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Review Article

A Systematic Review of Causal Machine Learning in Business

George Zevallos-Durand[1], Victor Guevara-Ponce[2], Ofelia Roque-Paredes[3], Orlando Iparraguirre-Villanueva[4]

[1,2,3]Instituto de Datos e Inteligencia Artificial (IDIA), Universidad Ricardo Palma, Lima, Perú.
[4]Universidad Tecnológica del Perú, Chimbote, Perú.

[4]Corresponding Author : eic-ijepe@honexus.org

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***Abstract* -** *Causal inference focuses on understanding and explaining cause-and-effect relationships between variables, while Machine Learning (ML) primarily seeks to optimize prediction. Objective: To determine how machine learning algorithms are being used for causal inference in scientific research in the business field, identifying trends, gaps, and opportunities for methodological development. Method: A systematic review of the literature was conducted following PRISMA guidelines. Searches were performed in international scientific databases, initially identifying 1,998 articles. After applying inclusion and exclusion criteria related to thematic relevance, study type, full-text availability, and methodological quality, only 17 articles were selected for final analysis. Results: demonstrated an emerging use of the intersection between machine learning and causal inference in business research. The applications identified focus on estimating causal effects in marketing, analyzing consumer behavior, and studying the impact of business policies. However, limited adoption of algorithms specifically designed for causal inference was observed, with regularized regression models and matching methods being the most widely used techniques, while more advanced approaches, such as causal forests or doubly unbiased machine learning, were rare. The small number of articles (17) compared to the initial universe is an indicator of the existing gap. Conclusions: Finally, in the business world, the potential of integrating ML with causal inference has not yet been fully exploited.*

***Keywords* -** *Machine learning, Causality, Causal inference, Business, Causal machine learning.*

1. Introduction

There are 3 fundamental tasks in data analytics: description, prediction, and causal inference; the latter is largely neglected in data science [1]. In this regard, Facure [2] emphasizes that not all problems in business are solved with predictive machine learning models, but many seek a cause-and-effect relationship. Likewise, Ellsaesser et al. [3] point out that a deep understanding of causal relationships is important to achieve business success. It is noted that the literature highlights the importance of causal inference in scientific research, and it would seem to be at odds with predictive machine learning algorithms, but this need not be the case [4]. Predictive modeling can also be successfully applied to detect causal effects, and not just correlations [5-8].

In the business context, decision-making based on causal information is required; it is necessary to go beyond the correlations between the different variables that model a real business situation, so knowing what results will be obtained by performing certain actions is important for the success of the company [9]. A change of focus towards causal inference allows companies to give a rigorous analysis to their observational and experimental data [10], since it facilitates the evaluation of various actions aimed at improving the performance of the strategies proposed [11].

Causality is approached from 2 frameworks: on the one hand, the potential outcome approach, and on the other hand, directed acyclic graphs [12]. The potential outcome approach indicates that the effect of a treatment is equal to the difference between receiving the stimulus and not receiving it [13]. For example, in an advertising campaign, if a customer is offered a coupon (treatment group), he will have a certain level of expenditure, and his potential outcome will be the level of expenditure if he had not received the coupon (control group). The difference between the potential outcomes makes it possible to define the causal relationship between the variables analyzed. However, here appears the fundamental problem of causal inference, which is that the treatment and control outcomes cannot be observed simultaneously [14]. In this example of the advertising campaign, this means that it is not possible to both give and not give the coupon to the same customer at the same time. Likewise, the potential outcome framework provides the theoretical support to approximate causal relationships when experiments are not possible, i.e., only observational data are available [15].

Directed Acyclic Graphs (DAGs) are visual representations of the causal relationships between variables, using nodes and arrows [16]. A well-structured DAG can convey in a simple way the assumptions and theories that support the researcher's hypotheses, which makes the estimation of causal effects easier and more intuitive [17].

