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Review

Artificial Intelligence-Based Methods for Business Processes: A Systematic Literature Review

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Citation: Gomes, P.; Verçosa, L.; Melo, F.; Silva, V.; Filho, C.B.; Bezerra, B. Artificial Intelligence-Based Methods for Business Processes: A Systematic Literature Review. *Appl. Sci.* **2022**, *12*, 2314. https://doi.org/10.3390/app12052314

Academic Editor: Vincent A. Cicirello

Received: 5 January 2022
Accepted: 17 February 2022
Published: 23 February 2022

Abstract: Companies are usually overloaded with data that they may not know how to take advantage of. On the other hand, artificial intelligence (AI) techniques are known to "keep learning" as the data increase. In this context, our research question emerges: what AI-based methods, in the literature, could be used to automatize business processes and support the decision-making processes of companies? To fill this gap, in this paper, we performed a review of the literature to identify these techniques. We ensured the usage of methods since they allowed reproducibility and extensions. We applied our search string in the Scopus and Web of Science databases and discovered 21 relevant papers pertaining to our question. In these papers, we identified methods that automated tasks and helped analysts make assertive decisions when designing, extending, or reengineering business processes. The authors applied diverse AI techniques, such as K-means, Bayesian networks, and swarm intelligence. Our analysis provides statistics about the techniques and problems being tackled and point to possible future directions.

Keywords: artificial intelligence; method; business process; AI-based methods; systematic review

1. Introduction

Business process management (BPM) is a discipline that involves concepts, methods, and techniques, to design, enact, measure, and configure business processes [1]. Adam Smith, Frederick Taylor, and Henry Ford were essential precursors of today's configuration of BPM, by respectively showing the advantages of the division of labor, science management, and production lines in the industry.

The beginning of the computational era, around 1950, marked another profound impact in BPM. It changed company structures, since they began to rely on information systems. It became imperative to model cross-organizational processes that could document procedures and generate insights [2].

In recent decades, we–the world–has become a digital society; data are collected everywhere. Data come from mobile phones, personal computers, and smart home appliances. As data are "constantly growing", organizations face challenges surrounding the exploration of such data, in regard to adding value to their operations [3]. Business Intelligence (BI) tools and process-aware information systems (PAISs) may help to extract knowledge from data via computer tools and decision-makers. However, these tools may be limited when dealing with large volumes of data, since the output has to be analyzed further by specialists in an environment where time is critical.

Artificial intelligence (AI) is used in learning algorithms, i.e., to make decisions in milliseconds within a "Big Data" context. AI machine learning and deep learning subfields, for instance, have shown great success in complex tasks, such as natural language processing, speech recognition, computer vision, medical diagnosis, recommendation systems, and many others [4]. It has been successfully applied in several disciplines, including biology, experimental psychology, communication theory, game theory, mathematics, statistics, logic, and philosophy [5]. Swarm intelligence is another AI branch primarily employed for optimization tasks. This field contains diverse bio-inspired metaheuristics capable of finding relevant solutions in high-dimensional search spaces. Swarm intelligence algorithms have good results in a wide range of tasks, including telecommunications, industries, social sciences, and military operations [6]. AI techniques have changed the corporate world by providing quicker and less error-prone techniques.

Business processes (BPs) are becoming increasingly powerful, with the incorporation of techniques from the digital era. Due to these changes, organizations can concentrate on decision-making and business strategies other than manual and repetitive operations. This new context also leads to more mature and predictable processes, highly scalable operations, and an overall improvement in an organization's performance [7].

Artificial intelligence is critical because of the complexities of the changes required to integrate a new organization into a larger one [8]. Investors and business leaders are unanimous in their belief that AI and machine learning are transforming their organizations, by lowering costs, streamlining operations, managing risks, accelerating growth, and boosting innovation [9]. However, when a business problem or opportunity is identified as having the potential to be transformed and optimized by AI, it is not always clear on how to execute and develop the solution. Here, we consider optimization from a business perspective. Therefore, we are interested in improvements in a company's business processes that directly leads to better decision processes, to achieve the company's goals. For example, we can cite AI solutions that automatize manual and time-consuming procedures, provide insights to decision-makers, or align process goals with a company's business goals. Thus, the question from this paper emerges: what AI-based methods, in the literature, are used to automatize business processes and support the decision-making processes of companies? This paper answers this question through a systematic literature review (SLR). It is important to note that (i) we did not include multiple academic databases in our search, and (ii) we excluded AI usage that was not associated with a method, for example, an approach focused solely on improving a model. Instead, our selected approaches used AI as part of a method composed of multiple steps to reach a specific goal. The remainder of this paper is organized as follows. Section 2 presents the related studies, the background concepts, and context for this paper. In Section 3, we describe the search and selection criteria used to identify the relevant studies. Section 4 presents the profiles of the identified papers and the classification of the AI-based methods. Finally, Section 5 presents the discussion and Section 6 the conclusion, limitations, and future work.

2. Background

This section presents related works as well as fundamental concepts for the understanding of this SLR.

2.1. Related Work

Garcia et al. [10] performed a systematic mapping of process mining techniques and their applications in different industry segments. They included 1278 reviewed articles from 2002 to 2018 and identified process discovery, conformance checking, and architecture and tool improvement as the most active topics in the field. Healthcare, ICT, and manufacturing were the most recurring fields of application. Similarly, Maita et al. [11] conducted systematic mapping to assess the process mining field. They analyzed 705 papers from 2005 to 2014 by identifying types of process mining and data mining tasks and techniques used in the literature. In 38% of the analyzed papers, they observed that graph structure-based techniques were applied, 9% used evolutionary computing, and 6% decision trees. The authors concluded that little relevance was given to computational intelligence and machine learning techniques in the field of process mining. Regarding the types of process mining, the authors observed that the most performed tasks were process discovery, business process conformance, and business process enhancement, in that order. The two previously mentioned papers mapped the (then) current works in the process mining field by identifying relevant statistics, such as recurring topics and areas of application. In contrast, our work is an SLR that focused on the application of AI methods in the business process field. Taymouri et al. [12] conducted a systematic literature review on the methods used for process variant analyses. This field consists of a set of approaches used to analyze related event logs that differ on specific predicates, such as the country of operation of a company. The authors selected 29 studies and created a taxonomy regarding the type of input data required, the provided outputs, type of analysis, and algorithms employed. Pourshahid et al. [13] performed an SLR on aspect-oriented approaches for BP adaptation. They focused on articles that applied ideas of aspect-oriented programming into a business process adaptation area. Their review contained 56 papers whose methods were mapped. Rojas et al. [14] conducted an SLR on the usage of process mining in the healthcare domain. They identified categories, emerging topics, and future trends of the 74 selected papers. As with Taymouri, Pourshahid, and Rojas, our SLR also focused on a specific theme in the business process context. However, our topic differs from previous works as it focuses on AI methods, not specifically in process mining, but applied in the business process field. Neu et al. [15] performed an SLR in deep learning methods for process prediction. Their study considered pre-processing techniques, network topologies, and the type of prediction used. The contrast with our work is that the authors focused on a specific type of model for a specific problem, whereas we cover different AI-based methods applied to the business process field.

