APPLICATION OF DATA SCIENCE IN PROSPECTIVE STUDIES: A LITERATURE REVIEW

Silvia Soledad Moreno Gutiérrez

Autonomous University of Hidalgo State. Ex. Hda. Sn. Servando s/n. Tlahuelilpan Hgo.

ABSTRACT

At a global level, the analysis of the future currently represents a strategic alternative that has been accepted by organizations in order to reduce uncertainty, to reorient and strengthen decision-making, to reduce risks and to configure plausible scenarios. Thus, strategic prospective (SP) studies constitute the most widely applied alternative; however, artificial intelligence (AI) and its machine learning (ML) techniques have also been accepted. SP studies offer a qualitative approach based on trends, key uncertainties, implications and expert opinion, while ML emerges as a quantitative tool for the exploitation of historical data and the identification of hidden patterns dedicated to predicting complex phenomena with high precision. Thus, ML has been considered of high strategic value. Considering the potential of both approaches, our present systematic review emerged, which aims to identify prospective studies that applied ML to strengthen their results and to offer readers a current overview that allows them to employ knowledge through the strategic integration of innovative tools. The review allows us to answer the following questions: Have ML algorithms been applied in the development of SP studies? Which algorithms have showed the best results and in what areas of knowledge? Three expert researchers participated in the review, and they selected 48 articles published in indexed journals over the last 5 years by applying eligibility criteria. The analysis of 11 was concluded in the areas of health, education, finance, mining and archaeology, with the preferred algorithms as follows: artificial neural networks (ANNs), random forest (RF) and logistic regression. The best performance, however, was from naïve Bayes with .99, followed by gradient boosting machine with .96, multivariate regression with .95 and ensemble generalized linear model with .94. Limitations of ANNs in financial analysis and RF in health were observed. To validate results, the following metrics were applied: confusion matrix, F1 score, area under the curve, confidence interval, and the Gini coefficient. Performances ranged from .75 to .99. The SP and ML have opposite approaches and correspond to different areas of knowledge, which is why the number of authors who address them together is small. Both, however, are complementary to the task of strengthening SP studies and providing reliability through analysis and quantifiable results.

KEYWORDS. Strategic prospective, machine learning, smart algorithms

INTRODUCTION

Knowing about and understanding the future are vital task for organizations, which, faced with the possibility of witnessing complex, unstable and turbulent phenomena that generate uncertain scenarios, strive to implement mechanisms to reduce uncertainty, strengthen decision-making and build strategic action plans for plausible scenarios, according to Gallo-León (2020). Anticipating a complex future could be useful for achieving better scenarios. Therefore, in the face of the challenging and uncertain panorama derived from the intelligent revolution, as well as the digital ecosystem that absorbs society daily, data and timely information gain strategic value and are considered a competitive advantage for those who employ them to transform the future.

Because prospective analysis has a descriptive and qualitative approach, it is appropriate to integrate AI techniques to strengthen it (Betanzos, 2023) by taking advantage of its profound social impact, its influence towards Society 5.0 and the predictive potential of its intelligent algorithms with generalization capability (Gallego-Nicasio et al., 2018; Hernández et al., 2022), which, when applied to early decision-making stages, could improve them (Granadillo et al., 2020).

These ML algorithms constitute an emerging technology that could change the approach to risk prevention (Salinas, 2023); in some countries, their application is considered a strategic value for the government (Alonso-Robisco & Carbó, 2022).

Foresight and scenario analysis methods are constantly evolving, although

AI-based prediction or forecasting could boost them. In Latin America, however, research on this topic, despite being essential, has been scarce (López et al., 2022). The reviewed literature exhibits various scientific works based on prospective or predictive methodologies with a demonstrated effectiveness. In most cases, however, the studies they are developed in isolation, limiting the potential that the qualitative and quantitative integrative approach could provide in the timely identification of unfavorable phenomena with social impact and when based on a complete analysis that includes the past, present and future.

