Exploring Interconnections Between Machine Learning and Operations Strategy

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Abstract. Within the data science and artificial intelligence fields of study, machine learning have supported performance improvement in medicine, manufacturing, law and even sport environments. The purpose of this paper is to investigate how machine learning has been used as a tool to improve the assertiveness of decision- making, providing competitive advantages in the wide field of operations management. This exploratory research analyzes the content of five machine-learning studies, relating each of them to Slack's strategy pillars: cost, speed, quality, flexibility and dependability. Research design was limited to Scopus' papers published exclusively in high impact journals. Results emphasize the important role of machine learning in organizational competitive advantages and limitations are used to address further research suggestions, extending the present investigation with a more extensive bibliographic portfolio analysis. The contribution of this paper is a matrix analysis of how machine-learning projects indirectly contribute to at least three strategy dimensions simultaneously. Complementarily, an illustration was built for a better comprehension of the interrelationships among the strategic pillars reinforced by the analyzed studies.

Keywords: Slack, machine learning, operations strategy, strategy, operations.

1 Introduction

Strategy has a variety of different concepts, with multiple perspectives and definitions, which are considered important for academic research, since this diversity can offer distinct horizons and guidelines (Mintzberg, 1987, Skinner, 1969). Porter (1996) reinforced this point of view and tried to differ strategy from operational effectiveness, since its importance is not enough to achieve competitive advantages. With Industry 4.0 and artificial intelligence scenario, organizational environment became even more aggressive among competitors, and Porter's analysis demonstrated that the essence of strategy is the choice to perform activities differently from the others. Therefore, the need of solutions to improve performance in various levels combined with technologies is a key factor for success.

In this context, the purpose of the present paper is to investigate how machine learning has supported operations strategy in organizations focusing on Slack's (2009) performance objectives: cost, speed, quality, flexibility and dependability. Among Slack's performance dimensions (2009), cost is the direct competition on rates while speed is the turnaround time between customers ordering a product or service and the point at which they receive it. Quality is the visual aspect of how well an operation does what it does. Dependability means that customers can rely on organization to receive their goods exactly when expected and finally, flexibility is the ability to change an operation to match customers' requirements. Since the dimensions influence positively or negatively on each other, the present study also analyzes an integration of performance objectives, comparing and relating their multiple gains, despite the tradeoffs.

Regarding the paper structure, Section 2 introduces a brief theoretical background of operations strategy and machine learning. Section 3 details the research design, which consists on the search terms for the paper selection on Scopus database. Sequentially, Section 4 brings the results, which are segmented by two subchapters, the selected papers with their content analysis and a following operations strategy matrix to allocate them in Slack's competitive advantage pillars. Finally, Section 5 presents the conclusions, addressing limitations and further research.

2 Literature review

This literature review presents firstly a brief theoretical background of operations strategy along with a following machine learning overview.

2.1 Operations strategy

In a decade of high manufacturing processes, the companies need to stand up for their competitors. Porter (1996) once said the only way to outperform is by preserving competitive advantages. These advantages are grounded by the costumers needs and are related to the continuous improvement methods applied on quality, flexibility, cost, time and productivity (Slack *et al.*, 2009). Focused on the core business, costumers and the companies' competitive advantages meet to perform strategically trying to achieve every aspect of improvement in order to reach exceptional performance. Strategy is essential for the competitiveness and according to Porter (1996), the competitive positioning is a matter of choosing the right factors to focus on, applying trade-offs.

Strategy is related to the company's plans, ploy, patterns, position and perspective (Mintzberg, 1987). Operations strategy develops internal guidelines to deal with the competition and the market threats, creating patterns to establish the intended company's behavior. Traditional strategy management has been challenged due to organizational competitiveness, demanding new frameworks and models considering the relationship between roles, capabilities and design theoretical recommendations for a performance measurement system (Pinheiro de Lima *et al.*, 2008).

Strategy purpose is to demonstrate how well grounded is the management process, its influence on the organization position on a specific market and the perspective sets of the internal characteristics of the company (Bititci *et al.*, 2011).