2.2. Business Processes and Business Processes Management

Business processes (BPs) allow workers and organizations to interact in structured ways. BP is typically defined as a series of steps that leads to the achievement of a given goal or the fulfillment of a particular business need [2]. Aligning an organization's perspective with its business processes is seen as a competitive advantage and is critical to business success [16]. The BP must collaborate with other processes in order to achieve common business goals [17]. However, due to the dynamic nature of today's corporate environment, these processes are increasingly vulnerable to a wide range of fluctuations, and they must be flexible to cope with these variations in order to remain viable [18]. The challenge is to provide versatility while providing process support and constant improvement.

In this scenario, the concept of business process management (BPM) emerges in response to the need for a field of study focused on managing and improving an organization's business processes. BPM is the discipline that combines knowledge from management science and information technology and applies this to operational business processes [2]. This discipline is a consolidated field because of its potential to boost productivity and reduce costs [19]. The BPM life cycle [20], shown in Figure 1, begins when business processes are built, from scratch or an existing model [19]; that is, the (re)design step of the process. The second phase is the system configuration, when the BP is implemented by setting up the corresponding information system. The process can then be executed and monitored in the enactment and monitoring phase. Finally, during the diagnosis phase, one can learn from the running process (e.g., collecting logs, data, and others) and apply changes to improve business processes. Adaptations may demand some modeling, resulting in a revised or a new version of the business process, and the life cycle will restart. There are other BPM life cycle models (e.g., Van Der Aalst [21], and Houy et al. [20]), which differ only in the number and nomenclature of the phases. However, they are fundamentally the same.

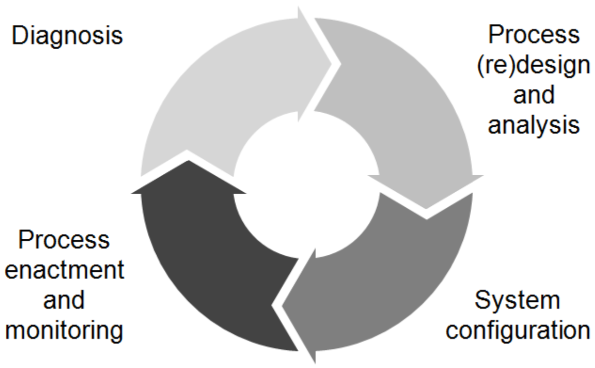

Figure 1. The BPM life cycle. Source: Adapted from ter Hofstede et al. [19].

2.3. Aligning Information Technology with Business

A few years ago, the golden rule used to be: organize first, then computerize. Processes were highly-structured and people-driven [22]. Nowadays, information systems can execute process tasks and provide insights from generated processed data. It is possible to roadmap the automation of essential business processes [19]. The application of workflow technology can result in significant cost- and time savings.

However, Davenport et al. [23] affirmed that it is not enough if the information technology is effective. It must be supported by the correct culture and organizational structure. Even if a company has a powerful and efficient system, e.g., it is easy to use, easy to comprehend, and populated with all of the needed content, if the right culture does not back the company, people may get unmotivated and reluctant to utilize the system. The system may go neglected and the investment wasted [23]. That encourages information technology systems to cooperate with business leaders by automatizing tasks and providing insights.

2.4. Method vs. Model

For this paper and a better overall understanding, it is relevant to distinguish between the term method and model to understand that they are not synonymous but complementary.

The discipline of design science has well-defined terms regarding IT artifacts used in information systems. For March and Smith [24], a model is "a set of propositions or statements expressing relationship among constructs". Here, constructs refer to concepts that form the vocabulary of a certain domain. The more practical definition refers to a model as a representation of a certain thing. In contrast, they define a method as "a set of steps used to perform a task". Offermann et al. [25] build on the definition of a method adding that people perform them to assist the development of a system and that they define deliverables of activities and roles. A method may interact with models, but they are usually different. An exception refers to "reference model", which aims to be replicable and serve as the foundation for the development of other models [26]. Figure 2 shows the definition for "method" and "models" and their intersection that refers to reference models. When it comes to models, the authors agree [25,26] that the term is often vaguely used. For example, it has been used to describe design models, metrics, languages or notations [25]. Many authors from our RSL have, for example, interchanged the terms "model" and "method" as synonyms. Therefore, we excluded these works from our SLR after careful analysis, since we aimed to present works with grounded methods. The importance of a method is its reproducibility. A method denotes a formula for carrying out an activity or procedure. Methods are a form of delivering final results, and the principle is to give support to develop something.

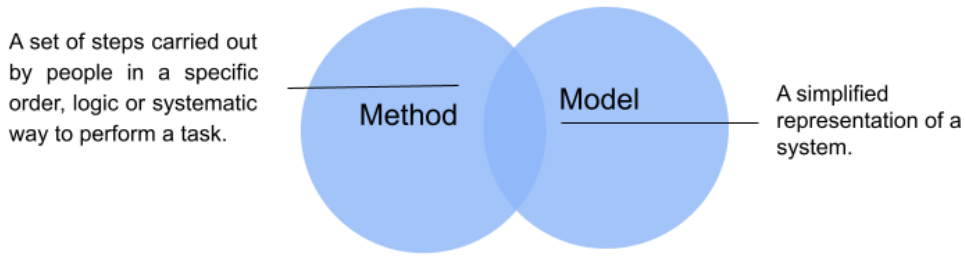

Figure 2. Definition of method and model. Source: adapted from March and Smith [24], Offermann et al. [25] and Merriam-Webster [27].

3. Methodology

We applied a systematic literature review to determine which AI-based methods for BPs were available in the literature for automatizing business processes and supporting the decision-making processes of companies. We identified AI-based methods from large volumes of articles by performing an SLR [28]. As a result, developers and decision-makers will be able to visualize AI-based methods to improve their business processes in a systematic manner. Based on [29–31], we divided our methodology into three stages: (i) planning, (ii) execution, and (iii) reporting and dissemination. First, we chose the academic databases, and studied how to select the relevant material. After, we determined the applicable search keywords based on our RQ and the best combinations of these keywords in the databases search. In the execution phase, we collected the articles and applied multiple criteria to select the most appropriate ones. In the third phase, we defined categories for the selected articles and summarized their main points, methods, techniques used, and problems tackled.

Our search space was based on the following RQ: which AI-based methods exist in the literature, to automatize business processes and support the decision-making processes of companies?

Scopus and Web of Science, two of the top eight academic databases [32], were chosen for our research. We developed four exclusion criteria to refine the selection of papers, as shown in Table 1. After this definition, we selected the keywords below to retrieve relevant papers based on our RQ:

- **Method:** a suitable study should, as one of its main outputs, have a method, its creation, or analysis.
- **Artificial intelligence:** a relevant study must include some level of automation and less human action, which could be identified as computational or artificial intelligence technique.
- **Business process:** an adequate study needs to focus on the processes in a business context.

