Performance Analytics Role in Operations Strategy

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Abstract. Within the data science and artificial intelligence fields of study, performance analytics have supported performance improvements in a variety of different settings, including medicine, manufacturing, law and even sport environments. The purpose of this paper is to investigate how diagnostic and predictive analytics have been used as a tool to enhance assertiveness on strategic decisions, providing competitive advantages in the wide field of operations management. This exploratory research analyzes the content of a bibliographic portfolio composition built by the application of a systematic literature review performed by PRISMA approach, which resulted in 48 articles. The results revealed an analysis of the methods and contributions have been achieved considered Slack performance dimensions of cost, speed, quality, flexibility, dependability and human resources. Findings consisted of a consistent summarized analysis of how diagnostic and predictive approaches have strengthened cost prediction projects, supply chain risk mitigation, quality detection improvements, predictive maintenance, after-sales service level and employee satisfaction and individual performance predictions in applications published in high quality papers, appreciated by the scientific community. The main contribution of this paper is the reinforcement of the role of performance analytics for operations strategy.

Keywords: Performance Analytics, Operations Strategy, Performance Measurement Systems, Diagnostic Analytics, Predictive Analytics.

1 Introduction

With the new technological era, companies with a strong data-driven decision-making culture present consistent performance advantages comparing to organizations where personal opinions of individuals, formed by their experiences and feelings remain predominant in decision processes (Kiron *et al*., 2012; Davenport, 2020). Data-driven culture, however, demands best practices and mentality reinforcement among professionals to be genuinely data-oriented, trusting on quantitative analysis brought by performance measurement systems (Berndtsson *et al*., 2018; Okoshi *et al*., 2019). Along big data evolution, performance analytics reached a four-dimensional step of descriptive, diagnostic, predictive and prescriptive, which demanded even more from company competences. Based on these organizational challenges of applying performance analytics for strategic directions, the following research question is proposed:

Which role has performance analytics played at guiding management decisions?

A systematic literature review is used as a guidance for this investigation and papers are analyzed considering Slack (2009) strategic oriented dimensions of cost, speed, quality, flexibility, dependability and human resources in operations. Slack conceptual classification was selected due to his acknowledged contribution to operations strategy academic research over many decades. The relevance of this study is reinforced by identifying successful recent applications in organizations and, in order to meet this purpose, this paper presents a previous theoretical background including recent topics of data-driven culture and performance analytics developed by Chapter 2, exploring substantial wider fields of study related to this paper. A following research design with systematic literature review methodology is exposed by Chapter 3 and the subsequent results and conclusions are presented by Chapters 4 and 5, respectively.

2 Theoretical Background

The benefits of data-driven decision making have been rigorously evaluated by the economist Erik Brynjolfsson and his colleagues at MIT and from Penn's Wharton School, in an investigative study of how data-driven decisions positively affects company performance. According to Provost and Fawcett (2013), Brynjolfsson research has developed a measurement to statistically test and classify the respective level of oriented management by data in organizations. The study concluded that the higher the level of data orientation, the more profitable it becomes, since the best-ranked companies in the data-based ranking showed a 4 to 6% increase in productivity, greater return of investment, better assets utilization and market value.

It is necessary to reinforce, however, that isolated data alone do not have a clear meaning and do not imply guidelines for actions. For Light *et al*. (2004), the highest step towards pure data is the transformation of data into strategic information and this step always depends on the analysis and understanding of the professionals who act upon them. Therefore, data converted into information receive meaning when connected to a context. An information may or may not be relevant depending on its nature and object of analysis. Knowledge, on the other hand, is the collection of information considered useful and eventually processed to guide action. The knowledge, hence, is created through a sequential process. Light *et al*. (2004) argue that in case of productivity information, for example, the managerial ability to relate connections among performance indicators of different dimensions to act about it represents knowledge.

