

Using Advanced Quantitative Methods to Study the Prevention of Social Problems

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Abstract

Social work has embraced prevention as one of its grand challenges—recognising the need to understand risk and protective factors for social problems that, if addressed, may prevent social disadvantage and mental health problems from occurring. To best study prevention, social workers must become fluent in understanding and using advanced methodologies that illuminate developmental processes, depict individual and subgroup differences, and rule out potential confounds so as to shed light on important risk and protective factors. The purpose of this article is to provide a simple introduction to four advanced methods: latent growth curves (LGM), mediation models, latent class/profile models and propensity score models. Latent growth curve models are helpful for understanding changes in the developmental course of a risk factor over time. Mediation models are useful tools for understanding how risk and protective factors may affect outcomes. Latent class and latent profile models allow researchers to understand how combinations of risk factors may be linked to youth outcomes. Propensity score models allow researchers to reduce the effects of selection bias on their estimates of the relationships between risk factors and outcomes. We discuss the research questions appropriate for each type of model, the type of data required, and the strengths and weaknesses of each approach. We also include suggestions for further reading.

Keywords: Quantitative methods, prevention, risk

Accepted: November 2016

Introduction

Social workers have increasingly been called to focus on prevention—that is, to expand our understanding of the potential causes of social disadvantage and mental and behavioural health problems and to design programmes that may reduce risk for these problems and prevent them from occurring (Fraser *et al.*, 1999; Hawkins, 2006; Catalano *et al.*, 2012; Uehara *et al.*, 2014; Hawkins *et al.*, 2015). Prevention of mental and behavioural problems may have benefits for the well-being of all youth. However, prevention may be particularly advantageous for disadvantaged youth, given the higher incidence of mental and behavioural health problems associated with discrimination, oppression and poverty (Barr, 2014; Kenny and Hage, 2009; Reiss, 2013; Reese and Vera, 2007). Thus, the prevention of social problems may be an effective avenue to reduce health disparities and promote social justice (Kenny and Hage, 2009).

Prevention science has increased our understanding of the aetiology of many problems including substance use and delinquency. For example, research has shown that early engagement in substance use and delinquency place youth at particularly high risk of deleterious outcomes that may extend into adulthood (DeWit *et al.*, 2000; Kendler *et al.*, 2013; Irons *et al.*, 2015; Nelson *et al.*, 2015). Thus, identifying factors that may decrease or delay substance use and delinquency may promote healthy development over the life course. Factors in the family, such as harsh parenting and low parental knowledge of youth activities, and factors in school, such as poor relationships with teachers, are two risk factors that have been linked to an increased risk of early substance use and delinquency (for a review, see Greenberg and Lippold, 2013; Van Ryzin *et al.*, 2012). In contrast, close parent–child relationships and bonds with school have been identified as protective factors that reduce the risk for negative youth outcomes. Importantly, programmes and policies that address these risk and protective factors may delay the onset and severity of risky behaviour.

Understanding risk and protective factors often requires the use of longitudinal data and quantitative methods that can capture the complexity and diversity of change over time (Collins, 2006; Hoffman, 2015). Consequently, in order to increase our focus on prevention, social workers must become fluent in understanding and using advanced methodologies that illuminate developmental processes, depict individual and subgroup differences, and rule out potential confounds so as to shed light on important risk and protective factors. Advances in prevention science have often gone hand in hand with advances in the development of methodologies such as latent growth curves, propensity score models, mediation models and latent class models. Social work programmes and conferences have made great strides in advancing our training in statistical methods. Students who desire advanced training can now find

seminars at national conferences (e.g. SSWR), universities and through various training organisations. For example, the Inter-university Consortium on Political and Social Research (ICPSR) and the Consortium for Statistical Development and Consultation (CSDC) at The University of North Carolina at Chapel Hill School of Social Work offer courses in advanced methods.

