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Review Article

Assessments of the Impact Analysis of Interventions Using Propensity Score Analysis (PSM)-Literature Review

Assen M
Senior Pharmacist, Boru Meda Hospital, Dessie, Ethiopia

***Corresponding author:** Assen M
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Abstract

Introduction: Propensity scoring is a powerful tool to strengthen causal inferences drawn from observational studies of different areas. A propensity score is used to choose treatment and control groups with simila baseline characteristics. A Propensity score is defined as the probability of the subject being assigned to the treatment group, given set of baseline characteristics. ***Objectives****:* To review the impact analysis of interventions using Propensity Score analysis**.** ***Methods:*** literature review in methodology was used. The review was conducted using reliable healthcare internet database namely; Google scholar, hinari and PubMed central. Eleven scientific articles were scrutinized to obtain results for the review. ***Result:*** The results of this review showed that a total of twenty four articles and books were reviewed and almost all of the reviewed articles and books were used Propensity Score analysis methods clarifying the notes and for their analysis of different titles of researches in different parts of the world. ***Conclusion:*** This review of assessed and reviewed, Propensity matching is a powerful tool for observational data analyses because it facilitates the comparison of outcomes between similar groups of patients and has impacts on the interventions.
Keywords: Impact, Analysis, Interventions, Propensity Score Analysis.

INTRODUCTION
BACKGROUND

Propensity Score Matching (PSM) is a statistical technique that allows researchers to more accurately measure social and behavior change communication (SBCC) program impact and to make a strong case for causal attribution. It helps researchers determine whether the program was actually responsible for the changes in knowledge, attitudes and behaviors that occurred. Impact evaluation of SBCC programs requires comparison between what happened as a result of a program and what would have happened in the absence of the program (a counterfactual). Randomized control trial designs (RCTs) accomplish this by randomly assigning some people to get a treatment and others to not get the treatment, and comparing the results between the two groups. In large-scale SBCC programs, such as entertainment-education programs that use mass media to reach a national audience, it can be impossible or undesirable to prevent some people from receiving the messages simply in order to create a counterfactual condition for the purposes of evaluation and interventions based on the result of the research [1].

It then compares the extent of behavior change among similar people who were exposed (the treatment group) and those not exposed (the matched comparison group). PSM gives us confidence that the only difference between the matched persons is the one we want to examine: exposure to a specific SBCC intervention. This allows researchers to evaluate behavior change while controlling for the variables that predispose some people to be exposed and to change. This way, without assigning some people to receive the Program and denying it to others, researchers can be certain that the predisposing variables are not the reason that an individual responded positively to an SBCC program – rather, it was the program itself that had an effect on the individual's behavior [1].

Propensity scoring is a powerful tool to strengthen causal inferences drawn from observational studies. The motivation is simple: To compare the effects of 2 treatment options, which we generically refer to as ‘‘A’’ and ‘‘B’’ with B being the more common one, we want to compare the outcomes of similar groups of patients receiving each treatment. Propensity scoring helps in selecting similar patient groups for comparison. Propensity scoring is common in the literature, and popularity of propensity scoring, we are concerned that its use is conceptually more intricate than many investigators realize. The consequence can be results that are misleading or difficult for readers, referees, and investigators to evaluate objectively. These concerns persist, despite the fact that they have been raised previously in the cardiothoracic surgery literature. The problem is compounded by inconsistent recommendations [2].

Traditional propensity score analysis is based on the theories of causal inference from Rubin and his colleagues [3]. Rubin realized that each covariate influenced a subject's probability of being assigned to a treatment or control group, which led to the conclusion that instead of matching participants in different groups on the basis of their vector of scores on a series of covariates, it was only necessary to match them on their predicted probability of being assigned to the treatment group. This predicted probability was labeled the propensity score, which is defined as

$$p(x) = \Pr(T = 1 \mid X = x),$$

Where p(x) is defined as the conditional probability that a person will be assigned to the treatment group, T is the treatment condition, and X = x is a realized set of covariate scores. Traditionally, propensity scores are calculated through a variety of methods from an existing data set after the treatment has been administered [4].

In the context of educational assessment, practitioners frequently attempt to draw causal inferences about the impact of their programs. Specifically, assessment professionals would like to claim that their programs or interventions directly impact student learning. However, given the quasi-experimental nature of the research, the extent to which one can make causal inferences in applied contexts is limited [5, 6]. Ideally, when attempting to make causal inferences about the impact of some variable, researchers randomly assign participants to conditions. However, the applied context of education often means random assignment to programs or interventions is neither feasible nor ethical. Because it mimics the strengths of true experimental designs, propensity score matching (PSM) provides an appealing alternative [7]. The current study introduces the concept of PSM, describes best practices for conducting PSM studies, and provides an applied example situated within the educational context [8].