From the predictive modeling side, machine learning algorithms are excellent for this purpose. According to Géron [18], they can be classified into supervised learning algorithms for classification (when the dependent variable is categorical) or regression (the dependent variable is continuous). For these supervised tasks, there are algorithms such as decision trees, support vector machines, neural networks, random forests, gradient boosting, and others. On the other hand, there are unsupervised tasks, which imply that there are no labels to predict; instead, they aim to find inherent patterns in the data space. In this area, algorithms such as k-means, principal component analysis, autoencoders, and more are often used.

As can be seen, machine learning algorithms seek a different goal than are aimed at by causal inference techniques; however, it is possible to reconcile these two cultures [4], especially in business environments [19]. This is the field of causal machine learning; the techniques used can estimate the Average Treatment Effect (ATE) using experimental and observational data [2]. However, wherein causal machine learning marks a breaking point for the better is in the estimation of the Conditional Average Treatment Effect (CATE), mainly through algorithms such as causal forests [20], double debiased machine learning [21], Bayesian Additive Regression Trees (BART) [22], and meta-learners [23].

The estimation of the CATE is important because it allows the detection of heterogeneous effects, which is because the same treatment does not have a homogeneous effect on the whole population, and it supports personalization [24]. This is traditionally done using regressions with interactions, also known as moderation analysis [25]. Nonetheless, this technique has limitations due to its sensitivity to incorrect specification of the model and the shape of the interaction [26].

Conversely, causal machine learning algorithms can effectively model complex interactions, even finding previously unexpected relationships. Causal forests [20] modify the loss function of the random forest to optimize the algorithm for causal estimates rather than predictions. In contrast, Bayesian additive regression trees [22] use a Bayesian approach to estimate many small trees that are regularized according to the priors, and then the trees are summed up to estimate the causal effect. These algorithms mentioned are a modification of their original prediction-oriented version. Meanwhile, meta-learners do not modify the algorithm, but rather the problem, such that the causal inference can be solved by prediction, for which the well-known machine learning algorithms mentioned above are used [23].

Finally, double debiased machine learning [21] is based on the already known Neyman orthogonalization, wherein the estimation bias is removed by residualizing, that is, removing the effects of confounding variables, so the causal effects are found robust.

As has been seen, machine learning algorithms offer significant advantages and capabilities in estimating causal effects; however, in business research, there is a knowledge gap regarding how to use these new tools to solve business challenges. Based on this situation, this systematic review seeks to answer the problem of: What is the scope of application of machine learning algorithms for causal inference in scientific business research? From this problem, we derive the main objective, which is to determine the scope of application of machine learning algorithms for causal inference in scientific business research.

Considering the general objective, 3 specific objectives are formulated. The first one is to identify which machine learning techniques for causal inference are applied in scientific research in business. The second objective is to distinguish what kind of research questions have been solved using machine learning algorithms for causal inference in scientific business research. Finally, we seek to specify what advantages and disadvantages machine learning algorithms for causal inference have in their application to scientific business research.

This systematic review is a novel contribution because it reports on how machine learning is applied to solve causal inference problems in business research. Similar reviews already exist, but focused on health care [27, 28], political science [29, 30], and sociology [31, 32], or focused on theoretical reviews about what is possible to do [33-35]. This study aims to expose what is being used, not the theoretical possibility, but the current practice of causal machine learning in business.

2. Materials and Methods

A systematic review involves synthesizing the development of an area of knowledge to identify future lines of research and current problems in that chosen area [36]. A recommended way to conduct this type of research is using the guidelines of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses, better known as PRISMA [37].

In the present proposed systematic review on the application of machine learning techniques for causal inference in scientific business research, PRISMA guidelines were followed. Special emphasis was given to the search strategy, inclusion criteria, and exclusion criteria.

2.1. Inclusion Criteria

The inclusion criteria indicate the characteristics that a given article must meet to be eligible for inclusion in the systematic review. The first criterion considered is that the studies address a specific business problem from a scientific approach; the area of application was not limited, so that they can be on topics such as finance, marketing, logistics, human resources, planning, among others. The important thing is that it is something related to business. Another important criterion is that they are studies that apply machine learning algorithms for causal inference and also show how the execution of the technique was carried out.