The purpose of this article is to provide a simple introduction to four advanced methods: latent growth curves (LGM), mediation models, latent class models and propensity score models. For each one, we discuss the research questions appropriate for this model, the type of data required, and the strengths and weaknesses of this approach. We also review published studies that have used each of these methods. Through examples, we demonstrate the unique information that can be gained from each method. Our goal is not to instruct the reader on how to conduct these complex analyses. Rather, it is to aid the researcher in identifying the appropriate method for a particular research question and to identify published resources for further learning. For this reason, the strengths of methodological approaches described within are summarised in [Table 1](#) and suggestions for further reading are presented in [Table 2](#). For those interested in learning more, we recommend that readers obtain the original articles for the examples presented in this paper.

Latent growth curve models

Latent growth curve models are an effective tool for understanding the development of risk and protective factors over time and their relations to youth outcomes, such as substance use ([Singer and Willett, 2003](#)). For example, latent growth curves allow researchers to investigate whether a risk factor decreases, or increases or shows a particular shape of curve in its trajectory over time. Further, these models allow researchers to test how changes in risk factors are related to youth outcomes.

Examples

In our work, we have used latent growth curve models to investigate how one risk factor for substance use—school bonding—changes over the middle-school period. Further, we examined how changes in school bonding were associated with youth substance use and delinquency ([Oelsner et al., 2011](#)). School bonding, or the relationships youth have with their schools, had been identified as an important protective factor for youth substance use. Yet, little was known about how school bonding changes over time, which may be important information for interventions designed to strengthen school bonding. To build knowledge in this

Table 1 Summary of methods

Method	Uses	Example research questions	Strengths/limitations
Latent growth curve models	<ul style="list-style-type: none"> Identifying developmental patterns and changes over time Investigating factors that may lead to increases or decreases in a phenomena over time 	<ul style="list-style-type: none"> How does a risk factor change over time? Are changes in these risk factors associated with youth substance use? 	<p>Strengths: Allows you to model change over an extended period of time and to capture effects that may occur later</p> <p>Limitations: Identifies trends in data; may be difficult to discern short shifts; requires longitudinal data with at least three data points</p>
Mediation models	<ul style="list-style-type: none"> Understanding underlying processes Identifying how risk factors influence youth outcomes Useful for modifying logic models 	<ul style="list-style-type: none"> How do risk factors affect youth substance use? What are the explanatory or intermediary mechanisms? 	<p>Strengths: Captures the underlying process that may link risk factors to an outcome; useful for theory and intervention development</p> <p>Limitations: These methods provide descriptive evidence of pathways, but the evidence does not support causal inferences</p>
Latent class models	<ul style="list-style-type: none"> Allow investigation of sub-groups with multiple risk factors Allows researchers to capture complexity A holistic approach to risk factors 	<ul style="list-style-type: none"> Are there groups of individuals with specific combinations of risk factors? How are combinations of these risk factors linked to youth outcomes? 	<p>Strengths: May capture the complexity of risk factors rather than isolating the effects of just one</p> <p>Limitations: Classes are sample-specific; caution must be drawn when classifying individuals into a particular subgroup; requires large sample size</p>
Propensity score models	<ul style="list-style-type: none"> Addressing issues of causality 	<ul style="list-style-type: none"> Are risk factors causally related to outcomes? How do you get a more reliable estimate of the relation between risk factors and outcomes given multiple potential confounders? 	<p>Strengths: Allows researchers to control for a host of potential confounders, increases confidence the relation between treatment and outcome is not biased by observed confounders</p> <p>Limitations: Need to measure many confounders; analysis can become more complicated when working with clustered samples</p>

important area, we investigated the developmental course of this risk factor.

The first step in our analysis was to identify the trajectory or shape of school bonding over time. As detailed in our paper, we proceeded through a series of steps, using fit indices and chi-square tests, to find