Considering the contribution of the SP to the knowledge of the future panorama (Cedeño et al., 2022), as well as the unprecedented impact of AI on the transformation of society and its prediction potential through ML, the present work seeks to offer an overview of the application of predictive models within prospective studies with a comprehensive approach.

PROSPECTING AND PREDICTIVE OR FORECASTING

Prospective analysis

According to Padilla-Ospina et al., (2020), the future is a consequence of the interaction between social factors that lead to future trends and changes in them. Foresight explores the future in the context of social sciences, seeking to identify scientific, technological, economic, technical and social situations that contribute to the evolution of the world. In addition to preventing possible events and risks derived from this transformation, its vision is holistic, and it analyzes qualitative and quantitative aspects. Moreover, its relationships are dynamic with evolutionary structures and an active vision of the future (Morocho et al., 2020). In its quantitative approach, however, foresight is only appropriate if there is numerical information regarding quantifiable phenomena (Ferrando et al., 2020).

Foresight addresses the long-term changing landscape as a nonlinear, complex, uncertain and undetermined approach. It is a strategic planning tool for identifying current trends, key uncertainties and the future implications that influence them. As a result, foresight reduces losses, takes advantage of opportunities, anticipates an adverse future and then configures a better outlook (Gallo-León, (2020).

Predictive analysis

Predictive or prognostic analysis is based on the exploration of qualitative or quantitative historical data that represent the behavior of a phenomenon, seek to estimate relationships between variables and identify future situations as a logical consequence (Cinelli & Gan, 2019). Therefore, traditional statistical and mathematical techniques have been applied, as well as modern AI and ML techniques capable of precisely identifying generalizable causal relationships between variables (Espinosa-Zúñiga, 2020), as well as hidden patterns in the data.

In cases of uncertainty, prediction is a valuable tool for prevention and strategic planning (Gallo-León, 2020). According to Gallego-Nicasio (2018), prediction and forecast have been considered synonymous.

Based on the above, Chart 1 shows prospecting and classic or traditional forecasting as opposite approaches.

Chart 1. Differences between classical and prospective prognosis

	Classic prognosis	**Prospective**
Vision	**Partial**	**Holistic Approach**
Variables	Quantitative, objective, known	Qualitative, quantitative, subjective, known, hidden
Relations	Static, fixed structures	Dynamics, evolutionary structures
Explanation	past explained by the future	future explained by the past
Future	Simple and true	Multiple and uncertain
Method	Quantitative deterministic models	Intentional analysis, qualitative and stochastic models
Attitude towards the future	Passive and adaptive	Active and creative

Source: Created by author with data from Hevia-Araujo (2005)

Both visions apply qualitative and quantitative variables, however, SP relies on scenario construction and groups of experts. Based on their opinions, qualitative analysis is performed that stimulates reflection and thinking; however, its methods provide subjective results, limited by its imprecision regarding the future and an inability to quantify the implications in each scenario. These methods require the complement of rigorous methods to quantify forecasting; thus, predictive techniques are applicable for addressing various social problems (Ferrando et al., 2020).

As Astorga et al., (2022) mentioned that ML creates the possibility of achieving prospective results faster at a lower cost and with greater precision. It can support where the empirical world is in the hands of those who, observing reality, must recognize patterns, given the bias derived from their disciplinary training.

Studies of this type have been conducted in the following areas: technology, education, travel agencies (Bello et al., 2018), finance for predicting the best analysis variables (Padilla-Ospina et al., 2020), public policies (Ordoñez et al, 2020), analysis to identify success factors in fashion (Velázquez et al., 2020), higher education (Moreno-Gutiérrez et al., 2022), health for optimizing therapeutic algorithms and rationalizing resources in emergency cases (Enguita et al., 2020), excavations, and concentrations of ceramic remains (Astorga et al., (2022, Prado et al., 2020), among others.

