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Review

Using Machine Learning in Business Process Re-Engineering

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Abstract: A business process re-engineering value in improving the business process is undoubted. Nevertheless, it is incredibly complex, time-consuming and costly. This study aims to review available literature in the use of machine learning for business process re-engineering. The review investigates available literature in business process re-engineering frameworks, methodologies, tools, techniques, and machine-learning applications in automating business process re-engineering. The study covers 200+ research papers published between 2015 and 2020 in reputable scientific publication platforms: Scopus, Emerald, Science Direct, IEEE, and British Library. The results indicate that business process re-engineering is a well-established field with scientifically solid frameworks, methodologies, tools, and techniques, which support decision making by generating and analysing relevant data. The study indicates a wealth of data generated, analysed and utilised throughout business process re-engineering projects, thus making it a potential greenfield for innovative machine-learning applications aiming to reduce implementation costs and manage complexity by exploiting the data's hiding patterns. This suggests that there were attempts towards applying machine learning in business process management and improvement in general. They address process discovery, process behaviour prediction, process improvement, and process optimisation. The review suggests that expanding the applications to business process re-engineering is promising. The study proposed a machine-learning model for automating business process re-engineering, inspired by the Lean Six Sigma principles of eliminating waste and variance in the business process.

Keywords: business process re-engineering; data mining; machine learning

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1. Introduction

An organisation, an enterprise, or a company comprises a set of organised and connected business processes and activities arranged in a sequence, requiring efficient and effective process management to achieve strategic targets, objectives, and goals [1].

In that sense, business processes are a systematic approach for managing work and achieving targets [2]. Furthermore, because of the dynamic nature of the business, organisations tend to evolve through growth, transformation, or expand the organisation marketplace [3]. This impacts the business processes; therefore, it has to be reflected in the processes to realign with the needs of the business. Furthermore, since the first industrial revolution when Henry Ford introduced the assembly production line, business processes have played a pivotal role in managing and enhancing productivity [4]. Therefore, process science emerged theoretically and practically innovated many tools and techniques, such as business process re-engineering, as a powerful technique to improve process productivity [5].

Furthermore, as a dynamic component, a business process is affected by events occurring in the external world and other internal processes in the same organisation [6]. Consequently, as business process management evolved and became a commodity for business management, it evolved from the initial business process re-engineering in the 1980s to a well-established management approach [7]. Additionally, business processes management strategies improved monitoring and controlled productivity, profitability, service delivery levels, and other business objectives [8]. Subsequently, when the business grows, transforms, or expands, business process efficiency gets affected. Similarly, process productivity gets impacted, especially in highly competitive industries [3], which poses the need to redesign the processes to cope with the business evolvements [9].

Furthermore, due to process automation and digital transformation, lots of manual work transformed into digital platforms. Enterprise Resource Planning (ERPs) is a good example [10]. That is because it laid the foundation for automating the process in digital platforms, also known as workflow management systems, which accelerated and impacted productivity, efficiency, and effectiveness [11].

Automation equipped the organisation with a wealth of data and detailed records [12]. The rapid advancements in information technology, automation, and digital transformation raised the bar to challenge the purpose of the process itself before looking at improving its performance or re-engineering it [13].

Process improvement as a concept was introduced initially in 1991 by James Harrington, who applied it to situations where incremental changes are made to process design to meet new requirements or increase an existing business process efficiency [9]. Business process improvement employs various strategies and approaches, such as business process re-engineering [5], which Michael Hammer introduced in the 1990s. The business process re-engineering entails redesigning the process from scratch—rethinking and radically redesigning the business process achieves dramatic improvements [9]. Any change in the activities and the business process flow is re-engineering [3,14]. Re-engineering a business process will sometimes transform every aspect of an organisation, including organisation structures, values, and reward systems [15], maximising the impact of the change on the organisation culture.

Additionally to all the above, because of the globally recognised value of business process re-engineering and its positive impact on the financial status and operational productivity [1], business process re-engineering became part of the top continuous improvement strategies. Therefore, demand for business process re-engineering expertise and techniques increased tremendously; consequently, associated costs jumped exponentially.

A thought might occur: if business process re-engineering projects are expensive and complex, why do organisations insist on going that route? This is because the real challenge is the need for evolution and continuous improvement. If the process did not evolve, there would be a risk of losing market space and competitive advantages. For example, Nokia has been leading the mobile phones production industry for years, until they could not cope with the accelerated progress in the global mobile phones market. As a result, Nokia was out of the market after being the leading organisation.

The above sequence of advancements from the founding of the business process to the need to continue improving and re-engineering it, motivated the questioning of the existence of any automated artificial intelligence ways to reduce the cost and improve the outcomes of business process re-engineering projects.

Therefore, considering the above-listed challenges, there was a need to investigate alternative, unconventional ways to deliver better outputs with reduced cost and time.

As there were an enormous amount of digital data that became available, the next step was to utilise data mining and process mining [14] to analyse data to solve problems and develop insights [16]. Nonetheless, data science focuses on data-related subjects, such as data quality, without considering business process-related issues, such as improving process performance. Therefore, process mining emerged to reduce the gap between data science and process science [17].

Furthermore, artificial intelligence and machine learning progressively show the value of utilising available data. Its value enables learning knowledge from data to uncover hidden patterns and innovate new solutions [18] to complex real-life problems.

The hypothesis is that because the process data are available, there is an opportunity to utilise that data through machine learning to automate the business process re-engineering. However, the data might not be available immediately and may require formulation.

Therefore, there is a need to consider making new data sources and to qualify them as input features for a machine-learning algorithm.

Consequently, as highlighted above, a wealth of data are generated, analysed, and utilised because of the digitalisation and automation of business processes, which is motivated by the fact that data mining and machine learning is an option. Therefore, this study aims to bridge data mining and machine learning with business process re-engineering as a possible solution.

Knowing the capabilities of machine learning influenced this study's central question: To what degree has research contributed to shaping machine-learning utilisation in automating business process re-engineering?