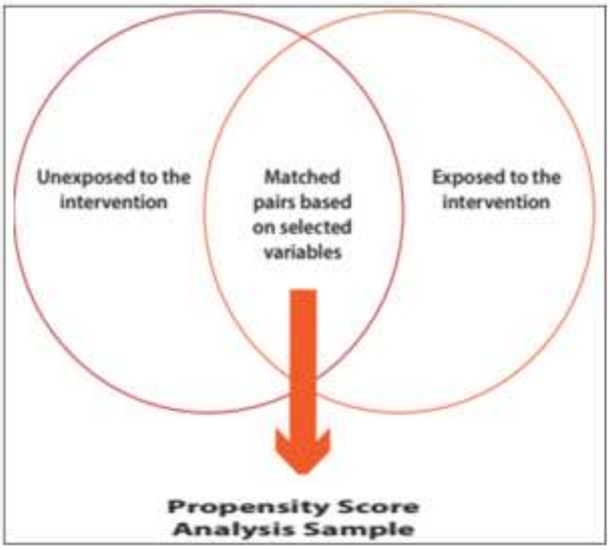

Fig-1:

From the history point of view the concept of PSM was first introduced by Rosenbaum and Rubin [9] in a paper Entitled "The Central Role of the Propensity Score in Observational Studies for Casual Effects." And the Heckman [10] also played a role in the development of propensity score matching methods. He focused on selection bias, with a primary emphasis on making casual inferences when there is non- random assignment. He later developed the difference-indifferences approach which has applications to PSM.

The propensity score is the conditional probability of being treated based on individual covariates – Rosenbaum and Rubin demonstrated p scores can account for imbalances in treatment groups and reduce bias by resembling randomization of subjects into treatment groups Propensity score techniques used to compare groups while adjusting for group differences - Regression adjustment– Matching– Stratification (sub classification) [11].

Help find matches from comparison group so that measured confounders can be equally distributed between treatment & comparison groups and Helps improve precision of estimates of treatment effects cannot account for unmeasured confounders – only control for observed variables and only to the extent that they are accurately measured [12].

Steps in PSM

The steps during the analysis of PSM the following steps are used.

- Identify appropriate data (large sample size)
- Define the treatment (and control) and outcome
- Select the covariates of interest
- Estimate the propensity scores
- Use the propensity score to 'match' the groups: matching, weighting, stratification, etc.
- Assess the 'matching' using balance diagnostics methods
- Run the analysis of the outcome on the propensity score-adjusted sample [13].

Types of PSM model

In PSM analysis number of models are used from those models the followings are as examples (a) Marginal model; ignoring multilevel structure (b) Fixed effect model; adding cluster specific main effect /to address the bias due to Measurement error. Specify a different intercept for each cluster (dummy variable for cluster membership). Number of parameters increase with the number of clusters. When there is a large number of small clusters, estimates can be biased (c) Random effect model; do to the shrinkage of random effect specify a different intercept for each cluster, but assume these intercepts across clusters follow a distribution. More parsimonious, borrow strength across clusters. No balancing within each cluster. Random effects models can easily fitted with build-in Packages [14].

And the following Four Models are Described by Guo & Fraser [15].

- Heck' l man's sample selection model [16-18] and its revised version. Which Estimating treatment effects [19] Heckman's [18] sample selection model that eliminates the possible sample selection bias is estimated in two steps. In first step, a participation or selection equation is estimated by Maximum likelihood probit regression, in which decision to work in labor market or not is used as response variable that depends on different explanatory factors. From the coefficients estimated from probit regression, Inverse Mills Ratio (IMR) is calculated. In second step, wage function is estimated with IMR as an additional regress or that will account for the bias due to nonrandom nature of the sample of wage earners. Significant coefficient for IMR Points at the presence of the sample selectivity [20].
- Propensity score matching [9], optimal matching [21], propensity score weighting, modeling treatment dosage, and related models Hirano, Imbens, and Ridder [22] propose an estimator that weights the units by the inverse of their assignment probabilities and show that nonparametric series estimation of this conditional probability label the propensity score by Rosenbaum and Rubin [9], leads to an efficient estimator of average treatment effects. Can include PS in final analysis model as a continuous measure or create quantiles and stratify. Rosenbaum & Rubin [9] showed that perfect stratification based on PS will produce strata where average treatment effect within strata is an unbiased estimate of the true treatment effect [23].
- Matching estimators [24, 25] the estimation of the propensity score, the selection of a matching algorithm and the estimation of the treatment effect and matching techniques is to match treated individuals with untreated units that are similar or close in terms of X. When X is a single variable, as in the example above, the meaning of the word "similar" is clear: if we take a treated and an untreated unit, the closer their values of X.
- Propensity score analysis with nonparametric regression [10, 26] implement a trimming procedure to discard the nonparametric regression results in regions where the density of the propensity score in the nontreated population is small In nonparametric regression methods one typically chooses smoothing parameters to balance bias and variance of the estimated regression function [27].

Types and nature of variables dealt under multilevel modeling

Choosing Variables for Propensity Scores

The nature and types of variables dealt with PSM analysis commonly used are the following which Include: Propensity score has been developed and applied in cross-sectional settings (single level data).

Common Variables in PC

Patient variables

Demographics (age, gender, ethnicity/race, marital status, insurance status, domicile [home v. LTC/institution]) Illness-related factors (primary dx, comorbid conditions, severity of illness [APR-DRG]) Prior utilization (ED visits, hospitalizations, output visits, home health/hospice enrollment, days in LTC).

