Paper RE03

Enhancing Interpretation of Propensity Score Matching through Advanced Data Visualization in Real-World Studies

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ABSTRACT

Propensity Score Matching (PSM) is a foundational statistical technique in clinical research, widely used to estimate causal effects by balancing covariates between treated and control groups. Although numerical metrics offer precise evaluations, they often fall short in conveying the full analytical picture—particularly when interpreting complex score distributions or subtle imbalances in covariates. Sole reliance on numerical outputs can obscure meaningful patterns and limit actionable insights.

This proposal underscores the value of integrating advanced data visualization techniques into PSM workflows. Transforming complex statistical outputs into visually intuitive formats enables more effective assessment of matching quality, identification of residual biases, and drawing of more informed conclusions. To illustrate this approach, an interactive dashboard has been developed as a case study. It demonstrates how visual tools can complement quantitative outputs, enhance communication of results, and support data-driven decisions in real-world clinical research.

INTRODUCTION

Propensity Score Matching (PSM) is a critical statistical tool in real-world clinical research, particularly for analyzing observational studies where randomization is not feasible. Its primary purpose is to mitigate confounding biases by balancing baseline covariates between treatment and control groups, thereby enabling more robust causal inferences. By creating comparable groups, PSM aims to mimic the conditions of a randomized controlled trial, adjusting for confounding in observational research and providing a method to control for selection bias. This methodological approach is essential for assessing treatment efficacy and safety in complex real-world settings where ethical or practical constraints prevent direct randomization.

Despite its importance, traditional applications of PSM predominantly rely on numerical outputs such as balance metrics, p-values, and statistical tables to convey findings. While these metrics are statistically rigorous, they often present limitations in fully capturing the complexities inherent in large-scale healthcare data. Numerical summaries can obscure subtle patterns, outliers, and diagnostics that remain hidden within traditional tables, making it difficult to assess the quality of matching and the effectiveness of confounding control. This reliance on abstract numerical summaries can hinder transparency and interpretability, particularly when complex patient data is involved.

Consequently, there is a need for methodologies that clarify these intricate details and bridge the gap between statistical outputs and practical, decision-oriented insights. Advanced visualization techniques offer a promising solution to address these limitations.

THE CASE FOR ADVANCED DATA VISUALIZATION

IMPROVED INTERPRETATION OF SCORE DISTRIBUTIONS

Advanced data visualization techniques translate complex statistical results into intuitive and interactive graphics. Visualizations provide clear representations of data structure, match effectiveness, and covariate balance. For example, propensity score density plots visually depict score distributions, while augmented frequency plots illustrate how trimming and matching reshape the analysis population. Such tools enable a clearer assessment of covariate balance pre- and post-matching, allowing exploration of multidimensional data trends and improving interpretability of PSM results.

EASIER IDENTIFICATION OF RESIDUAL BIASES

Beyond displaying distributions, advanced visualizations enhance the ability to identify residual biases and subtle imbalances that might escape notice in numerical tables. Techniques such as directed acyclic graphs (DAGs), study design diagrams, and balance diagnostics can reveal underlying causal relationships and improve transparency in confounding control. Interactive visualizations highlight outliers, trends, and clinically significant patterns, enabling comprehensive quality assessments and reducing biases inherent in nonrandomized studies.

ENHANCED COMMUNICATION FOR STAKEHOLDERS

One of the most significant advantages of advanced visualization is its ability to bridge communication gaps among diverse stakeholders, including clinicians, researchers, and policymakers. By translating intricate statistical findings into transparent, actionable insights, visualizations promote clearer communication of results to a broader audience. Interactive dashboards demystify complex decisions and present patterns in an accessible format, facilitating accurate assessments of therapeutic efficacy and safety. This clarity supports informed decision-making and fosters reproducibility in observational research.

NEED FOR PROPOSED FRAMEWORK

Integrating advanced visualization into PSM workflows transforms the interpretation and communication of matching quality. Traditionally, PSM relies heavily on numerical diagnostics such as balance tables and summary statistics. While precise, these outputs often fail to convey the full analytical picture, especially when dealing with complex covariate structures or subtle imbalances.

The proposed framework embeds visualization at critical stages of the workflow—before matching, after matching, and during sensitivity analysis—creating a more intuitive and transparent process. It introduces three key visualization components:

- Density plots to examine propensity score distributions across treatment groups.
- Covariate balance plots to compare standardized mean differences before and after matching.
- Interactive dashboards to consolidate multiple visual elements into a single, user-friendly interface for real-time exploration of matched datasets.

