices/trbc-business-classification#

Table 2
Review protocol.

Review phase	Detail	Outcome
1. Keywords identification	Since our research purpose concerned a specific group of techniques, the name and the scope of such techniques led the keywords identification.	"*Process mining*", "*Process analysis*", "*Data mining*"
2. Search strings construction	"*Process analysis*" and "*Data mining*" were combined by the *AND* logical operator for focusing on the data mining applied to business processes. This search string was combined with "*Process mining*" by an *OR* operator for obtaining a wider overview of the specific techniques;	"*Process mining*" OR ("*Process analysis*" AND "*Data mining*")
3. Identification of additional keywords	The search string led a first query in the Scopus database in "Title, abstract, keywords". The list of keywords resulting from the query was analysed through the Scopus analytics. The frequency of occurrence of "*Process mining*" and "*Data mining*" outnumber the frequency of all the other keywords. Moreover, the other keywords (*e.g.* "*petri nets*", "*business process*", "*process model*") are a conceptual subset of the two main ones.	No additional keywords were identified
4. Database selection	The main database for our query was Scopus because it is the largest abstract and citation database of peer-reviewed literature. ISI Web of Science (WoS) was also considered for triangulating the results.	Scopus, ISI WoS
5. Exploitation of the search strings	To guarantee a wide coverage of the results, the query was orientated towards the highest comprehensiveness.	The query was performed in "Title, abstract, keywords" in Scopus and in "Topic" in ISI WoS
6. Review of the identified citations	This phase consisted of two skimming steps. In the first step, the body of papers from Phase 5 was sifted out by means of the inclusion/exclusion criteria (Table B1 in Appendix B). In the second step, title, abstract and keywords of the remaining papers were carefully read to assess if they fit our research topic and purpose. In this second step, the outcomes from the queries in Scopus and ISI WoS were aggregated and the duplicates were removed.	Input first step: 3560 hits on Scopus; 1673 on ISI **Output first step**: 697 journal papers and 1098 conference papers on Scopus; 618 journal papers and 411 conference papers on ISI; **Output second step**: 376 papers (185 in conferences and 191 in journals)
7. Reference cross-checking	Twenty additional papers were identified and skimmed according to the second stage of phase 6.	Twenty additional conference papers were identified
8. Quality assessment of the set of papers	The full body of the 396 papers was evaluated on the basis of quality criteria (Table B2 in Appendix B) and of a set of related evaluation rules (Table B3 in Appendix B). These criteria were adapted from Pittaway et al. (2004) in line with our research objective. The evaluation was supported by three senior researchers – not involved in the authorship of this manuscript – the background of which is consistent with the scope of this review. This method was preferred to bibliometric metrics, *e.g.* number of citations, to include also the most recent contributions.	Input: 396 papers (205 in conferences and 191 in journals) **Final output**: 145 papers (62 in conferences and 83 in journals)
9. Review of the articles	The selected 145 papers were reviewed through the lens of the seven dimensions of analysis. The indexing of the papers' content involved the three above-mentioned senior researchers.	Analysis of the articles
10. Elicitation of the scientific gaps	The results from the analysis led to the identification of eleven scientific gaps.	The scientific gaps and the corresponding research directions were formalised within a research agenda

and jointly discussed to reach a unanimous judgement. When the authors did not reach a consensus regarding the indexing, three independent senior researchers familiar with the topic and scope of the review were invited to participate in the process to resolve the disagreement. During the content analysis, some dimensions of analysis were cross-checked to provide further evidence that was not attainable using a single-dimension perspective. Finally, the evidence of the content analysis enabled us to identify the scientific gaps in the PM literature (Phase 10).

3. Results

Using the review protocol, we restricted the body of literature to 145 manuscripts – 62 conference papers and 83 journal papers. Fig. 1 and Fig. 2, developed by VOSviewer (version 1.6.16), illustrate bibliometric information on the selected works.

In Fig. 1, nodes portray the sources of the papers, while arcs represent the cross-citations between two sources. The sources that did not exhibit cross-citations were omitted from the network. The bigger the size of a node, the higher the number of papers from that source. The most frequent sources were *Lecture notes in Computer Science* (26), *Lecture Notes in Business Information Processing* (25), *Expert Systems with Applications* (9), *Decision Support Systems* (9), and *Information Systems* (6). However, *Information Systems* is the source showing the highest number of citations per paper.

Fig. 2 depicts the network of the keywords chosen by the authors of the papers and that were used more than one time. Each node is a keyword, and its size is proportional to the absolute frequency of the keyword occurrence. The arcs indicate the co-occurrence of different keywords. The most frequent keywords focus on BPM (*e.g.* business process modelling, predictive process monitoring, workflow management), particular aspects of PM (*e.g.* conformance checking, organizational mining, concept drift), and specific analysis purposes (*e.g.* fraud detection, performance evaluation).

The content of the 145 papers selected was probed through the lens of the seven dimensions of analysis. Almost one third of the papers (44 out of 145) are conceptual in nature, while the rest are empirical and exploit real datasets (93 out of 101) or only synthetic datasets (8 out of 101). In several works, the real datasets were repeatedly borrowed from the Business Process Intelligence Challenges[5], limiting the heterogeneity of the contexts and data explored (*cf.* De Weerdt et al., 2012).

The empirical papers employed at least one PM algorithm family. The three most adopted families were Fuzzy (39 out of 101), Heuristic (24), and α (6), but also other less used algorithms (*e.g.* Inductive, Region-based, Declarative) were used. amongst the most recent algorithms, Inductive Miner has attracted growing interest (three papers in 2019) and we expect it to play an increasingly relevant role in PM-based studies. Interestingly, 19 works out of 101 did not specify the algorithm used.

The following sections (3.1–3.3) present the most relevant evidence from the review by combining the dimensions of analysis to offer more advanced perspectives on the current PM literature. To facilitate the graphical interpretation of the results, the 145 papers were coded by a progressive number (Table C1 in Appendix C).

[5] See https://www.win.tue.nl/promforum/categories/process-mining for data repository.

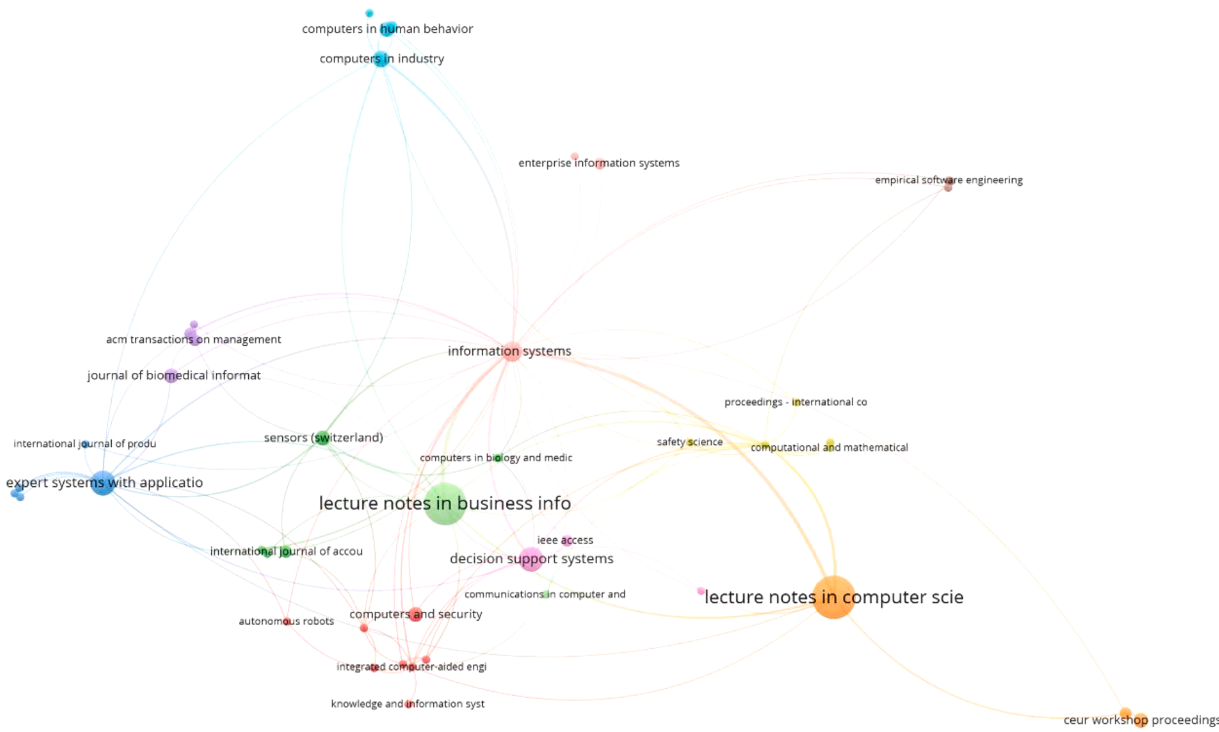

Fig. 1. Citation-Source network.

