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Evaluating the effect of data standardization and validation on patient matching accuracy

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ABSTRACT

Objective: This study evaluated the degree to which recommendations for demographic data standardization improve patient matching accuracy using real-world datasets.

Methods: We used four manually reviewed datasets, containing a random selection of matches and non-matches. Matching datasets included Health Information Exchange (HIE) records, public health registry records, Social Security Death Master records, and newborn screening records. Standardized fields including last name (LN), telephone number (TEL), social security number (SSN), date of birth (DOB), and address (ADDR). Matching performance was evaluated using four metrics: sensitivity, specificity, positive predictive value, and accuracy.

Results: Standardizing address was independently associated with improved matching sensitivities for both the public health and HIE datasets of approximately 0.6% and 4.5%. Overall accuracy was unchanged for both datasets due to reduced match specificity. We observed no similar impact for address standardization in the death master file dataset. Standardizing last name yielded improved matching sensitivity of 0.6% for the HIE dataset, while overall accuracy remained the same due to a decrease in match specificity. We noted no similar impact for other datasets. Standardizing other individual fields (telephone, DOB, or SSN) showed no matching improvements. Since standardizing address and last name improved matching sensitivity, we examined the combined effect of address and last name standardization, which showed that standardization improved sensitivity from 81.3% to 91.6% for the HIE dataset.

Conclusion: Data standardization can improve match rates, thus ensuring that patients and clinicians have better data on which to make decisions to enhance care quality and safety.

INTRODUCTION

Every time a patient visits a hospital, health system, outpatient provider, clinic, pharmacy, long-term care provider, or public health agency, new information is generated. This information is stored in independent clinical repositories and, critically, no single unique identifier exists to easily and definitively combine this disparate information into a single comprehensive patient record,[1, 2]. Even within single large institutions, like a health system or hospital, the internal billing systems, laboratory information systems, and electronic health records may effectively function as independent data silos relying on different patient identifiers to manage information (some of which may or may not exist in other systems). Fragmented patient information risks patient safety, hinders data aggregation for clinical decision support, prevents physicians from having comprehensive medical information, deters effective population health approaches, creates inefficiencies by delaying care, limits public health reporting, and severely reduces the utility of electronic data for clinical research,[3, 4]. Using transaction volumes among health systems exchanging data within the Indiana Health Information Exchange (IHIE),[5], we extrapolate a lower-bound estimate of 30 billion HL7 messages transmitted (and requiring matching to a patient's record) for the US health care system annually. Consequently, even a small improvement in matching accuracy can potentially improve integration of a significant volume of clinical data into the appropriate patient record nationally.

The US is the last industrialized nation without a national unique identification system,[6]. As a result, health care organizations must rely on patient matching algorithms driven by varying combinations of patient demographics and other identifiers. Matching algorithms can be effective, achieving match rates above 90% when implemented properly,[7]. However,

algorithms must be paired with high quality, standardized data elements to optimize matching accuracy. Problematically, patient demographic data are captured in varying formats by health care organizations and health information technology systems. This lack of consistent approaches to data standardization has generated multiple best-practice recommendations, but no consensus on specific standardization approaches. Several organizations, including the Agency for Healthcare Research and Quality (AHRQ),[8], the Health Information Management Systems Society (HIMSS),[9], the Bipartisan Policy Center,[10], the eHealth Initiative,[11], the Markle Foundation,[12], the Sequoia Project,[13], and the Office of the National Coordinator for Health IT (ONC),[14-16], have either promoted or published best-practice approaches for optimizing patient matching, including data standardization.

While patient record linkage in the US requires effective patient matching algorithms, recommendations for patient demographic data standardization have not been formally evaluated using real-world demographic data from diverse settings. Patient data generated through actual clinical care and business processes contains numerous inherent limitations, errors, and variations. Additionally, data generation and collection processes can be idiosyncratic by organization or by type of health care provider. Thus, this study seeks to evaluate the degree to which recommendations for demographic data standardization improve patient matching accuracy in real-world datasets.

METHODS

Using patient demographic data from four health datasets, we compared baseline matching accuracy to matching results after implementing best-practice recommendations. Matching

represented four distinct use cases: hospital-to-hospital linkage, deduplicating a public health registration file, linking death records to clinical data, and matching newborn screening laboratory data to health information exchange (HIE) registration data.

Datasets & Use cases

This analysis used four manually curated gold-standard analytic datasets, which contained a random selection of true-positive and true-negative matches,[17-23]. Through the manual curation process, we know the true match status for each record, which is a significant advantage over databases where the true matches are unknown.

HIE for hospital-to-hospital record matching. This dataset reflected demographic records from two geographically proximal hospital systems participating in an HIE. The data contained 50,000 sampled gold-standard pairs with 35,152 (70.3%) true positives and 14,858 (29.7%) true negatives,[19, 20]. Patients from hospitals in close proximity cross over to other nearby institutions at significant rates,[24], thereby creating the need to identify common records. The need to identify and capture information on patients seeking care from other institutions is dramatically increased by new value-based purchasing models like Accountable Care Organizations (ACO),[25-27].

Public health registry for de-duplicating. This dataset comes from the Marion County Health Department (MCHD), Indiana's largest public health department. The registry contains a master list of demographic information for clients who receive public health services such as immunizations, Women, Infants and Children (WIC) nutrition support, and laboratory

testing,[21, 22]. The registry also tracks health trends of populations and supports other public health activities, and duplicate patients can be unintentionally added. This dataset contained 33,005 sample pairs with 1,950 (5.9%) true positives and 31,055 (94.1%) true negatives. We de-duplicated the complete patient registry. De-duplication is a process for identifying multiple copies of the same person in a single patient registry.

HIE and vital records for ascertaining death status. These data reflect a combination of the Social Security Death Master file and HIE data. This dataset contained 20,000 pairs with 16,873 (84.3%) true positives and 3,127 (15.7%) true negatives. Accurately and comprehensively updating health records with patients' accurate death status is critical to robust clinical quality measurement, public health reporting requirements, and high quality clinical research,[7, 23].

