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# Artificial Intelligence in Business Simulation Analysis

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**Abstract**

**Purpose:** Research on business simulation and machine learning has attracted immense interest in the last few years. The aim of this study was to provide a comprehensive view of machine learning in business simulation. To review the use of artificial intelligence in business simulation analysis. A review of the literature, however, shows little systematic reviews on the application of machine learning techniques to business simulation, yet systematic reviews have gained prominence in the academic jargon.

**Methodology:** Thus, this study does reviews systematically a total of 123 shortlisted articles that focus on the machine learning techniques in the business simulation process.

**Findings:** There are immense algorithms of machine learning which can be used in a business simulation, although this study was able to review ten machine learning algorithms in the business simulation process. As a whole, the machine learning algorithms have been deployed to yield lead-time production in the industry. In inventory and storage, machine learning has been applied to improve efficiency in identifying inventory patterns that would have never been revealed and thus saves on costs. Future direction was also discussed.

**Keywords:** *Machine learning, Business Simulation, Algorithms, Business trends, Artificial Intelligence*

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## Introduction

The world is advancing towards a digital future. Digital transformation for industries and businesses is expected to mirror and feature Industry 4.0 technologies (Aleksendri & Carlone, 2015). One of the most prominent technologies in this era includes era, which includes the use of blockchains, IoT, and Cloud computing to use artificial intelligence in doing business simulations. Dirican (2015) defines the use of artificial intelligence as being the ability of machines to perform things that human beings are capable of doing such basic communications and are thus referred to as being intelligent. Artificial intelligence with automation has provided various opportunities in business industry (Donepudi, 2018). The use of artificial intelligence in business simulations leads to better problem solving, increased accuracy in market prediction, and a higher speed and integration of a greater amount of inputs into the systems. Artificial intelligence is not a newer subject in technology, neither is it a new area of study (Saka, Dogan, & Aydogdu, 2013; Frayret et al., 2007); however, it is until only recently that the technological advancements have identified that the potential of artificial intelligence in several disciplines and industries (Min, 2010; Efendigil, Onüt & Kahraman, 2009), and thus, raising its concerns over its adaptability in various areas of study s (Martínez-Lopez ´ & Casillas, 2013; Rekha, Abdulla, & Asharaf, 2016), not forgetting the in business simulation process. While some areas of study within information technology are only concerned with firms' competitive necessity, the use of artificial intelligence has emerged as a competitive advantage for those firms that apply its practice (Feo, & Resende, 1995). Many companies are moving away from aspects of remote monitoring of the performance of its products in the market to new areas such as control, optimization, and also to advanced AI systems, which are aimed at improving the functionality within their markets (Redding & Turner, 2015).

Despite having heavy investments in the information systems and its capabilities, still many business struggles with achieving a competitive advantage, which can be gained through efficient resource management for those factors of production, which are rare, valuable, imperfectly imitate, and those that are non-substitutable in the market. Thus, there was a need for organizations to apply artificial intelligence in the simulation of big data, which was captured from within their systems to ensure that they maintain a competitive advantage in the market (Regal & Pereira, 2018; Quin & Camacho-Velazquez, 2011). Vera-Baquero et al. (2015) pointed out that the latest advancements in technology have created an environment in which it is possible for organizations to cooperate on the integration of the wider business informational services in large and complex business environments. Such systems often tend to contribute to producing a large set of information that is beyond the boundaries of the company that needs to be analyzed. This trend has precipitated the need for analysis of event data and by cooperations. Pioro and Medhi (2004), in their study, stated that the logistics networks do generate close to 1.6 billion new data every single month. The analysis of such volumes of data is often referred to as Big Data Analytics, and in essence, it does not refer to anyone singular technology or method. The analysis of such volumes of data was not possible without the use of artificial intelligence. Big Data Analytics, in most cases, uses a combination of various IT-enabled resources to gain information, predict related outcomes to solutions, answer fundamental research questions and to support in the decision making process, thus help in creating a competitive advantage for companies (Martínez-Lopez & Casillas, 2009; Gholami & Fakhari, 2017; Mayr et al., 2018; Geem & Roper, 2009; García, Villalba & Portela, 2012).