Regarding the more general inclusion criteria, studies published from 2010 onwards were considered because this is the year in which machine learning algorithms gained great momentum in business practice with the launch of the Kaggle platform [38]. Likewise, studies published only in English were considered because it is the most widely used language worldwide to report scientific findings [39].

2.2. Exclusion Criteria

The exclusion criteria indicate which characteristics an article should not have, and if it does have them, then it will not be included in the review. Thus, studies that apply only traditional causal inference techniques, i.e., based on regressions or experiments, without any machine learning algorithms, were excluded. They were not considered relevant given that this systematic review seeks to understand the intersection space between these explanatory techniques and predictive algorithms. Likewise, articles that are systematic or literature reviews were not included because they do not show a timely application of the methods sought to be analyzed. In this line, theoretical studies that focus on developing techniques and explaining their operation, and that do not apply them to any specific business problem, were also not considered because this research is intended to show the use given to these techniques, not their operation.

Similarly, studies that applied techniques of interest to engineering problems (optimizing production lines, reducing waste, improving manufacturing times, among others) or trading (predicting prices of stocks, bonds, or any asset in the stock market) were not considered because they are areas of study in themselves and different from business sciences. In addition, studies that are book chapters were also excluded because they show how the techniques could be used with didactic examples, but they do not apply them directly to a business problem.

2.3. Search Strategy

The search strategy refers to all the steps and procedures followed in order to obtain the articles included in the systematic review. In this research, 3 databases were chosen, which are Scopus, Springer, and IEEE Xplore; they were considered for their thematic relevance, scope, and availability of the articles. The same search term was used in all 3 databases, which is shown in Appendix A. This was composed based on the 3 thematic areas identified with the PICOC methodology [40], on the one hand, words related to machine learning, then to causal inference, and finally to various disciplines within the business area.

Likewise, filters were added to each database to facilitate compliance with the inclusion and exclusion criteria. In Scopus, in addition to the query, the following filters supported by this platform were applied: (1) range: 2010 - 2024, (2) type of document: article and conference paper, (3) type of source: journal and conference proceeding, and (4) language: english; thus, a total of 872 articles were obtained. In Springer, the following filters were applied: (1) range: 2010 - 2024, (2) language: english, and (3) discipline: business & management; thus, the search yielded 809 articles. Finally, in IEEE Xplore, the filters applied were: (1) range: 2010 - 2024 and (2) type of source: journal and conference; 317 articles were collected.

The following chain was applied "("machine learning" OR "Decision trees" OR "random forests" OR "neural networks" OR "deep learning" OR "support vector machines" OR "ensemble methods" OR "linear regression" OR "penalized regression" OR "lasso" OR "ridge" OR "elastic net") AND ("causal inference" OR "causality" OR "potential outcomes" OR "directed acyclic graphs" OR "structural causal model") AND ("business" OR "business research" OR "finance" OR "marketing" OR "research operations" OR "management" OR "human resources" OR "accounting" OR "advertising" OR "market research" OR "operations")".

After applying the query and filters mentioned above, a total of 1998 articles were collected: 872 from Scopus, 809 from Springer, and 317 from IEEE Xplore. These were exported in RIS format to the Rayyan software [41] to speed up the process of evaluation and inclusion of the articles. In this phase of exporting the articles, there was a problem with a RIS file that ended up uploading 67 extra records, which resulted in starting the identification stage with 2065 articles. Of these, 167 were found to be duplicates (many probably due to the problem when exporting the RIS file), so they were eliminated, and this stage ended with a total of 1898 valid records. The evaluation phase began with the 1898 articles, of which the title and abstract were reviewed to assess their relevance, so 1757 articles were excluded, leaving 141 valid records. These were evaluated again in greater depth, and 116 were eliminated, leaving 25 articles at this stage. Finally, 8 of these were excluded because it was not possible to obtain them. The inclusion phase resulted in 17 publications being considered that met all the stipulated inclusion and exclusion criteria, and so these are the ones that were finally analyzed for this systematic review. Figure 1 shows the process described to include the articles.