Laboratory results and HIE for newborn screening (NBS). This dataset included demographic data for newborns screened for congenital diseases (e.g., sickle cell anemia, congenital hypothyroidism, etc.) as reported by multiple hospitals and private laboratories across these state and clinical records from the HIE. These data are limited to patients less than 1 month of age,[17, 18]. This dataset contained 15,000 sampled gold-standard pairs with 13,456 (89.7%) true positives and 1,544 (10.3%) true negatives. Not all infants are appropriately screened for harmful or potentially fatal disorders that are otherwise unapparent at birth,[28]. Although public health authorities can link vital records data with newborn screening results to identify unscreened infants, such processes may be delayed and some cases may remain undetected by this process,[29].

All four datasets contained subsets of the following fields: Medical Record Number (MRN), Social Security Number (SSN), Last name (LN), First name (FN), Middle name (MN), Gender (G), Birth Month (MB), Day of Birth (DB), Birth Year (YB), Street name (STR), Zip code (ZIP), City (CITY), State (ST), Telephone number (TEL).

Data preparation & standardization

We standardized patient demographic data following the recommendations outlined in a 2014 report to ONC,[16]. We selected the recommendations from the report to ONC given the comprehensiveness of the evaluation as well as the agency's responsibility to advance health data interoperability and ability to enforce or encourage standardization of data.

Figure 1 illustrates the data preparation process. First, we created a uniform analytical format for all datasets, with each dataset containing record pairs representing potentially matching patient records. To prevent an unmanageable and unnecessary number of record pairs from being created, we used a commonly applied technique in record linkage called "blocking.",[30] Blocking refers to the process of grouping similar records together to form candidate matches. It is analogous to sorting socks by color before pairing them. Candidate matches are then evaluated to identify true matches. Fields suitable for use as blocking fields ideally have high variety of values and a low missing value rate. Blocking increases the proportion of true matches among possible pairs while decreasing the number of pairs to be evaluated.

We standardized fields from across each dataset as follows,[16]:

Last (LN): We applied the last name normalization rule defined by CAQH,[31], which requires the removal of special characters such as apostrophes " ‘ ", hyphens "-" , etc., and suffixes such as "Jr.", "III", "MD", etc. Examples include: "O'BRIEN"→"OBRIEN", "SMITH JR."→"SMITH", and "JONES-THOMAS"→"JONESTHOMAS".

Telephone number (TEL): Telephone numbers were standardized in adherence to International Telecommunications Union Recommendation E.123,[32]. This required converting raw telephone numbers into the standard format (123) 456-7890. Examples include: 232 832-5555→(232) 832 5555, 2328325555→(232) 832 5555, 0002863866→286 3866, and 832-5555→832 5555.

Social Security Number (SSN): Invalid SSN numbers were identified based on rules provided by the Social Security Administration (SSA) and replaced with null values,[33]. For example, if the first three digits were "000" or if the last four digits were "0000", or the SSN lacked 9 digits, then the SSN was deemed invalid. Examples include: 000004197→(null), 111220000→(null). The standardization method also removed hyphens: 123-45-6789→123456789. Additionally, SSNs that appeared in advertisements were deemed invalid and were thus replaced with null values. For example, 078051120→(null).

Birth date (DOB): All dates were converted to the format MM/DD/YYYY. Incorrect date values such as February 30 and September 31 were replaced with blank values.

Month values greater than 12 and day of month values greater than 31 were nullified. Dates earlier than January 1, 1850 were also invalidated, because our data source records do not include patients born before such a date. Examples include: 2/15/197→(null), 9/28/→(null).

Addresses (ADDR): We applied US Postal Service certified address standardization rules,[34] to correct and standardize address data including individual components (e.g., standardizing "Boulevard" to "Blvd", "Drive" to "Dr", etc.) as well other formatting errors that would render the addresses undeliverable by the postal service. Examples include: 6275 E WILSON CRK DR→6725 WILSON CREEK DR E, and 1902 N MARKET #312→1902 MARKET ST APT 312. Because street address and Zip code fields are strongly correlated with city and state fields, we used only street and zip code in our analysis.

To both identify as many true positive matches as possible and eliminate many obvious non-matches, we created multiple blocking schemes,[35] for each dataset with up to 32 (2^5) possible field standardization combinations. We used the Expectation Maximization algorithm,[36] to configure the matching algorithm for each combination of (a) dataset, (b) blocking fields, and (c) standardization fields. Finally, we used the Fellegi-Sunter (FS) probabilistic matching algorithm to identify matches for all datasets. The FS algorithm assigns a match score to each record pair based on the number and type of agreeing fields, producing algorithm-determined matches and non-matches.

Analyses

The matching performance was evaluated using four metrics: sensitivity, specificity, positive predictive value (PPV), and overall accuracy, as indicated by the percent correctly classified as either true matches (sensitivity) or non-matches (specificity), along with accurately identified pairs. These metrics were established based on the selection of match-score thresholds, defined in the algorithm as the likelihood of a correct match, where record pairs with a match-score at or above the threshold were classified as matches and those with a matching score below the threshold were classified as non-matches. Because match accuracy measurements will vary by the choice of matching score threshold, we elected to use two different match thresholds based on independent criteria: (1) optimizing the Youden's J-statistic,[37], which is the sum of sensitivity and specificity minus 1, and (2) optimizing the F-score, which is a weighted harmonic mean of the sensitivity and positive predictive value. The use of these measures to optimize algorithm performance is well documented in the literature,[38, 39].

Using both criteria for selecting matching score thresholds, we evaluated whether standardizing fields individually or collectively resulted in differences in each matching accuracy metric using the generalized estimating equations approach with logistic regression. Estimated mean differences as well as 95% confidence intervals were calculated based on the model to evaluate the changes. This evaluation was performed for every blocking scheme and dataset since the samples of record pairs were randomly selected within each blocking scheme. Data from multiple blocking schemes were then pooled together for a dataset to examine the overall effect of field standardization.

RESULTS

HIE for hospital-to-hospital record matching

The HIE record pairs were created using five blocking combinations, including SSN; LN FN DOB; TEL; LN G DB YB ZIP; and FN G DB YB ZIP. Blocking fields are not used as matching fields. Consequently, when day and birth year are used as blocking fields, only birth month is used as a matching field in that particular blocking combination. Similarly, when the zip code is used as a blocking field, street address will be used as a matching field in that particular blocking combination.