Some researchers such as Choo (1998) and Duan and Cao (2015) also praise the value of information for companies and defend the best way to analyze the environment in which data is inserted is not limited to understanding, but to assess information as knowledge that becomes available and make it useful at opportune moments. Mayer-Schonberger and Cukier (2013) compare the value of data to an iceberg floating in the ocean, where only a single small fraction is visible while most of it is submerged and, consequently, only innovative companies are able to extract deep knowledge and convert value into strategic advantages.

According to Duan and Cao (2015), the definition of data-driven principles is aligned with the organizational culture, which is conceptualized by a complex union of values and beliefs that give rise to the essence of how a company conducts its business. Davenport (2020) also places data-driven culture as a driver of an organization with a common vision and clear goals, with full transparency of the contribution of those involved. However, Vidgen *et al*. (2017) and Esteller-Cucala *et al*. (2020) argue that for the real transformation of a traditional company into a data-driven company, it is a premise to invest in procedures for organizational change, not just filling gaps in knowledge and, in addition, it is a strong request to work on changing the mentality of professionals, ensuring leadership involvement with effective communication. The effort to achieve data-driven orientation, however, goes a step beyond and also implies assertiveness to establish the proper analytics dimension for each management purpose. Therefore, within data science field, a conceptual framework classifying four branches of performance analytics has been explored (Kim and Yu, 2015; Lepenioti *et al*., 2020). The overview of its four-dimensional classification is exhibited by Figure 1.

Descriptive analysis basically describes a phenomenon, unraveling what happened through the visualization of scenarios, diagnostic analysis assesses goes a step further investigating why certain events or occurrences may have happened through statistics and convenient hypothesis tests to confirm theories or even find root causes. While descriptive and diagnostic analytics are focused on the past, predictive analytics is focused on predicting potential future outcomes based on historical databases.

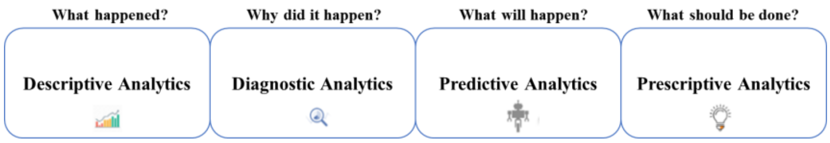

Fig. 1. Four dimensions of data analytics.

Finally, prescriptive analysis goes beyond describing, explaining and predicting, implying what actions should be taken in the future to optimize the processes, offering smart decisions through data engineering simulations combined with algorithms.

3 Research Design

The present research consists of developing a systematic literature review with the ambition to identify recent applications of diagnostic and predictive analytics and their respective contributions to operations strategy. For this reason, the first methodological step involved the definition of the search terms, connecting both two topics contemplated by the present study: performance analytics and operations strategy. Their respective search terms are presented by Table 1, which were chosen to be commonly used as synonyms in performance analytics and operations strategy environments.

Table 1. Research axes.

1st axis: Performance Analytics	Boolean Operator	2nd axis: Operations Strategy
("performance analytics" OR "performance analysis" OR "data analytics" OR "diagnostic analytics" OR "predictive analytics")	AND	("operations strategy" OR "operations management" OR "manufacturing" OR "decision making")

The method selected for the systematic literature review is the PRISMA, Preferred Reporting Items for Systematic review and Meta-Analysis (2009) and the procedural performed steps are described by Figure 2.