This question has three investigation areas:

1. Knowing the fundamentals: What available frameworks, methodologies, tools, and techniques are used in re-engineering a business process?
2. Investigating related work: Were there any attempts to automate the business process re-engineering using machine learning?
3. Laying out the foundation: what data attributes and datasets are required for a machine-learning model to train and test in order to automate business process re-engineering?

The paper is structured as follows: in Section 2, there is a literature review on business process re-engineering, its manual implementation frameworks, methodologies and tools, the use of machine learning and data mining, and attempts to automate it. The findings in Section 3 highlight the main findings. The discussion in Section 4 discusses the proposed model to automate the business process re-engineering and the conclusion in Section 5.

2. Literature Review

Business process re-engineering became one of the most popular change-management approaches because it promotes doing things effectively for better overall quality. However, it is estimated that around 70% of business process re-engineering implementations have failed due to a lack of proper framework or methodology [15].

Multiple frameworks and methodologies are available for the business process re-engineering management. Most frameworks and methodologies usually look at the process change in three main phases: (1) the process status as it is (as-is) highlighting the challenges and the need to change, (2) the process of redesigning mutable alternative designs of the process, and (3) the impact on the running instances of the process. Below are selected examples of frameworks and methodologies.

This review looks at available business process re-engineering frameworks, methodologies, tools, and techniques to investigate the related data generated, analysed, and utilised throughout the process. Finally, the study reviews related work that utilises machine learning for business process management in general and business process re-engineering in specific.

2.1. Frameworks

A framework is a structured way of working in order to manage progress towards achieving targets and objectives [19]. Business process re-engineering as a well-established process redesign model has many frameworks. From available frameworks, in this review, the researchers looked at the Mendling framework, Motwani framework, Al-Mashari and Zairi framework, Robert's framework, Lowenthal's framework, and Cross framework. In addition, TOGAF (The Open Group Architecture Framework), a framework from the information technology practices, was considered and mapped to the principles of business process re-engineering frameworks. More details about these frameworks are below:

- Mendling framework: distinguishes the re-engineering process into three levels: process relations, process modelling, and process execution and performance [20]. This framework outlines the tasks at each level, segregates the strategic tasks of the implementation process, and illustrates the difference between modelling a business process and using it in daily operations. The framework provides techniques that enable the organisation to identify and model business processes with a prioritisation mechanism. At the process model management level, and because of the impeded continuous improvement concept, new versions of the same business process get released to production between now and then, which requires a reliable way to distinguish running cases based on the process model version. This framework proposes a continuous process improvement in a cycle of tasks that enables the process owner to have visibility on the process performance at all the time with prompt identification for any need for improvement.

- Motwani framework: unlike Mendling, it does not consider having a repository for all business processes as a knowledge pool. Instead, it looks individually at each change requirement. The Motwani framework has six phases:
    1. Understanding the scope of work.
    2. Initiating the project with agreed upon and measurable objectives.
    3. Programming requires baseline and benchmarking.
    4. Transforming the process from the old version to the new version.
    5. Implementing the change.
    6. Evaluating success mapped to the objectives.

According to Motwani et al., a clear vision of the ideal process is required, which emerges as the final redesign goal [21].

- Al-Mashari and Zairi framework is a holistic framework, as they describe it, for business process re-engineering implementation [15]. This framework begins by looking at the internal and external change drivers, then benchmarking to determine the scope of the change, the degree of the change, and the change radicalness. The implementation phase has categorised the tools and techniques into enabling, facilitating, integrating, and implementating the tools and techniques. However, it has a critical gap in evaluating the outcome, as it is not adequately covered. The philosophy of this framework sums up the revolutionary magnitude of change based on breakthrough, one-time, or episodic approaches [22].
- Robert's framework took the steps very carefully where situational assessments plugged in nearly all stages, forming a continuous improvement process that starts again when it ends. The cycle begins with assessing and analysing the current opportunities and capabilities to propose a redesign, which triggers iterations of risk assessment and impact on the organisation output, a transition plan is made, and pilot testing conducted. This will give either the confidence to go ahead with the new process design and amend improvements, or corrections will be made to the proposed process with iterations to improve it before implementing the change in the production environment. When all tests pass the requirements, the framework recommends implementing the required modifications before implementing and transitioning to the new process. As a final stage, Robert's framework closely tracks the recent process performance and reinitiates the cycle again for further improvement. However, using practical change management tools to manage the resistance to change is a factor for failure or success of the business process re-engineering projects [23].
- Lowenthal's framework is a simple and basic framework of four phases [15], with a high-level sequence of steps:
    1. Preparing for the change.
    2. Planning.
    3. Redesigning the process.
    4. Evaluating the change.

The simplicity in this framework does not give much attention to analysing the need for the process redesign or benchmarking in depth. After implementing the change, it does not explicitly cover phases, such as testing, training, organisation change, and process performance monitoring. In general, Lowenthal's framework will not work for massive and complicated process redesign projects that require more details and focus. Instead, it is more suitable for implementing small incremental changes.

- The Cross framework distinguishes the tasks into three main phases (Analysis, Design, and Implementation) with a detailed list of the activities in each stage. The analysis phase covers the requirements analysis part very well. It gives explicit attention and consideration to the consumer requirements and makes changes driven by the customer needs, which provides more value and relevancy to the customer. In addition, it impacts the assessment of changes and their success or failure. Baseline analyses and current process reviews are also used with the customer requirements to build a 3-dimensional view of the design specifications. In the design phase, Cross et al. introduced a list of design principles helping the redesign team qualify the design options at a high level of design. This produces a detailed re-engineered design for the process. The new design is then injected into cycles of testing involving clients, in order to get their feedback until it achieves a satisfactory level and consensus agreement on the new process. The new process will then be moved to the implementation phase to transform the business into the new process. However, the Cross et al. framework does not address the impact on process performance after the implementation. Similarly, it does not address the continuous improvement concept [15].
- TOGAF (The Open Group Architecture Framework) is a comprehensive framework widely used in industry to manage information technology architecture in complex environments with impeded continuous improvement concepts. However, the study did not find any relevant academic research implementation for business process redesign, optimisation, or improvement research. This might be because TOGAF is an information technology framework applied to improve information technology architecture and performance, which is an opportunity, as information technology empowers business processes. [24]

Part of the review compares between the frameworks above, as illustrated in Table 1. The purpose of the comparison is to confirm the areas that each framework covers throughout the process, as the comparison table maps the frameworks in the following areas: need analysis and scoping, alignment with business strategy, benchmarking, developing alternative processes designs and qualifying the best out of them, testing involving end-users, training and knowledge management, handling process performance, transition from the old version to the new version of the redesigned processes, evaluating success factors, promoting for continuous improvement, and indicators of empowering data in the processes.