Table 1 lists the proportion of records standardized for demographic fields in each dataset. Note address and telephone fields exhibited the highest proportion of transformed records, while last name exhibited a small amount of change within the newborn dataset. Standardization had little impact on birth date and social security number. While telephone number underwent significant transformation, the changes largely altered formatting rather than content, and thus did not result in improved match accuracy.

Table 1: Proportion of records standardized for demographic fields in each dataset

	Datasets			
Demographic Field	HIE	Public Health	Newborn	Death
address	33.8%	26.5%	0.9%	24.1%
dob	0.0%	0.1%	0.0%	0.0%
last name	0.7%	0.2%	5.4%	0.1%
ssn	0.2%	0.0%	0.0%	0.5%
tel	88.6%	70.6%	92.3%	35.2%

The SSN block contains 27,083 record pairs with 26,591 (98.18%) true matches. In this block, the only noticeable difference in matching accuracy occurs with address standardization. When thresholds are chosen to maximize the Youden's J-statistic, there is a 1.3% (95%CI = 1.2%-1.5%) increase in sensitivity and a 3.5% (95%CI = 1.9%-5.1%) decrease in specificity. This results in a 1.3% (95%CI = 1.1%-1.4%) improvement in the overall accuracy, where the percent of record pairs correctly classified increases from 90.7% without address standardization to 92% with address standardization.

The LN FN DOB block contains 32,171 record pairs with 64,778 (88.20%) true matches. Again, in this block, address standardization makes the only noticeable difference in matching accuracy when thresholds are chosen to maximize the Youden's J-statistic. There is a 3.3% (95%CI = 3.1%-3.5%) increase in sensitivity and an 8.2% (95%CI = 6.9%-9.4%) decrease in specificity. The overall accuracy is improved from 84.9% without address standardization to 87.6% with address standardization, indicating a 2.7% (95%CI = 2.5%-2.9%) absolute improvement.

The TEL block captured 21,415 record pairs with 11,604 (54.19%) true matches. Field standardization does not result in meaningful changes in any matching accuracy metrics, regardless of how the matching score thresholds are selected.

The LN G DB YB ZIP block contains 24,406 record pairs with 23,064 (94.5%) true matches. Again, in this block, address standardization has the only noticeable effect when thresholds are chosen to maximize the Youden's J-statistic. Sensitivity increases by 3.2% (95%CI = 2.9%-3.5%) and specificity decreases by 9.5% (95%CI = 8%-11.1%) after address is standardized. The

overall accuracy is improved from 77.7% without address standardization to 80.2% with address standardization, indicating a 2.5% (95%CI = 2.2%-2.8%) improvement.

In the FN G DB YB ZIP block, there are 25,569 record pairs with 23,158 (90.6%) true matches. Standardizing the address again shows a large effect when thresholds are chosen to maximize the Youden's J-statistic. Sensitivity increases by 8.3% (95%CI = 8%-8.6%) and specificity decreases by 11.6% (95%CI = 10.5%-12.6%) after address is standardized. The overall accuracy is improved from 82% without address standardization to 88.3% with address standardization, indicating a 6.3% (95%CI = 6.1%-6.6%) improvement. In addition, last name standardization increases the sensitivity by 2.9% (95%CI = 2.8%-3%) and decreases the specificity by 1.9% (95%CI = 1.7%-2.1%), leading to a 2.2% (95%CI = 2.1%-2.3%) improvement of the overall accuracy.

When data from all five blocking schemes are pooled, the estimated matching accuracies are shown in Figure 2. It is obvious that standardizing DOB, SSN, or TEL does not improve any matching accuracy metrics. Standardizing the address appears to have a larger effect, while last name standardization shows a relatively smaller effect when matching thresholds are chosen to maximize the Youden's J-statistic. When using the F-score to select matching score thresholds, no field standardizations show a difference in accuracy metrics. These findings suggest that address and last name standardization improve matching performance, but the magnitude of improvement will be influenced by the choice of score threshold.

Combined Field Standardization

In the FN G DB YB ZIP block, since standardizing address and last name improved matching sensitivity, we further examine the combined effect of address and last name standardization. Estimated matching accuracies when both address and last name are standardized, compared to when only one field is standardized or no field is standardized, are shown in Figure 3. Standardizing both address and last name improves the sensitivity to 91.6% from 81.3% (increase = 10.3%, 95%CI = 10%-10.6%) when only last name is standardized or 87.1% (increase = 4.5%, 95%CI = 4.4%-4.7%) when only address is standardized. The dual standardization decreases the specificity to 75.8% from 89.9% (decrease = 14.1%, 95%CI = 13.2%-15.6%) when only last name is standardized or 81.4% (decrease = 5.6%, 95%CI = 4.8%-5.8%) when only address is standardized. The increased sensitivity has greater importance as vast majority of the record pairs in the data are true matches. As a result, the overall accuracy improves to 90% with dual standardization from 82.1% (increase = 7.9%, 95%CI = 7.6%-8.3%) when only last name is standardized or 86.5% (increase = 3.5%, 95%CI = 3.4%-3.8%) when only address is standardized.

Laboratory results and HIE for newborn screening

The NBS data was blocked using three schemes, with TEL, LN FN, and MRN as blocking variables. The TEL block contains 11,029 record pairs with 9,739 (88.3%) true matches. In this block, neither LN nor DOB standardization results in changes in matching accuracy, regardless of the criteria used for the selecting the matching score thresholds. The LN FN block contained 2,716 record pairs with 2,583 (95.1%) true matches. None of the four matching accuracy measures are changed by the standardizing the fields, regardless of how matching score

thresholds are selected. The MRN block contained 9,179 record pairs with 9,038 (98.46%) true matches. Field standardization again does not result in improved matching accuracy. The matching accuracies estimated based on pooling all three blocking schemes together are shown in Figure 4. Standardizing DOB, LN, or TEL does not improve any of the four matching accuracy metrics.