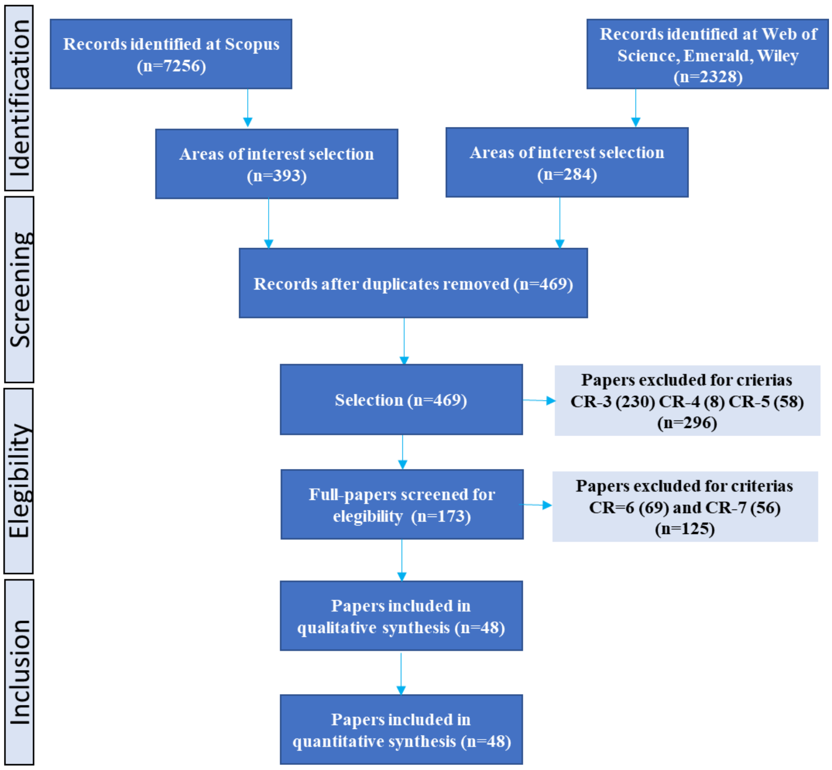

Fig. 2. Systematic Literature Review.

In the identification stage, as a result from search of the terms found in Scopus database resulted in 7,256 and 2,328 from Web of Science together with additional publishers. In order to restrict articles from the areas of interest, selection tools were applied, according to the selection criteria 1 and 2 of Table 2 for Scopus and Web of

Science, respectively, resulting in a total of 469 pre-selected works for eligibility after the removal of duplicates.

Table 2. Criteria and their filters.

Criteria	Filters
CR1	Scopus Exactkeywords: Decision Support System, Decision-making, Performance Assessment, Performance Analysis, Cost Effectiveness, Forecasting, Scheduling, Productivity, Production Control, Predictive Maintenance,Quality Control, Quality of Service, Manufacturing, Process Control, Supply Chain Management
CR2	Web of Science Research Areas: Business Economics or Engineering or Operations Research Management
CR3	Full and Open-access papers available for download
CR4	English written papers
CR5	Restriction of academic papers published in Journals or International Conferences
CR6	Selection of either recent papers or higher 50 citation numbers in case of publications before 2016
CR7	Reading selection to limit publications with adhrence to research

In the following step, CR-3, availability filter was applied, limiting open-sources and then exclusively English written papers, CR-4, published exclusively in academic journals or international conferences (CR-5), removing 296 and selecting 173 articles for the eligibility stage. In the eligibility stage, CR-6, articles with low scientific relevance were excluded, following the criteria that articles with date of publication before 2016 were considered only with citation number higher than fifty. Finally, at CR-7, full-papers were completely read, rejecting some papers that did not properly address the research ambition, electing a total of 48 papers with strong contribution to be included in the bibliographic portfolio composition, which can be fully found in Appendices.

4 Results

The bibliographic portfolio presents forty-eight articles, composed 87.5% by journals and 12.5% by international conferences. Figure 3 presents the portfolio over the years, revealing the highest concentration belongs to the last five years.

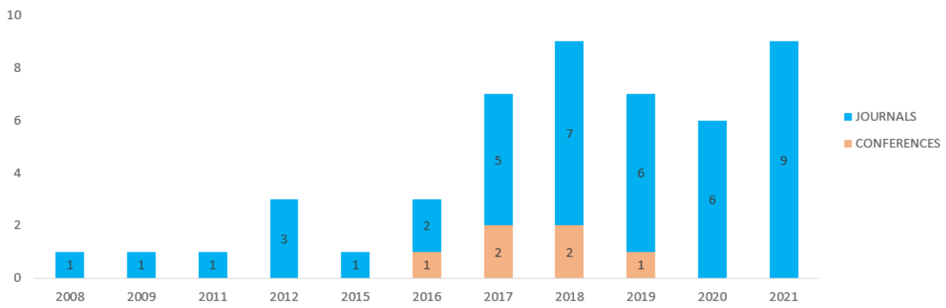

Fig. 3. Portfolio over the years.