The term "Method" was part of our string search to find works that proposed a sequence of well-defined steps to achieve a specific goal, as in the March and Smith definition [24]. In addition, with the term "Artificial Intelligence", we targeted works using intelligent techniques covered by the artificial intelligence umbrella. This umbrella included sub-fields, such as machine learning, neural networks, evolutionary computation, expert systems, etc. Therefore, we relied on the authors and indexed keywords from the two used repositories. Finally, the AI-based methods were addressed to "Business Process", our last keyword. Though the terms above are the most related keywords for our RQ, we included synonyms to comprehend all possible works. Therefore, we included: referential model, computational intelligence, organizational, administrative, and workflow, respectively. Our academic database search was structured as follows: (method OR "reference model*") AND ("computational intelligence" OR "Artificial Intelligence") AND ((business OR organizational OR administrative) w/2 (process OR workflow)). The expression "w/2" denoted a two-word distance between the two terms in question, regardless of order.

Using these keywords, we derived a search string submitted in the chosen academic databases. The retrieved papers had the three terms included in their titles, keywords, or abstracts, to include as much information as possible from the database on this subject. The search included papers from 2000 to May 2021. The authors chose these years to have a reasonable representative subset. Afterward, we extracted the articles, removed the duplicates, and filtered them with the exclusion criteria, as explained in Table 1.

The process was as follows: (i) we began with the search terms in the two academic databases (Scopus and Web of Science), retrieving 387 papers, after removing duplicates; (ii) we excluded articles in languages other than English, as English is regarded as a standard language in the scientific community, and publications with a high impact and global reach use it as their standard language (C1); this phase withdrew six papers; (iii) in sequence, we read the titles and abstracts of the 381 remaining papers and eliminated papers with titles and abstracts outside the scope of this research (i.e., papers that did not create (or research) a method, and papers that did not develop a method for a business process); there were 68 remaining papers (C2); (iv) we read the content of the papers to determine whether or not they fell within the scope; however, we could not access some papers in full, thereby we removed the full-text articles that were not fully available (C3); 7 were eliminated in this phase; (v) finally, we read the remaining articles in greater depth and excluded those outside the scope of this research, (i.e., articles that only mentioned a method's use in creating a model, without delving into it; papers that developed the method only conceptually/theoretically without AI or computational techniques; articles that described methods to improve the performance of the system architecture or computational methods, rather than a business process); 40 papers were removed in this phase. After applying the selected criteria, our research resulted in 21 papers related to the theme. We show the step-by-step procedure of the filtering process in Figure 3.

Table 1. Exclusion criteria.

Exclusion Criterion	Justification
C1: articles written in a language other than English	English is regarded as a standard language in the scientific community, and publications with high impacts and global reach use it as the standard language. As a result, research that was not written in English was excluded.
C2: titles and abstracts outside the scope of this research: AI methods used to optimize business processes	Outside the scope were: (i) articles that did not create or research a method. (ii) Articles that did not develop the method for a business process.
C3: articles not fully available	The study excluded papers that only had abstracts available throughout the data-gathering period.
C4: articles outside the scope of this research: AI methods used to optimize business processes	Outside the scope were: (i) articles that only mentioned a method's use in creating a model without delving into it. (ii) Papers that developed the method only conceptually/theoretically, without AI or computational techniques. (iii) Articles that described methods used to improve system architecture performance or computational methods rather than a business process.

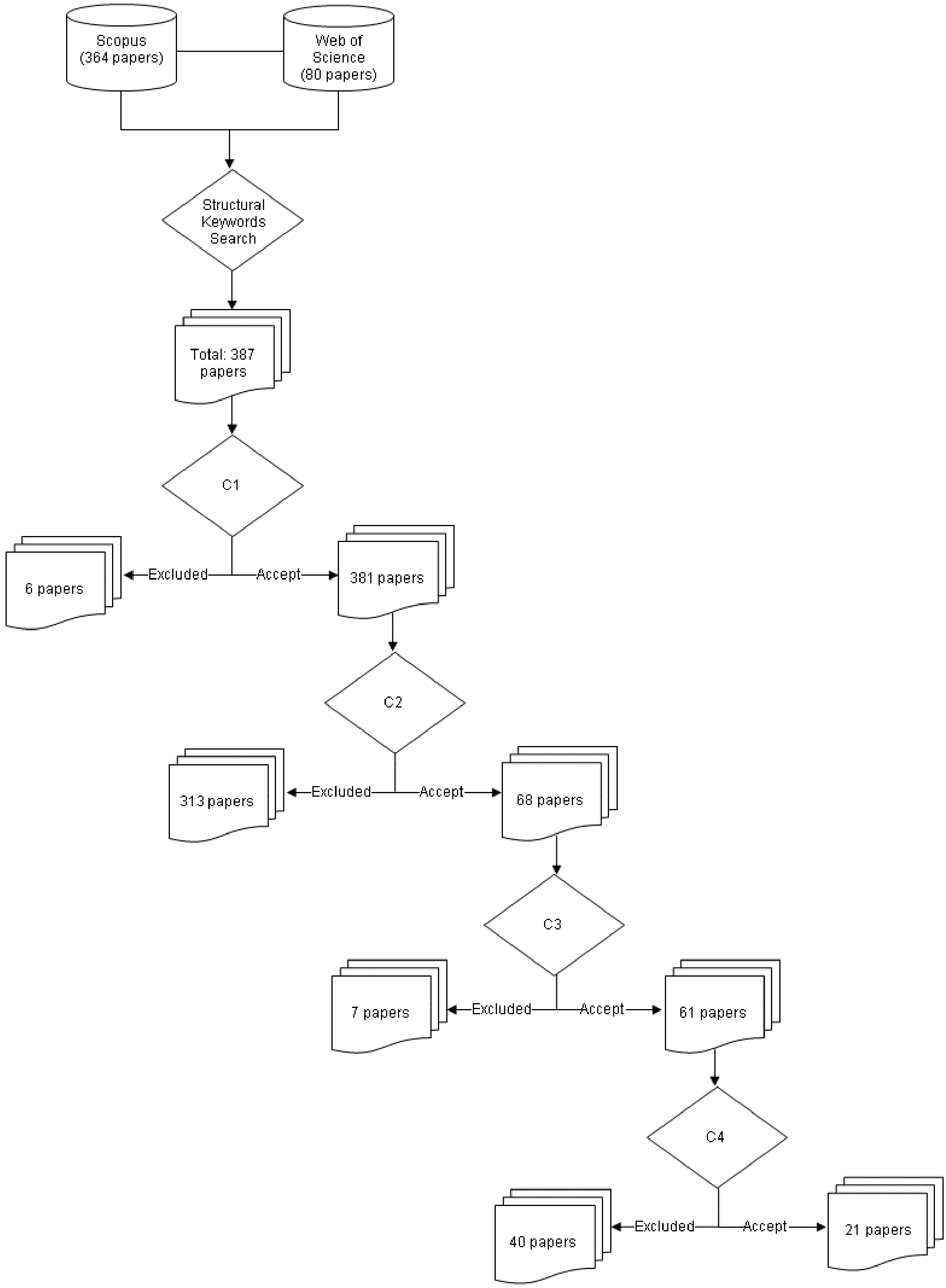

Figure 3. Filtering process [33].

4. Results and Analysis

We analyzed the 21 selected articles based on their profiles and presented methods from the systematic literature review.