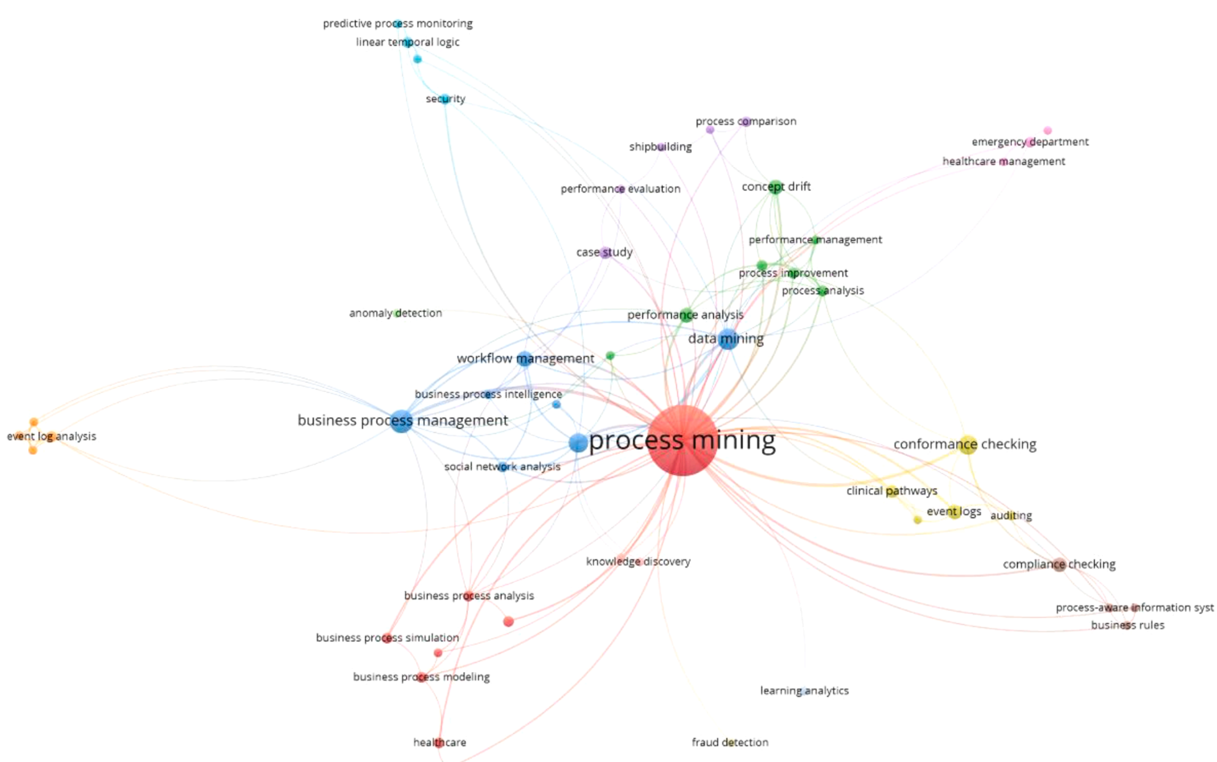

Fig. 2. Keyword network.

3.1. *Process mining types and perspectives*

Type of Process Mining and *Process Mining perspective* were considered in both conceptual and empirical contributions. Most papers do not include any explicit statement on the PM perspective(s) considered. Fig. 3 cross-tabulates *Type of Process Mining* and *Process Mining perspective* to offer a more advanced overview. The numbers in blue refer to the empirical papers, while the numbers in black refer to the conceptual papers.

With respect to the type of PM, "discovery" was the most investigated

	Process	Time	Organisational	Case
Enhancement	9, 24, 31, 37, 41 26, 46, 71	9, 24, 31, 37, 41 26, 29, 45, 71	49 29, 45	9, 24, 31 45
Conformance	4, 9, 12, 17, 32, 38, 53, 61, 65, 77, 79, 104, 106, 115 10, 13, 15, 23, 25, 43, 46, 47, 56, 67, 68, 70, 72, 84, 88, 91, 97, 99, 101, 113, 120, 122, 124, 125, 136, 139, 140, 144	9, 20, 38, 79, 104, 106 10, 15, 43, 47, 56, 67, 88, 97, 99, 101, 122, 140, 144	77, 79, 104 10, 56, 68, 97, 99, 101, 122	9, 12, 79, 104, 106 10, 43, 124, 140
Discovery	3, 9, 24, 31, 32, 34, 35, 37-39, 41, 55, 58, 62, 77-79, 82, 98, 100, 104, 106, 108, 115, 121, 127, 131 6, 8, 10, 11, 15, 16, 18, 19, 21-23, 26, 27, 33, 42-44, 48, 50, 52, 57, 59, 63, 64, 67-76, 80, 81, 83-90, 93, 94, 96, 97, 99, 101-103, 109-111, 113, 114, 116-120, 122, 124, 126, 128-130, 132-138, 140-145	9, 24, 31, 35-38, 41, 54, 66, 79, 82, 94, 95, 98, 104, 106-108 5, 7, 8, 10, 15, 19, 22, 26-29, 33, 40, 43, 44, 52, 57, 59, 63, 67, 71, 73-75, 80, 86, 88, 89, 93, 94, 96, 97, 99, 101, 102, 109-112, 117-119, 122, 123, 129, 135, 137, 138, 140, 143-145	1, 2, 34, 36, 54, 66, 77-79, 92, 100, 104, 107, 131 7, 10, 14, 22, 28-30, 52, 57, 60, 64, 68, 69, 74, 75, 81, 83, 85, 87, 93, 94, 97, 99, 101, 105, 109, 112, 117, 119, 122, 138, 145	9, 24, 31, 79, 92, 104, 106, 121 10, 21, 40, 43, 44, 64, 86, 105, 116, 124, 129, 130, 140, 143

Fig. 3. Distribution of the papers across the PM types and perspectives.

(127 times out of 145), while "conformance" and "enhancement" much less (43 and 11 times, respectively). Forty papers involved two or more PM types. This finding is consistent with the evidence from previous literature reviews on PM (*e.g.* Rojas et al., 2016; Thiede et al., 2018). As regards the PM perspectives, 123 manuscripts dealt with the process perspective, 75 the time perspective, 50 the organisational perspective, and 24 the case perspective.

Fig. 3 also highlights that:

- The case perspective is the least investigated, irrespectively of the PM type;
- "Enhancement" is the least explored type, irrespectively of the PM perspective;
- The time and organisational perspectives are challenged less in the conformance type than in the discovery type;
- The ratio between empirical and conceptual papers was 2.68 for discovery, 1.87 for conformance, 0.83 for enhancement.

3.2. Business functions and process mining perspectives

To elicit a practical overview of the empirical PM contributions (101 papers out of 145) within Porter's Value Chain, we cross-referenced *Business function* and *Process Mining perspective*. We excluded Taylor et al. (2012) (paper 16) because it does not clarify the business function in which the case was developed. Fig. 4 shows the distribution of the empirical works across the two above-mentioned dimensions.

Of all the business functions, Operations accounted for most of the papers (67 out of 101). Furthermore, the distribution of these papers decreases across the four perspectives. This is consistent with the same trend shown in Fig. 3. Further major evidence from Fig. 4 is:

- HRM and R&D have been completely disregarded:
- Marketing & Sales and Logistics have scarcely been considered (five or fewer papers);
- In line with Fig. 3, the case and organisational perspectives, particularly the former, have been studied very little from an empirical standpoint.