Together, these tools enhance clarity, reduce reliance on static tables, and empower researchers to make informed decisions quickly and confidently.

CASE STUDY

REAL-WORLD CASE STUDY

A real-world case study in non-small cell lung cancer compares IO+Chemo versus ChemoOnly therapies in approximately 1,200 patients. Propensity scores were estimated using logistic regression, and IPTW (Inverse Probability of Treatment Weighting) was applied to adjust for baseline differences. The following visualizations illustrate key diagnostics for assessing balance and overlap, following the workflow shown in Figure 1.

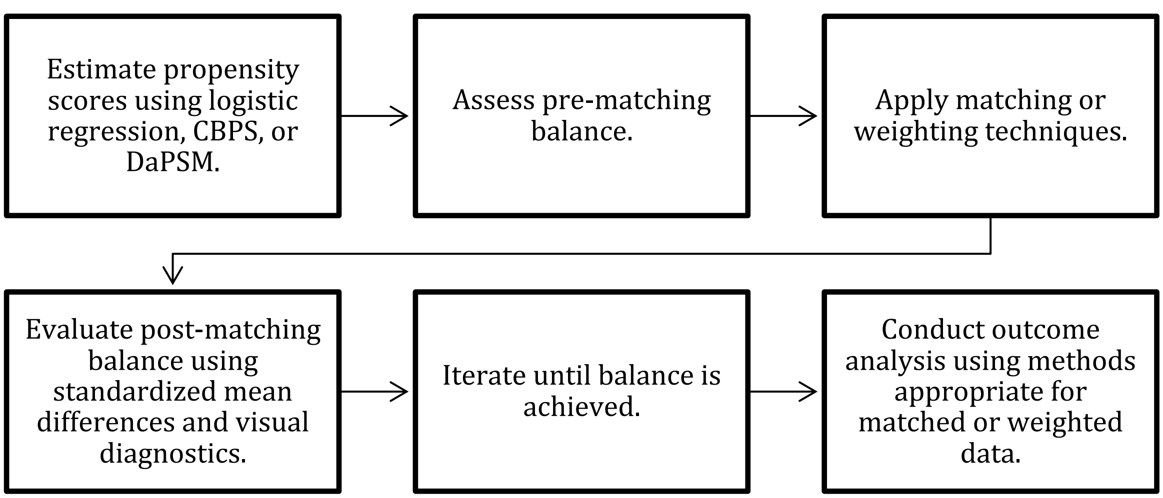

Figure 1 PSM workflow

DASHBOARD OVERVIEW

To demonstrate the practical application of the proposed framework, an interactive dashboard shown in Figure 2 was developed as proof of concept. Designed for usability and flexibility, the dashboard serves as a central hub for visual diagnostics in propensity score matching (PSM), integrating multiple layers of visualization to provide a comprehensive view of matching quality and covariate balance.

Key features include a propensity score distribution panel for interactive density plots, a covariate balance tracker for pre- and post-match comparisons, automated residual bias alerts, and export tools for generating visual summaries. By moving beyond static tables, the dashboard addresses critical gaps in interpretation, uncovers patterns hidden in numerical summaries, and supports collaborative review through a shared platform.

By moving beyond static tables, the dashboard addresses critical gaps in interpretation. It uncovers patterns hidden in numerical summaries, supports granular analysis of individual covariates, and fosters collaborative review through a shared, interactive platform for stakeholders. This approach not only strengthens analytical rigor but also enhances communication across multidisciplinary teams.