Data science and ML

Data science constitutes an emerging and evolving interdisciplinary area that applies statistical, mathematical, computational and AI techniques to exploit data for prediction purposes (Lemus-Delgado & Pérez-Navarro, 2020). It applies various methodologies (De-la-Hoz et al., 2019). The most widely accepted methodology because of its emphasis on business in addition to its technical aspect is the cross-industry standard process for data mining (CRISP-DM), which is composed of six stages: 1) business understanding, 2) data understanding, 3) data preparation, 4) modeling, 5) validation, and 6) deployment (Gómez et al., 2019).

To learn the behavior of historical data and the relationship between variables for identifying hidden patterns and glimpsing possible processes, ML techniques are applied (Prado et al., 2020; Carrasco-Pardo et al., 2021) and are characterized by their high potential for prediction as applied to the various areas of food industry (Prado et al., 2020). Some of these modern techniques deliver results that exceed those reported by classical statistical techniques (Prado et al., 2020).

Modern ML techniques

An artificial neural network (ANN) is an AI technique that consists of neurons organized in layers, with the input layer receiving data, the hidden ones processing them, and the output layer delivering results. This technique allows representing complex phenomena of nonlinear behavior and applies deep learning in cases of high complexity. Convolutional neural networks (CNN) networks are an example (Astorga et al., 2022).

Support vector machine (SVM) is a classification algorithm capable of identifying the equation of a hyperplane that optimally separates two classes where the distance to the closest point is the minimum (Prado et al., 2020).

Random forest (RF) is a nonparametric classification algorithm capable of recognizing complex patterns of variable interaction. It applies a set of decision trees (DTs), and each is trained with different blocks of data from a set. The results are combined to achieve a prediction capable of generalizing (Alaa et al., 2019).

Logistic regression (LR) is an algorithm for classifying qualitative or categorical variables, and its output is the probability of belonging to an element to a given class. Furthermore, it applies a logistic operator (logit) to transform a categorical variable into a numerical one, and it is modeled using the inverse of the result (Padilla-Ospino et al. al., 2020; Yupari-Azabache et al., 2021).

Gradient Boosting Machine (GBM) is an algorithm that starts with a weak shallow tree as a predictor and trains another tree of equal depth to predict residuals in the previous prediction. Furthermore, it assigns greater weight to incorrect classifications, builds a new tree, and executes the previous process as iterative. GBM concludes when there is no improvement in the error. The trees are then combined to make the prediction, and the weights of each are averaged to achieve the final class (Padilla-Ospina et al., 2020).

Generalized linear model ensemble type (GLMNET) is an algorithm that fuses the Lasso and Ridge regression models to forecast by building a GLM and unsupervised learning (Granadillo et al., 2020).

Naïve Bayes (NB) is a supervised learning algorithm based on Bayes' theorem. It has multiclass output with the assumption of independence between predictor variables (Vangara et al., 2020).

The application of these techniques is frequent in various areas of knowledge to support decision-making (Aracena et al., 2022).

METHODOLOGY

The present review applied eligibility criteria that consisted of identifying works published in indexed journals over the last 5 years: from 2020 to 2024, as well as some works from before that because of their relevance. These studies addressed prediction and prospective in a complementary way. The bibliographical sources are journals indexed in Scopus, Scielo, Elsevier and Dialnet.

The search strategy consisted of identifying the topic according to the keywords prospective and prediction using ML with traditional and modern techniques. Thus, began the selection of articles focused on anticipating the future in the face of problems in various areas of knowledge. Prospective works were chosen that apply prediction as a tool for analyzing variables relevant to the study. Various proposals were identified and reviewed individually, and publications prior to 2020 were excluded except for some because of their relevance, as well as theses and internet pages.

The data selection process was performed through the exhaustive reading of each article to observe the applied technique, classic or modern learning algorithm, the variables involved, the validation metrics and its results. The metrics may be different for some cases as they depend on the technique applied. To evaluate the risk of bias, we had three expert researchers in the area review each published article. Initially, the review was done independently, and at the end the findings were discussed jointly. Works that achieved highly precise results were considered.

The synthesis of the review was created based on the aforementioned variables and appears in Chart 2.