4.1. Profile of Papers

In this section, we conducted a broader examination of the papers, focusing on the quantity across countries and places of publication. We also extracted information about their keywords through a co-occurrence network.

Figure 4 shows the distribution of the selected papers throughout the world. We noticed that Japan had the most papers. Europe, as a continent, had 52.4% of the total number of papers, with Italy, Germany, and Poland having two papers each. China and Iran also presented two publications each. There were three papers found in the Americas via our search.

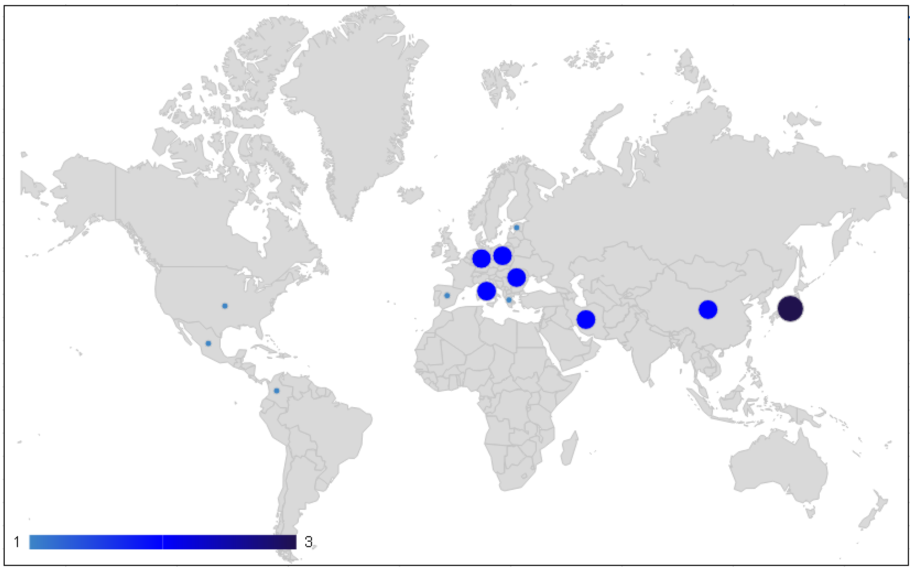

Figure 4. Papers per country. Bigger and darker circles indicate more papers per country. Source: the authors (2021).

Regarding the vehicles of publication—the discovered articles were published among journals and international conferences. Most of them, 76.2%, were submitted at conferences, and the remaining were published in journals. The publishers' subject areas are depicted in Figure 5. The term size was proportional to the number of publishers in the subject. As we can see, the most prevalent subject, present in 95.2% of the publishers, was computer science. Likewise, the second most relevant term was mathematics, present in 47.6% of the publishers. Finally, 9.5% of publishers focused on the business theme, i.e., business perspective and business, management, and accounting.

Figure 5. Publisher subjects—word cloud. Source: the authors (2021).

We performed an analysis related to the keywords of the papers. This analysis was conducted on VOSviewer, a software tool used for constructing and visualizing bibliometric networks. We used the Scopus archive in the software, which contained our 21 selected papers. We created co-occurrence networks with the main keywords (i.e., the authors selections and the keywords that Scopus identified as strongly present). See Figure 6, with two interactions (i.e., terms appearing in at least two papers), and no manual adjustments. The circle size and color, automatically determined by VOSviewer, reflect the individual keyword's frequency of occurrence and cluster type, respectively. This diagram allowed us to combine the paper's main topic, i.e., AI-based methods for business processes, and the related thematic board, in the articles.

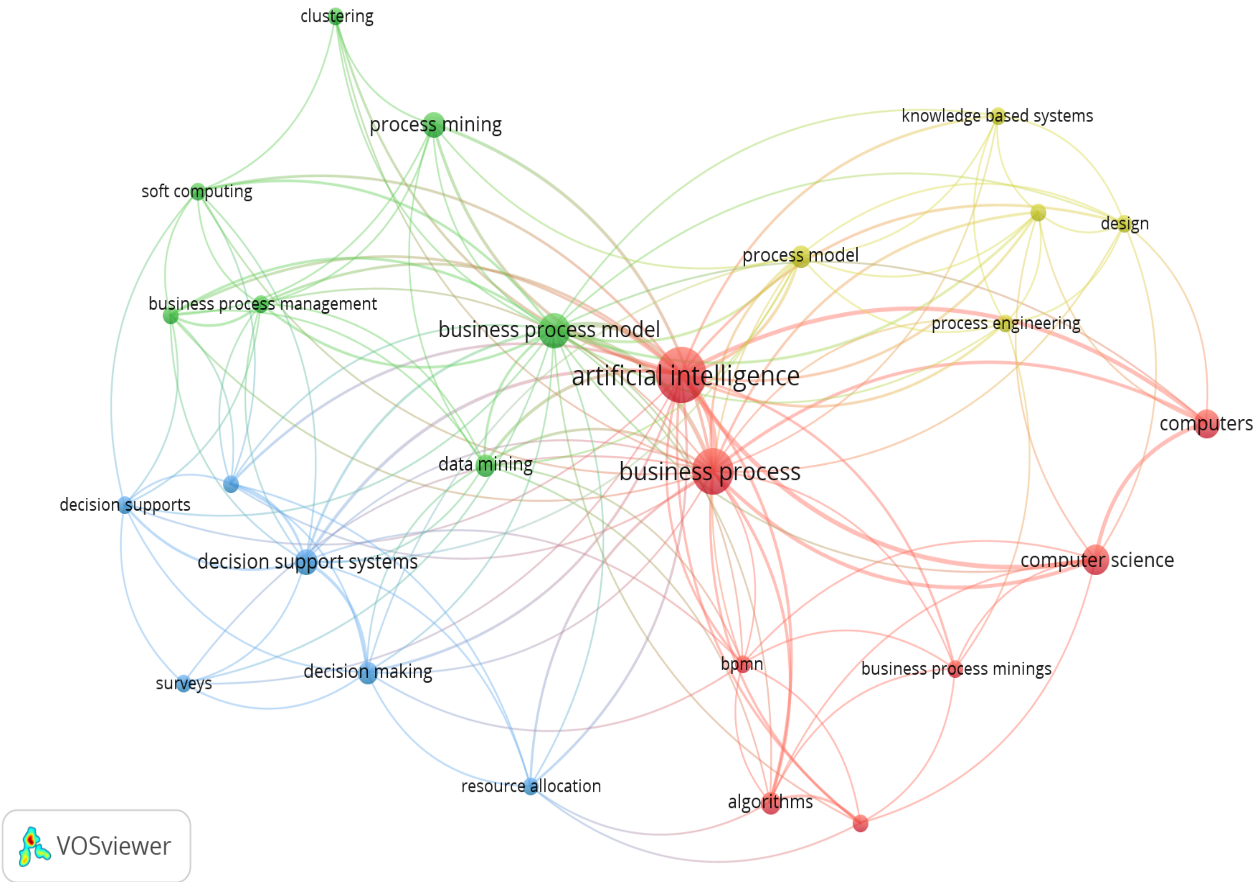

Figure 6. Keyword co-occurrence network. Source: the authors (2021).