Figure 2 Case Study Dashboard

VISUALIZATION INTERPRETATIONS

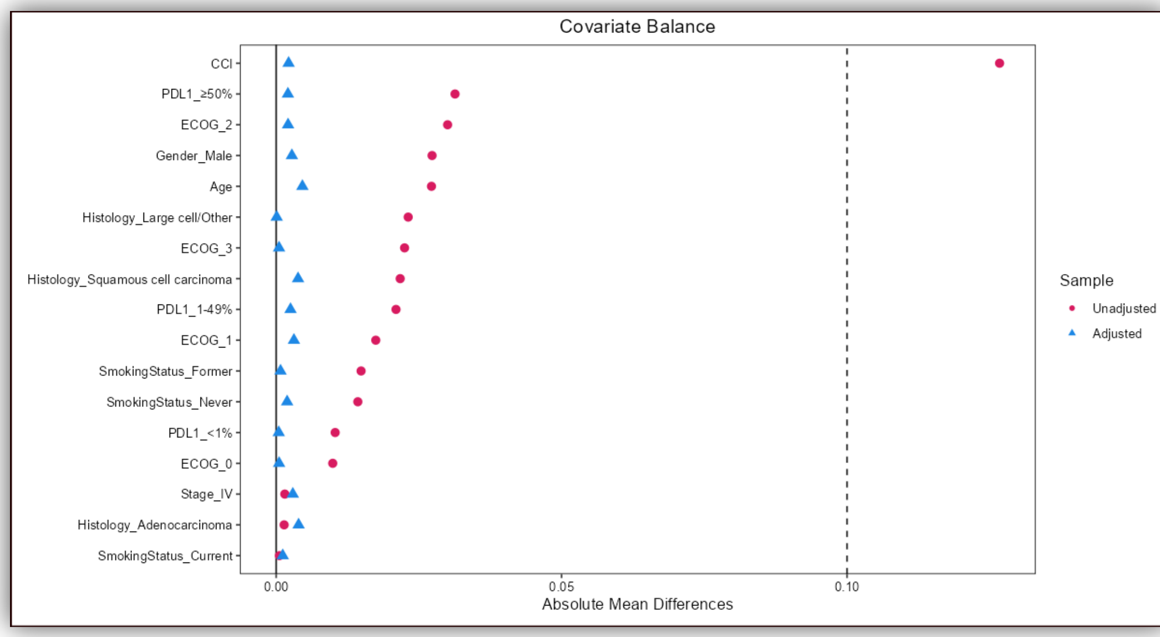

Figure 3 Covariate balance plot

COVARIATE BALANCE PLOT (FIGURE 3): This plot displays absolute standardized mean differences for each covariate before and after matching. Red markers indicate pre-matching imbalance, while blue markers show post-matching differences clustered near zero, suggesting effective bias reduction and improved validity of causal inference.

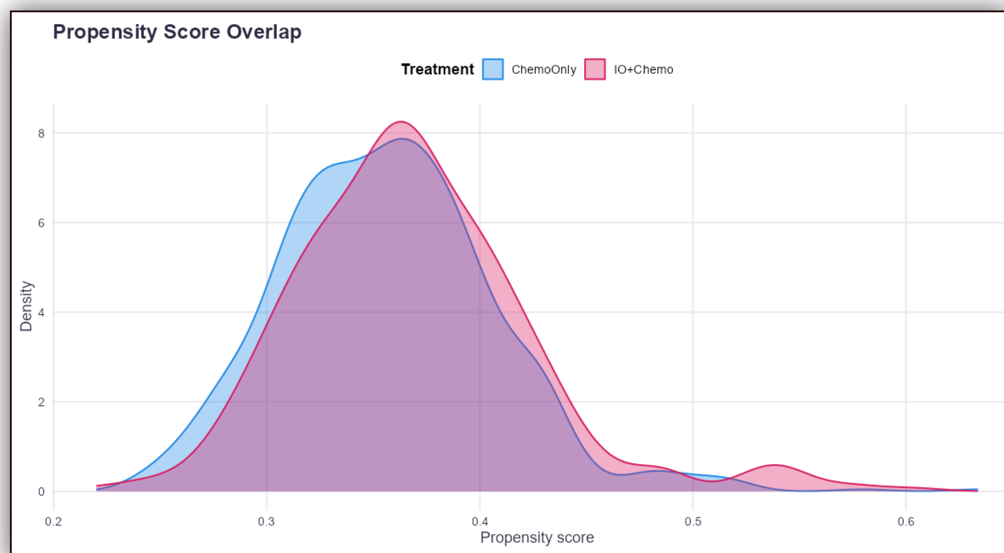

Figure 4 Propensity distribution plot

PROPENSITY SCORE OVERLAP PLOT (FIGURE 4): Density curves for IO+Chemo (pink) and ChemoOnly (blue) illustrate score distributions. Substantial overlap indicates comparability and feasibility of weighting, while limited overlap would signal potential bias.