All these definitions guide the organization to achieve its unique strategy, which provides the necessary differences to reach competitive advantages with faster results (Bititci *et al.*, 2011). However, defining a strategic process plan is not an easy task and cannot be static (Hayes, 1985). Once the company's strategy is created, it has to be continually analyzed to identify its efficiency and evolution. Nelly (2006) shows the relationship between strategy and performance gains, concluding that the strategy objectives in action can bring not only unique performance results, but also a combination of categories, like cost and quality. As the competition arises, the competitors tend to find new ways to compete and the managers need to choose new trade-offs to shape the strategy plan. Hayes (1985) highlighted that the company has to establish its corporate goals, find alternative paths to achieve these targets and marshal what is necessary in capabilities to implement and follow defined strategies. Even so, easy-ways-means method itself does not guarantee organizational performance, since the strategy happens in the long-term with all employees playing a respective role in its work execution and developing their proper capabilities strengthen the competitive strategy (Skinner, 1969). Okoshi *et al*. (2019) have recently found performance results depend on policies and capabilities that are addressed and managed by companies' decision areas.

Personal capabilities and competitive technologies are some key recourses for outstanding performance, once they can possibly be unique and not easily copied by competitors (Hayes and Upton, 1998). This approach focusses on innovative operation tools and it has been enhanced by this new technological era. Within Industry 4.0 context, artificial intelligence reinforces operational advantages with a faster and more reliable work execution. However, the benefits are not exclusively limited to shop-floor and operational activities, since data science is an inter-disciplinary field that uses not only scientific methods and processes, but also algorithms and systems to extract knowledge and insights from structured and unstructured data (Moorthy and Gandhi, 2017). Therefore, competitive indicators together with consistent advanced knowledge are also provided by artificial intelligence, bringing important relevance for strategy definitions. In this context, the present study links machine learning to organizational strategic goals.

2.2 Machine learning

Performance fulfillment has a high value service that goes beyond management and control, enabling communication, roles and informational skills to translate the strategy and challenge predefined concepts by senior leadership (Neely and Alnajjar, 2006; Pinheiro de Lima *et al*., 2008). Machine learning has been used as a tool to provide this meaningful knowledge. However, most of the frameworks postulating the best practices, which should be adopted in performance analytics projects, do not involve the respected data complexity. In this context, Dutta and Bose (2015) developed a new framework with the purpose to provide organizations a holistic roadmap in conceptualizing, planning and successfully implementing Big Data projects. The procedural steps involve a step-by-step project map with a cross functional project team, adoption of innovative visualization techniques, and a consistent top management commitment to data driven decision making.

Machine learning is an interdisciplinary research area, which combines ideas from several branches of science namely, artificial intelligence, statistics, information science, mathematics and many others. The main purpose of machine learning approach is on the development of fast and efficient learning algorithms that can make predictions on data (Moorthy and Gandhi, 2017). Therefore, machine learning is also known as predictive analytics, which aims to determine what is likely to happen in the future. The predictions are based on statistical techniques that fall under the general category of data mining (Ouahilal *et al.*, 2016). This quantitative accuracy for predictions is extremely important for an assertiveness in decision-making processes, although the computational time of the algorithms are critical in terms of cost and project viability (Moorthy and Gandhi, 2017). In this digital era context, a recent study revealed real-time data, connectivity and interoperability are some of the most important key factors for a successful digital manufacturing adoption (Da Silva *et al*., 2019)

Machine learning projects have been increasingly managed by healthcare environment, providing accurate diagnosis, helping to predict cancer, chronic kidney disease (Charleonnan *et al.*, 2016) and even the effectiveness of music therapy (Raglio *et al.*, 2020). However, its multidisciplinary has also reached sport analysis, quantifying the relation between performance and success in soccer (Pappalardo and Cintia, 2018) and the educational setting, predicting academic performance with matriculate score and previously semester and pre-university exams as predictors' variables (Halde *et al.*, 2017). Organizational field was not left behind. Some companies have applied artificial intelligence for customer retention (Sabbeh, 2018), identify potential customers based on purchase behavior (Choudhury and Kur, 2019) and even employee performance prediction through historical datasets (Jayadi *et al.*, 2019) This study consists on analyzing how machine learning has contributed to operations strategy pillars defined by Slack *et al.* (2009).

3 Research Design

The research design consisted on a Scopus' search following the initial ProKnow-C steps for axes' definition, although our portfolio composition consists of exclusively five papers in a first iteration (Ensslin *et al*., 2010). Machine learning and operations strategy themes were searched with the reunion of 1st and 2nd axes linked by Boolean Operator "AND", as presented by Figure 1.