Table 1. A comparison between the discussed business process re-engineering frameworks.

Framework	Mendling	Motwani	Al-Mashari and Zairi	Robert	Lowenthal	Cross et al.	TOGAF
Need analysis and scoping	✓	✓	✓	✓	✓	✓	✓
Alignment with business strategy	✓	✓	✓			✓	✓
Benchmarking	✓	✓	✓			✓	✓
Alternative modeling and qualifying	✓	✓	✓	✓	✓	✓	✓
Organisational change impact	✓	✓	✓	✓			✓
Testing end-user engagement	✓	✓	✓	✓		✓	✓
Knowledge management	✓	✓		✓			✓

Table 1. *Cont.*

Framework	Mendling	Motwani	Al-Mashari and Zairi	Robert	Lowenthal	Cross et al.	TOGAF
Handling running instances	✓			✓			✓
Process performance monitoring after implementation	✓	✓		✓			✓
Evaluation and setting success factors	✓	✓	✓	✓	✓	✓	✓
Promoting for continuous improvements	✓			✓			✓
Data use in decision making	✓	✓	✓	✓	✓	✓	✓

The comparison above suggests considerable differences between the framework in terms of covered areas. Nevertheless, it does not necessarily reflect consistent framework performance in implementation projects.

Selecting a proper framework is one success factor where other success factors play an accumulative role in overall successful implementation. However, it indicates how critical it is to cover areas in the implementation projects to ensure a higher success rate. The comparison also indicated that data empowerment is present in all frameworks, a positive indicator for data mining and the machine-learning implementation model.

2.2. Methodologies

Business process re-engineering empowers well-proven methodology implementations. A methodology is an approach that uses governance frameworks, tools, and techniques to manage project progress for successful implementation [25]. Multiple proven methodologies are used for business processes improvement and re-engineering projects, such as Six Sigma, Lean Thinking, Lean Six Sigma, Total Quality Management, Kaizen, and Poka-Yoka [26].

In our review, we covered Lean, Six Sigma, Lean Six Sigma and Kaizen, as these are the most relevant methodologies to business process r-engineering projects:

- Lean methodology began with a manufacturing emphasis and was referred to as lean manufacturing for many years. Gradually, organisations learned that the same principles also applied to non-manufacturing processes [27]. John Y. Shook, and the Lean Global Network team [28], emphasise that Lean creates the most value for the customer while minimising resources, time, energy, and effort.
- The Six Sigma methodology was initially founded by Motorola, when facing extreme pressures from overseas competition, mainly Japan. Therefore, around 1987, Bill Smith and others began improvement projects that, in many ways, looked similar to TQM projects. Eventually, Mikel Harry and others helped Smith formulate this approach into an overall business initiative to protect Motorola's pager business. They named the initiative "Six Sigma". The name was based on the desire to reduce variation to the level that specification limits for in crucial process metrics, six standard deviations away from the target [27]. General Electric also played a very significant role in the development of Six Sigma as a methodology. General Electric CEO JackWelch loudly proclaimed that General Electric was jumping into the Six Sigma game in late 1995. Jack Welch defines Six Sigma as a quality program that, "when all is said and done", improves customer experience, lowers costs, and builds better leaders [27,29]. The Six Sigma methodology starts with identifying the need for an improvement initiative. However, when Motorola designed the initial version of the Six Sigma steps, it replaced the four phases of Measure, Analyse, Improve, and Control by

General Electric. It did not have the Defining step. The Define phase was added before the Measure phase afterwards, in order to form the well-known Define, Measure, Analyse, Improve, and Control process (DMAIC) [27,29]. However, when a product or a service is under significant design change requirements or at an early stage of development, the five phases of Six Sigma change to Define, Measure, Analyse, Design, and Verify (DMADV). The change is to achieve a Six Sigma level right from the initial design, which is also called the Design For Six Sigma (DFSS) [27,29]. The Six Sigma methodology is a well-disciplined and structured approach used to enhance process performance and achieve high quality and low levels of variability [29].

- Lean Six-Sigma methodology eliminates waste and variation, following the DMAIC structure, as in the Six Sigma methodology, to achieve customer satisfaction regarding quality, delivery, and cost. In addition, it focuses on improving processes, satisfying customers, and achieving better financial results for the business [29].
- Kaizen, as a term, was coined by Masaaki Imai, as "KAI" means changes, and "ZEN" means improvement. The focus of the Kaizen methodology is to eliminate the activities that do not add value to the process [30].

Comparing these methodologies on their scope, objectives, technology empowerment, and data utilisation is in Table 2 below as a summary. The comparison suggests that all methodologies consider information technology a key enabler in deriving business process re-engineering projects. Additionally, the study indicates that all methodologies rely heavily on data to shape and derive change in the process design.

Table 2. A comparison between business process re-engineering frameworks.