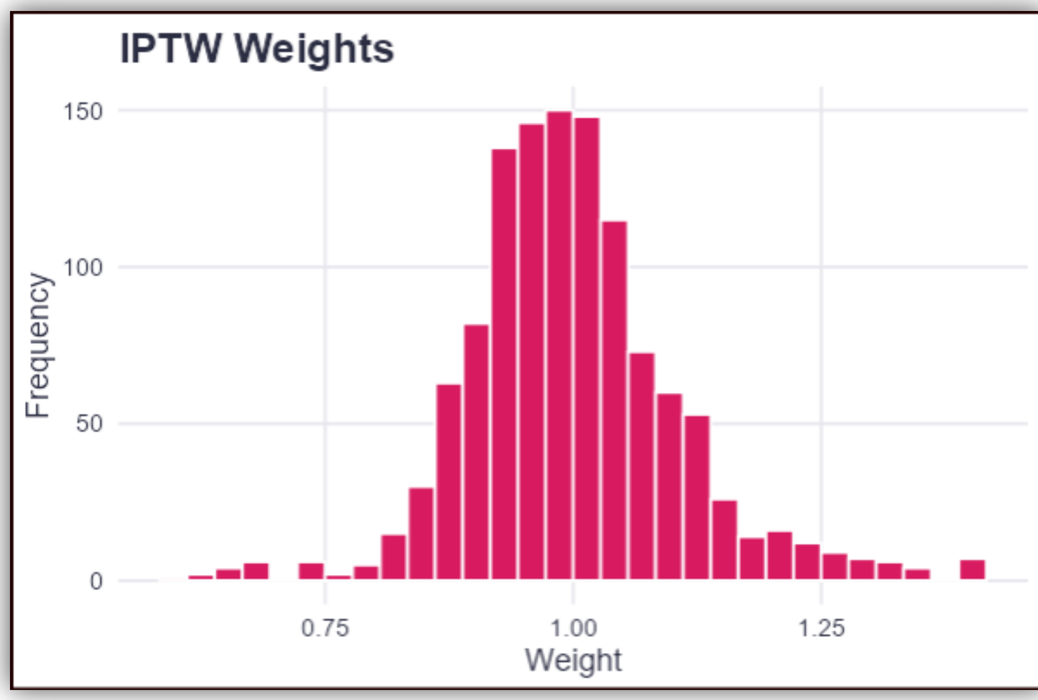

Figure 5 Weight diagnostic plot

WEIGHT DIAGNOSTIC PLOT (FIGURE 5): This plot examines the distribution of observation weights after IPTW. A narrow, centered distribution reflects stability, whereas extreme weights may inflate variance and compromise robustness.

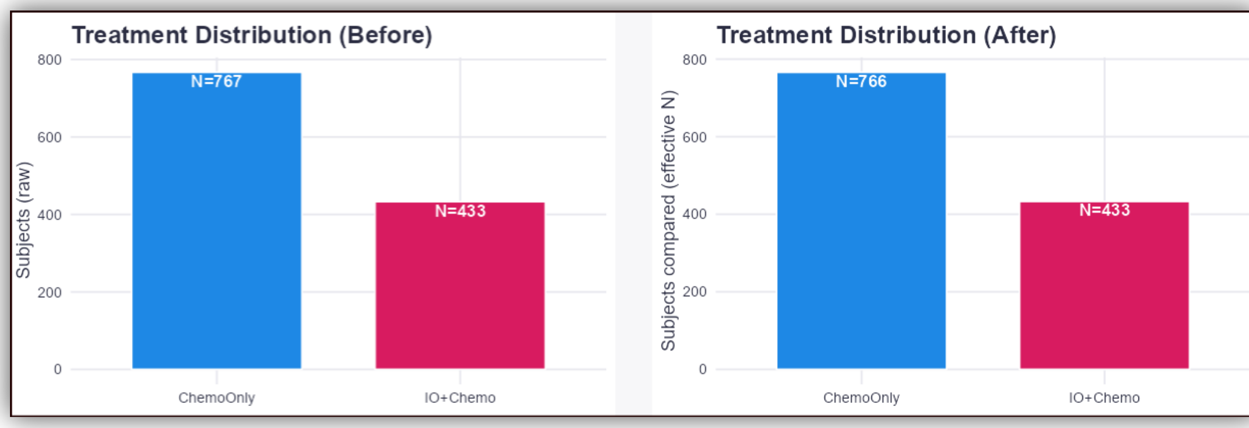

Figure 6 Treatment distribution plot

TREATMENT GROUP DISTRIBUTION PLOT (FIGURE 6): Group sizes before and after weighting remain nearly unchanged, confirming that IPTW retains all subjects and preserves effective sample size, thereby maintaining statistical power.