Over the years, data analytics have been named in different ways. In a study, Davenport (2014) views that the general activity involved in making sense of data has been revolutionized and that it has evolved from being necessary towards the business decision and is now linked with business intelligence, big data, business analytics, and BDA, which all in most cases requires the application of business simulations. There are different goals that are characterized in each stage of historical data analytics. In the same fashion, Chen, Chian, and Storey (2012) did a study to evaluate the evolutionary traits of data analysis and simulation from business information to Big Data and did evaluate that BI has the biggest range of coverage and the longest history as it appears from as early as the 1990s. Since 2007, BA and Big Data have received immense attention in 2007 with a steep increase over the last few years.

**Research Gap**

Along with the importance of artificial intelligence in the industry, there exist immense interests that have been given to AI in the academic jargon. These interests by various researchers and academicians have affected various fields, including business research, with an immense research on how artificial intelligence can affect this industry from a holistic perspective (Canhoto & Clear, 2020; Dirican, 2015; Soni et al., 2020). In these researchers, business simulations have been recognized as being one of the fields in which artificial intelligence can benefit immensely. While the interests in the connection of artificial intelligence and business simulation ranks high from the industry practitioners (Clifton & Frohnsdorff, 2001; Cardoso et al., 2013; Ransbotham et al., 2017; Carbonneau, Laframboise & Vahidov, 2008), there still exists the need to explored the contribution of artificial intelligence to the industry. Various studies reviewed such a gap and need (Dubey et al., 2020; Min, 2010; Chong & Bai, 2014). Thus, this study would address these gaps through systematic reviews and the achievement of the research objectives.

**Literature Review**

In the modern business environment, digitization in shopping has reshaped the manner in which customers purchase products, consumer behavior, and taste and preference towards certain products, which has made the supply and the demand patterns to be as disruptive and discontinuous as never seen before. Such changes necessitate that business organizations catch up faster in a bid to maintain competitiveness in business markets and avoid uncertainty and financial risks when doing business. Thus, firms need to make use of technology in amassing market trends and big data analytics towards maintaining a competitive edge and staying in tune with the market dynamics. In a bid to increase visibility in the business, a lot of leading-edge organizations have upgraded to resource sharing of their inventory data, which has done business to be more and more data-intensive. In the realization of the role and the significance of data towards business simulation, many business organizations have tried all the possible ways to improve their data management to improve decision making. One of these consequences has been in the application of machine learning towards business simulation; however, this is still far from being fully utilized.

The poor application of machine learning techniques and systems to the business simulation process is the existence of shortages in understanding the latest business development in machine learning algorithms, which expands to the knowledge of the taxonomies and the lack of the guidelines that would guide the practitioners in selection of the best machine learning algorithms to be used in the selection of the right business simulation activities. For example, the introduction of cloud computing in business is a major technological breakthrough but it needs appropriate deployment and planning (Donepudi, 2016). Thus the main objective of this study is to lucubrate on clarification of the various research trends and the machine learning application within the industry through the use of existing research articles. While there exists hardly any systematic reviews conducted on the application of artificial intelligence in business simulations, Min (2009) was the first-ever research to conduct a systematic review based on the application of artificial intelligence on business simulation analysis. The author in this study based his study on his general knowledge of algorithms and selected 28 articles that he uses for analysis. This article links the AI tools with that of business activities. He extracts seven AI tools and reviews the applications of these tools in business environments. While some machine learning algorithms, such as the Neural Networks (NNS), are mentioned as being mathematical modeling techniques in the paper, they have been put in parallel space with artificial intelligence.