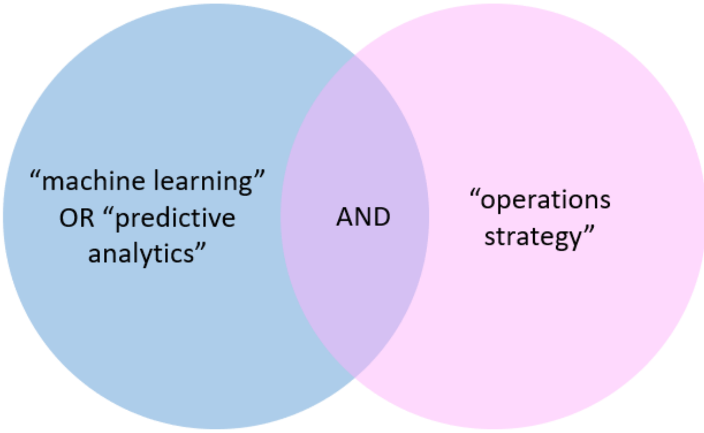

Figure 1. Search terms.

The search expression was limited to title, abstract and keywords. Only open-access papers written in English were searched and relevance filter was applied, as presented by Figure 2.

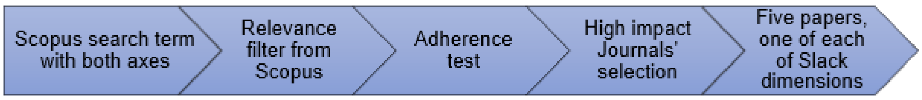

Figure 2. Search methodology.

Scopus presented 1293 papers and adherence test as applied to certify the assertiveness of search terms. On the following step, only high impact journals were included, rejecting 897 and resulting in 396 papers. Finally, as authors, we selected five machine learning studies that directly addressed each of Slack strategic pillars based on title and abstract details.

4 Results

Five papers published in high impact journals were selected from our Scopus search for our content analysis of their respective machine learning projects through Slack's strategic pillars (2009), as presented in Table 1.

Table 1. Machine learning selected studies.

	MACHINE LEARNING STUDIES OVER STRATEGY PILLARS	CITATIONS	JOURNAL H-INDEX
COST	LOYER, J. L.; HENRIQUES, E.; FONTUL, M.; WISEALL, S.: Comparison of Machine Learning methods applied to the estimation of manufacturing cost of jet engine components. International Journal of Production Economics, v.178, p. 109–119 (2016).	57	172
SPEED	CAVALCANTE, I. M.; FRAZZON, E. M.; FORCELLINI, F. A.; IVANOV, D.: A supervised machine learning approach to data-driven simulation of resilient supplier selection in digital manufacturing. International Journal of Information Management, v.49 (n. March), p. 86–97 (2019).	49	99
QUALITY	CORREA, M.; BIELZA, C.; PAMIES-TEIXEIRA, J.: Comparison of Bayesian networks and artificial neural networks for quality detection in a machining process. Expert Systems with Applications, v.36 (n.3 pt.2), p. 7270–7279 (2009).	194	184
FLEXIBILITY	SUSTO, G. A.; SCHIRRU, A.; PAMPURI, S.; MCLOONE, S.; BEGHI, A.: Machine learning for predictive maintenance: A multiple classifier approach. IEEE Transactions on Industrial Informatics, v.11 (n.3), p.812–820 (2015).	273	115
DEPENDABILITY	KO, T.; HYUK LEE, J.; CHO, H.; LEE, W.; LEE, M.: Machine learning-based anomaly detection via integration of manufacturing, inspection and after-sales service data. Industrial Management and Data Systems, v.117 (n.5), p.927–945 (2017).	14	96

The selected bibliographic portfolio presents only high impact journals with considerable impact on science community.

4.1 Content analysis

This section presents a brief content analysis of the selected studies, identifying their respective strategic achievements.

- **Study 1 – Cost**

A cost management project of the manufacturing sector was applied using a comparison of machine learning approaches to estimate the cost of jet engine components. Production volume and material cost itself were some of the predictor variables in the dataset composition. Loyer et al. (2016) applied five distinct algorithms and followed the machine learning literature in terms of predictive accuracy, goodness-of-fit, and also aspects as interpretability and computational time. Gradient Boosted Trees and Support Vector Regression presented superior accuracy and the best execution time, compared to all the other methods. On the other hand, Multiple Linear Regression, the worst performed algorithm in terms of accuracy, presented the best interpretability and easiness to fit and train. The study proved machine learning is an effective, affordable and competitive approach for statistical cost modelling in manufacturing processes. It is noticeable that cost is the main target of the study, but in the long term, Loyer et al. (2016) defend the cost estimation could be part of a decision system used by industrial engineers to identify outlier components. Hence, the benefits can be enhanced by the whole supply chain system, providing more flexibility and quality in operations. A further research was addressed to apply the same analyses with other jet engine parts to certify whether the conclusions remain valid in other scenarios.