Author	**The purpose of the study**	**Prediction technique**	**Participants**	**Validation results**
Padilla-Ospina et al., (2020)	Identify relevant financial variables for SME innovation to build forecasts and prospective study	LR SVM GBM RF CNN	239 Colombian SMEs	CNN better performance Accuracy.79 AUC.72 Cohen's kappa .35
Prado et al., (2020)	Model copper and gold mineral prospectively mapping	SVM	400 data banks	F1 score .8 from non-mineralized test locations
Granadillo et al., (2020)	Evaluate and forecast financial profiles in the telecommunications sector	Conglomerates GLMNET RF	75 companies	Homo .527 Hetero 1.358 Precision .9466 Sensitivity .933 Specificity.93.33

Ferrando et al., (2020)	Characteristics, clinical evolution and factors associated with ICU mortality of critically ill patients infected with SARS-CoV-2 in Spain: prospective, cohort and multi-center study	Multivariate regression	663 patients	Confidence interval .95
Prado et al., (2021)	Methodology for creating prospective mercury maps by applying ML techniques	ANN	24,798 points in the Almadén syncline, 77 mineralized localities, and 24 geological features	Favorable results
Astorga et al., (2022)	Recognition of archaeological images to promote enthusiast prospecting	residual CNN	379 images of lithic and ceramic remains	confusion matrix .933 success
Miranda et al., (2022)	Machine learning in university educational environments for cases of academic dropout	NB LR DT	Data on enrolled students from 2017 to 2020 AUC	Precision .99 .78 .49
Manetti et al., (2022)	Proposal for prospective analysis combining prediction with quantitative and qualitative methods in educational area	Fuzzy logic deflector method	24 experts with transdisciplinary and transgenerational profiles	62 projection-expert coincidence. 126 educational programs related to macro fields and mega trends
Madrid-Vázquez et al., (2024)	Machine learning models based on ultrasound and physical examination for airway evaluation	Multivariate analysis RF	400 patients	AUC .75
Villareal-Torres et al., (2024)	Build classification model for student dropout rate using ML, predictive and prospective methodology	BGM	20 items applied to 237 students through a survey	Coef. Gini .9220 AUC .9610 and Log Loss .2424
Ko et al., (2024)	Machine learning methods for the development of a predictive model of delirium during admission to cardiac intensive care units	LR	2774 patients	AUC .86

Chart 2. ML methods in prospective studies

As shown in Chart 2, the number of prospective studies that have applied ML techniques to identify most relevant variables and to predict phenomena, parameters, trends or results is small.

RESULTS

During the search process, 48 published works were recovered, of which a total of 25 were evaluated to decide their eligibility. Finally, 11 were selected and exhaustively reviewed for meeting the expected content characteristics, constituting new published studies, its characteristics are set out below.

The study performed by Padilla-Ospina et al. (2020) was aimed at identifying relevant financial variables of SME innovation to build forecasts and a prospective study; five modern ML techniques were also applied. CNN performed best, however, and their accuracy results were 79%. Prado et al., (2020) carried out mineral prospectivity mapping by applying ML to estimate decision limits between mineralized and nonmineralized locations, and they applied SVM with results of 100% and 80%, respectively, for each class in mineral prospectivity mapping.

Granadillo et al., (2020) built an ML-based method to predict financial profiles and productivity in the telecommunications sector of 75 companies, which were classified into three clusters. By applying the GLMNET algorithm, they achieved 98% accuracy. Ferrando (2020) conducted a prospective, cohort and multi-center study to predict the evolution of intensive-care patients with COVID-19, medical complications, infections and mortality. Six hundred and sixty-three patients participated. The multiple regression was applied, with a confidence interval of .95.

Pardo et al., (2021), using a proposed methodology, created prospective maps based on expert opinions as a support tool for specialists in the area. Furthermore, by applying ML ANN to extract relationships and patterns between the variables involved, the results were favorable. On the other hand, Astorga et al. (2022) performed image recognition to promote pedestrian prospecting by applying CNN and achieved 93% success.