3.3. The process mining managerial focus in business functions and sectors

To highlight the managerial impact of the empirical papers, we cross-tabulated the *Managerial focus, Business function* and *Sector* dimensions (Fig. 5). The work by Taylor et al. (2012) (paper 16) was excluded from Fig. 5 because it does not specify the business function, sector, and managerial focus that it addressed. The contribution by Fleig et al. (2018) (paper 50) was considered within this analysis, but it is not reported in Fig. 5 because it does not state the sector considered.

The most relevant findings were:

- The most frequent managerial focus is the operational focus (81), followed by tactical (8), tactical-operational (9), and tactical-

	Process	Time	Organisational	Case
Infrastructure	64, 69, 75, 84, 102, 114, 123, 124, 129, 130, 141, 145	75, 102, 123, 129, 145	60, 64, 69, 75, 145	64, 124, 129, 130
HRM				
R&D				
Procurement	10, 22, 46, 50, 63, 68, 83	5, 10, 22, 63	10, 22, 68, 83	10
Service	11, 26, 43, 73, 80, 85, 97, 109	26, 40, 43, 73, 80, 97, 109	85, 97, 109	40, 43
Mkg & Sales	18, 50, 67	67	30	
Operations	6, 8, 13, 15, 19, 21, 25, 27, 33, 42, 44, 46-48, 52, 56, 57, 59, 67, 70-72, 74, 76, 81, 86, 87, 89-91, 93, 96, 99, 101, 103, 109-111, 113, 116-120, 122, 125, 126, 132-139, 142-144	7, 8, 15, 19, 27-29, 33, 44, 45, 47, 52, 56, 57, 59, 67, 71, 74, 86, 89, 93, 96, 99, 101, 109-112, 117-119, 122, 135, 137, 138, 143, 144	7, 14, 28, 29, 45, 52, 56, 57, 74, 81, 87, 93, 99, 101, 105, 109, 112, 117, 119, 122, 138	21, 44, 45, 86, 105, 116, 143
Logistics	23, 88, 94, 128, 140	88, 94, 140	94	140

Fig. 4. Distribution of the empirical papers across the business functions and the PM perspectives.

strategic (2)[6]. We did not find any empirical papers with a purely strategic address.

- Healthcare is the most populated sector, with most papers within the Operations function. The papers regarding the other sectors are more uniformly distributed across the business functions.
- With only two exceptions (papers 10 and 69), the Infrastructure, Procurement, and Logistics papers present an operational focus.
- Energy & Materials was the least explored sector – only two papers.

4. Discussion

In line with the structure of Section 3, this section consists of three parts (4.1–4.3) which discuss the results and highlight the scientific gaps.

4.1. Insights from process mining type – process mining perspective

"*The idea of Process Mining is to discover, monitor and improve real processes*" (van der Aalst et al., 2012, p. 172), where "discover" presumably corresponds to the discovery type, "monitor" to the conformance type, and "improve" to the enhancement type. Nonetheless, according to our results, the three PM types have not been investigated to the same extent: "enhancement" is the least probed, "conformance" the second, while "discovery" has attracted the most interest. This is consistent with the priority that PM academics have assigned to process discovery over the other types during the last decade (van der Aalst, 2016). The evidence we found might be due to two reasons.

First, almost always, discovery enables the conformance and/or enhancement types. Indeed, the awareness of how business processes

[6] The work by Fleig et al. (2018) (paper 50) is one of the two tactical-strategic papers and pertains to the Marketing & Sales and Procurement functions.

	Energy & Materials	Industrials	Consumer Goods	Consumer Services	Healthcare	Utilities	Financial	Technology
Infrastructure	145	69, 124, 129	102, 130	114	123	60, 64	75	84, 141
HRM								
R&D								
Procurement		22, 63	22	22		5, 46	10*, 68, 83	
Service				11, 109*	109*	40	26, 73*, 80, 97	43, 85*
Mkg & Sales	67*		67*	18		67*		30
Operations	67*	29, 42, 76, 89, 113, 119	67*, 90, 143	86, 109*, 119, 126, 138, 142	8, 13*, 14, 21, 27, 33, 44, 52, 59, 74, 87, 91, 93*, 96, 99, 101, 103, 109*, 111, 112, 116, 117, 120, 125, 132*, 133-137	6, 7*, 15, 44, 46, 57, 67*, 71, 122, 139	19, 25, 28, 45, 47, 56, 81*, 105, 110	48, 70, 72, 103, 118, 144
Logistics		88, 94, 140	23, 128					

n: operational focus;
n: tactical focus;
n*: tactical-operational focus;
n*: strategic-tactical focus.

Fig. 5. Distribution of the empirical papers across the business sectors and functions.

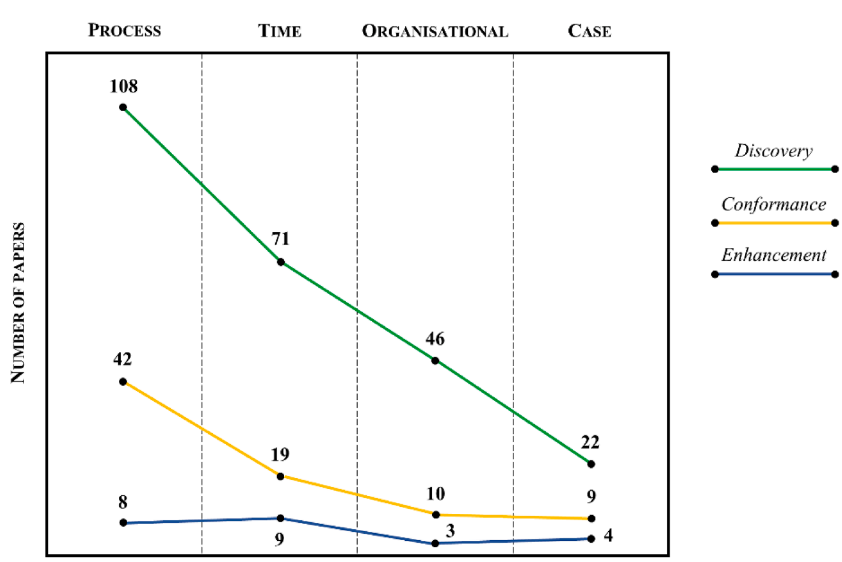

Fig. 6. Distribution of the papers across the Process Mining perspectives.

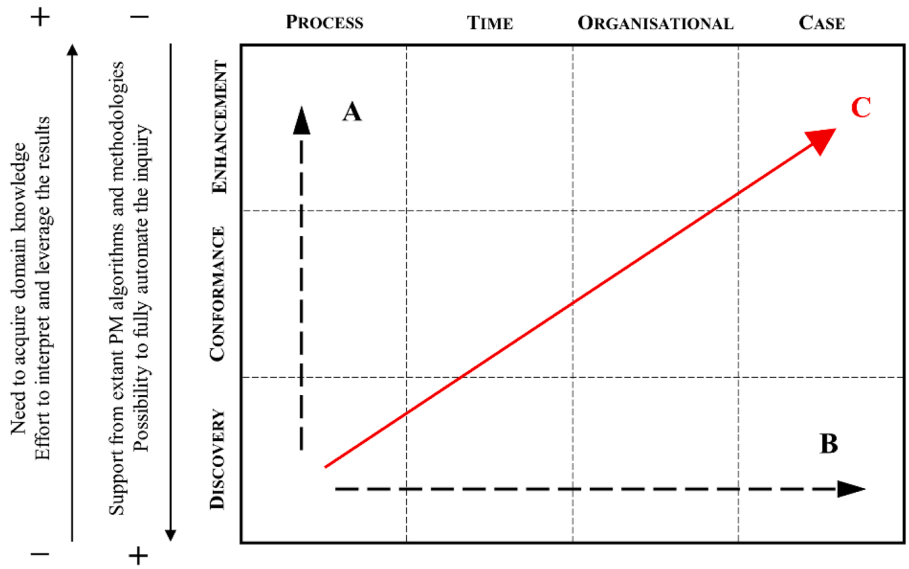

Fig. 7. Graphic summary of the PM types and perspectives in the Business Management-orientated literature.

are actually carried out provides reliable process models to check or to enhance.

