Directed Acyclic Graphs for Oral Disease Research

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Appendix

Definitions of Terms

Confounding is the "distortion of a measure of the effect of an exposure on an outcome due to the association of the exposure with other factors that influence the occurrence of the outcome. Confounding occurs when all or part of the apparent association between the exposure and outcome is in fact accounted for by other variables that affect the outcome and are not themselves affected by exposure" (Porta 2008). A mediator is a "variable that occurs in a causal pathway from a causal (independent) variable to an outcome (dependent) variable. It causes variation in the outcome variable and itself is caused to vary by the original causal variable" (Porta 2008). Finally, effect measure modification is "variation in the selected effect measure for the factor under study across levels of another factor. There is effect modification when the selected effect measure for the factor under study varies across levels of another factor. An effect modifier may modify different measures in different directions and may modify one measure but not another" (Porta 2008).

Additional Information Comparing Structural Equation Models and Directed Acyclic Graphs

In the domain of causal modeling, structural equation models (SEMs) and directed acyclic graphs (DAGs) represent 2 distinct types of causal models. Although DAGs are able to graphically depict bias due to confounding as well as other kinds of biases (e.g., conditioning on a collider) that are not readily obvious with other approaches, DAGS are qualitative tools; SEMs provide a way to quantitatively assess effects (Greenland and Brumback 2002). SEMs had their initial origin in causal relationships surrounding genetics (Wright 1921). Although the intent of SEMs is to describe and quantify causal relationships (e.g., "psychosocial stress causes inflammatory system changes"), SEMs have become greatly misused. In particular, the cause-effect relationship inherent in SEMs as originally developed has been sidestepped as a result of relegating causal assumptions to an implicit attribute and due to the absence of a symbolic syntax to explicate causal assumptions as separate from statistical assumptions. This occurred because the causal aspects of SEMs were inadequately formalized by the original developers (Freedman 1987). See Pearl (1998) for greater detail. In contrast, DAGs emerged distinct from SEMs in light of causal diagrams being reinterpreted as a formal probability model, for Dental Research 2016 Reprints and permissions: sagepub.com/journalsPermissions.nav DOI: 10.1177/0022034516639920 jdr.sagepub.com G.D. Slade², which lead to the inclusion of graph theory and subsequently the

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recognition that DAGs could be used for formal causal inference; see Greenland and Pearl (2006) for greater detail. In particular, we note that DAGs, in keeping with their basis in graph theory, necessarily use a specific language for identifying the structure as well as the process intrinsic to that structure. Although double-headed arrows are incorporated into SEMs to indicate correlation of errors among a pair of variables (Pearl 1998; Spirtes et al. 1998), DAGs are nonparametric graphical tools and hence double-headed arrows are not permitted. Although it is largely misconstrued that coefficients from SEMs indicate the presence or lack of causal relation, SEMs just like DAGs rely on the causal assumptions of the researchers: assumptions rooted in scientific knowledge, prior studies, logical arguments, and temporal sequence of etiologic events (Bollen and Pearl 2013). For more on DAGs and SEMs, refer to Spirtes et al. (1998), Pearl (1998), and Greenland and Brumback (2002).

Appendix References

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