The study by Miranda et al., (2022) addressed three ML algorithms to predict university students' dropout rate as input for the prospective analysis regarding of graduated professionals. Only the NB algorithm delivered favorable results of .99 accuracy, contrary to what was obtained through LR and DT.

Manetti et al., (2022) generated a prospective study proposal, based on qualitative and quantitative research and data, with experts to analyze the world evolution and future behavior according to trends. The study began by analyzing qualitative data from 24 experts, then its quantification by using intelligent models to detect future educational needs and applying the deflector method. The authors achieved 62% projection-expert coincidence.

Madrid-Vázquez (2024) analyzed a prospective, nonconsecutive cohort that continued over time of those patients undergoing surgery, using RF algorithms to predict difficult airway and achieving a .75 AUC. Villareal-Torres et al., (2024) constructed a model to predict school dropout rates using ML and a predictive, observational and prospective methodology where data were collected through questionnaires applied to 20 postgraduate students in education. The GBM model was favorable with .96 AUC**.**

On the other hand, Ko et al., (2024) created an LR model to predict delirium in patients in a cardiac intensive care unit. To identify variables of greater relevance they applied RF, GBM, partial least squares and Plmnet-elastic, and the model was validated using the hold-out method in prospective simulation. It was supported by a retrospective study and required prospective interventional studies to verify the performance of the model, with the participation of 2774 patients who applied LR and achieved an AUC of .86.

Other authors conducted prospective studies to identify clinical variables that influence resistance to antidepressant treatments and the severity of symptoms by applying ML to predict the most appropriate treatment for the patient (Perera-Lluna et al., 2022). Erazo-Castillo et al., (2023) proposed AI as a key foresight tool for anticipating risks in organizations, optimizing resources and strengthening decision-making in audits. They performed prospective and predictive analysis since the subject requires knowledge of the past and also the future.

Based on our review, the ML applied techniques have been as follows: ANN, SVM, GLMNET, multivariate regression, NB, RF, GBM and LR, with ANN being the most frequent. In each case, relevant validation metrics were applied, and the performance results of the models ranged from.75 to .99. The best performance of the algorithms was achieved in educational topics with NB of .99, followed by GBM with .96, multivariate regression with .95 in health and GLMNET with .94 in financial analysis, as well as CNN with .93 in archaeological topics.

The LR with .86 in mental health and the SVM with .8 in mineral analysis were considered acceptable results although with a lower performance. In financial aspects, the CNN achieved .79, in health RF .75, and in the deflector educational issue .62. They still require more attention, however.

The areas of knowledge that these studies have examined according to their frequency have been health, education, mining, finance and archaeology.

The approach found in ML in prospective analysis focused on identifying relevant variables and contributing through prediction to determining trends and possible unfavorable events. It is widely useful for SP since it allows constructing rigorous models corresponding to current phenomena and futures (Padilla-Ospina, 2020).

CONCLUSIONS

In the literature review, various SP studies and a greater number of predictive proposals applying ML were identified; however, in most cases they were developed in isolation, making clear the acceptance of each approach and exhibiting the poor use of their complementarity that is applicable in the prevention of social problems.

SP and prediction have opposite approaches, with one being qualitative based on the future, and the other being quantitative based on the past. They are complementary and mutually inclusive, however. The first, however, provides direct support to the continuous planning process and the second to anticipate these results. On the other hand, combining the possibilities of different areas of knowledge, such as strategic planning and AI, will allow innovative studies to be performed that take advantage of the points of view and advantages of each disciplinary area, as well as their emerging tools to strengthen and ensure the results.

In the few cases where the authors performed SP with ML, the most widely accepted and preferred intelligent techniques were ANN and LR. The best performance, however, was obtained through the least known algorithms: NB, GBM, multivariate regression and GLMNET, which achieved favorable performances between .94 and even .99. These results allow us to observe the suitability of combining a qualitative and quantitative approach in order to obtain certainty about the future by reinforcing subjective results through quantifiable tools and basing its analysis on both historical data, current trends and uncertainties that reflect reality.

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