Second, with respect to discovery (*cf.* De Weerdt et al., 2012) and conformance (Caron et al., 2013b; van der Aalst and De Medeiros, 2005), the enhancement type suffers from a shortage of specific methodologies, algorithms, and plug-ins because:

- It involves a greater number of decision variables, as its scope is potentially more extensive and includes resource allocation, business process and information flow redesign, scenario analysis, and others;
- It is not limited to diagnostic activities and tends to be strongly context-bound;
- It is not fully automatable, since computer science academics have favoured research related to discovery and conformance, which are more easily automatable.

Just like the PM types, not all the PM perspectives have been studied to the same extent. Fig. 6 shows the distribution of papers across the perspectives cross-referenced with the PM types: the green line corresponds to the discovery type, the yellow line to the conformance type, and the blue line to the enhancement type.

The process perspective included the highest number of papers. This may be due to the small number of data attributes it requires and to its capability to yield immediate results that are readily actionable from a managerial standpoint.

Time was the second most investigated perspective because, through a low incremental effort with respect to the process perspective, it enriches the control flow with time details extracted from additional and easy-to-find data (*i.e.* timestamp). The attainable evidence may enable improvements in the process efficiency and in the corresponding service time. For example, van der Aalst, Schonenberg and Song (2011) analysed the service time of a Dutch municipality in order to predict the completion time of the future process instances. Stefanini et al. (2018) estimated the service time in an emergency department by relying on the Fuzzy Miner algorithm applied to an event log retrieved from the hospital information systems.

The organisational and case perspectives were the least explored because they need more advanced data attributes, which are not always obtainable. Even when these attributes are available, they may be scattered across different tables, views, or even databases, and this makes it harder to create an adequate event log. Moreover, the completeness and reliability of such data may often be questionable. For example, from the organisational perspective, a process owner may be specified as the resource that apparently performs all the activities within a process instance, but with no indication as to which resource actually carried them out.

The organisational perspective has mostly been explored only after probing the process perspective (Caron et al., 2013a; Park et al., 2014; Roldán et al., 2018) and/or the time perspective (Alvarez et al., 2018; Hompes et al., 2017; Kouzari and Stamelos, 2018). In a few cases, it was the only perspective that was considered. For example, *e.g.* Ferreira and Alves (2012) leveraged PM to discover the social networks at different levels of abstraction within the emergency department of a mid-sized hospital.

The case perspective has not been analysed without considering at least one other perspective because it is a more fine-grained approach that builds on analyses conducted through a process, time, and/or organisational lens. For example, Jans et al. (2011a) leveraged all four perspectives to audit the procurement cycle in a multinational financial institution. Therefore, the case perspective was critical in detecting violations of company procedures and of the Segregation of Duties. Suriadi et al. (2017) extended the organisational perspective with the case perspective in order to analyse the prioritisation behaviour of human resources during operational activities, so as to detect the most frequent patterns and to evaluate their effect on the business processes.

Despite its potentially useful applications, the case perspective is the least explored, and the related managerial PM literature is still in its infancy. However, it is particularly promising for management academics because it goes to the deepest level of detail of a business process. In doing so, it enables the identification of the root causes of unexpected or non-compliant results within groups of cases.

Fig. 7 summarises the PM types and perspectives in the Business Management-orientated literature.

Moving along Arrow A, *i.e.* from discovery to enhancement, highlights that the support offered by specific PM algorithms and tools and the possibility to automate the PM activity decrease. At the same time, the need to acquire domain knowledge and the efforts required to interpret the results and make decisions drawing from them increase.

Moving along Arrow B, *i.e.* from the process and time perspectives to the organisational and case perspectives, provides insights that may be more interesting to management rather computer science, while the operational efforts to prepare and arrange the event log increase greatly. Nevertheless, the support from the PM algorithms does not decrease.

Arrow C merges the insights described by Arrows A and B and thus highlights where the state of the art of PM may fall short from a Business Management standpoint. PM should be more widely exploited for holistic managerial purposes. Furthermore, the impact that PM-enabled solutions may potentially exert on business processes needs further empirical investigation. This is corroborated by the limited number of empirical papers involving the organisational and case perspectives (Fig. 6).

We thus identified the following management-orientated gaps:

- There is a lack of contributions involving the organisational and/or case perspectives, particularly for the conformance and enhancement types (*first gap*).
- There is the need to further investigate the enhancement type (*second gap*).

4.2. Insights from business functions – process mining perspectives

This section discusses the results regarding the intersection between *Business function* and *Process Mining perspective* by starting from Porter's primary processes (Operations, Service, Marketing & Sales, Logistics) and proceeding with the secondary processes (Infrastructure, Procurement, R&D, HRM).

The Operations function was covered by the most papers. Operations processes were amongst the first to be thoroughly digitalised and they often yield event data that can be promptly used for multi-perspective PM applications. For instance, Alvarez et al. (2018) combined time and organisational perspectives to discover role interaction and collaboration models in the emergency department of a university hospital. Roldán et al., (2018) exploited process, time, and organisational perspectives to detect bottlenecks and inefficiencies in multi-robot missions, such as the use of an unmanned aerial vehicle fleet in an emergency context. There is an extensive corpus of PM papers in Operations and the need for further PM research from the case perspective is already underlined by the first gap we identified. Therefore, no additional gaps were formalised within the Operations scope.

Unexpectedly, the Service function has been much less investigated despite "Service" being a primary activity according to Porter (1985) which is strongly digitalised and which has become a high-margin business (Altekin et al., 2017) and a source of significant revenue streams (Durugbo, 2020). Nonetheless, the scientific literature presents some Service-focused empirical contributions. For example, Cho et al. (2017) evaluated the effect of best practices for redesigning business processes in the customer reservation change process of one of the largest travel agencies in Korea. Syamsiyah et al. (2017) analysed the form handling process within Xerox Services to compare different process variants and to deduce actionable insights regarding the most common process behaviours. However, there are some areas of the Service scope that may be characterised by a good, albeit overlooked, potential for PM-enabled improvements, *e.g.* after-sales activities. PM may be helpful in analysing and checking time performances, the roles involved, bottlenecks, and frauds in after-sales activities, such as warranty management, field technical assistance, and recalls, whose cost is constantly growing (Hu et al., 2017).

Therefore, we argue that there is a lack of papers aimed at clarifying PM capabilities and impacts in the Service function, especially in after-sales activities (*third gap*).

There are very few papers on Marketing & Sales. The most recent paper involving a PM application in Marketing & Sales dates back to 2009 (Măruşter and Van Beest, 2009)where the process and time perspectives were adopted for redesigning the booking process of a utility company. One reason for the little interest in Marketing & Sales may be the lack of suitable marketing event data due to the little support that workflow systems provide to this process. Marketing & Sales data have been analysed in a useful way using other data mining techniques (*e.g.* clustering, profiling, predictive modelling) that fit the objective of this process better than PM (Linoff and Berry, 2011). Moreover, the most recent marketing trends (*see* Kotler et al., 2017) do not make PM more attractive for marketing purposes. Nevertheless, PM might have potential in the sales sub-process. For example, the case perspective may enable analysis of the buyer process flow by comparing the experience of satisfied/unsatisfied customers or exploring the root causes of customer satisfaction/dissatisfaction from a sales process standpoint.

Hence, we contend that it is necessary to deepen the potential of PM in the sales process, particularly from a case perspective (*fourth gap*).