Contextual Variables

Setting (urban/rural, hospice/SNF beds in community, for-profit status, geographic region/zip code, hospital site/type), Time (year of death, season of year), Clinician characteristics (yrs. in practice, specialty, frequency of referral to PC/hospice) [12].

Types of research question which demands this type of modeling

Conceptualization of PSM Public Service Motivation can be understood as the research on a specific type of organization and its relationship with the people working in this sector [28]. Humans' beings, compared to machines [29], are able to combine their creativity and do have the ability to develop strategies in order to achieve goals. Brewer [30] additionally states that groups with different conceptions have different motives to work in the public sector. Moreover, autonomy and control play a great role in the fact, that the affection to regulate the behavior can be either related to their own characteristics (autonomous) or related to external influences and the environment (control) [31]. Furthermore, employees with a high level of PSM are expected to be more internally motivated compared to people with a low level of motivation [32].

When PSM analysis is elaborated more in the view of analyzing multilevel data in R and STATA software.

Software for doing matching: R

- R is a very flexible (and free) statistical software package www.r-project.org
- Add-on packages will do a variety of matching methods and diagnostics (also free)
- Twang [33]: GBM estimation of propensity score, good diagnostics
- Matching (Sekhon): automated matching method MatchIt [34]: very flexible, links in other methods. Will show sample Match It code and output throughout; will show more details at endsoftware R and S tata have the most in terms of dedicated propensity score packages/functions. SAS and SPSS have some, but limited, user-written macros and functions Will focus on the Match It package for R today [35].

Sample size determination in PSM analysis

PSM requires data from both the treatment group and a potential comparison group. Both samples must be larger than the sample size suggested by power calculations (i.e., calculations that indicate the sample size required to detect the impact of an intervention) since observations outside the region of common support are discarded. At least 200 subjects in total – Remember logistic regression rule: at least 10 events should be observed for every covariate that is entered into the model [36].

Assumption of PSM analysis

In PSM analysis most of the time the following two main assumptions are most common ones which are listed below**.**

Assumption 1

Overlap (i.e., no extra pollution the overlap assumption means that given covariates X, the person with the same X values has positive and equal opportunity of being assigned to the treated group or the control group .because it ensures that there is sufficient overlap in the characteristics of the treated and untreated units to find adequate matches (or a common support).

Assumption 2

Ignorability (exogeneity, confoundedness, no.omitted, variable, selection on observables, etc.) There are no unobserved differences between the treatment and control groups; given the observed variables all covariates that affect both treatment and outcome must be included in the model. How do you determine this? All patients have a non-zero probability of receiving each treatment Disadvantages– Incorporates observed characteristics and thus doesn't account for unobserved factors, e.g., patient attitudes, socioeconomic status, and education level Modified if unobserved factors are correlated to observed factors. Large samples sizes may be needed to establish adequate variance [37].

Advantages of PSM analysis

The two main advantages of PSM are that it is always feasible if data are available, and it can be done after an intervention has finished, including in the absence of baseline data (although this is not ideal). If baseline data are unavailable, 'recall' can be used to reconstruct pre-intervention characteristics. This can be imprecise, however, and common sense should prevail when deciding which variables can be recalled accurately. This method ensures that the two groups of subjects are matched equally on all factors even before determining what these factors may be. - It is ideal for making casual inferences. It does not depend on conditioning on the observed covariates and can balance for both observed and unobserved covariates. Summarizes observed values into a single score less sensitive to model misspecification– Traditional techniques may be limited if accounting for only a few covariates P scores can diagnose comparability of groups before modeling stage – Distributions overlap? If comparison groups are too different difficult to balance groups P score is more robust approach and Address selection bias and offers precision [11, 36].

Disadvantages of PSM analysis

The main drawback is that PSM relies on matching individuals on the basis of observable characteristics linked to predicted likelihood of participation. So, if there are any 'unobserved' characteristics that affect participation and which change over time, the estimates will be biased and thus affect the observed results. An additional practical limitation of using PSM is the need for the assistance of a statistician or someone with skills in using different statistical package Expensive .Randomization may be infeasible or impractical because of ethical concerns. - There are issues of generalizability of study designs: - Subjects may not be representative of the general population - Ideally, a design would include the random selection of subjects and random allocation of the treatments to subjects. In observational studies, there may be random selection of subjects but not random allocation of treatments to the subjects. Therefore, there is assignment bias which is when the researcher has no control over the assignment of treatments to subjects or over what variables are collected. Although causal inferences cannot be made from observational studies, they are less expensive and more generalizable to the general population than randomization. The strong statistical independence assumptions must be satisfied absence of self-selection. Absence of selection based on unobserved characteristics needs large number of observations - especially the sample of untreated observations should be large to make possible selection of the untreated units sufficiently similar to treated observations. Incorporates observed characteristics and thus doesn't account for unobserved factors, e.g., patient attitudes, socioeconomic status, and education level Modified if unobserved factors are correlated to observed factors.

Large samples sizes may be needed to establish adequate variance in covariate distributions Conclusion Selection bias may create biased estimate of your outcome in observational studies P score methods used to adjust for selection bias Use with traditional risk adjustment techniques to reduce [11, 38].