Characteristics	**Methodologies**			
	Lean	**Six Sigma**	**Lean Six Sigma**	**Kaizen**
Scope	Eliminating unwanted activities	Reducing variance	Waste elimination and variation reduction	Small and incremental changes
Objective	Reduction in workflow time	Process standardisation	Process standardisation and waste reduction	Incremental continuous improvements
Use of information technology tools	Very high	Very high	Very high	Intermediate
Relying on data in decisions making	High	High	High	High
Change method	One time	Incremental	Continuing	Continuing incremental
Associated risk levels	High	Moderate	Moderate	Moderate

The comparison suggests that all methodologies empower tools to generate and analyse data to improve or re-engineer the business process. Furthermore, the methodologies, especially those that promote incremental and continuous improvement approaches, empower data to analyse the performance and initiate another improvement cycle.

2.3. Tools and Techniques

Furthermore, the review indicates that both frameworks and methodologies employ tools and techniques throughout the process. In addition, the review found many tools and techniques used in business process re-engineering for different purposes. There are tools used for process discovery and process visualisation in order to have a helicopter view of the flow of the process from one activity to another and to view the roles and responsibilities in an overview (Table 3). Other tools for business process management include monitoring the business process's quality or analysing aspects of the process like process performance, reliability, and efficiency.

Table 3. Tools used for business process re-engineering and optimisation.

Type	Tools and Techniques			References
Process discovery and visualizing	• Mylnvenio • ProM • Disco • Tree diagram	• Affinity diagram • Arrow diagram • Matrix diagrams	• Relations diagram • Process decision chart • Process mapping flowcharts	[5,31–33]
Quality management	• PDCA • DMAIC • IDEA • Pareto chart	• Control chart • 8Ds • Stratification	• Histogram • Scatter diagram • Cause-and-effect diagram • Checklists or check sheet	[26,27,29,33–36]
Analysis	• The force fields. • The 'measles' chart • Benchmarking	• Matrix analysis • The five whys • Multi-vari charts	• Total productive maintenance • Cycle time management (CTM) • Kanban production system	[26,29,36]

Nevertheless, an added value of using systemised tools and techniques, besides their impact on process improvement and re-engineering, is their practical use in generating, analysing, and visualising data throughout the process.

This review indicates that similar tools, as in Table 3 above, are implemented and used in business process re-engineering frameworks and methodologies. Additionally, the review indicates that using such tools is crucial to driving the implementation projects towards successful implementation.

2.4. Success Factors

Having a high success rate in implementation projects is the ultimate goal for any implementation team. However, business processes re-engineering projects were not always successful for multiple reasons, primarily associated with using best practices or industry standards in an industry field from other industrial experiences without adequately studying the unique requirements of the field [15]. Additionally, the failure rate is around 70% for business process re-engineering implementations, due to a lack of a proper framework or methodology appliance [15]. However, multiple factors play a vital role in the success and failure of a project. They can be looked at as indicators to predict the outcome of an implementation project and predict the percentage of the success chance.

Bhaskar [15] and Hashem [14] outlined the foundation of success and failure factors for a business process re-engineering implementation, which the researchers used to develop the following list of factors in Table 4. The researchers added a category level to classify the factors into driver, strategic, or enabler categories. The driver factors derive the need for change and raise the flag in the organisation when the business process requires improvement. The strategic drivers direct and steer the project to implementation. The enabler factors are necessary to enable the successful implementation. The below listed factors may lead to project success or failure, as described in the table below (Table 4).

Table 4. Implementation factors for success and failure.

Category	Factor	Success	Failure
Driver	Alignment of business strategy for BPR project and IT strategies	Aligned strategies	Lack of alignment and unclear strategy
Driver	The focus of the change	Driven by customer needs	Focuses on the process as a process and drives the change on structural or pure financial bases
Strategic	Clarity on business needs	Solid business case with a clear scope of work	Inadequate business case: unclear, unreasonable, unrealistic scope, and unjustifiable expectations from the BPR project
Strategic	BPR methodology and framework	Selecting the best methodology and framework for the project	Lack of innovation in process redesign
Strategic	Data empowerment	Data-driven change based on facts and figures	Not having sufficient data
Strategic	Change management strategy	Having a solid change management strategy, team, and change processes	Lack of change management
Strategic	Top management and critical stakeholders engagement, leadership, and motivation	Highly engaged, supportive, and committed	Lacking support, poor commitment, and poor leadership style
Enabler	Operation team engagement	Engaged and involved through the project	Non or minimal engagement
Enabler	Technology and digitalisation	Adoptive and change dynamically based on the need	Lack of reliable advanced technology
Enabler	Training and education	Provided to all levels	Lack of training and education
Enabler	Rewarding system	Fair	Unfair
Enabler	Organisation culture	Flat and less bureaucratic Structure	Bureaucratic
Enabler	Financial support	Adequate	
Enabler	Working environment	Collaborative and work towards shared objectives and targets	Lack of collaborative work
Enabler	Communication	Effective communication with all stakeholders	Ineffective communication
Enabler	Business process re-engineering team	Authorised, experienced, effective, and skilled	Insufficient authority that lacks experience and skills

The table above suggests categorising technology and digitalisation as enabling factors in the implementation projects for success. The review found that engaging the right people at all levels is vital to successful implementation. Their involvement and the knowledge they contribute is a critical factor. Organisational culture and human factors are vital in implementing business process re-engineering towards success or failure implementation. Generally, all factors affect the business process re-engineering projects, yet the human factor is dominant [37]. Therefore, an ontology-based knowledge of Map Methodology (PROM) reduces the failure ratio, solves business process re-engineering project problems, and overcomes difficulties [38].

Furthermore, empowering data and data analytics in driving the decisions throughout the implementation impacts the success or failure of a project.

Having clear visibility of the project implementation success and failure factors, as in Table 4 above, makes it possible to predict the success or the failure of a business process re-engineering implementation through empowering the data and utilising data science and machine-learning concepts.

Therefore, supporting the decision-making process with a machine-learning algorithms is needed. Quantitatively relating the business process activities (Borgianni et al., 2015) improves the selection of the best fitting framework and methodology.