The bibliographic composition presents a very diverse portfolio and with low reoccurrence of journals. However, Expert Systems with Applications is the journal with a highlighted position, with a total of five papers, followed by the International Journal of Production Research, contributing to three publications. Other high-impact journals were also honored, as exhibited by Figure 4. In relation to the six conference papers, CIRP Conference on Manufacturing Systems is the only that appeared twice. All the other four conference papers, on the other hand, had the scope related to Industry 4.0.

Fig. 4. Journals and Conferences.

In the perspective of the citation level, presented by Figure 5, it is noticeable that articles from the last five years have a lower accumulation of citations comparing to older ones, which can be possibly explained by the fact that they are more recent and consequently had little time exposure to the scientific community.

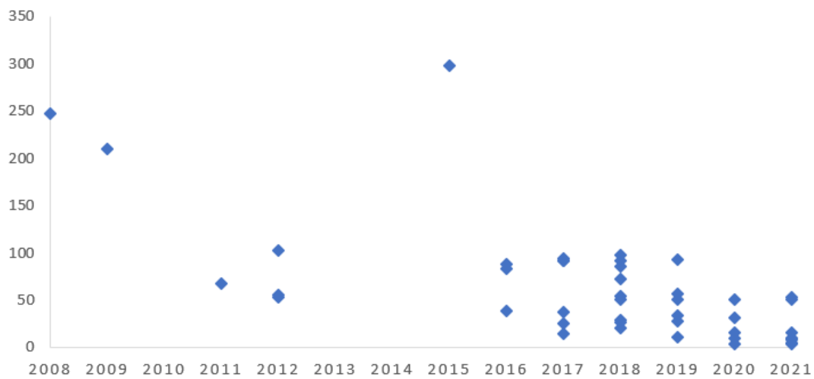

Fig. 5. Journals and Conferences.

Among the research centers present in the portfolio, United States is the country with the greatest portfolio contribution, possibly explained by the advanced artificial intelligence achievements enabled by the technological investments inside American companies and universities. Countries such as India, China, Italy and United Kingdom also occupy a prominent place, as exhibited by Figure 6. Most of the countries, however, had a single representation in the portfolio, which strongly implies that the topic has been widely researched by several university centers.

Fig. 6. Geographic heat-map.

Although there is no reoccurrence among the authors, some researchers of the most impactful works are Gian Susto, from the Information Engineering Center at the University of Padova, Italy, Maritza Correa, from the Instituto de Automática Industrial in Spain, and Cavalcante and Frazzon, from Mechanical Engineering research at Federal University of Santa Catarina, Brazil. Appendices section presents the list of bibliographic portfolio composition and their respective numerical references for content analysis exhibited by Table 3, that summarizes portfolio methods and contributions.

The systematic review of the literature content was analyzed into six perspectives: cost, speed, quality, flexibility, reliability and organizational development, related to the perspective of Slack *et al*. (2009) performance dimensions. Organizational development was added to this classification in order to include the strategic area of human development proposed by the same author, since this pillar corroborates to the competitive result of the five dimensions of cost, speed, quality, flexibility and dependability. It is an engaging perspective to match recent applications in performance analytics, since Slack conceptual classification was extensively acknowledged in operations management research.

The building of the proposed summary enabled the identification of recent contributions of performance analytics to diagnose the impact of lean practices on cost reduction, manufacturing costs prediction projects and dynamic replenishment of policies for inventory management. Moreover, mitigation of delay risks in supply chain and demand planning improvements with accurate cycle time forecasting have been also enhanced. In relation to quality perspective, failure detection projects have been contributing to reach better quality standards through the previous identification of process deviations. Machine learning projects focused on predictive maintenances and OEE monitoring have been strengthening flexibility in operations, minimizing the impact of unexpected events together with a dynamic production planning.

Table 3. Performance analytics contribution to operations strategy.