Interpretation in PSM analysis

During the analysis and interpretation in PSM analysis and drawing and best conclusion is made when the 2 crucial assumptions must be met for propensity matching to provide useful results. If this assumption is not met or violated for any reason, any study is needless as no conclusions can be drawn. And also considers the statistical significances of the p values of PS score from the statistical software analysis, any conclusion is drawn from the statistical significance.

For matched data, patients receiving treatment A have been grouped with a probabilistically similar pool of group-B patients. Therefore, the estimated effect size represents the average improvement of the group-A patients relative to similar patients in group B. This quantity is traditionally described in the literature as the average treatment effects in the treated, which is not the same as the average effect of treatment across the entire population, referred to as the average treatment effect. In most cases, we suspect that the average treatment effect in the treated is the desired quantity, as it describes the benefits and risks of treatment A relative to those for similar patients receiving treatment B, rather than as a potential benefit averaged across all patients. Both measures assume that all group-A patients in the initial dataset were included in the final analyzed groups. If many patients have been excluded, the interpretation may change, or results may become interpretable.

METHODOLOGY

Study Design

This review was conducted by reviewing the different available materials i.e. electronically like hinari, PubMed, Google scholar, which were conducted in various parts of the world with different titles by using PSM analysis methods.

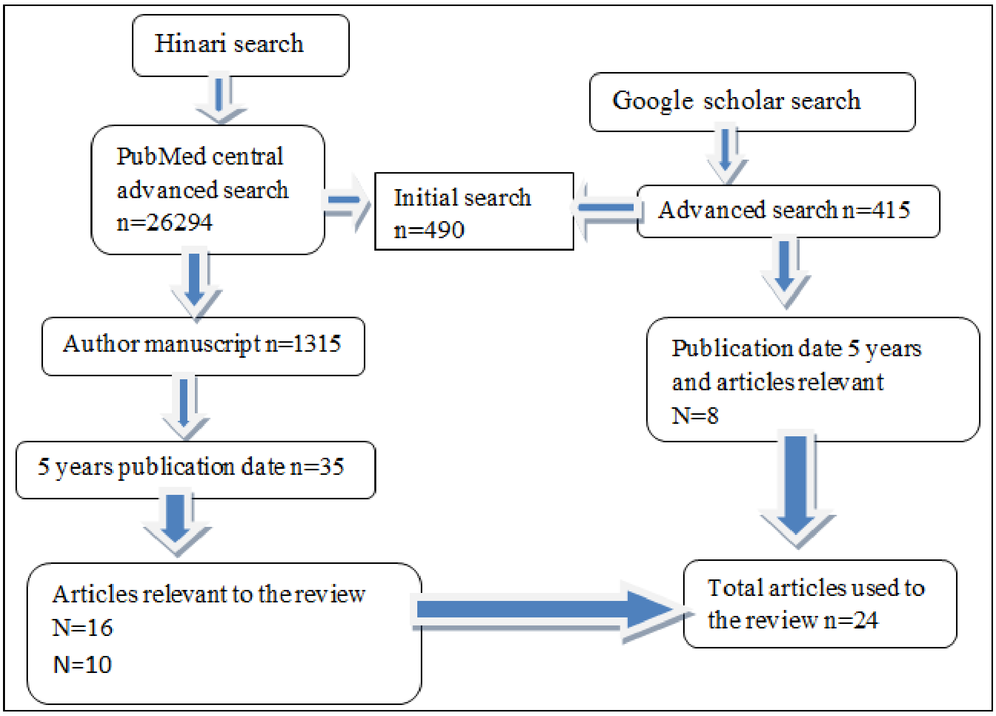

Fig-2: Review Selection Process

Inclusion Criteria

- Publications and books relevant to the review topic
- Literature available in The English Language
- Articles published from 2013-2018
- Articles have free access and contain full text

Exclusion Criteria

- Publications that are not in the English Language
- Publications before the year 2013
- Repeated articles in different database
- Publications not available online as free full text
- Literature not relevant to the revi

RESULT AND DISCUSSION

The results of this review showed that a total of 24 books and articles were reviewed which were done in different titles by using the impact analysis of interventions using Propensity Score analysis (PSM) which are showed in (Table-1).

Table-1: Result of the books and articles/reviews for Results of the articles/reviews for the impact analysis of interventions using Propensity Score analysis (PSM)

S. no	Titles/study	Author	Publication date	Sample size	PSM result	Impact on intervention
1	Propensity Score Matching	Kincaid DL, Delate [1]	2013		Propensity score matching approximates the condition ofa.randomized control trial design by creating matched groups with statistically equal likelihood of exposure to an Intervention.	Propensity score matching produces strong evidence of a causal relationship between an SBCC intervention and behavior change in large population-based observational studies.
2	Piecewise Propensity Score Analysis: A New Method for Conducting Propensity Score Matching With Polychromous Ordinal Independent Variables	Robert Bodily and Ross Larsen [4]	February 26, 2018	4	propensity stratification methods are recommended for simulating causal inference	this hypothetical version would have pedagogical and intuitive appeal to researchers and students.
3	Propensity score matching for selection of local areas as controls for evaluation of effects of alcohol policies in case series and quasi case control designs	F. de Vocht a,b,*, R. Campbell *et al.*, [39]	October 2015	6	PSM also generated appropriate matches for a quasi-case control study e	Intervention exposure was associated with the Outcome.
4	Propensity scores: Methods,considerations, and applications in theJournal of Thoracic and Cardiovascular Surgery	Timothy L. *et al.*, [2]	May 9, 2015	25	Propensity matching is a powerful tool for observational data analyses because it facilitates the comparison ofoutcomes between similar groups of patients	Characterization of the unmatched patients and An indication of the statistical procedures used for analyses.
5	A Propensity Score–Matched Analysis of Inflammatory	Patrick Berg, MD1, *et*	2017	39	The propensity score–matched subsets were matched.	Further, polyester stent-grafts induced the