- **Study 2 – Speed**

Cavalcante *et al.* (2019) proposed a supplier selection model using supervised machine learning. The authors considered supplier performance data with delivery date and quantity delivery to predict supplier dependability with on-time delivery, together with a make-to-order simulation model that involved suppliers, internal material flow and delivery forecasts to customers. Regarding to machine learning techniques, random forest, linear regression and k-nearest neighbors were performed along with hybrid algorithms. The combination of both approaches brought risk mitigation strategies in supply chain management. The redesign of supplier base and supplier investment analysis are an important contribution. Complementarily, the digital scope of machine learning and simulations provide a digital manufacturing analysis, enhancing a consistent velocity gain and cost reduction with a better supplier portfolio management. The study, however, needed to leave behind some estimations of probabilities of highly unpredictable events to take advantages from smart manufacturing data to predict supplier proneness to disruptions.

- **Study 3 – Quality**

Machine tool automation for quality defection improvement in manufacturing segment, can promote higher quality products in order to achieve competitive advantages. A case-study was investigated by Correa *et al.* (2009) on a machine learning project where surface roughness was defined as a predictive indicator for quality predictions. The researchers compared Bayesian Networks (BN) to Artificial Neural Networks (ANN) and tried a variety of measures and models with the same dataset, and as a result, Bayesian networks presented a superior assertiveness on quality prediction. It is important to recognize that this machine learning application is not limited to reinforce higher quality products, but also to provide a reduction in production time, since it also promotes a reduction in operational time with under-quality products and enhances speed with a faster work time in operations. These solutions proved to increase quality results on a very high level, but also request a distinguished expertise on the BN and ANN algorithms.

- **Study 4 – Flexibility**

A predictive maintenance case-study project was applied with a multiple classifier machine learning method. Since maintenance issues are unstable, it is a challenging task to find the best quantifying measures to predict failure risks and costs with assertiveness. Therefore, Susto *et al.* (2015) proposed a training algorithm of multiple classification modules with distinct prediction approaches to provide performance tradeoffs on frequency of unexpected breaks and unexploited lifetime. The authors successfully applied their proposed method in a semiconductor manufacturing company, where the chosen process was the replacement of tungsten filaments used in ion implantation, one of the most critical processes in semiconductor industries. Some of the predictor variables were pressure, position and quantity of electric charge. Support vector machines and k-nearest neighbors were the two chosen algorithms to perform, and the multiple machine learning classifiers working in parallel provided predictive knowledge to improve decision-making and feed the maintenance management system, to minimize downtime and its costs. This method highlights the improvements on flexibility and cost reduction which for Susto et al. (2015), can be even better when a second training iteration is applied minimizing the whole operating costs. Nevertheless, flexibility is an important achievement, from a lower downtime to an efficient maintenance management, in which operations become consequently faster and more flexible.

- **Study 5 – Dependability**

The degree of reliable products and processes brings critical indicators of a well performing industry, since they demonstrate the control and analysis of parameters in the production process. In some cases, the last step for product inspection is made by a cold test and trials, but even with all the applied control, a defect can appear only when the product is operating at a costumer. Ko *et al*. (2017) demonstrate a case study of an automated analysis tool, providing better product dependability using Lenzerini's formula combined to binary genetic algorithm-based wrapper approach. The case was applied using alter-sales service data from a heavy machine industry, which could identify engines with high probability defects before shipping the products to customers. This method highlights the importance of applying machine tool automation to increase dependability while reducing extra costs on the number of inspected items, human resources, and consequently, on the efficiency. Moreover, the case study also suggests that further studies need to be made so the machine learning model can find defects earlier than what was proposed using quality data from the machines' suppliers and the whole manufacturing process.

4.2 Operations strategy matrix

An operations strategy matrix analysis, presented by Table 2, was built based on a relation of the previous content analysis through Slack *et al.* (2009) strategic pillars.

Table 2. Operations strategy matrix analysis.