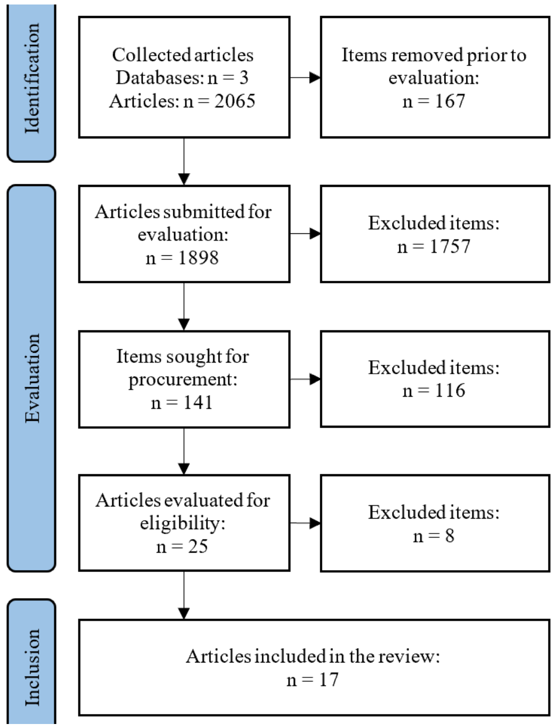

Fig. 1 Flow of the article inclusion process

3. Results

This section presents the results of the analysis of the articles. The authors and titles are found in Appendix B. Figure 2 shows the number of articles according to the year of publication in scientific journals. 2021 had the highest number of publications (5), while in 2016, 2020, and 2022, only one article was published per year. It is important to highlight that the inclusion criteria covered articles since 2010, and it is observed that there is no publication until 2016. This is striking because there were methods such as Bayesian Additive Regression Trees (BART) proposed by Chipman et al. [42] and meta-learners to estimate the importance of variables using a causal approach [43]. This situation of lack of application of these techniques highlights the importance of making scientific findings known both within the scientific community itself and to practitioners in different industries [44].

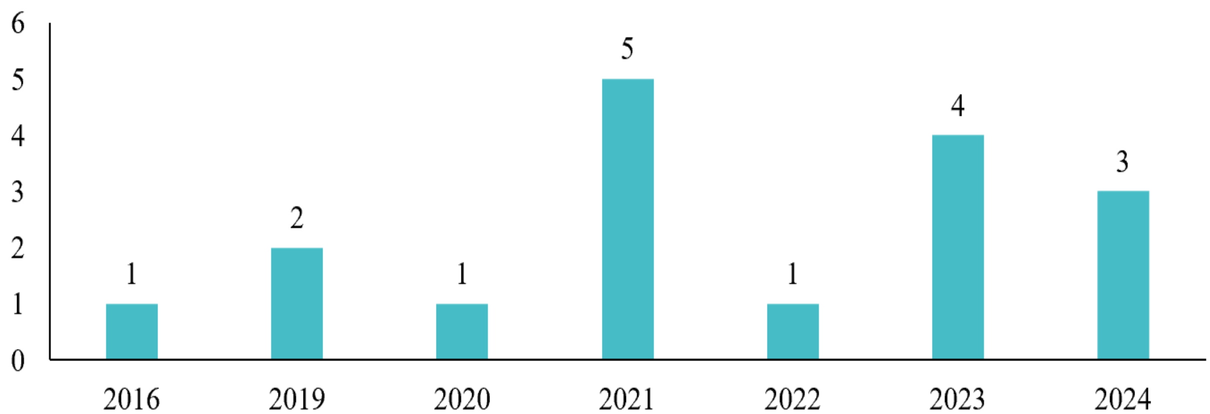

Fig. 2 Articles published by year

Of the total number of articles, only 1 article was selected from the IEEE Xplore database, 10 from Scopus, and 6 from Springer; the percentage distribution is shown in Figure 3. It is possible that most of the articles come from Scopus due to its multidisciplinary nature and broad scope in the areas of business sciences. The inclusion of only one article from IEEE Xplore can be explained by the fact that this database focuses more on technological applications and more conceptual issues regarding the algorithms used.