	Response With Endovascular Aneurysm Sealing vs Endovascular Aneurysm Repair	*al.*, [40]				greatest postoperative inflammatory response relative to EVAS and PTFE stent-grafts
6	Reporting and Guidelines in Propensity Score Analysis:ASystematic Review of Cancer and Cancer Surgical Studies	Yao *et al.*, [41]	March 22, 2017	33	propensity score analysis is a statistical technique commonly used to estimate causal treatment effects for clinical interventions in observational studies	The purpose of these guidelines is to set forth a comprehensive and clear checklist to maximize the value of research that leverages PS techniques
7	Studying Adaptive Learning Efficacy using Propensity Score Matching	Shirin *et al.*, [42]	2018	3422	Conducting a quasi experiment using propensity score matching (PSM) to construct two similar groups of learners to compare between.	Conducting further follow-up studies will help us more conclusively understand.
8	Propensity score matching in higher education assessment	Heather D. Harris [8]	May 2015	181	Propensity score matching (PSM) methods are quasi-experimental techniques that allow Researchers to control for known confounding variables.	How well do different common PSM techniques retain honors students in the comparison of program outcomes
9	Effects of family conversation on health care practices in Ethiopia: a propensity score matched analysis	Emaway Altaye *et al.*, [43]	2018	4684	Propensity.Score.matched analysis was used.toestimate average treatment effects of the FamilyConversation strategy on intrapartum andnewborncare practices,including institutional delivery, early postnatal and immediate.breastfeeding.	Evidence bases that involving husbands and mothers-in-law, as well as pregnant women.
10	effectiveness of the clinical pharmacist in reducingmortality in hospitalized cardiac patients: apropensity score-matched analysis	Zhai *et al.*, [44]	Feb 2016	5703	Pharmacists were consulted by the physicians to correct any drug-related issues that They suspected may cause or contribute to a fatal outcome in the cardiology ward.	The 343ignificant reduction in the mortality rate in this patient population observed in this study is "hypothesis generating" for future randomized studies
11	Quantitative impact evaluation of the SHOUHARDO II Project in Banglades	TANGO, International Inc. [45]	May 2015	45	Propensity score matching (PSM) analysis indicates no impact of the project on child stunting. This can be attributed to the inability to control for a known, yet unobservable, factor affecting participation in the project's MCHN activities: the purposeful targeting of children who were already undernourished	PSM analyses all indicate that the project's interventions led to improvements in a broad array of determinants of stunting, improvements which are

						necessary for reducing stunting
12	Effect of acommunity intervention.programme.promoting social interactions on functional disability prevention for older adults: propensity score matching and instrumental variable analyses, JAGES Taketoyo study	Hikichi H, *et al.*, [35]	April 2015	2421	A community health promotion programme focused on increasing social interactions among older adults may be effective in preventing the onset of disability	Community salons promote the opportunity for older residents to interact socially and thereby avoid functional disability
13	Propensity Score Methods Using SAS®	R. Scott Leslie, MPH [11]			Selection bias may create biased estimate of your outcome in observational studies	Observables vs. unobservables: Instrumental variable method account for unobservable
14	Observational & Quasi-experimental Research Methods	Helene Starks, PhD MPH [12]	October 2014	-	Multivariable modeling vs. propensity scores to control for confounding.	Practice designing an analysis (variable selection,balancing/matching your sample)
15	PROPENSITY SCORE MATCHING A PRACTICAL TUTORIAL	Cody Chiuzan, PhD [13]	march 19, 2018	-	Standardized differences were calculated to compare.patients'features before and after matching with imbalance being defined as an absolute value greater than 0.10 (small effect size) Matching was performed using the nearestneighbor algorithm with a caliper distance of 0.0001.	A propensity score-matched analysis to create comparable risk groups in the laparoscopic and robotic colectomy cohorts with respect to demographic, comorbiditie, and operative characteristics.
16	Propensity Score Methods with Multilevel Data	Arpino and Mealli [14]	March 19, 2014		Balancing property: balancing propensity score also balances the covariates of different groups.	Propensity score has been developed and applied incrosssectional settings (single level data)
17	Estimation of the Mincerian Wage Model Addressing its Specifcation and DifferentEconometric Issues	Sajjad Haider Bhatti [23]	Dec 2013	27136	Comparing simple and adaptive estimations, we prefer adaptive specification of parametric model for both countries.	Differences in coefficients proved worth of such specification. We have also estimated model semi parametrically
18	How To Use Propensity Score Analysis	Lisa Kaltenbach, MS [20]	April 11, 2008		Useful when adjusting for a large number of risk factors & small number of events per variable.	PS methods work better in larger samples to attain distributional