Public health registry for de-duplicating

The MCHD data was blocked using two schemes, one with SSN and the other with last name and LN FN as blocking variables. The SSN block contains 2,141 record pairs with 1,508 (70.43%) true matches. In this block, the only observed difference in matching accuracy occurs with address standardization when thresholds are chosen to maximize the Youden's J-statistic. There is a 0.3% (95%CI = -0.1%-0.7%) increase in sensitivity and a 2.4% (95%CI = 1.1%-3.6%) decrease in specificity. This, however, does not change the overall accuracy due to the fact that very few record pairs are non-matches. Standardizing other fields or using the F measure for threshold selection does not lead to changes in any matching accuracy metrics.

The LN FN block contained 31,420 record pairs with 978 (3.11%) true matches. Standardizing address appears to slightly increase the sensitivity and decrease the specificity by less than half-percent changes, regardless of how matching score thresholds are selected. The leads to a 4% (95%CI = 3.3%-4.9%) and 1% (95%CI = 0.4%-1.7%) reduction in positive predictive value when selecting matching score thresholds by optimizing the Youden's J-statistic and F-score, respectively. However, these did not change the overall percent of correctly classified pairs due to the vast majority of record pairs being non-matches.

When data from both blocking schemes are pooled, the estimated matching accuracies are shown in Figure 5. Standardizing DOB, LN, SSN, or TEL does not improve any of the four matching accuracy metrics. Standardizing address appears to have some effect, but this is negligible.

HIE and vital records for ascertaining death status

The SSDMF data was blocked using two schemes, one with SSN, and the other with LN FN DOB as blocking variables. The SSN block contains 18,615 record pairs with 16,758 (90%) true matches, while the LN FN DOB block contained 16,798 record pairs with 15,527 (92.4%) true matches. Standardization results in no changes for any matching accuracy metrics, regardless of how matching score thresholds are selected. This is shown by the same matching accuracy before and after field standardization for every field and every threshold selection criterion in Figure 6.

DISCUSSION

Our research found that standardizing certain individual demographic data fields yields incremental improvements in match performance among hospital-to-hospital exchange, while combined standardization can produce more meaningful improvements, which would further ensure that patient data can be linked across organizations to improve care coordination and lower costs. Specifically, using a database of 100,000 records that represents hospital to hospital data exchange, we found sensitivity increases of up to 10%, which reduces the number of unlinked records in the dataset by nearly half.

Several limitations exist. First, while we observed increased false positive matches (decreased specificity) associated with data standardization, this is not unexpected. False positive matches can be mitigated by introducing deterministic exclusion criteria specific to the offending match pattern (e.g., declare a non-match if corresponding dates of birth disagree), an approach commonly taken when optimizing match performance for specific data sources. Second, our results are specific to the blocking schemes we selected. Other blocking schemes may yield different results. Third, while we used only one algorithm, the Felligi-Sunter (FS) model, this model is a common component of many patient matching systems. Fourth, we limited our analysis to datasets specific to Indiana. However, the data included in this study represent a broad spectrum of health care settings from rural to urban, hospital and clinic settings, and therefore the findings likely are to have applicability to hospital to hospital exchange on a nationwide scale.

Ultimately, we found that the recommendation by many policy organizations for enhanced standardization of certain data elements can yield matching improvements. Because last name and address information are commonly entered as unstructured text, they can exhibit meaningful variation. We hypothesize that last name and address standardization is associated with match rate improvement because it minimizes this variation. Consequently, we found utility in standardizing address and last name in combination, which can significantly reduce the number of unmatched records. Conversely, we did not find evidence for standardizing birth date and telephone. Given the limited degrees of freedom for information for these fields, we hypothesize that these fields require little standardization.

We also sought information on the costs needed to implement standardization by hospitals or health information technology vendors. While we could not find clear cost data, standardization and deployment of those standards in to their products by electronic health record (EHR) developers would help consolidate costs as opposed to having every healthcare facility conduct the standardization. We also note that the costs for standardizing the data as part of this project were limited, which may provide some context for nationwide standardization among vendors.

With an incomplete evidence base to more firmly support standardization, healthcare organizations, health IT developers and policymakers may be less inclined to pursue approaches with unclear value or they may implement methods that, upon further study, prove to be less effective and generalizable than initially perceived.

Given that accurate patient matching is essential for maximizing health data quality, where opportunities exist, health IT vendors should prioritize incorporating address standardization—which we found in this study can decrease the number of unlinked records by up to 20 percent—functionality into their patient registration products. Relying solely on individual vendors may result in incomplete implementation across the industry because some may elect not to implement address standardization. Little information exists on the degree to which organizations currently standardize data, though informal discussions and recommendations made by many groups suggest that there is not widespread use of the same standards. While data standardization would yield partial benefit even if only one party in a transaction standardizes the data, maximal benefit requires that all systems adopt the same standardization rules. Consequently, health IT policy makers, including ONC, should explore strategies for expanding

the evidence base for the value of data consistency and encouraging broad deployment of address standardization. These strategies may include updates to its certification criteria for electronic health records, issuing guidance to encourage the voluntary standardization of data, or incorporating standardization in to its plans to create a nationwide interoperability framework. Similarly, vendors and ONC should further examine the utility of last name standardization so that the increased match rates when used in conjunction with last name can be realized.

CONCLUSION

Standardizing certain demographic data on a broader scale can improve match rates, ensuring that patients and clinicians have better data on which to make decisions to enhance care quality and safety.

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Competing interests statement

The authors have no competing interests to declare.

Contributorship statement

Dr. Grannis contributed to the conception, design, acquisition, analysis, and interpretation of data for the work. Dr. Xu and Ms. Bo performed analysis and interpretation of data. Drs. Vest, Kasthurirathne, and Mr. Rising provided interpretation of data. Mr. Moscovitch and Ms. Torkzadeh contributed to conception and design.