As with the Marketing & Sales function, there have been few papers on PM in relation to the Logistics function. Only four papers were found, and none of these involved the case perspective. amongst the few examples, Paszkiewicz (2013) applied conformance checking to check the compliance of a warehouse management system of a manufacturing company to the picking rules. Repta et al. (2018) analysed the event data from Radio-Frequency IDentification (RFID) readers, Global Positioning System (GPS) devices, transport vehicles, and contact sensors placed on the exit/entry ramp of a warehouse to reconstruct the process model depicting the dynamics of the monitored environment. Despite the very limited number of contributions, Logistics processes, *e.g.* transportation, warehousing, handling, value-added services, are highly suitable for PM applications. This is because they are characterised by sequential, repetitive, and traceable activities (Mangan and Lalwani, 2016), whose event data are generated by workflow systems, mobile devices, and advanced Internet of Things (IoT) sensors (Repta et al., 2018). Thus, logistics process inefficiencies, bottlenecks, deviations, and anomalies may be effectively dealt with by PM from different perspectives. For example, Wang et al., (2014b) relied on both process and time perspectives to propose a methodology to acquire logistics process intelligence. From an organisational perspective, Sutrisnowati et al. (2015) assessed the lateness probability in container handling by including the resources that move the goods.

However, to the best of our knowledge, there are no works that address any logistics activity from a case perspective. This may be a missed opportunity since Logistics can strongly benefit from this approach. For example, it may be valuable to track a single logistics instance to dynamically update the logistics activity in order to cope with any unexpected event, *e.g.* traffic jams or health and safety emergencies. Another example may consist in analysing the accuracy of the stocking of specific material classes.

Accordingly, we believe that further research on the benefits of PM application to the Logistics function is needed (*fifth gap*).

With eleven papers, Infrastructure was the most addressed secondary process. The Infrastructure process encompasses a wide range of subprocesses, but some of them (*e.g.* legal, public relations, strategic management) are difficult to support with workflow systems. Thus, only some Infrastructure activities, such as Accounting, Finance, Quality Assurance, Document Management and IT Management, may be eligible for PM. For example, De Weerdt et al., (2013b) leveraged PM in order to expose organisational inefficiencies in the back office process of a major Belgian insurance company. As regards Accounting, Gerhardt et al. (2018) applied PM to map a reimbursement process in a healthcare context and to detect bottlenecks. In the Quality Assurance field, Zerbino et al. (2018) developed and validated a PM-enabled methodology for conducting IS audits. In addition, PM showed its potential in supporting financial and compliance audits (*e.g.* Baader and Krcmar, 2018; Jans et al., 2013), although no PM papers dealing with performance auditing were found.

Nevertheless, scientific works regarding the Infrastructure process remain limited. The relevance of this shortage is tied to the rising interest in digital advancements in Infrastructure activities, for example in smart audits.[7] In particular, Blockchain has the potential for radically changing those infrastructure activities that need stricter information traceability, transparency, and security, *e.g.* accounting and finance

[7] For instance, see the 1/2020 European Court of Auditors press release, available at: https://www.eca.europa.eu/en/Pages/NewsItem.aspx?nid=13397

Table 3
Content analysis of the empirical papers with tactical and strategic objectives.

ID	Reference	Managerial Focus *T*	*T-O*	*S-T*	Business Function	Objective
7	Nakatumba and van der Aalst (2010)		X		Operations	To enable better work allocation decisions by figuring out the effect of workload on service time.
10	Jans et al., (2011a)		X		Procurement	To enable review or redesign of the internal controls for detecting and analysing issues concerning financial reporting.
13	Dunkl et al. (2011)			X	Operations	To evaluate the compliance of empirical healthcare treatment processes to the guideline-based treatment; to provide input to the maintenance and evolution of the guidelines and to the health resource allocation.
14	Ferreira and Alves (2012)	X			Operations	To identify the clusters of best-performing health practitioners in the Hospital Emergency Service.
15	Buijs et al. (2012)	X			Operations	To compare PM-extracted models of processes shared amongst different organisations for suggesting improvements.
50	Fleig et al. (2018)			X	Operations	To design a PM-enabled Decision Support System to standardise the business processes in an ERP implementation project.
67	Măruşter and Van Beest (2009)		X		Mkg & Sales, Operations	To develop a methodology for comparing the simulation of an as-is business process to the simulation of a re-designed version of the same process; to compare the performance of the two simulations.
69	Li et al. (2011)	X			Infrastructure	To analyse and re-design the knowledge maintenance process.
73	Liu et al. (2012)		X		Service	To develop and validate a Business Process simulation methodology for supporting tactical and operational decision making.
81	Caron et al., (2013a)		X		Operations	To empirically investigate the applicability of PM to a standardised Enterprise Risk Management framework.
85	Wang et al., (2014a)			X	Service	To develop an analytical framework for the automated detection of helpful/unhelpful threads, constructive/destructive users, and functional/dysfunctional communities in an online Questions & Answers context.
86	Sedrakyan et al. (2014)	X			Operations	To analyse the modelling behaviour of novices for detecting worse/better learning performances and for improving the learning outcomes.
93	Fernandez-Llatas et al. (2015)		X		Operations	To monitor the health staff behaviour by means of Indoor Location Systems to assess the compliance to the clinical guidelines.
103	Xu et al. (2017)	X			Operations	To design a framework of a cloud-supported m-Health monitoring system to support personalised treatment planning.
109	Cho et al. (2017)		X		Service, Operations	To propose and validate a framework to assess re-engineered business processes in terms of performance and compliance to best practices.
112	Alvarez et al. (2018)	X			Operations	To discover organisational team patterns in Emergency Rooms (ER) for enabling improvements in the ER processes.
113	Janssenswillen et al. (2018)	X			Operations	To present a technique for exploring train re-routings for supporting capacity planning decisions.
116	Najjar et al. (2018)	X			Operations	To design, build, and cluster treatment patient pathways extracted from hospital administrative databases.
137	Benevento et al., (2019a)		X		Operations	To develop new PM-enabled, queue-based predictors that capture the current state of the Emergency Department to improve accuracy of waiting time prediction.

T: tactical.
T-O: tactical-operational.
S-T: strategic-tactical.

(Coyne and McMickle, 2017; Kokina et al., 2017), document management (Ølnes and Jansen, 2017; Pollock, 2019), Quality Assurance (Montecchi et al., 2019). However, the application of PM to Blockchain is still in its infancy (Di Ciccio, 2020; Klinkmüller et al., 2019).

Thus, we call for additional research efforts regarding the applicability of PM to the Infrastructure process in the light of the most recent digitalisation trends (*sixth gap*).

The Procurement process includes eight PM papers, with two main objectives. The first is the detection of issues, such as fraud and workarounds (Jans et al., 2011b, 2014; Outmazgin and Soffer, 2013; Reijers et al., 2007). For example, Jans et al. (2014) detected violations of internal controls in the procurement process of a leading European bank. The second is business process analysis and improvement (Dees et al., 2017; Fleig et al., 2018; Ingvaldsen and Gulla, 2006). In particular, Fleig et al. (2018) streamlined and standardised the IS-supported procurement process of three manufacturing companies by means of a PM-enabled Decision Support System.

Various macro-trends are currently re-shaping the Procurement process, *e.g.* the pervasiveness of new digital capabilities and an increased awareness as to what purchasing data can be collected and how they may be exploited (Gartner, 2019). Purchasing and Supply Chain activities increasingly require higher transparency and traceability (Kshetri, 2018), and cybersecurity (Ivanov et al., 2019). This has led to adopting advanced technologies for coping with these requirements, such as RFID and IoT sensors (Bienhaus and Haddud, 2018), and Blockchaining (Centobelli et al., 2021; Chang et al., 2019; Kopyto et al., 2020), which are likely to increase the event data volume and granularity across the Supply Chain. Hence, given the growing availability of event data, PM in Procurement may very well assume a more prominent role in the near future.

Thus, we stress the lack of research concerning PM applicability and usefulness in the Procurement process, particularly in those Supply Chains supported by the most recent digital technology paradigms (*seventh gap*).

R&D is one of the processes that has empirically been overlooked by PM academics. A possible cause is associated with the current kind of digital support required by R&D activities. R&D is typically supported by tools for Project Management and, more importantly, for requirement and specification management. These tools are person-to-person (P2P) tools, *i.e.* supporting processes that are mostly manual and/or human-driven. Therefore, given the strong human presence, it is difficult for P2P tools to generate an event log suitable for PM. Such a log is more easily yielded by person-to-application (P2A) tools, such as workflow management systems, which involve both human and automized interventions and interactions (van der Aalst, 2009). Thus, since P2A tools do not usually support R&D activities, it may be difficult to apply PM in the R&D process. Moreover, most information attainable from PM, *e.g.* time and scheduling performances or resource allocation, is already provided by Project Management software. However, the literature has not clarified how PM may be more useful than the extant R&D tools in analysing and improving the R&D process.