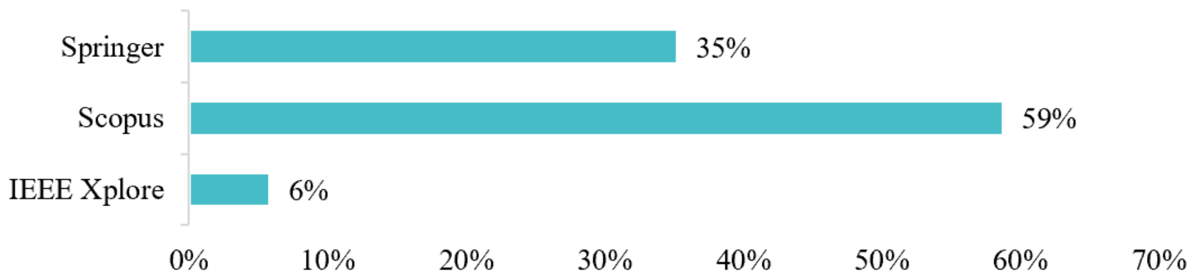

Fig. 3 Published articles according to the database

The largest number of articles was found in the United States with a total of 9, followed by the United Kingdom with only 2, and the rest of the countries had only one article each; Figure 4 shows this distribution of countries. It is important to mention that there are articles that were joint work of 2 or 3 countries, which is why the total number of countries is 20 and not 17. It is not surprising that most of the articles included were published in the United States, given that this country is one of those with the greatest investment in science and technology worldwide [45].

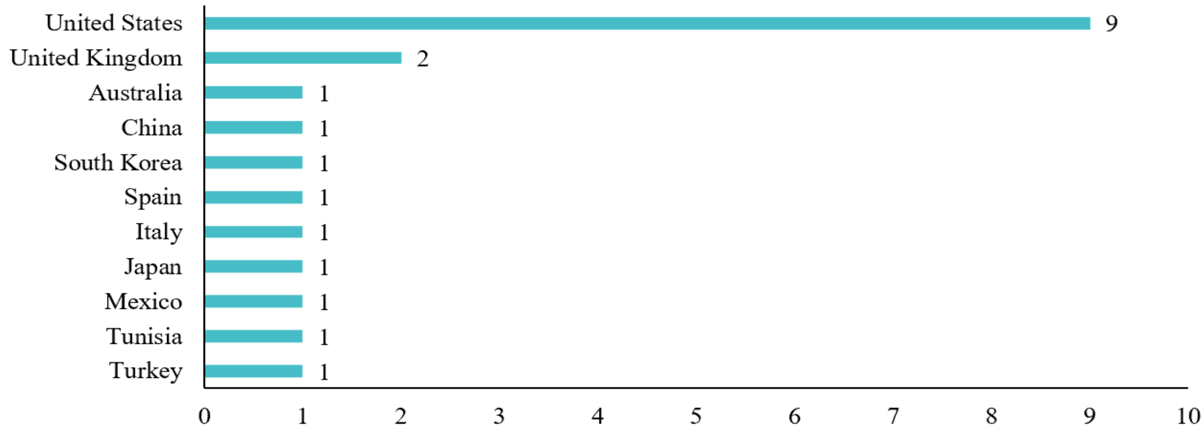

Fig. 4 Articles published by country

The business topics covered by the articles are quite diverse, but studies that seek to model consumer behavior (4) and improve digital media strategies (4) are predominant, and Figure 5 shows the distribution of these topics. Most of the applications are focused on marketing, and to a lesser extent, on finance, human resources, and management in general.