						balance of observed covariates
19	Propensity Score Analysis	Shenyang Guo, Ph.D. [27]	November 10-11,2017,		The randomized clinical trial is the “gold standard” in outcome evaluation. However, in social and health research, RCTs are not always practical, ethical, or even desirable.	Observational data - those that are not generated by mechanisms of randomized.experiments, such as surveys, administrative records, and census data.
20	The dark side of PSM - An analysis of the relationship between the level of Public Service Motivation and the level of Stress	Lena Hartl [32]	29 June 2016	50	The findings of the limited number of studies on the relationship between PSM and stress are ambiguous.	PSM has been known for its optimizing function in many relationships where stress is involved (a negative correlation between motivation and stress).
21	Population Stochastic Modelling (PSM): Model definition, description and examples	Mortensen and Søren Klim [46]	November 5, 2018		Before setting up a model in PSM it is a good idea to write it down on paper and note the dimensions of the state, observations and possible input and random effects	The function PSM template can be used for botlinear and non-linear models as shown below to print a template for the model.
22	Methodological Brief No.8: Quasi-Experimental Design and Methods	UNICEF OFFICE OFRESEARCH [36]	September 2014		Quasi-experimental research designs, like experimental designs, test causal hypotheses' quasi-experimental design by definition lacks random assignment	Quasi-experimental designs identify a comparison group that is as similar as possible to the treatment group in terms of baseline (pre-intervention) characteristics.
23	Matching and Weighting Methods for Causal Inference	Kosuke Imai [37]	january 18 - 19, 2013)		Make.causal.assumptions.transparent.byidentifying.counterfactuals make regressionmodels.robust.by.educing.model.dependence	Weighting methods generalize matching methods Sensitive to propensity score model specification Robust estimation ofpropensity score model

24	Propensity score matching (PSM)	Jerzy Mycielski [38]	January 2015		In PSM control group is chosen from the sample ofuntreated units on the basis of the similarity of the estimated values of the propensity scores	PSM we make no assumptions about the functional form of the relationship between the expected outcomes and the values of characteristics - relationship

The research done in Utah Valley University, in the western United States by using the PSM analysis methods stats that Propensity score analysis is widely used for simulating random assignment in observational studies, When true random assignment is not possible. In propensity score modeling, a number of covariates are used to estimate the probability that

An individual will belong to 1 of 2 groups. Prospective participants are then matched on their probabilities of belonging to the 2 groups rather than on the exact set of covariate values (as in traditional matching methods). However, traditional propensity score analysis can only be used in studies with 2 groups, such as an experimental and a control group. In this article, they propose a new method called piecewise propensity score analysis (PPSA) for ordinal polychromous grouping variables. They compared PPSA with another method of conducting propensity score analysis with ordered categories, marginal mean weighting through stratification (MMW-S; Hong, 2010, 2012) in a 3 5 4 study across three model Misspecification conditions, five matching methods, and four sample sizes (1,000, 5,000, 10,000, 21,753). They found no significant difference between PPSA and MMW-S methods across conditions. They recommend linear regression, simple mean difference, or propensity stratification methods for simulating causal inference [3].

The other research done in University of Sheffield, Sheffield, UK by using the analysis methods of PSM for intervention based on the expected result they proposed that the use of Propensity Scores for matching (PSM), which is in essence a model to estimate the probability/propensity that a study unit which has not received the intervention (usually a study participant) is similar at baseline to another unit from the ‘intervention group’, based on a set of key characteristics. As such, it reduces the problem of comparison across large numbers of key variables to a 1-dimensional problem; i.e. the minimization of the difference, or distance, between case and control propensity scores [5].

The research done in Department of Public Health Sciences, University of Virginia by using PSM analysis methods on the titles of Propensity scores: Methods, considerations, and applications in the Journal of Thoracic and Cardiovascular Surgery they recognized the importance of brevity, propensity-scoring methods must be described well enough for those results can be evaluated and replicated. Most of their recommendations can be implemented with 1 or 2 paragraphs. In some cases, additional tables may be provided in online appendices. Although different analyses are appropriate for different datasets and clinical questions, they proposed that articles on studies utilizing propensity matching include the following eight steps as follow:

- The original sample sizes for the pools of patients in each group.
- The sample sizes available after matching.
- The type of regression model used to estimate the propensity scores.
- The variables considered for inclusion in the propensity model, the variables included in the final model, and the inclusion criteria.
- The type of matching algorithm used.
- Diagnostics demonstrating the quality of the resulting matches.
- Characterization of the unmatched patients.
- An indication of the statistical procedures used for analyses [2].