As a result, further research may be necessary to investigate the usefulness of PM in the R&D process and to evaluate whether it is worthwhile integrating PM concepts into the existing Project Management tools (*eighth gap*).

Although there are some PM studies that have taken into consideration human resources in different business processes, the HRM process has not been specifically investigated by any empirical work. HRM encompasses a wide set of activities, which are partly P2P and partly P2A. P2P activities, such as job interviews, are not supported effectively by workflow systems (van der Aalst, 2009). P2A activities, *e.g.* payroll management, time and attendance management, are strongly supported by Human Resource Information Systems. However, these systems provide information akin to that yielded by PM, such as scheduling and time performance or resource analysis, and with a higher level of detail (Noe et al., 2015). Therefore, the potential for applying PM in HRM may be limited, but the literature appears not to shed light on this issue.

Accordingly, we underline the lack of exploratory contributions that assess the usefulness of PM within HRM (*ninth gap*).

4.3. Insights from business function – business sector – managerial focus

Event data are mostly provided by workflow systems, which are operational in nature. Thus, the managerial focus most effectively dealt with by PM is operational. However, PM might also be employed in pursuing tactical and/or strategic objectives (van der Aalst, 2016). Table 3 gives an overview of the major research efforts attempting to attain such high-level objectives.

Table 3 confirms the enabling role of PM in attaining tactical and/or strategic objectives. However, there have been no comprehensive implementations and evaluations of the proposed medium- and/or long-term issues. Therefore, the usefulness and effectiveness of PM in supporting the effective achievement of such goals have not been documented.

Thus, we emphasise the need for research that can empirically investigate the applicability, value, and effectiveness of PM in tactical and/or strategic decision making (*tenth gap*).

As regards business sectors, the distribution of PM papers in Fig. 5 suggests that Healthcare is the most explored. This evidence may not be surprising because the keyword network in Fig. 2 already showed that healthcare-related keywords (*e.g.,* emergency management, clinical pathways) were amongst the most frequent. The interest in Healthcare is confirmed also by the existence of reviews on the application of PM in this sector (*e.g.* Rojas et al., 2016; Ghasemi and Amyot, 2016). This may be due to three reasons. First, healthcare processes are particularly suitable for any PM application because this sector includes numerous activities that are heterogeneous, and specific to each customer/patient (Mans et al., 2015; Rebuge and Ferreira, 2012). Second, healthcare processes are strongly supported by workflow systems in order to comply with legal requirements (van der Aalst, 2016). Third, the healthcare sector is of paramount concern for economic and social reasons (OECD, 2019).

Two other relatively well-explored sectors are Financial and Utilities. PM has been widely exploited in the Financial sector given that the regulatory requirements mean that financial processes yield high volumes of event data. These data are used in PM applications, such as financial and compliance auditing (Accorsi and Stocker, 2012; Jans et al., 2014, 2011a, 2011b; Samo et al., 2015).

On the contrary, the Utilities sector has received little interest because most Utilities-focused contributions rely on Dutch municipality data made publicly available by the Business Process Intelligence Challenge (*e.g.* Bozkaya et al., 2009; Buijs et al., 2012; Hompes et al., 2017).

As reported in Fig. 5, several PM applications have been developed across the other sectors in a quite equally balanced way, with the exception of Energy & Materials. Despite this, sector-specific PM-enabled research has mostly been done in the Healthcare sector (Forsberg et al., 2016; Kovalchuk et al., 2018; Stefanini et al., 2018) and Financial sector (Jans et al., 2014; Jans, van der Werf, et al., 2011; Suriadi et al., 2013), while it remains limited in the others.

Most empirical PM research exploits data related to one or more sectors only for validating general PM-enabled methodologies. This is tied to the need to generalise the presented approaches, but it has rarely led to sector-specific, PM-enabled suggestions. This evidence may be due to a prevalent focus on proposing PM-orientated advancements, rather than identifying and dealing with sectorial managerial issues. Indeed, there are several sector-specific problems where PM can be particularly useful, but which the PM literature has overlooked.

Below, we present a number of non-exhaustive examples of such opportunities within the Sectors defined in Table A1. Some of the examples may be developed in different sectors because they are linked to cross-sectoral issues.

- *Energy & Materials*: to highlight the network of decentralised electricity sources and loads and its operations flow by exploiting the event data from the network control unit for analysis and monitoring purposes; to evaluate if the activities of a vehicle fleet for Precision Farming, extracted from an event log generated by field sensors, GPS sensors, and unmanned vehicle systems, comply with the agricultural production requirements.
- *Industrials*: to monitor operations and settings of the industrial machinery in production lines for PM-enabled predictive maintenance purposes (*e.g.* Ruschel et al., 2020); to identify and evaluate logistics best practices that may be shared in multimodal/intermodal transportation networks.
- *Consumer Goods*: to leverage geo-localised data to extract the shipment flows across distribution networks for predicting potential delays and vector/warehouse capacity overloads; to support monitoring and comparison of automated systems in warehousing (see Robotic Process Automation, *e.g.* Geyer-Klingeberg et al., 2018).
- *Consumer Services*: to trace athlete behavioural patterns in team sports for assessing individual and team performances (*e.g.* Kröckel and Bodendorf, 2020); to identify retail customer pathways for improving store layout and overall customer satisfaction based on sensor data (*e.g.* indoor location system sensor, see Dogan et al., 2020).
- *Healthcare*: to improve coordination in conjoint care treatments by combining healthcare process data from different health organisations; to track long-term patients' behaviours from sensor data for conceiving personalised health plans.
- *Utilities*: to check the compliance of bureaucratic processes concerning the provision of public and utilities-related services with normative and enforced-by-law requirements.
- *Financial*: to track the consensus instances in a blockchain network for detecting anomalous patterns in the transaction validation process; to discover customer behavioural patterns in the insurance sector for supporting the development of tailored insurance policies by exploiting the event log extracted from black boxes.
- *Technology*: to enhance the understanding of project team dynamics in the software development process by mining the PM-enabled social network parameters, *e.g.* in conjoint software development environments.

Hence, we suggest that it is necessary to harness the potential of PM to conduct more sector-specific research orientated towards practical managerial issues (*eleventh gap*).

5. Conclusions

PM has mainly been developed, honed, and applied by computer scientists, who have transformed it into one of the most powerful families of techniques to bridge the gap between Data Science and Process Science. To better address the managerial challenges and to extract more value from the application of PM in Business Management, PM has required the active involvement of Management academics, in line with the interdisciplinary nature of PM.

Although the literature on exploiting PM in Business Management is not as mature as that of Computer Science, it has greatly increased over the last five years. However, there is still a need to obtain a thorough understanding of the business contexts and functions in which PM is applied and in which managerial areas and purposes PM can be useful. Moreover, the current scientific literature does not present an up-to-date research agenda specifying the directions the application of PM can take in Business Management.

We thus posed the following RQs: "*Which are the most used PM types, perspectives, and algorithms in the Business Management field?*" (RQ1); and "*In which business sectors, business functions, and decision-making levels has PM been mostly exploited?*" (RQ2). Accordingly, we carried out a

Table 4
The proposed research agenda.