2.5. Data Mining and Machine Learning Use in Business Process Management

Thus far, the review looks at available frameworks, methodologies, tools, and techniques used in the manual business process re-engineering process, as well as the success and failure factors. Therefore, the next step is to investigate machine learning and data mining utilisation. For that, the review surveyed 60+ publications on subjects related to data mining and machine-learning applications for process management, process improvement, process re-engineering, process optimisation, process automation, process visualisation, process modelling, process planning, process discovery, and process behaviour.

The survey indicated a rising academic interest in studying and coupling process science, process mining, data mining, and machine learning (Figure 1). Over the years, this implies a considerable focus on process behaviour, process improvement, and business process management. However, the study indicates a shift in focus from understanding process behaviour and business process management in 2017 towards process improvement and optimisation in 2020, which is a natural evolution of the research focus from general to more specific research problems. In addition, machine learning growing capabilities have an optimistic outlook, and may be applied to more sophisticated challenges.

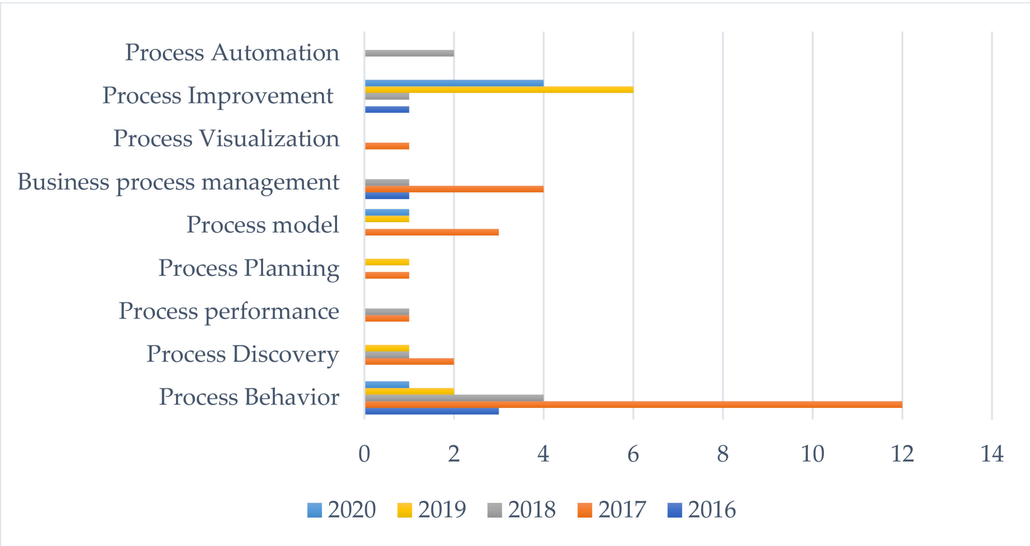

Figure 1. Level of focus on process mining subjects from the years 2016–2020.

Furthermore, the survey suggests that more papers were published in 2017 about process behaviour (Figure 2), indicating a trend driven by a group of researchers, such as Van Der Aalst and others.

Furthermore, the survey found that from the years 2017 until 2020, many process mining subjects were discussed and coupled with machine learning in different percentages.

With these findings, investigating literature on possible machine-learning implementations in business process re-engineering is the next step.

The study investigated previous implementations of machine learning and data mining for business process topics. The study found and reviewed 22 papers that qualified as per the selection criteria: an application of machine learning in the business process.

The findings in Table 5 indicate that machine learning was applied to process discovery, such as process event logs files, predicting process behaviour, improvement, and process optimisation.

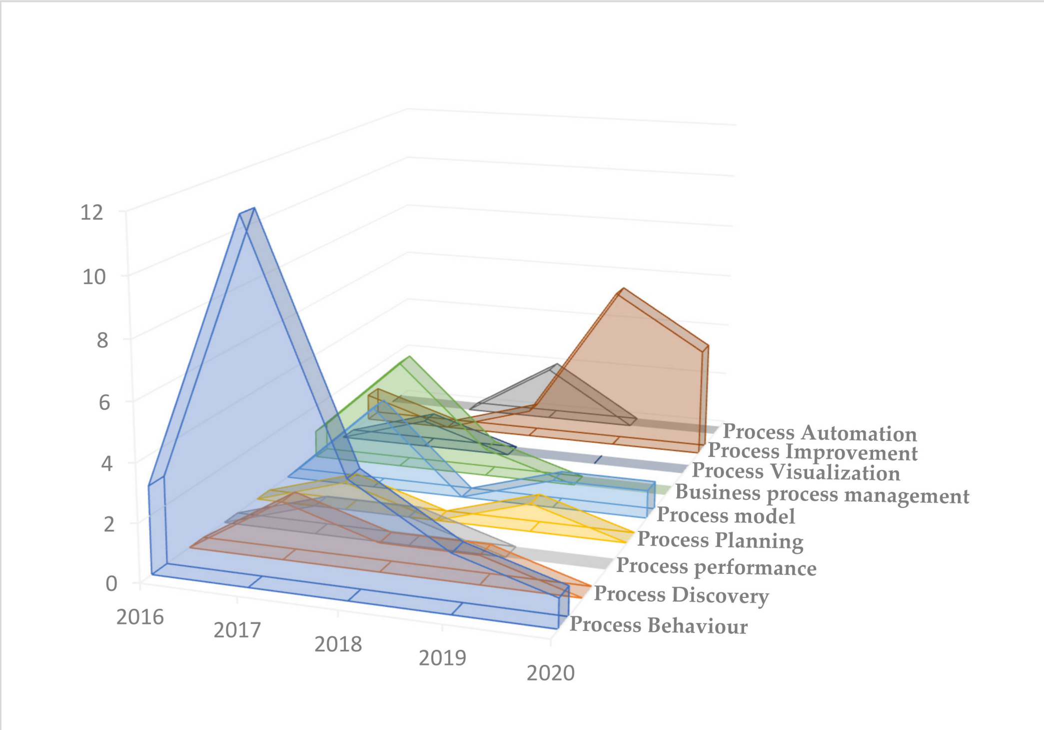

Figure 2. Level of coverage of process mining subjects from the years 2016–2020.