OBJECTIVE		METHOD	CONTRIBUTION
Cost management of materials and processes	D	Multiple regression analysis [16, 37], Variance Analysis [16]	Impact of lean practices on cost reduction [16, 37]
	P	ANN [4, 47], GBT [30] Linear Regression [12, 30], Naive Bayes [4], C4.5 Algorithm [39], GBT [30], SVR [30, 47]	Manufacturing costs prediction [4, 12, 30, 47] Inventory management policies to minimize costs [39]
Supply and Operations Management	P	Decision Tree [6, 7], Naive Bayes [7, 33], ANN [7, 44], K-NN [11], GNN [28], Random Forest [7, 8, 9,11], SVM [6, 7, 9, 10], Logistic Regression [9], Linear Regression [9, 10, 11, 26, 44]	Mitigation of delay risks with strategic supplier selection [6, 9,11] demand planning [7, 8, 10, 28], cycle time forecasting [33, 44] and inbound logistics activities [26]
Quality Management	D	Linear Regression Analysis, Correlations, Variance Analysis [19, 34]	Properties of quality deviations identification [19, 34]
	P	Naive Bayes [14], ANN [14], Logistic Regression [17] XG-Boost [38], Random Forest [38, 43]	Detection of quality failures in production processes [14, 17, 38, 43]
Flexibility and Scheduling Deviation Management	D	Monte-Carlo Simulation [48], Ishikawa and Pareto [32]	Identification of OEE highest losses [32, 48]
	P	ARIMA [25], KNN [42], GTB [3, 5], Random Forest [3, 5], XG-Boost [5], Linear Regression [5] Deep Q Network [45], SVM [3, 5, 42]	Predictive maintenance to minimize unexpected interruptions [3, 5, 42, 25] and dynamic production planning considering unexpected events [45]
Dependability Management	P	ANN [1, 15, 29, 31, 41], ARIMA [36], Linear Regression [1], SVM [15, 31, 36, 41], Decision Tree [24, 41], Random Forest [15, 41, 46], KNN [36], Naive Bayes [15, 36, 41], Logistic Regression [41], Genetic Algorithm [27, 46], CNN [40]	Integration of quality in after-sales services [27], forecasts for meeting deadlines [36], assertiveness in diagnoses [24, 29, 31, 40, 46] and robustness in the management of hospital operations [1, 15]
Human Resources Management	D	Correlation [22, 35], Linear Regression Analysis [13, 35], Confirmatory Factor Analysis [22] and Mann-Whitney U Test [21]	Identification of the effects of leadership styles and their respective performance impacts [13, 21, 22, 35]
	P	Decision Tree [2, 20], Naive Bayes [2, 23], ANN [18, 20]	Employee performance forecast [2, 20, 23] and turnover rates [18]

From dependability perspective, predictive analytics has been supporting the integration of quality in after-sales services, accurate deadline commitment and more assertive diagnoses of diseases and patient assistance in healthcare environment. Finally, in relation to human resources dimension, diagnostic analytics projects have enabled the identification of leadership styles and their assessed impacts on organizational performance while predictive approaches have been supporting employee performance forecasts and turnover rates based on historical events.

5 Conclusion

The developed systematic review presents a simple and consistent investigative overview of how diagnostic and predictive analytics projects have supported organizations to achieve competitive advantages in many different dimensions. This paper has succeeded on connecting the classic operations strategy concept to the recent topic of performance analytics approaches, providing the built of a summary of meaningful studies and their respective contributions through Slack *et al*. (2009) perspective.

Limitations, however, are useful to guide further research directions. In this context, although results revealed a preliminary analysis, bringing an overview of how performance analytics role enabled strategic decisions in the last years, the bibliographic composition is still too small for a meta-analysis, demanding expansion in further databases or even excluding the criteria related to the restriction of the last years, following an advanced effort to connect old studies to the new ones and investigate how projects have evolved and reinforced by operations strategy.

Furthermore, the present literature review can also be analyzed through other conceptual perspectives in order to extend findings to new contexts.

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Appendices: List of Bibliographic Portfolio Composition

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