The other research done in china Department of Pharmacy, shanghai east hospital, affiliated to Tongji University school of Medicine by using PSM analysis methods on the titles which says effectiveness of the clinical pharmacist in reducing mortality in hospitalized cardiac patients: propensity score-matched analysis PSM analysis was performed to adjust for potential bias and was used often in observational studies because of nonrandomized group assignment. They applied this statistical method to match each patient in Phase I to a patient in Phase II who had a PSM that was identical to five digits. If this could not be done, they then proceeded to a four-, three-, two-, or one-digit match. The patient was excluded once this threshold was exceeded. After PS matching, age, sex, nursing acuity score, and primary discharge diagnosis of patients were similar between Phase I and Phase II, and all-cause mortality changed from 1.7% during Phase I down to

1.0% during Phase II, and the difference was also statistically significant (P=0.0074).According to the consensus report in Phase II, the clinical pharmacists proposed 1,541 recommendations in which 1,416 were accepted by the cardiology physicians. They assumed that this had led to a decline in the mortality rate with statistical significance [13].

CONCLUSION AND RECOMMENDATIONS

CONCLUSION

Almost all of the articles and books which are included on this reviews used Propensity score matching for their analysis methods. One common purpose of research is to determine the effect of an intervention on an outcome. The gold standard for determining effects is a randomized control trial. A randomized control trial controls for unmeasured variables that may affect the outcome by randomly placing participants in either a treatment or control condition. Propensity matching is a powerful tool for observational data analyses because it facilitates the comparison of outcomes between similar groups of patients. Although propensity matching has become a popular technique, the methodology is actually quite complex

RECOMMENDATION

Based on the review I want to give the following recommendations are forwarded

To Researchers

There are some researches using PSM analysis methods especially in our country.

REFERENCES

1. Kincaid, D. L., Delate, R., Storey, D., & Figueroa, M. E. (2013). Health Communication Capacity Collaborative Propensity Score Matching An HC3 Research Primer.
2. McMurry, T. L., Hu, Y., Blackstone, E. H., & Kozower, B. D. (2015). Propensity scores: methods, considerations, and applications in the Journal of Thoracic and Cardiovascular Surgery. *The Journal of thoracic and cardiovascular surgery*, *150*(1), 14-19.
3. Rosenbaum, P. R., & Rubin, D. B. (1985). Constructing a control group using multivariate matched sampling methods that incorporate the propensity score. *The American Statistician*, *39*(1), 33-38.
4. Bodily, R., Larsen, R., & Warne, R. T. (2018). Piecewise propensity score analysis: A new method for conducting propensity score matching with polytomous ordinal independent variables. *Archives of Scientific Psychology*, *6*(1), 14-20.
5. Holland, P. W. (1986). Statistics and causal inference. *Journal of the American statistical Association*, *81*(396), 945-960.
6. Winship, C., & Morgan, S. L. (1999). The estimation of causal effects from observational data. *Annual review of sociology*, *25*(1), 659-706.
7. Luellen, J. K., Shadish, W. R., & Clark, M. H. (2005). Propensity scores: An introduction and experimental test. *Evaluation Review*, *29*(6), 530-558.
8. Harris, H. D. (2015). Propensity score matching in higher education assessment. *Masters Theses. James Madison University: Paper*, *55*.
9. Rosenbaum, P. R., & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*, *70*(1), 41-55.
10. Heckman, J. J., Ichimura, H., & Todd, P. E. (1997). Matching as an econometric evaluation estimator: Evidence from evaluating a job training programme. *The review of economic studies*, *64*(4), 605-654.
11. Leslie, R. S. (2012). Propensity Score Methods Using SAS. scott.leslie@medimpact.com
12. Starks, H., & Garrido, M. M. (2004). Observational & Quasi-experimental Research Methods. In *8th annual Kathleen Foley palliative care retreat method workshop*.
13. Propensity Score Matching A Practical Tutorial Cody Chiuzan, PhD Biostatistics, Epidemiology and Research Design (BERD) Lecture March 19, 2018.
14. Li, F., Zaslavsky, A. M., & Landrum, M. B. (2013). Propensity score weighting with multilevel data. *Statistics in medicine*, *32*(19), 3373-3387.
15. Nittoli, T., Dushin, R. G., Ingalls, C., Cheung, K., Floyd, M. B., Fraser, H., ... & Arndt, K. (2010). The identification of 8, 9-dimethoxy-5-(2-aminoalkoxy-pyridin-3-yl)-benzo [c][2, 7] naphthyridin-4-ylamines as potent inhibitors of 3-phosphoinositide-dependent kinase-1 (PDK-1). *European journal of medicinal chemistry*, *45*(4), 1379-1386.
16. Heckman, J. J. (1976). A life-cycle model of earnings, learning, and consumption. *Journal of political economy*, *84*(4, Part 2), S9-S44.
17. Heckman, J. J. (1978). Simple Statistical Models for Discrete Panel Data Developed and Applied to Test the Hypothesis of True State Dependance Against the Hypothesis of Spurious State Dependance. In *Annales de I'Insee* (Vol. 30, pp. 227-269).
18. Heckman, J. J. (1979). Sample selection bias as a specification error. *Econometrica: Journal of the econometric society*, 153-161.
19. Maddala, S. G. (1990). Censored data models. In *Econometrics* (pp. 54-57). Palgrave Macmillan, London.
20. Bhatti, S. H. (2012). *Estimation of the mincerian wage model addressing its specification and different econometric issues* (Doctoral dissertation, Université de Bourgogne).