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FIGURE 1

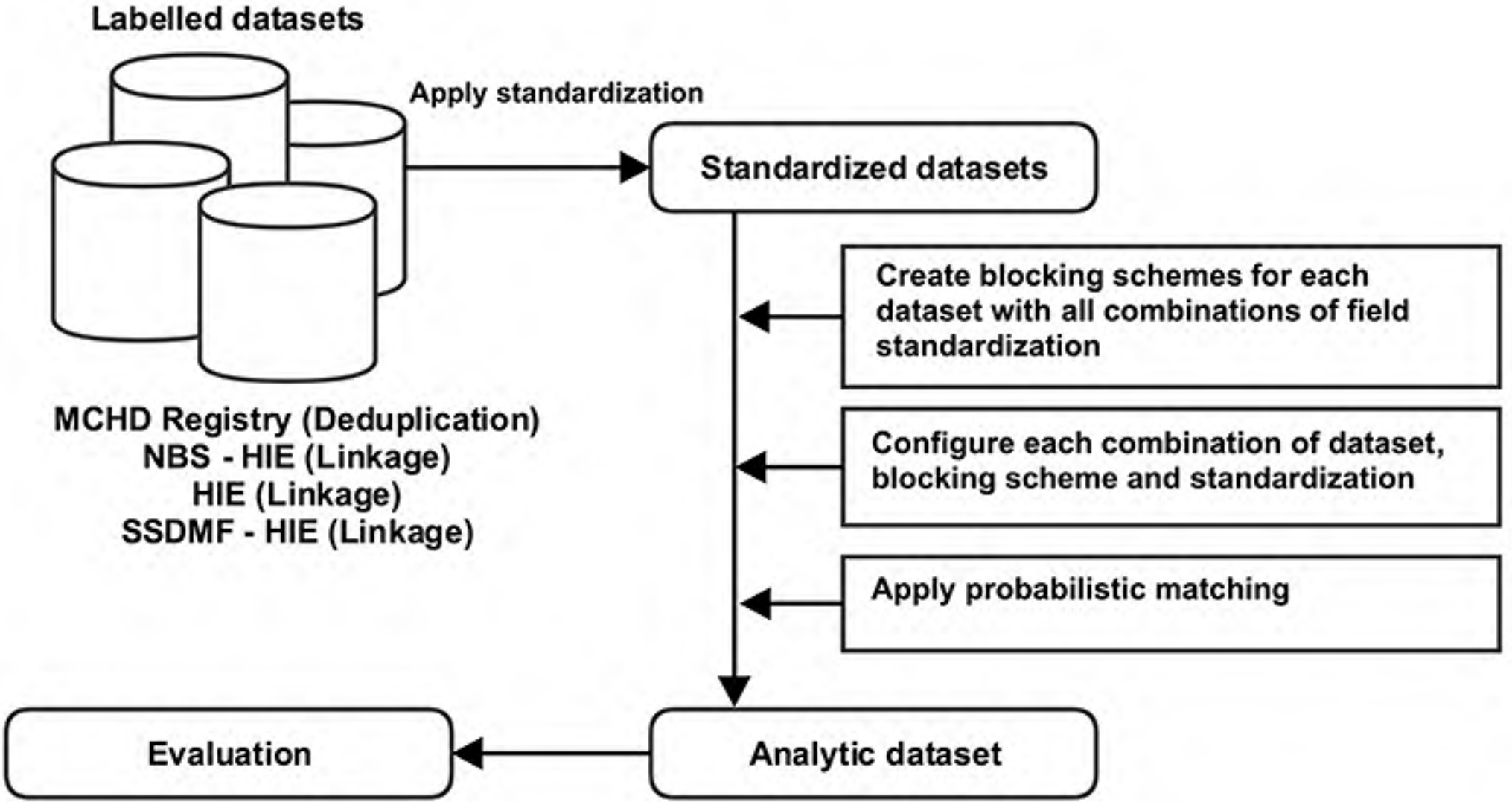
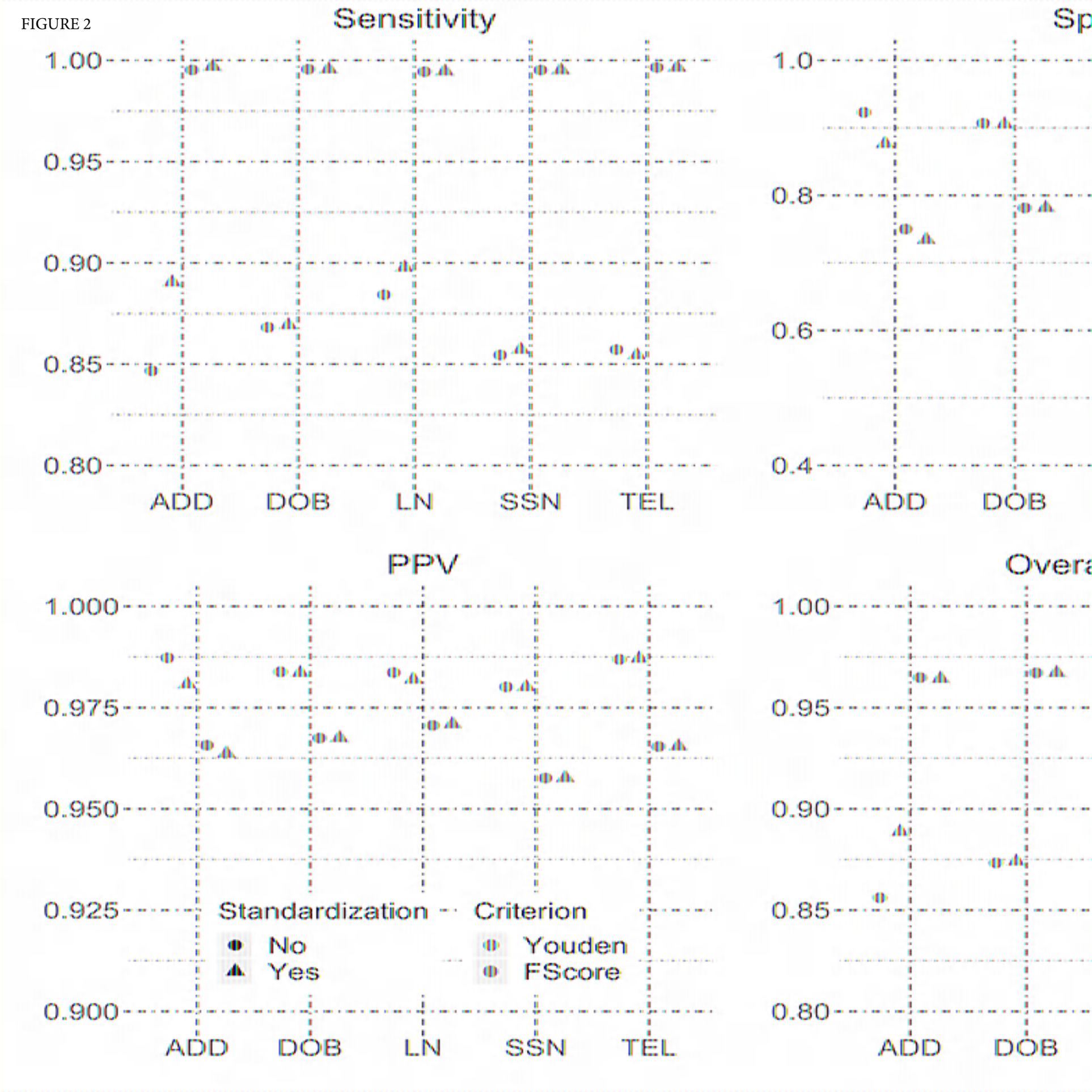