Table 2 Additional resources

Method	Additional resources
Latent growth curve models	Singer and Willett (2003); Curran et al. (2010)
Mediation models	MacKinnon (2008); MacKinnon and Fairchild (2009)
Latent class models	Collins and Lanza (2010); Lanza and Rhoades (2013)
Propensity score models	Guo and Fraser (2010); Shadish and Steiner (2010); Stuart and Rubin (2008)

the best-fitting model. Our final model on the trajectory of school bonding was quadratic: showing initial decreases that slowed down over time. It is important to note that the LGM models estimate the average developmental pattern of school bonding across all individuals, which are often termed ‘fixed effects’. However, individuals can vary extensively in their own trajectories, which can be seen in significant random effects. Thus, random effects captured individual variability in the developmental pattern of school bonding. Once we identified the appropriate trajectory for school bonding, we proceeded to investigate how certain predictors may affect the shape of this curve. For example, do youth substance use and delinquency affect the developmental course of school bonding? In our paper, we found that delinquency was linked with the initial level of school bonding at the first study time point, when youth were in Grade 6. Substance use was also associated with the slope of school bonding—that is, youth who used more substances had greater reductions in school bonding over time. In our study, LGM provided the opportunity to investigate changes in school bonding over time. Many of the effects of risky behaviour on school bonding happen early—by Grade 6.

Another way to use LGM models is to explore how variables experienced at certain time points along the growth trajectory account for performance at that specific time. In the example above, delinquency was related to initial school bonding levels at Grade 6 and substance use was associated with the rates of school bonding reduction over time. This pattern was observed across individual students in the sample. However, there was variability across students—some started with higher or lower levels of school bonding, some experienced decreased bonding more or less rapidly over time. Along with this variability across students, there may have been variability of school bonding change within students. That is, at different time points in their middle-school trajectories, another variable could have accounted for unexpected increases or decreases in school bonding that were not explained by students’ predicted trajectories or substance use. That kind of variation is called within-person variation, and extensions of LGM can be used to explore

across- and within-person variation simultaneously in developmental processes (Curran *et al.*, 2014).

For example, we used this technique to examine how time-varying effects of classroom instruction and composition accounted for within-child variability in academic performance from kindergarten to Grade 3 (Kainz and Vernon-Feagans, 2007). Like the example above, we first identified the average growth pattern of reading development from kindergarten through Grade 3. Then we used family and child characteristics to predict children's initial reading status and rates of reading growth over time. Because we hypothesised that classrooms have a large effect on student learning and that classroom instructional quality varies each year that a child is in school, we were particularly interested in how these changes in instructional quality along with the racial and poverty composition of schools affected learning in a particular year contained in the reading development trajectory. Using this method, we learned that high-quality instruction in kindergarten and Grade 1 led to higher reading scores that year than might have been expected given students' predicted trajectories and child and family characteristics. However, the power of high-quality instruction to disrupt trajectories was no longer apparent by Grade 3. We also learned that children who attended racially segregated schools performed lower than expected in reading each year from kindergarten to Grade 3. Moreover, the magnitude of the negative relation between school segregation and reading at a particular grade level increased steadily from kindergarten to Grade 3. By modelling within-person variability in performance across a change trajectory, we were able to uncover important aspects of the learning environment that predicted child reading skills at a given time point, highlighting the opportunity for specific interventions introduced at specific time points to produce better developmental outcomes.

Strengths and limitations

There are many benefits to using a LGM approach, one of which is that it allows researchers to understand change over time. This is critical in prevention science, as many of the effects of a risk or protective factor may not be apparent immediately, but may emerge over time (Hawkins, 2006). Statistically, these models account for the nested nature of longitudinal data, where participants provide many observations (Raudenbush and Bryk, 2002; Singer and Willett, 2003). However, a drawback to using LGM models is that at least three data collection points are needed for a simple linear model, and multiple data points are needed for more complex curves, such as quadratic or cubic shapes (Singer and Willett, 2003). Further, LGM models reveal average patterns of change over time in a sample—without multiple data points,

they may mask very short-term changes that are not sustained. They may also not capture patterns of change among subgroups. Advanced extensions of these models are available to explore subgroup differences (e.g. growth mixture models) and more complicated trajectories (e.g. curves with a spline).

Mediation models

Mediation models are an effective tool for understanding how a risk or protective factor may be linked to an outcome. That is, mediation serves to identify the underlying processes of risk and protective factors—specifically, why and how they work (MacKinnon, 2008). These models are particularly useful for creating and testing logic models for intervention development (Dishion and Patterson, 1999).