As we can observe from the keyword co-occurrence networks, artificial intelligence was the strongest term, appearing in 90.5% of the papers. The business process term was the second strongest, at 62%. This confirms that emphasis, in the published studies, was on the two fields that we focused on in our SLR. It is also possible to see four different clusters. The blue cluster is marked by the word "decision" and may relate to articles that support business decisions. The green cluster presents nodes that involve intelligent techniques, such as "process mining" and "soft computing". The yellow cluster contains the words "process engineering" and "design", which refers to the construction of business processes. Finally, the red cluster contains the two most frequent words, i.e, "business process" and "artificial intelligence"; the term "computer" was the most present. These may refer to papers that present computational algorithms techniques.

Table 2 summarizes the quantitative data of the 21 papers studied, presenting the individual profile of each paper, i.e., its title, authors, the country of the related university, the keywords, the publisher type, and the publisher area subjects.

Table 2. Profiles of the papers.

Year	Paper	Authors	Country	Keywords	Publisher Type	Subject Publisher Area
2008	Business process mining by means of statistical languages model.	Pelayo, D.R., Trejo Ramírez, R.A.	Mexico	-	Event	Computer Science
2009	A proposal for using parallel flows with the aid of DSS in ERP projects	Moghaddam, S.M., Shabgahi, G.L., Moghaddam, M.M., Nasiri, R.	Iran	Decision Support System; Enterprise Resource Planning; Parallel Flows	Event	Computer Science/Engineering
2010	Monitoring unmanaged business processes	Mukhi, N.K.	United States	Unmanaged processes, process compliance, probabilistic data	Event	Computer Science/Mathematics
2012	Business process optimization using bio-inspired methods—Ants or bees intelligence	Pop, C. B., Chifu, V. R., Salomie, I., Kovacs, T., Niculici, A. N., Suia, D. S.	Romania	Business process optimization, Ant Colony Optimization, Bee Colony Optimization, Resource Allocation	Event	Computer Science
2013	Application of Bayesian Networks to Recommendations in Business Process Modeling	Bobek, S., Baran, M., Kluza, K., Nalepa, G.J.	Poland	-	Event	Computer Science
2013	Context-Aware Predictions on Business Processes: An Ensemble-Based Solution	Folino, F., Guarascio, M., Pontieri, L.	Italy	Process Mining, Clustering, Prediction, Ensemble Learning	Event	Computer Science/Mathematics
2013	Method and system for in-place modeling of business process extensions as first-class entities	Witteborg, H., Charfi, A., Wei, W., Holmes, T.	Germany	Process Extensions, Extensibility, Business Process Modeling, Model Driven	Event	Computer Science/Mathematics
2013	Process discovery using ant colony optimization	Chinces, D., Salomie, I.	Romania	Business Process Mining, Business Process Discovery, Ant Colony Optimization, Artificial Ant, Event Logs, BPMN, Genetic Miner	Event	Computer Science/Engineering
2014	Automatic generation of questionnaires for managing configurable BP models	Jiménez-Ramírez, A., Weber, B., Barba, I., Del Valle, C.	Spain	Configurable Business Process Models, Classification Trees, Questionnaires	Event	Computer Science
2014	Developing the Evaluation of a Pattern-Based Approach for Business Process Improvement	Griesberger, P.	Germany	Business Process Improvement, Patterns, Evaluation	Event	Computer Science/Mathematics
2015	Business process reengineering driven by customer value: A support for undertaking decisions under uncertainty conditions	Borgianni, Y., Cascini, G., Rotini, F.	Italy	Decision Support Systems, Business Process Reengineering, Process Value Analysis, Monte Carlo simulation, Customer Perceived Satisfaction	Journal	Computer Science/Engineering
2016	Business process merging based on topic cluster and process structure matching	Huang, Y., You, I.	China	Correlated Topic Model, Topic distillation, Business process merge, gSpan, Process Sub-Graph	Journal	Computer Science/Mathematics
2016	Clustering Business Process Models Based on Multimodal Search and Covering Arrays	Ordoñez, H., Torres-Jimenez, J., Ordoñez, A., & Cobos, C.	Colombia	Clustering, Business Process Models, Multimodal Search, Covering Arrays	Event	Computer Science/Mathematics
2017	Combining Differential Privacy and Mutual Information for Analyzing Leakages in Workflows	Pettai, M., Laud, P.	Estonia	-	Event	Computer Science/Mathematics
2018	Constraint-based identification of complex gateway structures in business process models	Wiśniewski, P., Ligęza, A	Poland	Business process management, Graph theory, Decision support, Structure identification	Event	Computer Science/Mathematics
2019	A Method for Goal Model Repair Based on Process Mining	Horita, H., Hirayama, H., Hayase, T., Tahara, Y., Ohsuga, A.	Japan	Requirements Engineering, Business Process Management, Goal Modeling, Process Mining	Event	Computer Science/Decision Sciences

Table 2. *Cont.*

Year	Paper	Authors	Country	Keywords	Publisher Type	Subject publisher area
2019	Investigation of the effect of concept drift on data-aware remaining time prediction of business processes	Firouzian, I., Zahedi, M., Hassanpour, H.	Iran	Business Process, Process Mining, Remaining Time Prediction, Concept Drift	Journal	Mathematics
2020	A Resource Trend Analysis from a Business Perspective Based on a Component Decomposition Approach	Saitoh, Y., Uchiumi, T., Watanabe, Y.	Japan	Non-Negative Matrix Factorization, Capacity Provisioning, Resource Management, IT Operations Management, Business Semantics	Event	Computer Science/Business Perspective
2020	Business analysis method for constructing business-AI alignment model	Takeuchi, H., Yamamoto, S.	Japan	Artificial Intelligence, Business–IT Alignment, Enterprise Architecture, Business Process Analysis	Journal	Computer Science
2020	Complexity Clustering of BPMN Models: Initial Experiments with the K-means Algorithm	Fotoglou, C., Tsakalidis, G., Vergidis, K., Chatzigeorgiou, A.	Greece	Business Intelligence, Business Process Complexity, Data Mining, Cluster Analysis, Multi-criteria Decision Making, BPMN · K-Means	Event	Decision Sciences/Business, Management and Accounting/Computer Science/Mathematics/ Engineering
2020	Filtering infrequent behavior in business process discovery by using the minimum expectation	Huang, Y., Zhong, L., Chen, Y.	China	Business Process, Infrequent Events, Minimum Expectation, Process Mining	Journal	Computer Science

4.2. *AI-Based Methods—Categories*

This section discusses the classification of the AI-based methods for BPs. The classification was inspired by the dos Santos Garcia et al. [10] proposed categories. This study classified the approaches in six categories, shown in Figure 7.

The discovery and conformance categories refer to the same categories found in process mining. Discovery regards the creation of a process model from event log data. Conformance refers to comparing an existing process model with what happens in the process. Our "returned" papers in this category extracted signs on how the processes were executed in the context of unmanaged business processes. Security refers to methods that provide safety guarantees to the customer data. Support regards the methods that pre-process the logs in order to improve their quality. Decision support methods empower business specialists with knowledge and material that accelerate their decision-making processes. This can be done through decision support systems or other solutions that help managers manage the process complexities, individualize, or re-engineer business processes. Finally, enhancement involves methods that extend processes in multiple perspectives—for example, helping specialists merge and extend, with resource allocations, and the remaining process times. As suggested in Figure 7, decision support and enhancement categories present similar grounds because they both improve the interactions between the analyst and a system. However, while this is the main focus of the decision support category, the enhancement emphasizes the improvement of the system itself.