Labelled datasets
Apply standardization
Standardized datasets
Create blocking schemes for each dataset with all combinations of field standardization
Configure each combination of dataset, blocking scheme and standardization
Apply probabilistic matching
MCHD Registry (Deduplication)
NBS - HIE (Linkage)
HIE (Linkage)
SSDMF - HIE (Linkage)
Analytic dataset
Evaluation

FIGURE 2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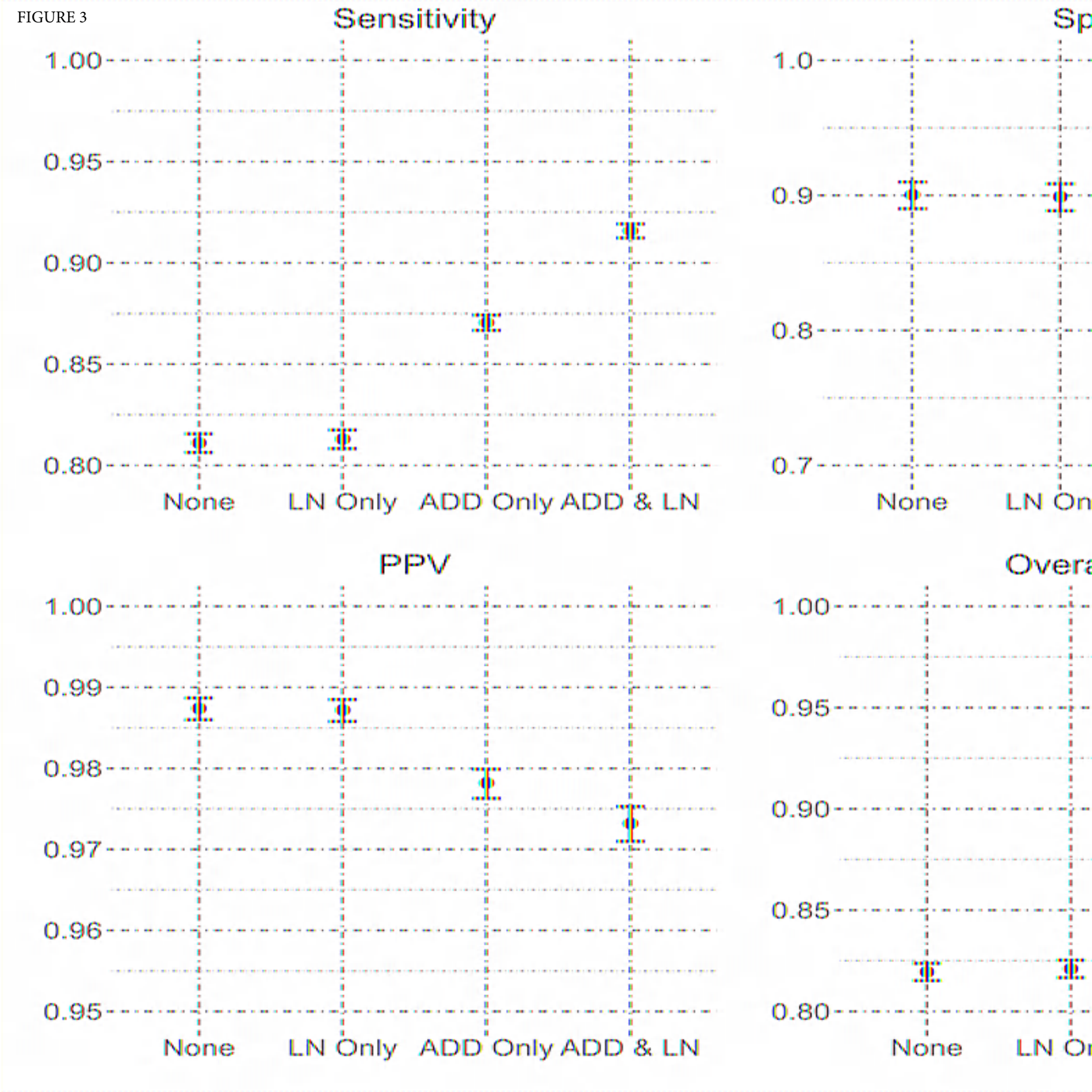
Sp
PPV
Overa
1.00
0.95
0.90
0.85
0.80
1.0
0.8
0.6
0.4
1.000
0.975
0.950
0.925
0.900
ADD
DOB
LN
SSN
TEL
Standardization
No
Yes
Criterion
Youden
FScore