Further, MIN takes a conservative attitude in linking machine learning and artificial intelligence to the expansion of business and crafting a cutting business edge. Accordingly, he reviews that that use of both artificial learning and machine learning has the ability to provide better results prediction for the specific and narrowly focused business information issues. However, he identifies that the solutions are hard for the ordinary decision-makers to follow aptly. Bravo et al., 2011) takes a different approach in the selection of articles and objectively retrieves 77 published articles from five different databases published between the years 1994 all through to 2014 and reviews the status of the application of the seven identified artificial intelligence systems in the business market and more specifically, how this could be adapted in both the textile and in the apparel industries. Bravo et al. (2011) identify that the gap between the artificial intelligence and business simulation models could have been caused by unbalanced risks, which hinders research-directed development in the industry. While the articles reviewed in this study were taken out objectively, it is important to note that machine learning algorithms of the AI techniques were listed out of seven techniques and was done so in a subjective way. Besides this, Bravo et al. (2011) only looked at the textile and the apparel industry in supply chain management, which thus reflected only a partial representation of the total business industry.

Francisco (2017) adopts a similar systematic analysis approach by reviewing articles published over a longer time span in his analysis. Furthermore, he creates a framework to be used to classify the 84 articles from 1995 to date through the applications used and the type of data sources involved. This review, however, takes up a pessimistic review of the applications of artificial intelligence, with the results showing that artificial intelligence took up a mere 11.9% of the techniques which are used in the analysis of supply chain management. Further, machine learning was merely taken as being mathematical representations rather than algorithms that can be used in accessing business simulations and functionality. Bryman (2007) take on an optimistic view of the application of machine learning and artificial intelligence tools towards the decision-making process and in sales production. Moreover, this study takes a look into the applications of artificial intelligence and machine learning to the understanding of the fourth technological revolution. This study establishes that the use of machine learning and artificial intelligence algorithms has a great impact on the routine, the standard, and the repetition of the supply chain management activities. However, they are quick to caution that the full automatization on the supply chain applications in replacing human-decisions with artificial intelligence and the machine learning algorithm still has a long way to go. Thus, there is a need for fast-tracking of the changes and innovations within the industry to ensure that such changes are met within a shorter period of time.

The literature identified above was a mere representation of the application of both machine learning algorithms and artificial intelligence in the business simulation models. These studies, however, failed to represent a comprehensive systemic review in multiple parameters. To be specific, a quick literature review of past studies has established some limitations with the application of artificial intelligence in the supply chain management and business simulation process. Firstly, no single study uses a systematic review of the analysis of the business trends in the usage of machine learning applications. These studies have surely failed to present a panoramic view of the machine learning application in business simulations and in supply chain management. Secondly, the machine learning algorithms for most of the studies were selected and also reviewed in a subjective way by searching for machine learning algorithms only through the usage of keywords. The main shortcoming of this approach is that some of the articles and research papers, which uses fewer machine learning algorithm keywords, could not be obtained in a statistical way possible and for the duration of the study. Inevitable, applications of the machine learning techniques for most of the studies failed to link the business simulation to the algorithms of machine learning and artificial intelligence. One of the issues presented hereby is that the machine learning algorithms were not clearly defined for the study; as such, the relationships between artificial intelligence and machine learning were not well justified in essence. The other factor taken into consideration is that the industries which apply business simulation and supply chain machine learning were not fully elaborated for the study.

This study have two theoretical perspectives. First, it is intended to promote new AI-related systems, with an emphasis on emerging markets, focused on conventional models. A logically sound mentality would cause conventional academic theories to be reassessed. It also provide rationality of microeconomic theory should be redefined to manifest new devices for making and increasing rational decision-making in the sense of AI (Bundy, 1997).

**Methodology**

First, the articles which focus on the trends in the application of machine learning and artificial intelligence in business simulation and in supply chain management would be collected, retrieved, and also analyzed in a descriptive way focusing on its year of study, the top journals, the research designs that are employed in the study the industry sector which the study focuses on. Secondly, the machine learning algorithms that are employed in all of these articles would be chosen and identified, and then it would be ranked based on their rank in the business simulation process. Finally, each of the machine learning algorithms would be analyzed, and each of its features would then be explored through six business simulation activities that involve the demand/sales estimation, production, inventory and storage, supply chain improvement, procurement, and supply chain management.