Examples

In our work, we have used mediation models to understand the process of parent–child communication and how it is linked to youth substance use (Lippold *et al.*, 2014b). In particular, we examined how youth disclosure of information, parent supervision and active parent efforts to monitor were linked to later youth substance use and delinquency. We were particularly interested in whether or not the effects of disclosure, supervision and monitoring on youth outcomes occurred through (i.e. were mediated by) parental knowledge. More specifically, our mediation model tested whether it was necessary for disclosure, supervision and monitoring to lead to knowledge for these factors to have effects on substance use. Our models used three waves of data, allowing us to obtain temporal precedence: our predictor variables (disclosure, supervision, monitoring) were measured at Wave 1, our mediator (knowledge) was measured at Wave 2 and our outcomes (substance use, delinquency) were measured at Wave 4. We found that parental knowledge mediated the links between both youth disclosure and parental monitoring with our outcomes. However, parental knowledge did not mediate the effects of supervision on outcomes. Thus, disclosure and monitoring were likely to lead to reductions in substance use and delinquency if parents were able to obtain knowledge from these communication processes. Further, little evidence emerged that parental supervision was linked to substance use or delinquency through these same processes. Thus, interventions to prevent youth substance use and delinquency may be most effective if they focus on parental solicitation and disclosure and teach families ways to engage in these behaviours that lead to knowledge of youth activities.

Social work and developmental theory may indicate that these pathways are likely to differ across groups, in which case moderated mediation can serve as an important theory-building and testing analytic tool (Preacher *et al.*, 2007). For example, we used moderated mediation in analysis of the Abecedarian sample—a random assignment to early education study that has followed children from infancy to adulthood (Pungello *et al.*, 2010). Our method proceeded in two stages. First, we examined whether the relation between risk factors in early childhood and educational attainment by adulthood were mediated by the learning environment in the home during childhood. Second, we tested whether the mediating effect of the learning environment was moderated by intervention condition (i.e. if the mediating links differed between participants in the experimental and control groups). Significant evidence of mediation was present at the first stage, indicating that, in the overall sample, the home environment mediated or partially explained the relation between early risk and subsequent educational attainment. In addition, there was also a significant interaction between risk and experimental group predicting educational attainment. This interaction indicated that the mediating effect was not identical in the experimental and control groups, providing a warrant to test the simple mediation model in each group. Within-group analysis indicated that mediation was present and significant for the experimental group, but not for the control group. This extension of the mediation model can serve social work researchers as they seek to build and test developmental theory by examining how and for whom risk and protective factors work.

Strengths and limitations

Understanding how risk and protective factors affect youth outcomes provides important information for the design of interventions and treatments to prevent youth problem behaviours. However, there are some limitations. Mediation models can be conducted on cross-sectional data. However, models are stronger if they are conducted on longitudinal data with data from at least three occasions (Collins, 2006). Gathering data from three time points allows researchers to establish the necessary temporal precedence in their models: stronger inferences can be made if the initial predictor variable occurs before the mediator and if the mediator occurs before the outcome (Collins, 2006). Although establishing temporal precedence increases our confidence of the direction of the mediating process, it is difficult to assess whether changes in the mediator cause changes in the outcome. Recent extensions include models that incorporate causal inference techniques into mediation models (Coffman, 2011).

Latent class and profile analysis

Mixture models are a category of analyses that involves detecting subgroups in a sample, where the members of the subgroup share a similar pattern of association on multiple measures. Regression techniques and the statistical methods described above are very useful for examining the predictive relations between one or a set of independent variables and a single developmental outcome, including when that single outcome is measured over time. However, there may be combinations of variables that share a complex relationship with developmental outcomes, and these complex patterns are difficult to detect with standard regression techniques.

Mixture models, such as latent class and latent profile analysis (Muthen, 2001; Sterba, 2013), are a useful tool for identifying combinations of risk and protective factors, and investigating their linkages to youth outcomes (Collins and Lanza, 2010; Lanza and Rhoades, 2013). In particular, latent class/profile models identify subgroups in the sample, given their scores on particular indicator variables. In the field of prevention, latent class models have been used to identify combinations of risk and protective factors in families and to investigate how these combinations of risk factors may be linked to youth outcomes (Lanza *et al.*, 2010, 2013). Latent class models detect subgroups that are correlated on a set of categorical indicators (e.g. yes/no; high, low, medium) and latent profile models represent subgroups that are correlated on a set of continuous indicators. Both latent class and latent profile models take a holistic approach to understanding risk and may shed light on how many different factors may work together to influence youth development.