Scope	Research Gaps (RGs)	Research Questions
Process Mining Types	**RG1**. Lack of contributions involving the organisational and/or case perspectives, particularly for the conformance and enhancement type.	*How may PM assist in monitoring the performance of single/groups of resources and in detecting significant performance variations when specific sequences of activities or combination of events occur?* *How may PM enable the discovery of the information sharing networks (e.g. exchange of e-mails, business chats for smart working) by a Social Network Analysis approach?* *How may PM support the dynamic comparison of a single case/instance process flow to acknowledged process patterns for preventing the occurrence of non-conformances? How may this comparison lead to formal updates of the corresponding de-jure models?*
	RG2. Need to further investigate the enhancement type.	*How may PM be integrated into a simulation system to assess the expected effects that exogenous or endogenous factors may yield on process performances?* *How to perform a process enhancement activity by structured methodological approaches? Is it feasible to devise a general, context-independent, PM-based methodology for such a purpose? Which may be the benefits?*
Process Mining in business functions	**RG3**. Lack of papers aiming at clarifying PM capabilities and impacts in the Service function, especially in the after-sales activities.	*How may PM be applied to devise and manage a product recall?* *How to embed PM within a fraud detection management system in after-sales activities? And which are the achievable benefits?* *How may PM help real-time or near-real-time online after-sales support in multi-channel Customer Relationship Management (e.g. social media, chat)?*
	RG4. To deepen the potential of PM in the Sales process, particularly from a case perspective.	*What are the advantages and the impacts of integrating the customer satisfaction analysis, based on external data, with the PM application to the on-line Sales process? How may it be realised across the different Sales sub-phases (e.g. negotiation, information)?* *How may the case perspective help in identifying patterns, involved resources, inefficiencies and deadlocks within the Sales process instances that involved a complaint?* *May PM be applied to develop a real-time monitoring of the Sales process instances to prevent claims or delays in managing the customers' requests?*
	RG5. Further research on the benefits of PM application to the Logistics function is needed.	*How may PM be applied in logistics network nodes to support operational, tactical, and/or strategic coordination of a logistics network in different settings (e.g. centralised vs. decentralised; single mode vs. multimodal/intermodal)?* *How may PM be practically employed to improve the real-time management of warehousing activities, such as analysis of picking & stocking patterns by IoT, GPS, and wearable sensors?*
	RG6. Additional research efforts on the applicability of PM to the Infrastructure process are needed in light of the most recent digitalisation trends.	*How may PM be framed as a Computer-Aided Audit Tool and Technique (CAATT) for collecting and analysing performance audit evidence?* *How may PM support the analysis of actual usage and the re-engineering of blockchain-based decentralised applications for Infrastructure activities, such as Accounting, Finance, Document Management, and Quality Assurance?*
	RG7. Lack of research concerning PM applicability and usefulness in the Procurement process, particularly in those Supply Chains supported by the most recent digital technology paradigms.	*How may PM contribute to monitoring and enhancing the procurement activities enabled by advanced digital technologies (e.g. IoT, RFID)?* *May PM be exploited across the different Procurement activities and, more in general, in Supply Chain Management?*
	RG8. Further research may be necessary to investigate the usefulness of PM in the R&D process and to evaluate whether it is worthwhile to integrate the PM concepts into the existing Project Management tools.	*Which may be the additional value of integrating PM within R&D-orientated digital tools for requirements' management (e.g. advanced Project Management software)?*
	RG9. Lack of exploratory contributions that assess the PM usefulness within the HRM scope.	*Which may be the role and the benefits of applying PM to the Person-to-Application HRM activities (e.g. payroll management, time and attendance management, on-line training) with respect to the support provided by the extant Human Resource Information Systems?*
Managerial focus	**RG10**. Need for research that may empirically deepen applicability, value, and effectiveness of PM in tactical and/or strategic decision making.	*How may PM enable the analysis and management of collaborative processes and networks within a corporate group (e.g. a centralised logistics/supply network) and/or within a multi-actor ecosystem (e.g. a closed-loop supply chain for Circular Economy).*
Process Mining in business sectors	**RG11**. To harness the PM potential to conduct more sector-specific research orientated towards practical managerial issues.	*How to exploit the event data stream collected from different sources (e.g. sensors and unmanned vehicle systems) to improve the precision farming operations?* *Which information inputs may PM yield and provide for predictive maintenance purposes?* *How may PM be applied to the optimisation of the smart contract management in a Blockchain network?* *To which extent PM may support Robotic Process Automation initiatives, such as monitoring and benchmarking of automated warehousing systems?* *How may PM help in improving the conjoint care treatments provided by multiple health organisations?*

systematic literature review in which we analysed 145 selected papers pertaining to the exploitation of PM for Business Management purposes.

As regards RQ1, the most adopted PM type is discovery, followed by conformance and enhancement. The most adopted PM perspectives are, in descending order, process, time, organisational and case, while the most used algorithm is Fuzzy Miner. This highlights that most PM potential in Business Management still remains untapped. Indeed, a significant number of PM applications are limited to a process discovery activity by easy-to-use, Fuzzy-Miner-based PM tools. While this may be highly instructive for business process analysts, it is merely the prelude to more in-depth insights obtainable through other PM types, perspectives, and algorithms.

With respect to RQ2, PM has been applied mostly in the Operations function of the Healthcare sector for supporting operational decision making. While other sectors and business functions have been investigated, the current PM application overview leaves ample margin for exploration in several other contexts for purposes that should also be linked to tactical and strategic decision making.

Based on a thorough analysis of these findings, we singled out eleven research gaps. Table 4 arranges these gaps in the four categories of Process Mining types, Process Mining in business functions, Managerial focus and Process Mining in business sectors, so as to draw up the research agenda we propose. The research agenda includes a non-exhaustive set of potential research questions that may directly deal with the gaps identified.

We believe that this review extends the scope of previous PM reviews (*e.g.* Ghasemi and Amyot, 2016; Rojas et al., 2016; Thiede et al., 2018; Williams et al., 2018) through Business Management-related theoretical dimensions, such as business function, managerial focus, and a complete spectrum of business sectors. Furthermore, it recommends novel directions for the application of PM that diverge from the proposals advanced by the current scientific literature and which address the use of PM for little-explored managerial objectives. The resulting research agenda suggests a wide range of unprecedented avenues for further research.

However, this work is not free from limitations. First, the review includes the four major conferences whose scope encompasses PM and BPM, but other well-known conferences were not considered. The main reason was to examine selected conferences of high repute, but putting more emphasis on journal papers. However, this limitation was mitigated by reference crosschecking, which extended the review to twenty additional prominent papers indexed in other conference proceedings. Second, some of the most renowned Business Management conferences, such as the Academy of Management's Annual Meeting or the EurOMA Annual Conference, are not indexed and are unavailable online. Hence, despite their suitability for our research purposes, we were not able to review their proceedings.

Future works could expand this review by adopting additional managerial dimensions or by focusing on specific business functions or sectors in order to provide further specialised insights in terms of research gaps and questions.

CRediT authorship contribution statement

Pierluigi Zerbino: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Writing – original draft, Writing – review & editing. **Alessandro Stefanini:** Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Writing – original draft, Writing – review & editing. **Davide Aloini:** Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Writing – original draft, Writing – review & editing.

Acknowledgements

We deeply thank Prof. Dr. Jan Mendling from the WU Vienna University of Economics and Business for his valuable comments on an early version of this manuscript.

Appendix A

Table. A 1

Table A1
The industry sectors considered in the review.

Sector	Detail
Energy & Materials	Oil & gas; alternative/renewable energy; energy equipment & services; chemicals; mining; paper & forest products; container & packaging; farming; others.
Industrials	Aerospace & defence; electronic & electrical equipment; construction & engineering; transportation; industrial services; others.
Consumer goods	Food; automobiles & parts; personal products; textiles and luxury goods; household goods; leisure goods; electronic goods; others.
Consumers services	Media; leisure; retail; personal; education; others.
Healthcare	Healthcare providers and services; biotechnology; medical & pharmaceutical research; others.
Utilities	Natural gas; water; telecommunications; electricity; others.
Financial	Banking; insurance; real estate investments; funds and trusts; others.
Technology	Software and services; hardware; information technology equipment; semiconductors equipment, others.

Appendix B

Table. B 1, Table. B 2, Table. B 3

Table B1
Inclusion and exclusion criteria.

Criterion	Detail	Justification
Source type	Only Journals papers and selected Conference papers	Webster and Watson (2002, p. 16) recommend to "*examine selected conference proceedings, especially those with a reputation for quality*". We asked two senior researchers – one from the Computer Science field and one from the Business Management field – to foster the identification of those relevant conferences whose scope encompasses PM. Thus, four conferences were singled out: *Lecture notes in Computer Science; Lecture Notes in Business Information Processing; CEUR Workshop Proceedings; ACM International Conference Proceedings Series.*
Language	English	–
Time window	2002 – 2019	The first PM paper was published in 2002
Subject areas	*Scopus*: Computer Science; Engineering; Mathematics; Decision Sciences; Business, Management and Accounting; *ISI WoS*: all the Computer Science, Engineering, and Mathematics categories; Operations Research Management Science; Business; Management;	The selected areas fit the topics covered by PM

Table B2
Criteria for assessing the quality of the papers.