**Article Selection**

The article selection process would take a structured approach in the filtering of the studies, and that would include in the systematic review. The studies collected would be analyzed through analysis of various variables in a bid to get a complete picture of the machine learning application in the business simulation process. To achieve the objectives of this study, the majority of the studies were collected from six academic databases which include the Emerald Insight, IEEE Explore, Scopus, Springer, Wiley, and Science Direct, while a smaller percentage of the studies were retrieved from Google Scholar as an addition to the studies collected from the other sources. The aim of this was to ensure that there exists complete coverage in the collection process.

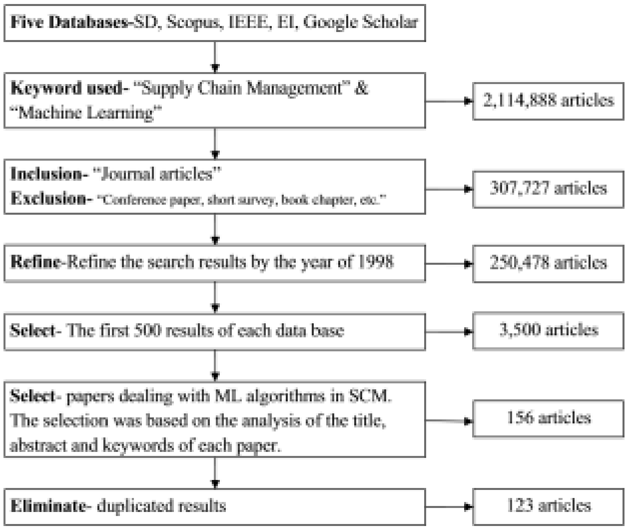


Figure 1. Process of paper selection

As identified in the figure above, the number of articles was initially 2,114 888. Despite the presence of the search specifications, which were applied to the research, there still existed some unwanted publications. This meant that another filter was then applied to the search results. During this initial phase, all the unwanted publications, including short surveys, conference papers, book chapters, and student essays, were then excluded from the analysis. After this first view, 307, 727 articles were left to be filtered in the second analysis. The second analysis narrowed down to focus on studies done after 1998. The total studies this far was recorded at being 250, 478.

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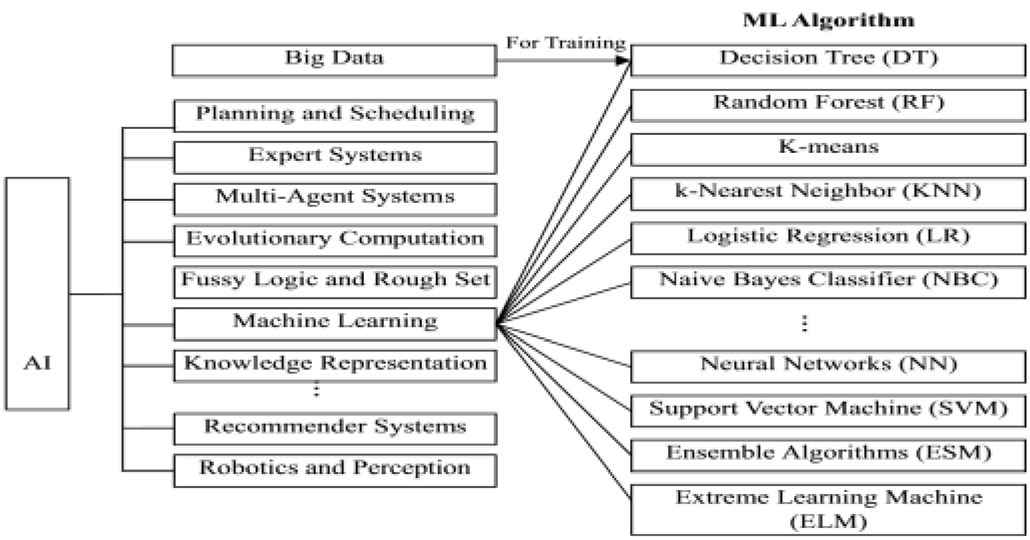