FIGURE 3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0.95
0.90
0.85
0.80
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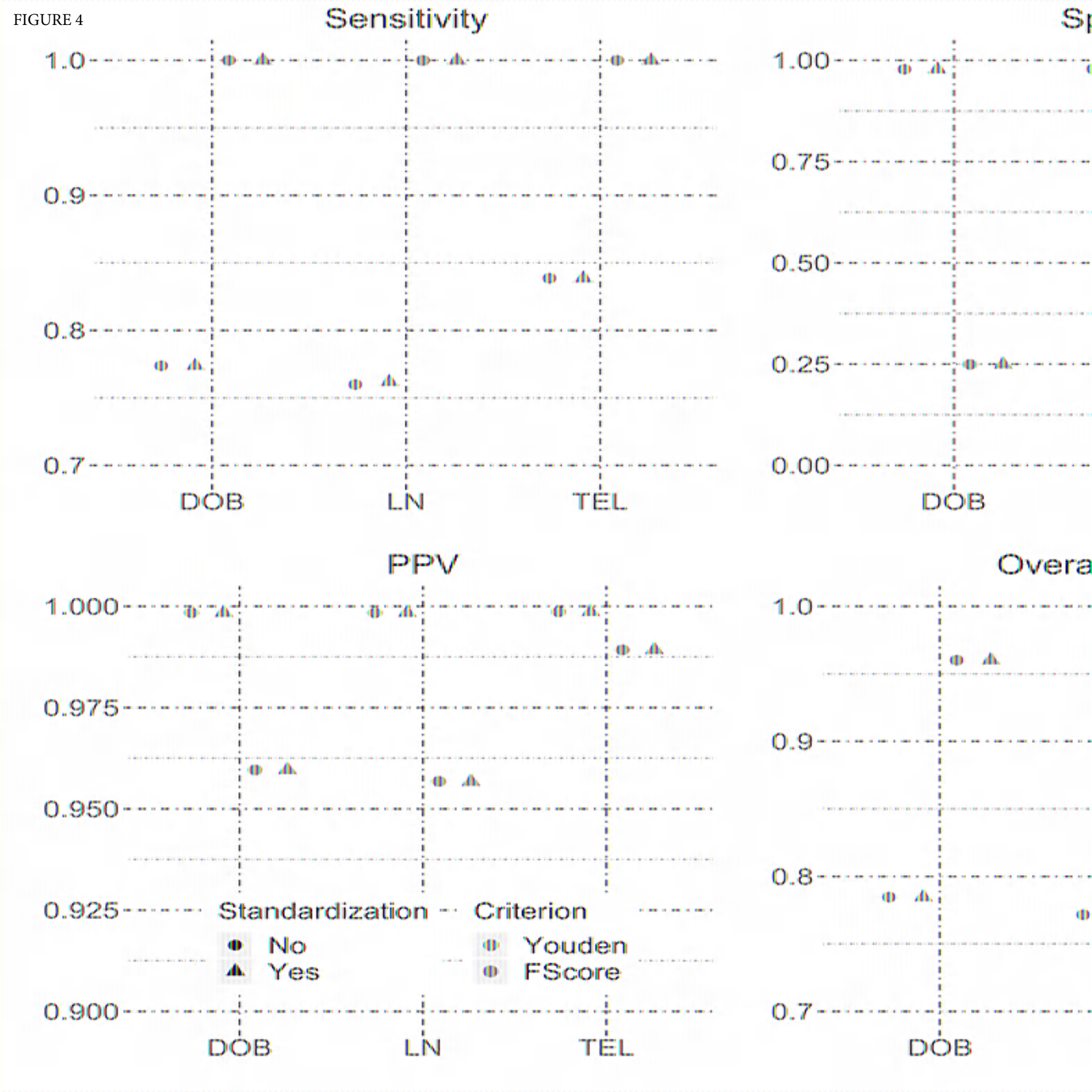
LN Only
ADD Only
ADD & LN
Sp
1.0
0.9
0.8
0.7
None
LN On
PPV
1.00
0.99
0.98
0.97
0.96
0.95
None
LN Only
ADD Only
ADD & LN
Overa
1.00
0.95
0.90
0.85
0.80
None
LN On

FIGURE 4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LN
TEL
Sp
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0.75
0.50
0.25
0.00
DOB
PPV
1.000
0.975
0.950
0.925
0.900
DOB
LN
TEL
Standardization
No
Yes
Criterion
Youden
FScore
Overa
1.0
0.9
0.8
0.7
DOB