	COST	SPEED	QUALITY	FLEXIBILITY	DEPENDABILITY
Study 1	x		x	x	
Study 2	x	x			x
Study 3	x	x	x		
Study 4	x	x		x	
Study 5	x		x		x

The present classification is given by the authors based on the previous content analysis, since it was perceptible that machine-learning projects brought competitive advantages in at least three of the five strategy dimensions of Slack's literature. It was noticeable that even if the project was designed to follow a single dimensional specific target, it supported some extra strategic advantages in the long term. Additionally, cost reduction was an important achievement obtained by all the selected studies, which made convenient a visual understanding of the interrelationship among the strategic pillars achieved by the analyzed studies, presented by Figure 3.

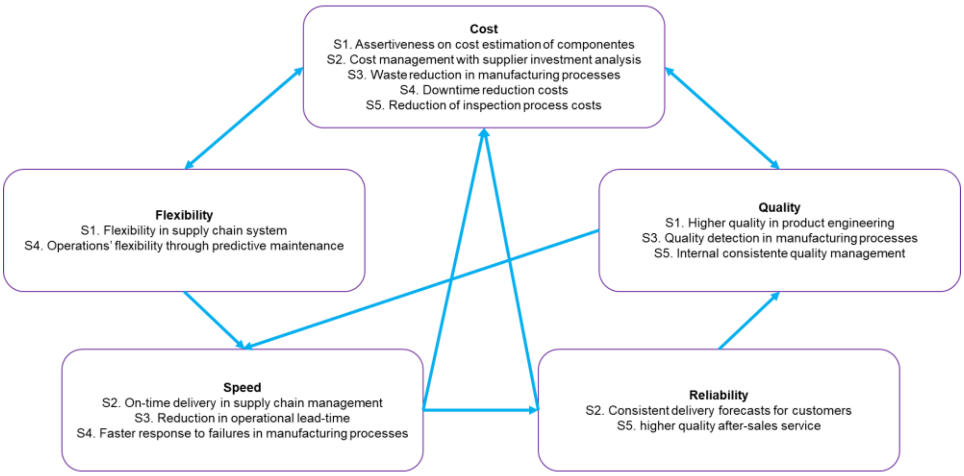

Figure 3. Interrelationships among strategic pillars.

The interrelationship illustrated reveals that only cost-flexibility and cost-quality have a mutual impact on each other, since all others present a single direction impact on another. Machine learning approaches of all studies had an impact on cost, even as a secondary competitive target or not specifically intended on their respective projects.

Quality strategic achievement was also meaningfully interrelated, reinforced by the implementation of a more consistent quality management of product engineering on Study 1 and a much more efficient quality inspection process provided by Study 5 after-sales service data. Speed, analyzed by Study 2 project, plays also a substantial role on influencing dependability for customers through on-time delivery together with a more consistent cost management of suppliers. Additionally, speed in operations is strengthened when a quality management or a predictive maintenance project is applied, as did Study 3 and 4, respectively.

The interrelationship among strategic pillars summarizes machine learning integration with operations strategy. Once the projects achieve better quality and make operations more efficient, they provide better economical results reaching cost and flexibility through accurate predictions of work execution. Therefore, depending on the project context and its strategic directions, dependability can also be part of the competitive advantages in the medium to long-term.

5 Conclusion

This paper presents a simple and consistent preliminary investigative overview of how machine-learning projects have helped organizations to achieve consistent competitive advantages in many different dimensions.

The interrelationship analysis has indicated cost as the common achievement of all analyzed studies while flexibility and dependability are connected to others although with a less significant interrelationship. This event can possibly be explained by the fact that these both dimensions are often only reached in the long-term, but this is a preliminary hypothesis that demands further investigation.

We have contributed to reinforce machine learning, an important subfield of artificial intelligence, as a strategy key to organizational environment with our content analysis. The built of a matrix perspective over Slack's pillars can also be used as a guidance to collect additional studies of machine learning projects. This is the following step, since limitations of the present study are related to its small bibliographic analysis. We expect to extend this preliminary investigation to offer deeper conclusions with the expansion of our proposed interrelationship analysis. Another important limitation to address is that the present initial analysis was made according to authors' content analysis, so another further research step is a taxonomy application to reinforce our findings with an extension of the portfolio.

Another important further research is to go beyond the expansion and the taxonomy, and conjointly relate the decision organizational areas that provide the capabilities that needs to be mobilized in process that enable project results.

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