Examples

For example, in our work, we have used LCA methods to understand how parent and youth reports of a number of behaviours related to parental knowledge of youth activities were linked to youth substance use (Lippold *et al.*, 2013). In particular, we were interested in understanding how parent and youth reports of a host of knowledge-related behaviours—such as child disclosure, parental monitoring, supervision, parental knowledge and the amount of communication—were associated with youth substance use. Prior studies had examined how specific aspects of parent–youth communication were linked to youth outcomes. Many of these studies had examined the effects of one aspect of parent–child communication on youth substance use (e.g. child disclosure), while controlling for other aspects (e.g. parental solicitation). Yet, families were likely engaging in many knowledge-related behaviours simultaneously, and parents and youth likely had different perceptions of these

behaviours. Because we wanted to identify the different patterns in which knowledge-related behaviours are related to youth substance use, we used latent class analysis to identify classes of families that used combinations of knowledge-related behaviours to examine how these classes were associated with youth substance use.

LCA analysis typically proceeds through two steps. In a first step, we used model identification procedures (Collins and Lanza, 2010) to identify the best-fitting model and the appropriate number of latent classes or subgroups. Model fit was determined by examining fit indices as well as utilising theory on parental knowledge. Our analysis revealed five latent classes that we termed High Monitors, Maternal Over-Estimators, Low Monitors, Communication-Focused and Supervision-Focused. These subgroups had distinct patterns of our knowledge-related behaviours, many of which included parent and youth perceptions of parental monitoring, parental knowledge, parent-child communication, supervision and youth disclosure. High Monitors were families that engaged in high levels of all knowledge-related behaviours according to mothers and youth (e.g. high in parental solicitation, child disclosure, supervision, knowledge and communication). Maternal Over-Estimators were families where mothers reported high levels of all knowledge-related behaviours yet youth reported low levels of knowledge-related behaviours. Communication-Focused families engaged in high levels of all behaviours except for supervision according to parents and youth. Supervision-Reliant families engaged in high levels of supervision but low levels of all other knowledge-related behaviours. Low Monitors engaged in low levels of all knowledge-related behaviours according to mothers and youth.

In a second step, we investigated how membership in these classes was linked to youth substance use. In LCA, multivariate regression is used to estimate the odds of engaging in substance use given membership in a particular class, relative to a reference group. Our analysis suggested that substance use was linked to increased membership in three of our classes: Low Monitors, Supervision-Reliant and Maternal Over-Estimators relative to the High Monitors. Youth in families that relied solely on supervision, and who had mothers who reported higher levels of knowledge behaviours than youth, were at increased risk for substance use, suggesting there may be types of families associated with increased risk of early youth substance use. Thus, our work may help social workers identify combinations of risk factors that may be present in families they work with. In particular, the results suggested that families where mothers over-estimate their knowledge and communication in relation to youth may be particularly important to target in interventions. Further, results suggest that programmes may be more effective if they target communication in families that is initiated by both parents (parental solicitation) and youth (child disclosure). Parental supervision

may be most effective when it occurs in combination with high parental knowledge and communication.

These models can work equally well with programme-level data and with continuous outcomes. We used latent profile analysis to explore subgroups of home-care providers based on the joint associations of multiple care quality measures (Forry *et al.*, 2012). The latent profile technique allowed us to examine home-care quality using five different quality measures commonly used by states to license home-care sites. These different measures captured different aspects of quality including safety, care-giver sensitivity, instructional supports and discipline practices. We found that subgroups existed in the sample where some home-care environments were consistently high on all quality measures, some were consistently low on all quality measures and some varied in the quality ratings across measures. Almost 88 per cent of the programmes studied were in the low- and moderate-quality groups, indicating a need for improvement. The identification of subgroups allowed us to predict the conditions associated with obtaining consistently high-quality ratings across measures. We learned that increases in years of education and experience were associated with membership in the high-quality group. These findings were used to guide national efforts to promote home-care quality.