Table 5. Examples of machine-learning tasks and algorithms used for BPM.

BPM Task	Algorithm(s)	References
Process discovery	Decision tree	[32,39–43]
Process behaviour prediction	Deep Learning	[32,35,44–47]
	Support Vector Machine	[32]
	Hidden Markov Model	[32,48]
	Expectation–Maximisation	[39,48–51]
Process improvement	Fuzzy	[52,53]
	Natural Language Processing	[33]
	Decision tree	[32,54]
Process optimisation	Mixed-Integer Linear Programs	[55]
	Support Vector Machine	[56]
	Greedy Algorithm	[57]

The review indicates that the decision tree algorithm used for process discovery applications is by Mannhardt, De Leoni [39], Kalenkova, Burattin [40], Leemans, Fahland [42], Verbeek and Mannhardt [43], Márquez-Chamorro, and Resinas [32]. The decision tree algorithm was appropriate for this problem type because it looked for hidden patterns in the provided process events and segmented process activities into flow scenarios. The most repeated pattern represents one option of the process flow scenarios with the possibility of having multiple exceptions to the original process flow.

Predicting the process behaviour was another application for machine-learning applications. The review indicates multiple algorithms used to solve it. For example, deep Learning neural networks were used by Márquez-Chamorro and Resinas [32], Zgodavova, Bober [35], Tax, Verenich [46], Chandramouleeswaran, Krzemien [47].

Furthermore, the study indicates that the number of implementations towards more complex problems like process improvement and optimisation are rare and not as popularly implemented as process behaviour prediction applications.

One exciting machine-learning application by Weichert et al. is optimising business processes for multiple industries, including machining, plastic manufacturing, and others. They applied machine-learning algorithms for defect detection, automatic visual inspection, and assembly fault detection. Weichert et al. claim an excellent level of use for machine learning in business process optimisation.

However, Weichert et al. indicated a scarcity in correlating the data, the amount of data, the machine-learning algorithms, and the respective production problems [34].

Khan et al. stressed initiatives to optimise the business process using machine learning and proposed a framework for automated re-engineering of business process modeling notation models by excluding inefficient activities [58]. Thus, Khan's work is tremendously essential in automating the process of business process re-engineering.

3. Findings

The literature review provided solid evidence that business process re-engineering is a very well established approach equipped with frameworks, methodologies, tools, and techniques. Additionally, the literature shows that the failure of a business process re-engineering project is associated with many factors. One of them is having a knowledgeable implementation team, which is consequential to selecting the right tools and techniques. In addition to that, in 2020 and beyond, the COVID-19 pandemic affected the world and caused lockdowns that paralysed many industries. Because of the lockdowns, many organisations accelerated the implementation of digital transformation projects to enable their workers to continue working remotely. Relatively, digital transformation helped many organisations to rethink, redesign, simplify, and re-engineer their business processes [59]. This resulted in a massive demand for digitalisation and, consequently, business process re-engineering. As such, business process re-engineering projects became enormously expensive and time-consuming. On top of that, redesigning a business process requires extensive knowledge in the functional domain of the process. To explain, for example, an aviation process, requires aviation knowledge, and likewise, medical processes require medical knowledge.

The review aimed to investigate the level of use of machine learning in automating business process re-engineering. In addition, the review indicated increasing academic progress and interest in integrating machine learning and optimisation methods in order to improve processes. The review correlated that with the accelerated advances in the business environments derived by digitalisation and the resulting available data [36].

Nevertheless, the review indicates hardly any extreme use of the available process data in order to apply machine learning and improve the business process, confirming the findings of Weichert, D. et al. [36].

It also confirms that there is hardly any significant utilisation of machine-learning tools and techniques for automating re-engineering business processes. However, the literature review found humble attempts to automate business process re-engineering.

4. Discussion

The hypothesis of this study is that a machine-learning model trained to re-engineer a defined business process automatically is doable. So far, through the literature review, the study found opportunities to achieve that through the Lean Six Sigma and Kaizen methodologies.

Mimicking Lean Six Sigma concepts of reducing waste and variations in the business process is possible based on these findings. The researchers engaged and interviewed selected experienced business process re-engineering practitioners and Lean Six Sigma Black Belt holders from multiple industries, such as aviation, education, public service, automobile, and telecommunication. The main objective of these interviews was to identify the data they use and rely on when deciding on the re-engineering process. The output from these interviews is an initial set of data attributes and data sources. These can qualify as inputs for a machine-learning model inspired by the Lean Six Sigma way of thinking.

In addition, it was found that business processes in an organisation are generally categorised as business support processes or core business processes. The core business processes are entirely different from one industry to another, depending on the industry core business model and other factors. Contrarily, business support processes, such as human resources processes, finance and accounting processes, supply chain management processes, and information technology processes are usually standard across industries, with slight exceptions. However, because of legacy, bureaucracy, and other corporate cultural issues, the activities of the standard business process diverts; therefore, more activities are added. This becomes even worse when introducing exceptions to the business process (parallel processes).

In this sense, a machine-learning model could contribute to re-engineering a business process in an industry or an organisation, based on a learned pattern from another industry or organisation, for the same process or function.

While designing our model, we considered the anticipated process complexities, which vary from one process to another. As such, the proposed model looks at each activity in the process separately. The machine-learning model takes the featured data, as inputs, and examines them against a supervised machine-learning approach. The model then labels the input and recommends an action against each activity. After examining all process activities, the outcome is a re-engineered version of the original process. Below, Figure 3 gives a high-level illustration of how the proposed model works.