4.2.1. Discovery Methods

Process discovery is an essential task in process mining [34]. It mainly consists of extracting a process model from an event log. Wiśniewski, and Ligęza [35] described a method used to discover parallel and alternative gateway structures in business process model and notation (BPMN) models. Their technique identifies these structures from a declarative specification and is based on a graph representation of business processes and constraint programming. A BPMN model was generated as the output. Chinces and Salomie [36] proposed the ACO BP miner. Their method employs a bio-inspired ant colony optimization (ACO) technique that finds optimal paths through graphs. They used it to discover process graphs from event logs. Their approach is a proof of concept. They were able to show that the algorithm could generate process graphs from the event log and that it is competitive with other approaches, such as genetic mining.

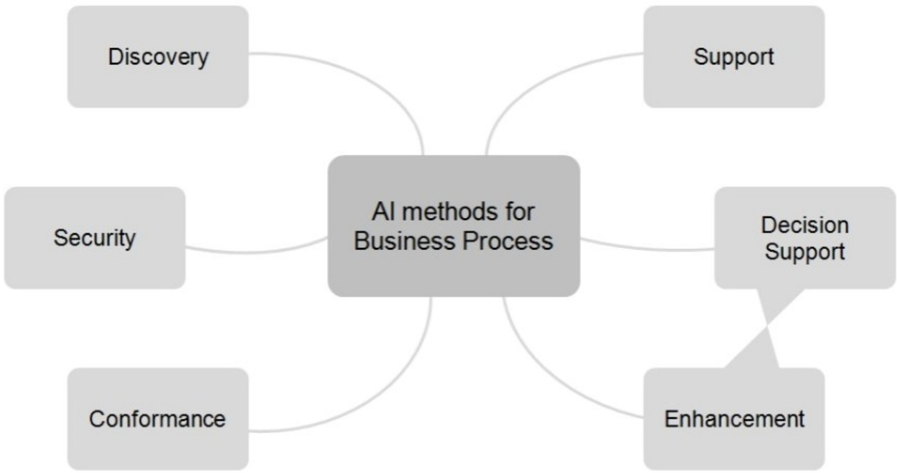

Figure 7. AI-based methods—categories.

4.2.2. Conformance Methods

Conformance checking is another pillar of process mining. It contrasts an existing process model with its respective event log to check the model adherence. The two papers found in our research string presented interesting ways of checking conformance. Mukhi [37] proposed a probabilistic provenance model to reconstruct process traces. The author addressed unmanaged business processes where missing information required making inferences about what happened in the process instances. The provenance model collected artifacts from other systems to create a provenance graph. This graph was queried in order to reconstruct process traces. Similarly, Pelayo and Trejo Ramírez in [38] proposed a method to mine text processes in business documents. They used the statistical language model (SLM) to identify (i) which process the text referred to; (ii) sub-process or process parts in text paragraphs; and (iii) activities that were executed. The "found" activities awere also reconstructed.

4.2.3. Security Methods

The security in business process refers to procedures that ensure anonymity and prevent leakages of the customer's data. In our research string, only one paper was identified in the matter. Pettai and Laud [39] developed and implemented a method to analyze leakages in workflows. They measured the information flowing from the inputs and outputs of the workflow. This information was characterized in terms of differential privacy and mutual information. They integrated both to measure an upper bound of the global leakage. They concluded that combining differential privacy with mutual information could increase workflow privacy guarantees compared to using either of them alone. The method's output was a mutual information-based quantification of the entire workflow leakages.

4.2.4. Support Methods

The support category refers to the returned methods that aim to pre-process data, to guarantee quality for further usage. We found one paper in this regard. Huang et al. [40] created a method to detect and filter infrequent behavior from real-world execution logs. The process was applied prior to the process discovery step and allowed the discovery of more consistent models. Their method considered the minimum expectation of the activity occurrence to perform the filtering. The minimum expectations related to the probability of occurrence of each activity.

4.2.5. Decision Support Methods

Companies may have multiple processes regarding the different products and contexts of their operations. There are also related processes derived from the same configurable process models [41]. In this scenario, a challenge arises in respect to the election of the most suitable process to serve as a base for an incoming product. Ordoñez et al. [42] aimed to overcome these challenges by presenting a method to find similar business processes in a repository. Their approach consists of searching and clustering processes. The search considers linguistic and behavioral data and allows the user to provide a process fragment, or even a list of activities, as input to their system. Then, the clustering is activated to find similar BPs. The clustering method is based on a multimodal search and covering arrays. Similarly, Jiménez-Ramírez et al. [43] proposed a method for automatically generating questionnaires to help business experts individualize BPs from extensive collections of similar models. This method uses classification trees and automatizes a time-consuming procedure. On the other hand, Bobek in [44] proposed a recommendation method to aid business experts in designing business processes. They proposed the use of Bayesian networks to recommend process fragments. Their method requires the availability of a repository of models in order to train the machine learning algorithm. This strategy can reduce the time needed for modeling processes and produce fewer error-prone models. The Bayesian network is an acyclic graph that provides a graphical representation of a probabilistic model, representing dependencies between aleatory variables. Figure 8 illustrates these AI-based recommendation systems present in the works by Ordoñez et al. [42], Jiménez-Ramírez et al. [43] and Bobek [44]. The analyst wanted to design a new business based on previous BPs present in a repository. Therefore, the analyst provided the system with desirable activities or process fragments. Next, the intelligent system used techniques, such as clustering, covering arrays, or Bayesian networks,to find similar BPs based on the analyst fragments. Finally, the system returned candidate match(es) to the analyst, helping in the final decision.

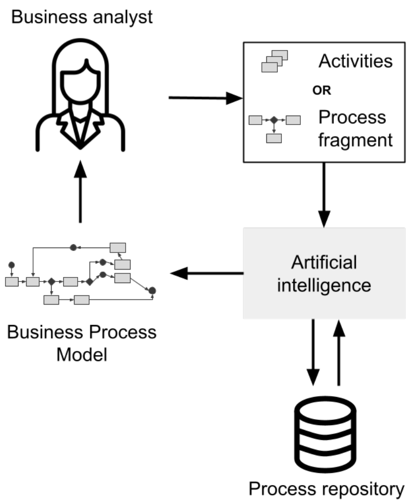

Figure 8. Overall description of business process recommendation methods based on artificial intelligence [42–44].