Strengths and limitations

Latent class and latent profile models can be helpful for taking a holistic approach to prevention. In this way, the classes identified may capture more complexity and further our understanding of how risk and protective factors may work together to influence youth outcomes. They are well suited to understanding complex processes that often underlie social work. In many cases, social work researchers will be interested in exploring individual and programme-level subgroups in their data to identify promising prevention methods. The latent class and latent profile analysis techniques can serve researchers by identifying subgroups, depicting individuals' likelihood of subgroup membership, and exploring antecedents and consequents of subgroup membership. However, LCA and LPA models have some limitations. LCA and LPA models identify subgroups in your data specific to your sample, and results may be inconsistent across different samples. Further, these methods are complex and may require large sample sizes (Collins and Lanza, 2010). Small samples may be unable to detect classes, especially small ones. Model identification needs to occur hand in hand with theory, as fit statistics may disagree regarding the best-fitting model. These models are relatively new, so the field is currently developing many advanced extensions, such as pseudo-class draws for classifying individuals into groups, LCA with

distal outcomes and integrating LCA models with models that assess causality (Lanza and Rhoades, 2013; Lanza *et al.*, 2013).

Propensity score models

Ideal experiments, where random assignment to intervention occurs successfully in a representative sample, are the most reliable way to detect the causal effect of an intervention on participant outcomes. However, in many cases, social work researchers wish to administer preventive interventions to target groups as needed, making random assignment undesirable. In other cases, social work researchers seek to understand the effect of a risk/protective factor on participant outcomes and random assignment to that risk/protective factor is neither desirable nor feasible. In these cases, propensity score techniques can be used to reduce bias due to observed confounders from estimates of the relation between preventive intervention or risk/protective factor and outcome (Rosenbaum and Rubin, 1983; Rubin, 2007, 2008; Guo and Fraser, 2010).

Confounders are characteristics of participants—observed and unobserved—that influence outcomes but are not the focus of study. For example, researchers focused on child development in the foster-care system might observe a statistical relation between foster-care placement and behaviour problems and, from this observation, could infer that foster-care is a risk factor for behaviour problems. However, foster-care placements are not randomly assigned, and so it is not defensible to claim that foster-care *causes* behaviour problems: children who are placed in foster-care may be different from children who are not placed in foster-care, and the background characteristics that comprise those differences (e.g. poverty, experiencing abuse/neglect) may be the real causes of behaviour problems. As such, these background characteristics are considered confounders.

Several techniques allow researchers to control for potential confounding variables by adding them as covariates to regression or other correlation-based models. However, these techniques, such as multiple regression or structural equation modeling, are often limited in power, making it difficult to account for more than a few potential confounders in any single model (Guo and Fraser, 2010). Alternatively, propensity score techniques approach random assignment by balancing groups on large numbers of observed confounders—with many studies using twenty or more confounders (Lippold *et al.*, 2014a).

Propensity score techniques typically follow a series of three steps. First, logistic or other regression techniques are used to model sample members' likelihood of having a specific risk/protective factor based on a large set of confounders. Then, the predicted probability of having a non-randomly assigned risk factor is used to form a sample where

individuals with/without a specific risk/protective factor are balanced on the large set of confounders. Conceptually, balancing the sample mimics randomisation by evenly distributing the confounders across groups that either do or do not have a specific risk/protective factor. Balanced groups are typically formed by matching, weighting or stratification. Finally, the effect of a risk factor on an outcome is estimated in the balanced groups, thereby improving the reliability of the estimated relation between risk/protective factor and outcome by eliminating variation due to observed confounders.