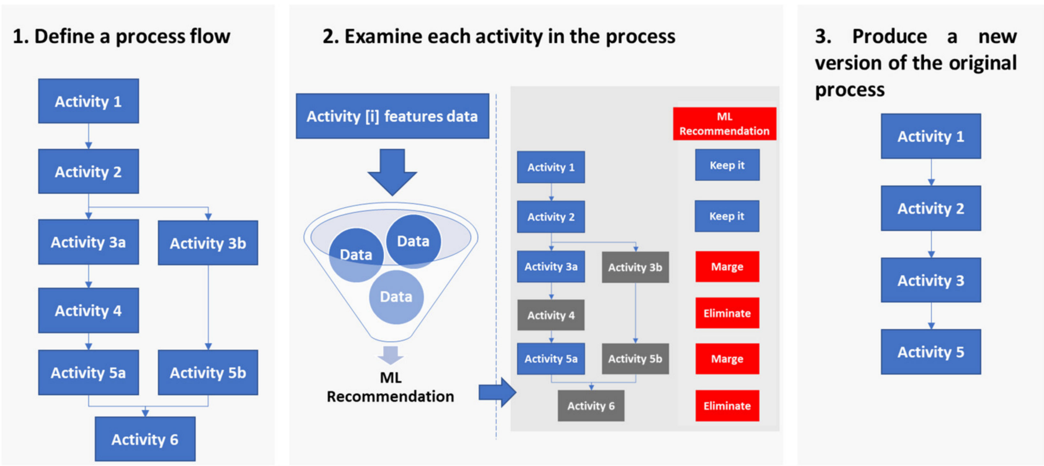

Figure 3. The proposed model of high-level illustration.

A machine-learning model requires data to learn from and test its accuracy in recommending and mapping labels to the feature records. However, there is a need to identify data attributes that can add value to the model in order to identify the required data sources and datasets.

Interviewing the Lean Six Sigma experts helps identify the following list of attributes (machine-learning features) as inputs to the machine-learning model:

- Process industry, e.g., aviation, telecommunication, manufacturing, and banking
- Process function, e.g., human resources, finance, supply chain, and production
- Process versions of history; the process version opens another dimension of the prediction model of the alternative process design.
- Activity performance against its KPIs: poor, good, and excellent. This attribute can be more accurate when the KPIs data are available.
- Activity operation cost value (acceptable? Yes or no).

- Customer satisfaction level (from one to five); some companies implement customer satisfaction at each step.
- Does it make a bottleneck? (Yes or no).
- Are there enough resources to do the task? (Yes or no).
- Is it digitalised? (Yes or no).
- Can it be automated? (Yes or no).
- Is it an audit compliance check step? (Yes or no).
- Is it being performed by the same actor as the previous step in the process? (Yes or no).
- Activity value to the process (1–10)? If less than three, should it be eliminated?
- How relevant is the activity to the process objectives? (Relevant or irrelevant).
- Is it a service provided to customers step? (Yes or no).
- Is it an internal activity or does it require external input? Internal is meant in the sense of the organisation, specifically, the function department.
- Stakeholder level. (VIP, owner, consumer, employee, and system).
- Is it business-to-business or business-to-customer?

Depending on the organisation's documentation policy, digitalisation, and automation, these data attributes can be available in the organisation. In modernised organisations, a digital business process management platform would have all the necessary data and more. Such platforms document all of the process lifecycles, from the initial process modelling, process versions updates, process activities, process audit logs, and process execution data, to the retiring of the business process. Some organisations even link their social media accounts to the business process management platform. Social media helps in improving the level of service and solving disputes with clients.

In general, we have identified the below-listed possible sources for the data. These could be functional modules in business process management platforms, stand-alone separated systems, or data repositories.

The data sources are:

- Process modelling repository
- Process execution data
- Process events logging database
- Process performance KPIs
- Process owner feedback
- Experienced process engineer decision

Except for the last item in the list above, the data can be on one platform, as highlighted above. Moreover, through the literature review, it was found that there are applications of machine learning that discover the process flow in event logs. Other implementations are to predict process behaviour, which can help learn the process performance.

Undeniably, there will be challenges with the data. However, the challenges are situational, i.e., each implementation initiative will have different challenges to overcome, and as the general guidelines are defined, this will help.

In order to bring the data sources closer to the identified attributes, Figure 4 below mapped the identified data attributes to possible data sources.

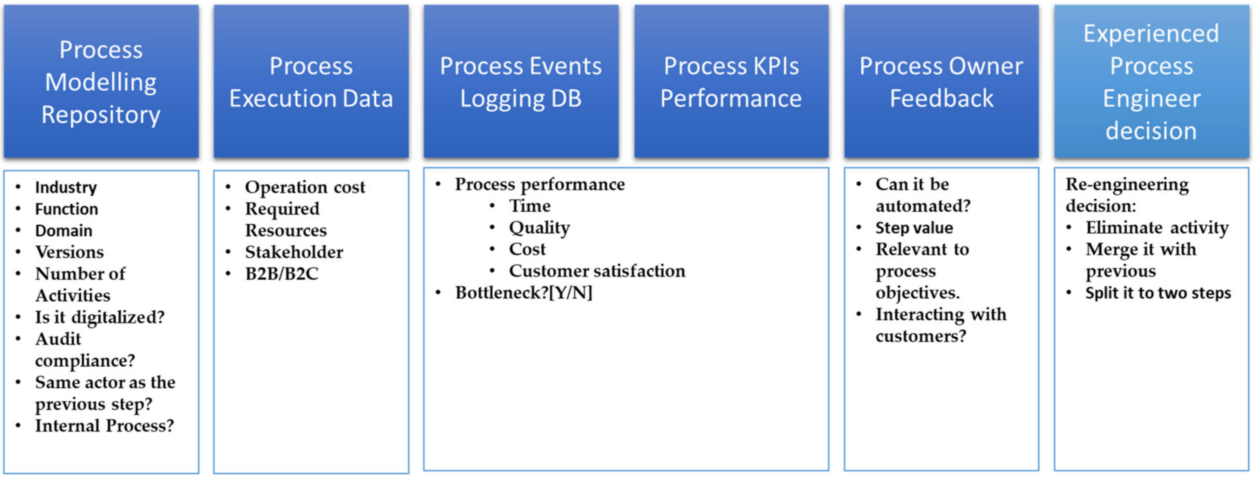

Figure 4. Possible data sources mapped to data attributes.