Fig. 2 Terms related to ML

With this, there still many studies left for analysis, and in that regard, a third filter was then applied to narrow down the articles. After this was done, 500 studies remained. The researcher then manually selected the best studies to be used in this analysis and after this was applied. This paper remained with 156 articles. Removal of duplication of these studies narrowed down the study into 123 articles from 75 journals.

**Justification of the Study Selection Process**

**Rules of Theme Selection**

AI, Big Data, machine learning, artificial intelligence, and machine learning algorithms are the four selected taxonomies for this study. However, machine learning exists as a subset of the larger artificial, which is often researched as an independent research domain that is often analyzed in close relationship with the other three domains. As evaluated in figure 2 above, machine learning is a subbranch of artificial intelligence that equips machines with the ability to learn from data that exists from data that has no programming features, i.e. it uses data from learning the raw data and analyzing the input to produce a given output. Arthur Samuel (1959) is accredited with the coining of machine learning. In his analysis, he pointed out that machine learning refers to the study of algorithms and the mathematical models in the computer systems to progressively improve the performance of the computer systems when performing specific tasks. Tom M. Mitchell's definition of machine learning has been widely used; "*A computer program is said to learn from experience E concerning some class of tasks T and performance measure P if its performance at* *tasks in T, as measured by P, improves with experience E.*” Unfortunately, this definition of machine learning has caused confusion by messing up the definition of both artificial intelligence and that of machine learning in the analysis.

**Identification of Algorithms in Business Simulation**

Machine learning explores how computers can be used in the acquisition of knowledge directly through data and in learning how to solve a set of problems through them. The use of machine learning solves various problems that exist through the use of machine algorithms. Generally, some of the machine learning techniques have been promoted through many neurological studies, with some spanning the process of controlling human evolution, and in some studies, structural optimization has been featured in place of experience optimization. The most basic methodological approach which has been taken into consideration by the machine learning in business simulation has been on the comparison of the proposed business model performance to that of the standard machine learning algorithm

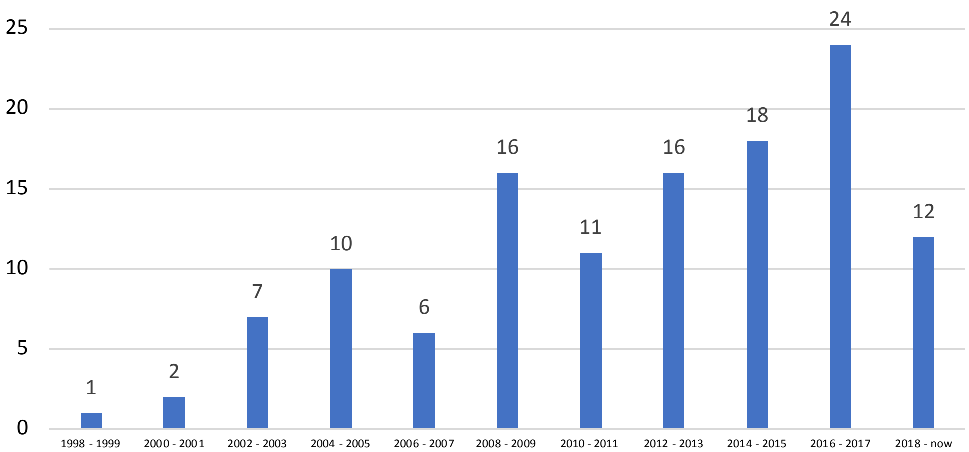

Figure3. Distribution of studies over the last 30years

**Results**

The three sections of this study are devoted to presenting the study results in the form of research trends, frequently used machine learning algorithms, and the distribution of the machine learning algorithm in the business simulation process, with the specific summary of this being on answering the research objectives that have been identified. Since both machine learning and business simulation exists in various research domains, there existed a number of journals from which various studies have been posted in.