Criterion	Absence (0)	Low (1)	Medium (2)	High (3)
Theory robustness	The article does not provide enough information to assess this criterion, or this criterion is completely disregarded;	Poor awareness of existing literature and debates; under- or over-referenced; low validity of theory;	Basic understanding of the issues around the topic being discussed; the theory is weakly related to data;	Deep and broad knowledge of relevant literature and theory relevant for addressing the research; good relation theory-data;
Methodological reproducibility	The article does not provide enough information to assess this criterion, or this criterion is completely disregarded;	The research design is flawed; data, if needed, are inaccurate; the methodology is not easily reproducible;	The research design may be improved; data, if needed, fit the research objective (s); the methodology allows for partial reproducibility only;	The research design is globally sound; data, if needed, are extensive and well-structured; the reproducibility of the methodology is complete;
Scientific contribution	The article does not provide enough information to assess this criterion, or this criterion is completely disregarded;	The scientific contributions are limited and low-relevant;	The scientific contributions are appreciable and refine existing concepts by incrementally filling one or more research gaps;	The scientific contributions propose radical advancements providing unprecedented perspectives;
Managerial implications	The article does not provide enough information to assess this criterion, or this criterion is completely disregarded;	The implications are very difficult to develop practically and/or are not relevant from a managerial standpoint;	The implications may be applied providing moderate managerial benefits;	The implications can be put in practice leading to significant managerial benefits;
Generalisability	The article does not provide enough information to assess this criterion, or this criterion is completely disregarded;	The outcomes could be generalised only to the context which the research was developed in;	The outcomes could be generalised to context similar to the one(s) considered in the research;	The outcomes can be generalised to a wide set of contexts;

Table B3
Rules for assessing the papers according to the quality criteria.

Rule code	Description	Justification
Rule 1	*Scientific contribution, Methodological reproducibility*, and *Managerial implications* ≥ 2	Selection of papers that present strong contributions through a sound methodology
Rule 2	*Generalisability* and *Theory robustness* ≥ 1	Several relevant PM articles concern very-specific contexts; PM literature is so fragmented that related acknowledged theories do not exist;
Rule 3	Total evaluation ≥ 10	To guarantee that the overall quality of the selected papers is medium on average (*cf.* Table B2)

Appendix C

Table. C 1

Table C1
Coding of the selected papers.

#	Reference	#	Reference	#	Reference
1	van der Aalst and Song (2004)	50	Fleig et al. (2018)	99	Senderovich et al. (2016)
2	Ly et al. (2005)	51	Yang et al., (2018a)	100	Schönig et al. (2016)
3	Günther et al. (2006)	52	Mans et al. (2008)	101	Forsberg et al. (2016)
4	van der Aalst et al. (2006)	53	van der Aalst and De Medeiros (2005)	102	Ruschel et al. (2017)
5	Reijers et al. (2007)	54	Song and van der Aalst (2007)	103	Xu et al. (2017)
6	Bezerra et al. (2009)	55	De Leoni and van der Aalst (2013)	104	Zhu et al. (2017)
7	Nakatumba and van der Aalst (2010)	56	Accorsi and Stocker (2012)	105	Suriadi et al. (2017)
8	Poelmans et al. (2010)	57	Bozkaya et al. (2009)	106	Wynn et al. (2017)
9	van der Aalst et al. (2010)	58	Weijters and van der Aalst (2003)	107	Martin et al. (2017)
10	Jans et al., (2011a)	59	Cho et al. (2019)	108	Márquez-Chamorro et al. (2017)
11	Bose et al. (2011)	60	van der Aalst et al. (2005)	109	Cho et al. (2017)
12	Maggi et al. (2011)	61	van der Aalst (2005)	110	Wang et al. (2018)
13	Dunkl et al. (2011)	62	Yang and Hwang (2006)	111	Stefanini et al. (2018)
14	Ferreira and Alves (2012)	63	Ingvaldsen and Gulla (2006)	112	Alvarez et al. (2018)
15	Buijs et al. (2012)	64	van der Aalst et al. (2007)	113	Janssenswillen et al. (2018)
16	Taylor et al. (2012)	65	Rozinat and van der Aalst (2008)	114	de Alvarenga et al. (2018)
17	Ramezani et al. (2012)	66	Rozinat et al. (2009)	115	Alizadeh et al. (2018)
18	Poggi et al. (2013)	67	Măruşter and Van Beest (2009)	116	Najjar et al. (2018)
19	Suriadi et al. (2013)	68	Jans et al., (2011b)	117	Kovalchuk et al. (2018)
20	Ramezani Taghiabadi et al. (2013)	69	Li et al. (2011)	118	Gupta et al. (2018)
21	De Weerdt et al., (2013a)	70	Da Cruz and Ruiz (2011)	119	Kouzari and Stamelos (2018)
22	Outmazgin and Soffer (2013)	71	van der Aalst et al. (2011)	120	Durojaiye et al. (2018)
23	Paszkiewicz (2013)	72	Samalikova et al. (2011)	121	Delias et al. (2018)
24	Pravilovic et al. (2014)	73	Liu et al. (2012)	122	Roldán et al., (2018)
25	Vanden Broucke et al. (2014)	74	Rebuge and Ferreira (2012)	123	Gerhardt et al. (2018)
26	Senderovich et al. (2014)	75	De Weerdt et al., (2013b)	124	Myers et al. (2018)
27	Maggi et al. (2014)	76	Lee et al. (2013)	125	Yang et al., (2018b)
28	Pika et al. (2014)	77	Caron et al., (2013b)	126	Conijn et al. (2018)
29	Park et al. (2015)	78	Zeng et al. (2013)	127	Lenkowicz et al. (2018)
30	Slaninová et al. (2015)	79	Jans et al. (2013)	128	Repta et al. (2018)
31	Sztyler et al. (2015)	80	Mahmood and Shaikh (2013)	129	Zerbino et al. (2018)

(continued on next page)

Table C1 (*continued*)

32	Kumar et al., (2015)	81	Caron et al. (2013a)	130	Baader and Krcmar (2018)
33	Pini et al. (2015)	82	Fernández-Llatas et al. (2013)	131	Ito et al. (2018)
34	Schönig et al. (2015)	83	Jans et al. (2014)	132	Benevento et al. (2019b)
35	Bala et al. (2015)	84	Samalikova et al. (2014)	133	Rojas and Capurro (2019)
36	Arias et al. (2016)	85	Wang et al., (2014a)	134	Rojas et al. (2019)
37	Nguyen et al. (2016)	86	Sedrakyan et al. (2014)	135	Antunes et al. (2019)
38	Verenich et al. (2017)	87	Caron et al. (2014)	136	Marazza et al. (2019)
39	Seeliger et al., (2017)	88	Wang et al., (2014b)	137	Benevento et al., (2019a)
40	Fani Sani et al. (2017)	89	Park et al. (2014)	138	Özdağoğlu et al. (2019)
41	Solti et al. (2017)	90	Lee et al. (2014)	139	Sonnenberg and Bannert (2019)
42	Lee et al. (2017)	91	Rovani et al. (2015)	140	Knoll et al. (2019)
43	Syamsiyah et al. (2017)	92	Suriadi et al. (2015)	141	Bernardi et al. (2019)
44	Hompes et al. (2017)	93	Fernandez-Llatas et al. (2015)	142	Juhaňák et al. (2019)
45	Hompes et al. (2017)	94	Sutrisnowati et al. (2015)	143	Dogan et al. (2019)
46	Dees et al. (2017)	95	Senderovich et al. (2015)	144	Li and De Carvalho (2019)
47	Lehto et al. (2018)	96	Partington et al. (2015)	145	He et al. (2019)
48	Ioannou et al. (2018)	97	Samo et al. (2015)		
49	Cabanillas et al. (2018)	98	Ferreira and Vasilyev (2015)		

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