# Psyc 513

# Article summaries – working draft 1

|  |  |
| --- | --- |
| Article name, authors, journey with link | **Electronic records for dementia research: Do behavioural disturbances, antihypertensives and antidepressants influence decline trajectories?**  Baker, Elizabeth, Iqbal, Ehtesham, Broadbent, Matthew, Stewart, Robert, Khondoker, Mizanur, Newhouse, Stephen J. and Dobson, Richard J.B. (2016) *Electronic records for dementia research: Do behavioural disturbances, antihypertensives and antidepressants influence decline trajectories?* In: UNSPECIFIED.  <http://www.alzheimersanddementia.com/article/S1552-5260(16)32508-0/abstract> |
| Question, issue, problem | * Conceptual – conceptualizing decline * Data requirements – what is required to measure decline * Statistical procedures to characterize decline * Impact of various factors on trajectories |
| Cohort | 3441 patients with at least three MMSE scores recorded |
| Data | Information on age, gender, ethnicity, qualification levels, cohabiting status, retirement status, Health of Nation Outcome Scales (HoNOS) and medications |
| Statistical approach | Latent Class Growth Analysis was used to identify key trajectories of decline.  Data referenced above were used to describe characteristics of the identified trajectory sub-populations in a multivariable multinomial regression analysis. |
| Results, Products | * We identified six trajectories of cognitive decline. Four of these trajectories differed in initial MMSE score, and showed increased rate of decline with lower initial MMSE. Two trajectories had very similar initial MMSE scores but differed in the rate of decline. * The severity of cognitive problems at baseline and prescription of Donepezil and Amlodipine was significantly higher in the slower declining trajectory. * In the faster declining trajectory, severity of behavioral problems and prescription of sertraline was significantly higher. |
| Practical implications | As stated by author(s):  As inferred by article reviewer: |
| Readiness | [are the results ‘ready’ for translation to various points in the service system? If not – what else needs to be done] |
| Consumers of the information   * Who (role) * What function * Context (where in the organization) | Who – clinicians – geriatricians; psychogeriatricians; Home & Community Care case managers….; [Older Adult Quality Council – however that is constituted in the Health Authority where the work is being conducted]  What function: direct care; clinical oversight  Context: point-of-service; Quality Councils |
| Comments |  |

|  |  |
| --- | --- |
| Article name, authors, journey with link |  |
| Question, issue, problem |  |
| Cohort |  |
| Data |  |
| Statistical approach |  |
| Results, Products |  |
| Practical implications |  |
| Readiness |  |
| Consumers of the information   * Who (role) * What function * Context (where in the organization) |  |
| Comments |  |

# Compendium of Research Designs Appropriate to Bodies of Data Extracted from EHR (and related) Systems

|  |  |
| --- | --- |
| Research Design/Statistical Approach – Name | Propensity score matching |
| Problem(s) Addressed | For observational data – addresses the problem of confounded variables used to define cohorts, or selection bias involved in assignment of persons to different groups.  “he possibility of bias arises because the apparent difference in outcome between these two groups of units may depend on characteristics that affected whether or not a unit received a given treatment instead of due to the effect of the treatment per se.” |
| Conceptual Requirements | You have to be working from a model that identifies the possible confounds or the factors that would bias selection. In other words, you need to have a reasonably complete model that identifies those factors whose expressions would be neutralized through randomization |
| Data Requirements | Cohort definers  Measures of confounding/selection biasing factors |
| Explanation – How the procedure works | * 1. Run logistic regression: * Dependent variable: *Y* = 1, if participate; *Y* = 0, otherwise. * Choose appropriate confounders (variables hypothesized to be associated with both treatment and outcome) * Obtain propensity score: predicted probability (*p*) or log[*p*/(1 – *p*)].   2. Check that propensity score is balanced across treatment and comparison groups, and check that covariates are balanced across treatment and comparison groups within strata of the propensity score.   * Use standardized differences or graphs to examine distributions   3. Match each participant to one or more nonparticipants on propensity score:   * [Nearest neighbor matching](https://en.wikipedia.org/wiki/Nearest_neighbor_search) * Caliper matching * [Mahalanobis metric](https://en.wikipedia.org/wiki/Mahalanobis_distance) matching in conjunction with PSM * [Stratification matching](https://en.wikipedia.org/wiki/Stratified_sampling) * Difference-in-differences matching (kernel and local linear weights) * Exact matching   4. Verify that covariates are balanced across treatment and comparison groups in the matched or weighted sample  5. Multivariate analysis based on new sample   * Use analyses appropriate for non-independent matched samples if more than one nonparticipant is matched to each participant   Note: When you have multiple matches for a single treated observation, it is essential to use Weighted Least Squares rather than OLS. |
| Reference, sources | <https://en.wikipedia.org/wiki/Propensity_score_matching>  See also: Secondary Analysis of Electronic Health Records |

|  |  |
| --- | --- |
| Research Design/Statistical Approach – Name | Severity adjustment |
| Problem(s) Addressed | Non-random assignment of persons to different treatment conditions |
| Conceptual Requirements |  |
| Data Requirements |  |
| Explanation – How the procedure works |  |
| Reference, sources |  |

|  |  |
| --- | --- |
| Research Design/Statistical Approach – Name |  |
| Problem(s) Addressed |  |
| Conceptual Requirements |  |
| Data Requirements |  |
| Explanation – How the procedure works |  |
| Reference, sources |  |

# Cohort Selection Methodologies

|  |  |
| --- | --- |
| Methodology – short descriptor | Based on diagnosis |
| Examples – where this approach might work | * Diagnostic criteria are sufficient to create a cohort that is homogeneous with respect to emergent co-morbidities, etiology and response to treatment (the ideal case) * Clinically uni-dimensional acute illness or injury, amenable to clinical resolution within a reasonably clearly specified period of time. * Example – appendicitis (????) |
| Examples – where this approach might be limited | * Chronic conditions associated with variable emergent co-morbidities, e.g,. Type II diabetes * Chronic conditions where the base cohort definition is clinically heterogeneous, e.g., “concurrent MHSU disorders” * Mood disorders (e.g., major depression; anxiety disorders) where the estimates of lifetime prevalence are much higher than the fraction of that population that are treated. |
| Strengths | Clear delineation of problems addressed by research |
| Limitations | * Very generic; issues around relevance of results for persons who are contending with clinically significant co-morbidities * Doesn’t work well if diagnosis does not lend itself to stratification by severity * Doesn’t work well for chronic conditions associated with emergence of different constellations of co-morbidities at different points in time |
| Strategies for addressing limitations | * Multi-dimensional case definitions * Include [longitudinal] encounter data in case definitions |
| Comments |  |

|  |  |
| --- | --- |
| Methodology – short descriptor |  |
| Examples – where this approach might work |  |
| Examples – where this approach might be limited |  |
| Strengths |  |
| Limitations |  |
| Strategies for addressing limitations |  |
| Comments |  |

Based on distal factors (non-medical determinants of health profiles)

Based on exposure, etiologic factors (proximal factors)

Based patterns of service utilization (quantitative within specified periods of time, or lifetime)

Based on patterns of service utilization – longitudinal (trajectories)

Based on treatments, procedures

Based on lab results

Based on pharmaceuticals prescribed

Based on outcomes (working backwards designs, e.g., decision tree analysis)

Based on products of unsupervised machine learning algorithms applied to unstructured data

Based on combinations (specify)

# Conclusions

* Ultimately, significant confounding cannot be adjusted away by the most sophisticated statistical techniques, and thoughtful and careful examination of the limitations of any observational study must be transparent (p. 76, Secondary Analysis of EHRs)