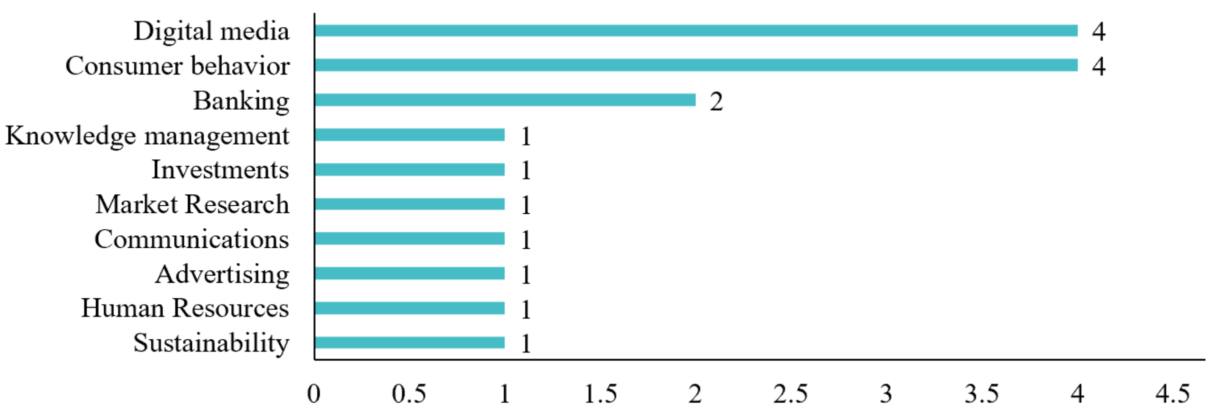

Fig. 5Articles published by the business area

Different statistical (e.g., probit regression) and causal (e.g., regression discontinuity) techniques were applied together in the articles to meet the objectives of these investigations.

The most popular techniques were propensity score analysis and Bayesian networks, with 3 papers each employing them. Table 1 (Statistical techniques used) shows the different techniques used.

In addition to the traditional techniques mentioned above, machine learning algorithms were also used to perform the different estimates required.

The most used algorithms were neural networks (5) and random forests (4). Table 1(Machine learning algorithms used) shows the other techniques used.

Table 1. Traditional techniques and Machine learning techniques

#	Traditional techniques used	Quantity	Machine learning techniques	Quantity
1	Propensity score	3	Neural networks	5
2	Bayesian networks	3	Random Forests	4
3	Structural equations	1	XGBoost	3
4	Process 3.0	1	Bayesian neural networks	2
5	Bayesian regression	1	Support Vector Machines	2
6	Discontinuous regression	1	Stochastic gradient descent	1
7	Logit regression	1	K nearest neighbors	1
8	Probit regression	1	Lasso regularization	1
9	Latent class segmentation	1	Recommender system	1
10	Bayesian time series	1		

4. Discussion

This systematic review of 17 quantitative studies reveals a marked trend toward the use of advanced methods, such as machine learning and traditional statistical analysis techniques, to address complex causal inference questions. This convergence of techniques not only expands analytical capabilities in research but also demonstrates the relevance of these tools for solving practical problems in business fields. Key findings, implications, and limitations are discussed below. Regarding the key application areas are varied, such as mobile banking [46, 47]; consumer behavior [48-51]; corporate communications [52], knowledge management [53], investments [54], market research [55], digital media advertisements [56-59]; advertising [60], human resources [61] and environmental sustainability [62]. This demonstrates the versatility and great applicability of this type of technique to solve different business problems.