FIGURE 5

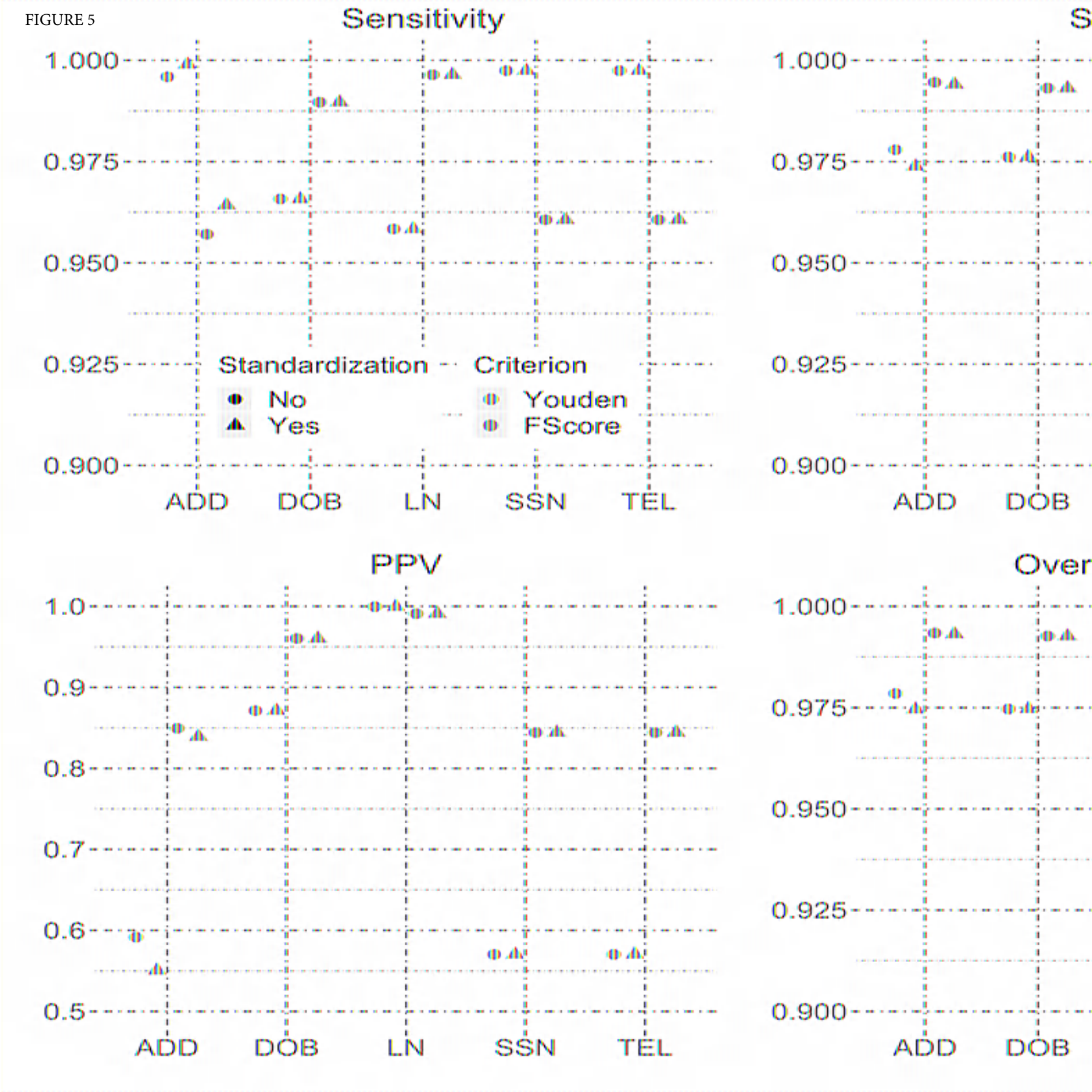
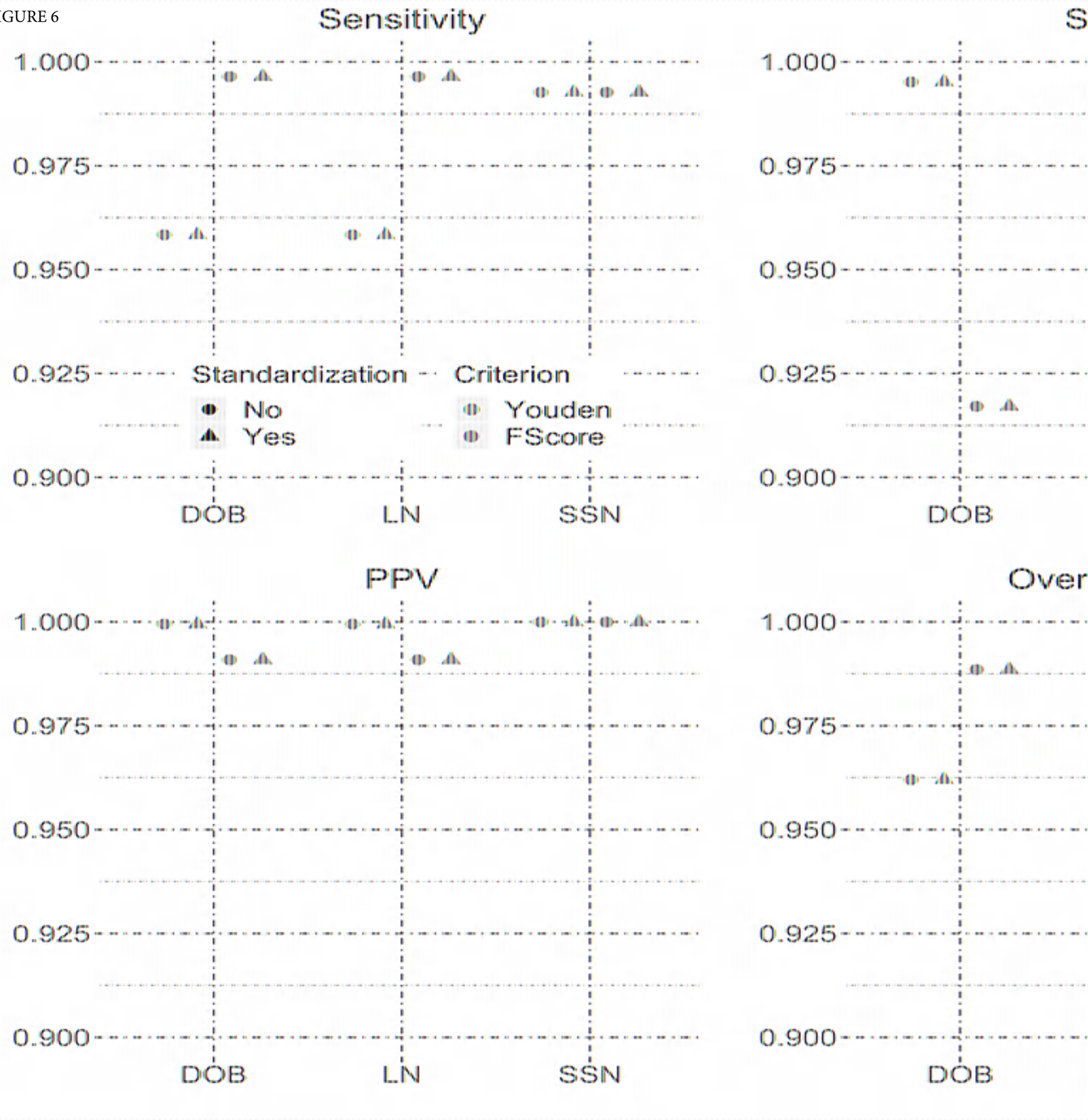

Sensitivity
S
PPV
Over
1.000
0.975
0.950
0.925
0.900
1.0
0.9
0.8
0.7
0.6
0.5
ADD
DOB
LN
SSN
TEL
Standardization
No
Yes
Criterion
Youden
FScore

FIGURE 6


Sensitivity
PPV
1.000
0.975
0.950
0.925
0.900
DOB
LN
SSN
Standardization
No
Yes
Criterion
Youden
FScore