**Frequency of Machine Learning Algorithms**

It is important to note that only 10 out of the 32 commonly recognized machine learning algorithms have been used and applied in the business simulation process. For most of the studies, machine learning algorithms have been neglected, such as deep learning algorithms analysis. Such deficiency might be ascribed based on the unfamiliarity of the business simulation researchers using the most common machine learning algorithms. Garcia et al. (2019) note that most of the machine learning algorithms that could have been used to suffer from low interpretability, making it complicated.

**Table 1: Distribution of the Machine Learning Algorithms**

| **Name** | **General usage** |
|---|---|
| Decision Tree (DT) | Discriminant models; mutliregression and classification; regularized Maximum Likelihood Estimate |
| Random forest (RF) | Classification |
| K-means | Clustering; Classification |
| K-Nearest neighbor (KNN): | Discriminant models; multi-regression; classification |
| Logistic regression (LR) | Regression |
| Naive Bayes classifier (NBC) | Generative model |
| Neural Networks (NN) | Regression; classification |
| Support vector machine (SVM) | Regression/classification |
| Ensemble algorithms (ESM) | Regression; classification |
| Extreme learning machine (ELM) | Regression; classification |

To help in improving the current situation, the Table above does provide a brief overview of the ten machine learning techniques, which helps in facilitating a clear understanding of the algorithms used by business simulation researchers.

**Table 2: The Citation of the Cited Authors**

| Authors | Numbers | Percent |
|---|---|---|
| Chang Ouk Kim | 3 | 2.44 |
| H.C.W. Lau | 3 | 2.44 |
| R.J. Kuo | 3 | 2.44 |
| K.L. Choy | 2 | 1.63 |
| Matthew Chiu | 2 | 1.63 |
| Mojtaba Maghrebi | 2 | 1.63 |
| Other authors in number | 108 | 87.80 |
| Total | 123 | 100.00 |

Judging from the trends in the application of machine learning in the business simulation and also on the frequently used machine learning techniques, the potential of machine learning to simulate, analyze and tackle business problems and retrieval of information for the business simulation process has not been effectively explored as identified by this studies. However, some researchers have pioneered the efforts and the application of machine learning in various business environments. Planning for demand/sales estimations can, at times, be a difficult task as a good forecast would imply that one works through the often murky and complex estimation systems. In this case, a good estimation model would involve the relation of parameters that are associated with multiple explanatory variables and linking this to their dependent variables through the use of non-linear analysis. The introduction of non-linear analysis to the machine learning algorithms would improve the accuracy that is involved in predicting forecast sales and the degree of inventory required to do business.

Another field in which machine learning has been applied is that of procurement and supply chain management. Any given organization's success lies in the efficacy of its procurement process to satisfy the company and the customers with quality high-end products. Thus, most organizations have adopted a scoring point analysis procedure that requires information based on the given suppliers' performance history. The key advantage with the use of machine learning in this regard is that it offers flexibility to cope with missing values in the analysis. Machine learning has also been applied to easing the production process by improving factory scheduling accuracy and production planning. Machine learning algorithms make it possible to balance the constraints involved, making it possible and effective to analyze data presently than in the past. With machine learning, manufacturers can reduce the latency involved in the production process and improve products and services' delivery. In their study, Juez et al. (2010) employed SVMs in multiple factors to simulate production in the lead-time before manufacturing in the aerospace industry.

## Conclusions

A number of potential directions exist on the machine learning techniques which can be used in supply chain management. First, there is a need to make the business simulation more practical. Most of the studies reviewed focuses on the mathematical aspects of machine learning rather than its practical applications.

## Policy Implications

Thus, there is a need for policymakers to draft policy which would make it possible to practice through machine learning. Secondly, there is a need to increase objectivity in the business simulation models and variety to be improved in terms of research and how it can be applied in the market.

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