Decision support is also important in the context of business process reengineering. This is a recurring need of companies, since they constantly demand innovation and improvements in their products and methods. In this scenario, Borgianni et al. [45] presented an algorithm to support decision making when reengineering business processes. Their method finds the main weaknesses of a business process and identifies the most promising directions for process innovation. The proposed decision support method can be helpful in multiple situations, including those characterized by a lack of time and the inability to conduct appropriate customer surveys. Griesberber [46] developed an evaluation mechanism that allows the reuse of successful patterns found in previous solutions in the domain of business process improvements. This reuse can have multiple benefits, such as a reduction in the development time of new solutions. A limitation of the work is that it was instantiated to a specific project; further discussion is required to make the proposal more general. Figure 9 illustrates the decision support during process reengineering for approaches by Borgianni et al. [45] and Griesberber [46]. The decision support system receives multiple business processes from a repository. Then, it identifies reusable patterns and weaknesses to be tackled during process reengineering and feeds this information to the analyst.

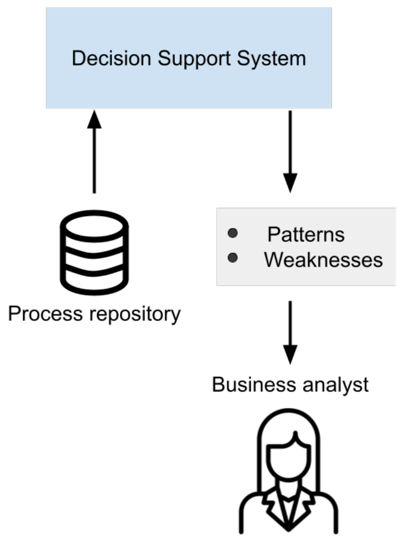

Figure 9. Overall description of decision support systems that empower the analyst decision making process [45,46].

Decision support can come on other fronts of business processes, for example, by providing tools and aligning goals of business analysts with other teams. In this sense, Horita et al. [47] proposed a method for repairing goal models based on the adjustments of the equivalent BP. A goal model is helpful for outlining company objectives and, therefore, has a complementary relationship with business process models. The authors first repaired business process models using process mining techniques in their method. Next, they adjusted the goal model based on refinement patterns. Similarly, Takeuchi and Yamamoto [48] proposed a method to align business and IT teams. They used ASOGA and an analysis table for that purpose. Finally, Fotoglou et al. [49] presented a method to assess the complexity of process models by using clustering techniques. The method combines three complementing complexity criteria: NOAJS, CFC, and CNC, in a single weighted metric. Next, the K-means clustering technique is applied to find threshold values for efficient categorization.

4.2.6. Process Enhancement Methods

Resource unavailability or misuse may create bottlenecks in business processes and hurt service level agreements. Managing resource allocations may prevent such issues and optimize resource usage. In this sense, Pop et al. [50] proposed bio-inspired methods to optimize process flow and resource allocation. Their approach started with the business process requirements, regarding tasks, decision gateways, and available resources. Next, it employed bio-agents to provoke changes in the model structure and allocate resources. Finally, after the agent's interaction, the best fit configuration was returned. In Saitoh et al. [51], the authors improved a method to analyze resource trend usage in business processes. According to the authors, this could be useful for provisioning resources and detecting failures. Their method decomposes numerous data sources into business process components. The authors concluded that their improved method could identify workload patterns that simultaneously appear in multiple resources and identify increasing, monthly, and changing trends of resource usage in BPs.

Extending a process is a recurring activity in organizations. It is usually performed when innovating or adjusting process models. Witteborg et al. [52] created a method for easily extending a business process. It detaches the extension from the code layer of the system and allows the expansion reuse in other contexts. The method proposed by Moghaddam et al. [53] improves the success of the implementation of enterprise resource planning (ERP) systems in companies. Their method constructs parallel flows to assist the main flows in ERPs. Their two main flows are time and quality estimations. The former regards calculating the time duration in each unit of the main flow and aims to prevent delays. The latter captures the conditions in which the current process is passed to the following units so that they can be ready to handle the process properly. In contrast, Huang and You [54] focus on a method to merge multiple business processes into a single one. This is relevant in the context of business restructuring or optimization. Their method starts by applying correlated topic modeling to cluster similar processes. Next, a graph mining technique of minimum depth-first (DFS) is applied to find patterns in the set of processes, in terms of sub-graphs. Afterward, tags are created from the sub-graphs, and a string similarity algorithm is employed. Finally, the sub-graphs are merged, and a final business processes is produced.

Another interesting field tackled by some authors is predicting the remaining path or time in an ongoing business process instance. This may help in contractual procedures, such as service level agreements. It is also important in order to apply countermeasures that can help prevent a process from taking too long or following an undesired path [34]. In this sense, Folino et al. [55] proposed a method for the prediction of performance metrics for on-running process instances. In their method, they first clusterize processes of the same variant and then attribute to each cluster a predictive model. The model used was predictive clustering trees, and they validated their approach in real-life logs. Moreover, Firouzian et al. [56] developed a method to predict the remaining path and time for ongoing traces of business processes. Their method considers concept drifts and consists of three distinct phases. Firstly, an annotated transition system is constructed with the aid of fuzzy support vector machines to predict future trace path. Next, the duration of future activities is predicted with support vector regressors. Finally, a concept adaptation method is employed to assign weights to the model's prediction, based on the time interval of the prediction.

5. Discussion

Our SLR, to answer the RQ "Which AI-based methods, in the literature, are used to automatize business processes and support the decision-making processes of companies?" found 387 papers, with about 5.5% of them being relevant to our question. In the research phase, we noticed that, in the filtering process, when applying the exclusion criterion C2 and C4, papers use the term "method" sometimes as a synonym for a system, model, or framework; demonstrating the need for greater attention on the distinctions of these concepts, as explained in Section 2.4.

Figure 5 demonstrates that the most prevalent subject, present in 95.2% of the publishers, is computer science, and almost 50% approach the mathematics subject, fields related to AI, and methods, respectively. On the other hand, even though the methods are for business processes, less than 10% of publishers are focused on the themes, i.e., business perspective and business, management, and accounting. As evidenced by the keyword co-occurrence network (Figure 6), the most relevant keywords are "artificial intelligence", "business process", and "business process model". These keywords are central and are the mostly connected, which shows the adherence between our search string and the returned papers. These keywords are connected to various others, such as "decision support systems", "process mining", "computer science", and "process model". These methods were split into six categories: discovery, conformance, support, security, decision support, and enhancement. We noticed that the categories with the most papers were decision support and enhancement. The discovery methods category corresponded to methods that allowed the process discovery for business processes. The AI-based methods presented in this category used ant colony optimization and graph representations to discover a process from an event log and a declarative specification, respectively. The conformance methods category contained techniques that helped reconstruct incomplete traces of a process. The methods from this category used graph and statistical language models to cross-system information and mine text documents to identify missing parts of process traces. The security method category was represented by a work that used a mathematical approach, i.e., triangle inequality and the max-flow min-cut theorem, to measure information leakage for a running process in a workflow. The work identified in the support methods followed a statistical approach by relying on minimum expectations of activities to filter infrequent behavior of event logs prior to process discovery. Decision support methods contained works intended to aid analysts to (re)design or improve business processes, align team goals and identify process complexities. In this sense, the works applied techniques of clustering, i.e., covering arrays, and classification trees, to identify good candidate processes in large repositories, to serve as a base for the design of a new process. Another work used Bayesian networks to suggest business process fragments with the same goal. The Monte Carlo simulation was used to detect process weaknesses and directions for innovation. K-means clustering was employed to group business processes by complexity. Finally, the process enhancement methods had, as its main goal, the improvement of business processes themselves. Some works applied ant colony optimization, artificial bee colony, and matrix factorization to optimize resource allocation in BPs. Others focused on the extension and merge of BPs by using graphs. The last two works proposed using support vector machines and clustering trees to predict the remaining time of ongoing BPs instances.