Below, Figure 5 is a prototype illustration of the machine-learning model in action. In this example, the machine recommends keeping the activity step1 and justifies it because of the step value.

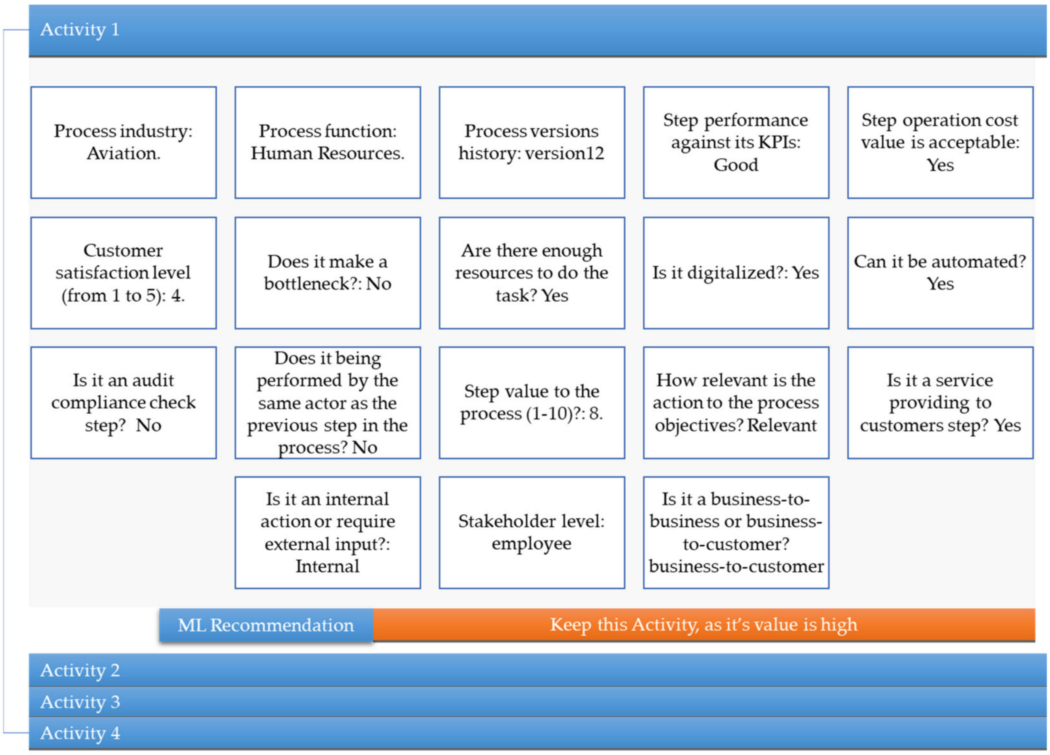

Figure 5. Illustration of the machine-learning model in action.

The identified list of input attributes is evolving and can be expanded and challenged with more attributes. As expected, adding more to the list will make the ML output more accurate because some of the new features could be better than the existing ones. Therefore, its evolving nature should improve its performance. Below, Table 6 is a projected sample data of records of attributes with supervised and predicted label results. If we added the industry and function attributes to them, they would impact the predicted result in one way or another. Relatively, identifying new attributes would give us better options in selecting better input for better output.

Table 6. Sample data of ML model attributes.

Step ID.	Performance	Is Bottleneck	Enough Resources	Automated	Audit Step	Same Actor as the Previous or the Next Step	Step Value	Relevant	Prediction Result
1	Poor	No	Yes	No	No	No	6	Relevant	Keep
2	Good	Yes	No	No	No	No	5	Relevant	Keep
3	Poor	Yes	Yes	No	Yes	Yes	2	Relevant	Merge
4	Excellent	No	Yes	Yes	No	No	8	Relevant	Eliminate

Another important aspect is the amount of available data. Considering the size of an organisation, the number of processes they have, and their complexity, determines the available amount of data. In a middle-sized organisation, the number of active business processes can reach up to 200 (the number is a projected number based on experience, as learned from the interviews, and there is no reference to support it yet to match to reality) processes between human resources, finance, accounting, supply chain management, and information technology departments. The organisation can have more processes, depending on its core operation.

The illustration in Figure 5 and the sample data in Table 6 suggest having three output results for the supervised machine-learning algorithm: keep the activity, merge with previous, or eliminate the activity. However, through examining more data, the model would mature and would recommend more accurate and reasonable results like automating and merging activities, eliminating activities from the process, splitting an activity into two, or other recommendation classifications. The sample data and the ML model are at an early stage of development, requiring experimental work as future work for the researchers.

The outcome from the model then needs to be verified. Hence, since business process re-engineering relies heavily on industry and functional knowledge, the verification will require engaging experts on the subject matter. The expected outcome of implementing the proposed machine learning would be a leaner process if the process were not at its leaner shape. In addition, such a tool can be a practice of continuous improvement for evolution and providing better insights.

5. Conclusions

In conclusion, this study indicates that business process re-engineering is a scientifically matured field. The study found that business process re-engineering is equipped with many solid frameworks, methodologies, tools, and techniques; this is an eye-catching finding because of the amount of generated and analysed data through the re-engineering process. The data are enormously helpful for analysing the process performance, scientifically deciding the need to re-engineer a business process, and finding a re-engineered business process for the evolving business requirements.

The review also found few efforts to utilise machine learning for business process re-engineering. This confirms that academia could contribute more to automating business process re-engineering with artificial intelligence and machine learning.

This study proposes a novel solution to automate the business process re-engineering, and is inspired by relevant Lean Six Sigma methodology principles, derived from the core concept of eliminating waste and variants.

In future work, the researchers intend to experiment and qualify the proposed solution in multiple case studies. In addition, we are aiming to develop a platform publicly available for experts to exploit and challenge.

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