The joint use of machine learning and more traditional statistical methods stands out. In this sense, the research of Gelper et al. [60] uses the causal forests algorithm to estimate the heterogeneity in the effects of looking at another screen while watching a TV program. On the other hand, Rudd et al. [50] integrate neural networks with Bayesian directed acyclic graphs to identify causal relationships. In both cases, they show how this integration of predictive techniques with explanatory ones can overcome the limitations of the latter. Following this line, Kuesten et al. [55] combine the random forest algorithm with Propensity Score Analysis (PSA) to select relevant covariates, while Kwon et al. [62] apply neural networks to detect nonlinear relationships and then evaluate the relative importance of the relationships found with a sensitivity analysis. This way of working, where predictive and explanatory methods are used in sync to determine causal effects, shows that it is possible to improve the quality of the findings by using techniques that are more sensitive to the nature of the data. These articles show important applications, such as Shimizu et al. [51], who explain how the use of uplift models with XGBoost can optimize the allocation of marketing resources and thus also improve the Return On Investment (ROI) of advertising campaigns. Similarly, Rudd et al. [37] find latent factors (not directly observable) that influence the retention of pension fund customers, thus showing the use of these techniques to achieve greater effectiveness of business strategies. Likewise, from the methodological side there are also improvements such as the Enhanced Graph Learning (EGCI) model developed by Wang et al. [59], which is designed to incorporate causality concepts in recommendation systems, since they correct the fact that a user may pay attention to an item not because he likes it but because it is popular, i.e., popularity acts as a confounding factor. The authors highlight the potential of counterfactuals to correct biases in recommended systems using machine learning algorithms. This is an important contribution because it point out an application that has not been sufficiently explored in the literature.

Likewise, the research by Wang et al. [59] shows how, by integrating the "do()" operator proposed by Pearl [17], it is possible to determine causal relationships. This is achieved because this operator eliminates product popularity biases, which improves the accuracy of recommender systems. What the operator does is indicate that a variable has been intervened upon, which isolates the effects and allows Causality to be inferred. It is important to note that recommender systems require large volumes of data to be useful and must identify complex patterns among the data [63]. This situation seems to be alien to causal inference; however, Wang et al [59] innovate by demonstrating that Causality can improve the performance of this type of model.

On the other hand, one way to optimize marketing campaigns is with uplift estimation, which allows identifying customer segments where the campaign is more effective [64]. This is a problem that requires linking causal inference with machine learning, and this is precisely the approach followed by Shimizu et al [51]. The authors use the XGBoost algorithm because of its good predictive capability and thus estimate heterogeneous effects to determine which customers to focus on. In these scenarios, the use of machine learning algorithms is especially useful because they can detect interactions between variables and distinguish noise to give better predictions and consequently improve the estimation of causal effects [57].

In causal inference, the commonly used techniques are instrumental variables and linear regressions [65]. However, recent advances in new algorithms that integrate prediction and Causality, such as causal forests [20] and doubly unbiased machine learning [21], which are applied in the research of Calbo-Valverde et al. [47] and Gordon et al. [57] respectively, reveal the importance of these methods because they allow more robust estimates that are less dependent on the parametric specification of the models.

This systematic review focuses on what is currently being done in the academic practice of the business field, rather than what is theoretically possible. In this sense, it has been found that research on the use of machine learning algorithms for causal inference, better known as causal machine learning, has prioritized theoretical and methodological development regarding how these tools work [33-35]. Nevertheless, this has not contributed to the adoption of these new techniques to address real-world problems; this review provides solid evidence in this matter.

Furthermore, it is important to highlight the relevance of adopting causal machine learning in business academic research, as has been done in healthcare [27, 28], political science [29, 30], or sociology [31, 32]. Theoretical research is very important to lay the groundwork for why the algorithms are useful, but it is also important to jump into practical applications. Having better algorithms for data analysis, but not using them, is the same as not having them at all because no benefit materializes.

5. Conclusion

The advent of new machine learning algorithms has represented an important advance in predictive modeling and, given the current integration, also in explanatory modeling. This is a transcendent advance because it allows researchers and practitioners to model causal relationships in complex business situations that require technologies capable of dealing with large volumes of data and nonlinear patterns. This systematic review analyzes and lists the applications and advantages of this integration of data modeling approaches. Thus, the results of the selected articles are compared, and the contributions of each are identified. This review concludes that machine learning algorithms improve the approach to problems involving the identification of causal effects, since they can capture nonlinear relationships and complex interactions between variables that the most common statistical methods are not able to model adequately. The use of algorithms such as Bayesian neural networks [46], graph convolutional networks [59], support vector machines [52], causal forests [60], Bayesian causal graphs [50], and doubly unbiased machine learning [57], among others, have made it possible to obtain more accurate estimates of causal effects in a variety of contexts.