Although we focused on AI methods, one can see that not all papers used an artificial intelligence technique. Figure 10 shows the techniques used by the authors in our systematic review divided into three categories: pure mathematical, computational techniques, and artificial intelligence. The pure mathematical category contains 28% of the 21 returned papers. This category comprehends the implementation of pure mathematical and statistical procedures by the authors as a step of their experiments. The computational techniques refer to those that implement simulations, including searches in graphs and procedural algorithms. This category encompasses 33% percent of the papers, such as the works by Borgianni et al. [45], Mukhi and Nirmal [37], and Horita et al. [47]. The artificial intelligence category contained 39% of the papers and refers to those works that also implemented a learning technique in at least one of the steps of their methods. The two most used techniques in this category were clustering and trees. Some works also used more than one technique, such as Folino et al. [55], where both ensemble learning and classification trees were used. Other works used only one of the mentioned techniques, such as the work by Bobek et al. [44], which used Bayesian Networks to recommend process fragments in BPs, and Fotoglou et al. [49], who used the K-means to cluster BPs by their complexity.

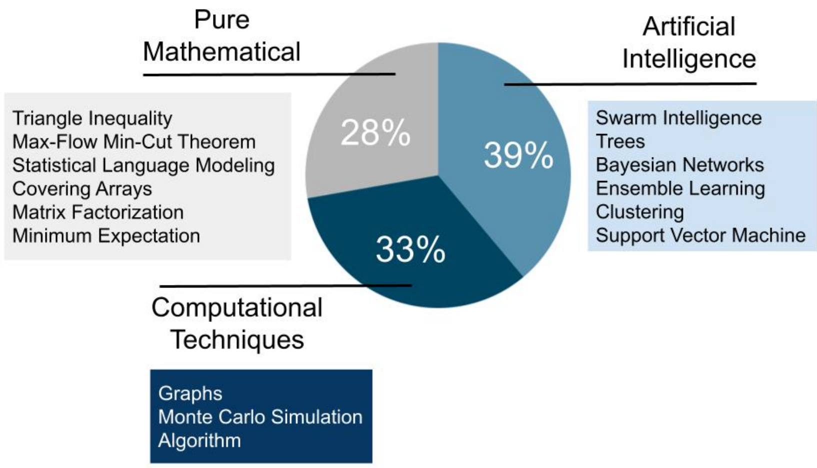

Figure 10. Techniques used by authors. Source: the authors (2021).

6. Conclusions

This paper performed a systematic literature review to answer the research question: which AI-based methods, in the literature, are used to automatize business processes and support the decision-making processes of companies? We focused, therefore, on papers that followed well-defined methods with AI as one of its steps. Previous works have performed literature reviews with other focuses, without ensuring that a method was applied. Methods are important because they can be replicated and refined in future works. Our review focused on the Scopus and Web of Science repositories, beginning with 387 papers and finishing with a selection of 21 papers. Although we focused on AI-based methods, some of the selected papers only presented computational or mathematical techniques. We see this as an opportunity for future approaches that can reuse these methods and incorporate AI techniques.

We performed a quantitative and qualitative analysis of the selected papers that ranged from 2008 to 2021. In our quantitative analysis, we identified aspects, such as country, keyword co-occurrence, and vehicle of publication of the papers. The keyword co-occurrence helps to understand which areas the selected works are concentrated. The qualitative perspective explored the content of the papers. We used a taxonomy with six different categories inspired in the work by Garcia et al. [10]. We found that the decision support and enhancement categories better answered our research question by presenting methods with AI, computational, or mathematical techniques. A business analyst, a repository of processes, and an intelligent system are often involved in the decision support category. Their interactions allow the automation of manual tasks and the generation of insights to the analyst. In contrast, in the enhancement category, we highlighted methods to extend and merge business processes in the context of business restructuring or optimization. In this work, we also listed all techniques used by the papers.

By analyzing our results, we believe that the trend involves an increase in intelligent techniques in methods for business processes. In the big data era, companies accumulate an immeasurable amount of data that serves as input for artificial intelligence-based algorithms. We also think there is a need for systematic use of AI in the analyzed methods. Many techniques can be used in the presented contexts. For example, regarding identifying patterns based on a repository of business processes, clustering of business processes could be considered to identify similar BPs. This could be done by extracting features from the graph of each BP and applying a clustering technique, such as K-means or DBSCAN. This can help identify patterns of each group in terms of structure and quality metrics. In regards to prediction tasks, we think that advanced deep learning [57] techniques, such as transformers [58], could be used to predict subsequent activities or anomalies, since a trace can be seen as a sequence of words. In addition, other recent artificial intelligence approaches can be incorporated into the current solutions. For example, active learning [59] and self-learning [60] techniques can allow the usage of massive amounts of data by models in the context of supervised and unsupervised learning. The methods shown in this article can be expanded with the incorporation of these new techniques and be reused in different contexts.

6.1. Practical Implications

In this article, we collected and categorized AI-based methods for business processes in the literature. This will assist researchers, by having a single and systematic "source of search" in this subject, allowing researchers to create more structured and grounded models. In addition, developers and decision-makers will be able to visualize AI-based methods to improve business processes in a systematic manner. Furthermore, the article calls for standards in the concepts of model, method, and methodology, clarifying the nomenclature for future work and learning. It also encourages the convergence of business and computational fields.

6.2. Limitations

The first limitation of this paper is that we just used two academic databases (Scopus and Web of Science). The second limitation is the misuse of the word method, e.g., as a synonym for a model by authors. This makes it difficult to split those works that indeed present methods in the sense of replicable and well-grounded step-by-step procedures that optimize business processes.

6.3. Direction for Future Research

There is still much to be explored in this subject. Based on our results, we believe that it is necessary to research more into the alignment between the IT and business fields, and value the knowledge, creation, and utilization of the methods, as they are foundations for well-structured systems and models. Finally, our purpose for the forthcoming paper is to develop a multi-criteria decision model to determine the priority order for process automation in an enterprise, then, based on that, to determine the AI-based method(s) found in this paper that are appropriate for that BP.

Author Contributions: Conceptualization, P.G., B.B. and F.M.; methodology, P.G., B.B. and F.M.; formal analysis, P.G., F.M. and L.V.; investigation, P.G.; writing—original draft preparation, P.G. and L.V.; writing—review and editing, L.V., C.B.F. and F.M.; visualization, P.G., L.V. and V.S.; supervision, B.B. and F.M.; project administration, B.B. and F.M.; funding acquisition, B.B. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded in part by Fundação de Amparo a Ciência e Tecnologia do Estado de Pernambuco, grant number SIN-0249-1.03-20, and by Coordenação de Aperfeiçoamento de Pessoal de Nível Superior -CAPES -Finance Code 001.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

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