21. Rosenbaum, P. R. (2002). Overt bias in observational studies. In *Observational studies* (pp. 71-104). Springer, New York, NY.
22. Hirano, K., Imbens, G. W., & Ridder, G. (2003). Efficient estimation of average treatment effects using the estimated propensity score. *Econometrica*, *71*(4), 1161-1189.
23. Kaltenbach, L. (2008). How to use propensity score analysis. *Unpublished lecture. April*, *11*.
24. Abadie, A., & Imbens, G. (2002). Simple and bias-corrected matching estimators for average treatment effects.
25. Abadie, A., & Imbens, G. W. (2006). Large sample properties of matching estimators for average treatment effects. *econometrica*, *74*(1), 235-267.
26. Heckman, J. J., Ichimura, H., & Todd, P. (1998). Matching as an econometric evaluation estimator. *The review of economic studies*, *65*(2), 261-294.
27. Propensity Score Analysis Shenyang Guo, Ph.D. November 10-11, 2017, Chicago, Illinois.
28. Rainey, B., Wicks, E., & Ovey, C. (2014). *Jacobs, White and Ovey: the European convention on human rights*. Oxford University Press, USA.
29. Butz, H., Szabó, P. M., Khella, H. W., Nofech-Mozes, R., Patocs, A., & Yousef, G. M. (2015). miRNA-target network reveals miR-124as a key miRNA contributing to clear cell renal cell carcinoma aggressive behaviour by targeting CAV1 and FLOT1. *Oncotarget*, *6*(14), 12543.
30. Brewer, J. (2000). *Ethnography*. McGraw-Hill Education (UK).
31. Liu, L., Oza, S., Hogan, D., Perin, J., Rudan, I., Lawn, J. E., ... & Black, R. E. (2015). Global, regional, and national causes of child mortality in 2000–13, with projections to inform post-2015 priorities: an updated systematic analysis. *The Lancet*, *385*(9966), 430-440.
32. Hartl, L. (2016). *The dark side of PSM-An analysis of the relationship between the level of PSM and the level of stress* (Bachelor's thesis, University of Twente).
33. McCaffrey, A. P., Meuse, L., Pham, T. T. T., Conklin, D. S., Hannon, G. J., & Kay, M. A. (2002). Gene expression: RNA interference in adult mice. *Nature*, *418*(6893), 38.
34. Ho, S. N., Hunt, H. D., Horton, R. M., Pullen, J. K., & Pease, L. R. (1989). Site-directed mutagenesis by overlap extension using the polymerase chain reaction. *Gene*, *77*(1), 51-59.
35. Hikichi, H., Kondo, N., Kondo, K., Aida, J., Takeda, T., & Kawachi, I. (2015). Effect of a community intervention programme promoting social interactions on functional disability prevention for older adults: propensity score matching and instrumental variable analyses, JAGES Taketoyo study. *J Epidemiol Community Health*, *69*(9), 905-910.
36. White, H., & Sabarwal, S. (2014). Quasi-experimental design and methods. *Methodological Briefs: Impact Evaluation*, *8*, 1-16.
37. Matching and Weighting Methods for Causal Inference Kosuke Imai Princeton University Methods Workshop, Duke University Duke (January 18-19, 2013).
38. Propensity score matching (PSM) Jerzy Mycielski Uniwersytet Warszawski January 2015.
39. De Vocht, F., Campbell, R., Brennan, A., Mooney, J., Angus, C., & Hickman, M. (2016). Propensity score matching for selection of local areas as controls for evaluation of effects of alcohol policies in case series and quasi case–control designs. *Public Health*, *132*, 40-49.
40. Berg, P., Stroetges, R. A., Miller, L. E., & Schoefferle, J. (2017). A propensity score–matched analysis of inflammatory response with endovascular aneurysm sealing vs endovascular aneurysm repair. *Journal of Endovascular Therapy*, *24*(5), 670-674.
41. Yao, X. I., Wang, X., Speicher, P. J., Hwang, E. S., Cheng, P., Harpole, D. H., ... & Pang, H. H. (2017). Reporting and guidelines in propensity score analysis: a systematic review of cancer and cancer surgical studies. *JNCI: Journal of the National Cancer Institute*, *109*(8), djw323.
42. Shirin. (2018). Studying Adaptive Learning Efficacy using Propensity Score Matching.
43. Altaye, D. E., Karim, A. M., Betemariam, W., Zemichael, N. F., Shigute, T., & Scheelbeek, P. (2018). Effects of family conversation on health care practices in Ethiopia: a propensity score matched analysis. *BMC pregnancy and childbirth*, *18*(1), 372.
44. Zhai, X. B., Gu, Z. C., & Liu, X. Y. (2016). Effectiveness of the clinical pharmacist in reducing mortality in hospitalized cardiac patients: a propensity score-matched analysis. *Therapeutics and clinical risk management*, *12*, 241-250.
45. Smith, L. C. (2015). Quantitative Impact Evaluation of the SHOUHARDO II Project in Bangladesh.
46. Mortensen, S., & Klim, S. (2013). Population Stochastic Modelling (PSM): Model definition, description and examples.