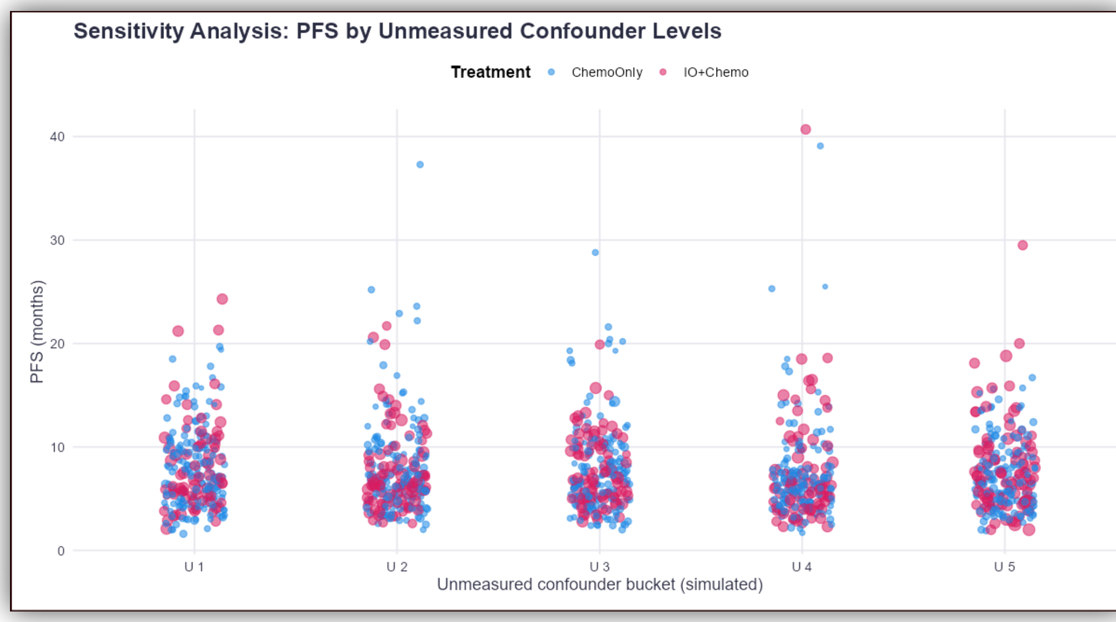

Figure 7 Sensitivity analysis plot

SENSITIVITY ANALYSIS PLOT (FIGURE 7): This plot evaluates robustness to hidden bias by simulating an unmeasured confounder. PFS remains consistent across confounder levels, indicating that treatment effect estimates are unlikely to be materially influenced by unmeasured confounding.

IMPACT ON REAL WORLD STUDIES

Integrating advanced visualization into PSM workflows has significant implications for real-world clinical research. By making balance assessments more transparent and intuitive, this approach strengthens confidence in causal inference and reduces the risk of misinterpretation—particularly in studies involving complex covariate structures. Visual outputs are easier to understand and share, improving engagement among clinicians, statisticians, and decision-makers.

Moreover, this framework supports transparency and reproducibility, two cornerstones of modern research. Visual outputs can be archived alongside datasets, creating an auditable trail of matching decisions. Interactive dashboards enable reproducible workflows, where every adjustment and outcome is documented, ensuring that analyses can be replicated and validated by independent reviewers. This level of clarity is invaluable for regulatory submissions and peer-reviewed publications.

LIMITATIONS AND FUTURE DIRECTIONS

Despite its advantages, the adoption of advanced visualization in PSM workflows faces several challenges. Technical barriers remain, as researchers must become familiar with visualization tools and integrate them into existing statistical environments. Resource constraints, including time and expertise required for dashboard development and maintenance, may also hinder implementation. Furthermore, the absence of universally accepted visualization standards for PSM could slow widespread adoption.

Future research offers opportunities to overcome these limitations. Automation could play a key role, with machine learning algorithms suggesting optimal matching strategies based on visual diagnostics. Scalability is another priority, as dashboards must evolve to handle large-scale datasets and multi-treatment scenarios common in real-world evidence studies. Finally, interoperability with popular statistical platforms such as R, SAS, and Python will be essential to streamline implementation and encourage broader use.

CONCLUSION

Integrating advanced data visualization into PSM workflows offers a powerful enhancement to traditional analytical methods. By moving beyond static numerical outputs, this approach provides clearer insights, improves transparency, and strengthens confidence in causal inference. The interactive dashboard exemplifies how visual tools can bridge interpretation gaps, enabling researchers to identify residual biases and communicate findings effectively. While challenges in adoption remain, the potential for automation, scalability, and interoperability signals a promising future. Embracing these innovations will elevate methodological rigor and support more informed, data-driven decisions in real-world clinical research.

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