It is important to highlight that these algorithms not only allow estimating the Average Treatment Effect (ATE), which is usual, but also heterogeneous effects, known as Conditional Average Treatment Effect (CATE). This is an important advantage because it identifies customer segments more likely to convert. For example, Carbo-Valverde et al. [47] use causal forests to detect in which type of bank customers digitization is more viable; this type of analysis would be very complex with more traditional methods, such as regressions with interactions [2]. It is this ability to identify heterogeneity in customers that allows personalization in the commercial relationship with them. Another didactic example is the research of Shimizu et al. [51], who solve the problem of which customers it is convenient to deliver coupons to an e-commerce company.

Table 2 shows the main findings of the research. The machine learning algorithms used in conjunction with the causal inference techniques and the subjects where they were applied are indicated, as well as the authors of the articles where they were applied. The term hybrid algorithms refers to techniques that have been created by integrating explanatory and predictive components.

Table 2. Use of machine learning algorithms in causal inference

Category	Detail	References
Machine learning algorithms	Neural networks	[35, 37, 41, 48, 49]
	Random Forests	[34, 38, 42, 43]
	XGBoost	[34, 38, 45]
	Bayesian networks	[33, 40]
	Support Vector Machines	[39], [34]
	K nearest neighbors	[34]
	Lasso regularization	[36]
	Recommender systems	[46]
Statistical techniques	Propensity scores	[55, 58, 57]

	Structural equations	[46]
	Bayesian regression	[52]
	Discontinuous regression	[48]
	Logit regression	[47]
	Probit regression	[49]
	Time series	[56]
Hybrid algorithms	Causal forests	[47, 60]
	Doubly unbiased machine learning	[57]
Business topics	Digital media	[56-59]
	Consumer behavior	[48-51]
	Mobile banking	[46, 47]
	Knowledge management	[53]
	Investments	[54]
	Market research	[55]
	Corporate communications	[52]
	Advertising	[60]
	Human Resources	[61]
	Environmental sustainability	[62]

5.1. Limitations

Regarding the limitations of this research, it is important to mention that these were not included. This is a limitation because these are mostly applied research, i.e., they seek to solve a specific business problem; we chose to exclude them because these studies are largely done to obtain an academic degree and are not necessarily peer reviewed.

An unavoidable limitation is the publication bias in the articles collected. Research where the causal effect is null may not be published because it is erroneously considered to lack utility. Thus, very interesting business applications may not see the light of day, not because they have a poor methodological design or incorrectly apply data analysis techniques (in this case, machine learning algorithms in causal inference), but because the independent variable does not influence the dependent variable.

5.2. Recommendations

The reliance on large volumes of data for machine learning algorithms to recognize meaningful patterns is an obstacle in areas where data are limited or not well structured. Thus, in the knowledge management study by Téran-Bustamante et al [53], it was highlighted that, while Bayesian networks can be useful for modeling Causality, their performance is highly dependent on the quality of the data and the quantity of observations available. In sparse contexts, machine learning models may not be as effective in estimating the causal effect as expected, so it is important to study and understand performance in small sample situations.

It is important that the authors clearly specify what assumptions they accept when posing causal relationships between variables, for DAGs are a very valuable tool because they make transparent considerations about confounding effects, selection bias, and measurement error, among others, in their research [66]. Machine learning algorithms are excellent for making predictions and are at the core of business strategies; however, researchers and business managers must recognize that not all business problems are predictive. For example, XGBoost can be used to predict when a customer will leave the company, but this model will not say anything about the reasons why the customer decided to leave, and this is where causal inference comes in to answer these important questions. Therefore, causal inference needs to be applied more vigorously, not only in scientific business research but also in everyday business practice.

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