Example

In a recent study, we used propensity score methods to improve the estimated relation between one risk/protective factor (parental knowledge of youth activities) and one outcome (youth substance use) (Lippold *et al.*, 2014a). Prior studies had found a link between low parental knowledge of youth activities and youth outcomes, such as substance use. Yet, it was unclear whether knowledge was causally linked to youth outcomes—or whether these associations could be better explained by several confounding factors, such as pre-existing youth problem behaviours or other aspects of the parent–child relationship. For example, one potential confounder in the linkages between parental knowledge and youth outcomes was whether or not parents and youth had a warm relationship. Parents who are warm, supportive and affectionate may be more likely to have knowledge of youth activities and also may be less likely to have children who use substances. It is possible that the associations between knowledge and youth outcomes are not causal in nature, but are driven by other factors in the parent–child relationships, such as warmth. Consequently, we used propensity score techniques to account for thirty-three potential confounders of the linkages between parental knowledge and youth problem behaviour.

We used inverse propensity score weighting to mimic randomisation by balancing the confounders across groups defined by different levels of parental knowledge. Note that, in this example, the non-randomly assigned risk factor was parental knowledge. First, we conducted a regression that yielded a propensity for level of parent knowledge based on thirty-three potential confounders such as demographics, measures of the parent–child relationship and other parenting characteristics. The propensity score was then converted to a weight: individuals with a low probability of having their reported level of knowledge given their levels of confounders were up-weighted and those with a high probability of having their reported level of knowledge given their levels of confounders were down-weighted. The weighting techniques allowed us to create a sample where our confounders were evenly distributed across levels of

knowledge. Second, we checked the balance of the sample—to test whether the propensity score technique resulted in the confounders being evenly distributed across levels of our predictor variable, parental knowledge. We were able to demonstrate that, after applying the propensity weights, parental knowledge was no longer significantly correlated with our confounder variables, suggesting that the propensity methods were effective and that the sample was effectively balanced. Third, we used the weighted (balanced) sample to assess the average causal relationship (ACE) between a predictor and an outcome. Using the balanced sample, we assessed the average causal effects of parental knowledge on youth substance use. Our final analysis in the weighted sample revealed that parental knowledge was significantly associated with substance use, providing greater certainty that the observed confounders were not biasing the estimated relation.

Strengths and limitations

Propensity score techniques are effective tools for reducing bias due to observed confounders when examining the relation between risk/protective factors and youth outcomes. Thus, they may be especially helpful for identifying malleable factors and powerful interventions that drive better youth outcomes. Propensity score techniques vary widely and include weighting, matching and stratification methods. In addition, propensity score techniques include methods for modelling categorical and continuous treatments. Recent extensions of propensity score models include applications to latent class models (Lanza *et al.*, 2013) as well as mediation models (Coffman, 2011). Common across the different methods, however, is the assumption that all confounders are included in the model propensity score model. Therefore, increasing the number and scope of confounders will likely strengthen the analysis. Models will be strongest when they include all confounders that are associated with the outcome variables and any variables that may lead to selection into the intervention condition. In the event that important confounders are not available for inclusion in the propensity score model, that is they remain unobserved, hidden bias may still corrupt estimates of the relation between treatment and outcome.

Conclusion

Marshalling social work research for prevention, so that social and individual problems can be diminished and quality of life improved for many, is a critical agenda worldwide. Preventing mental and behavioural health problems may be an effective strategy to reduce health disparities

and subsequently promote social justice and the well-being of all youth (Kenny and Hage, 2009). Prevention science has been identified as a grand challenge in social work (Uehara *et al.*, 2014) and an important strategy to promote the well-being of all youth. Advances in research methods can serve this agenda by providing new and reliable evidence of the prevention approaches that significantly reduce problems and improve quality of life. Advanced methods such as latent growth models, mediation models, latent class models and propensity score techniques provide exciting new opportunities to promote knowledge of risk and protective factors and their linkages to youth outcomes. This knowledge can be used to bolster social work researchers' capacities to design and evaluate effective interventions. Thus, social work doctoral programmes may be enhanced by training students in these advanced methods and by providing opportunities for students to apply these methods to their own research agenda. Training in advanced methods may give students the necessary tools to understand the aetiology of social disadvantage and behavioural and mental health problems for youth and further, to successfully evaluate whether programmes and policies improve youth well-being. Identifying the most appropriate method and understanding its strengths and limitations is an important first step in learning and applying these advanced methodologies to social work. We encourage readers to read the published studies reviewed here, to access the resources we have identified for further reading in Table 2 and to seek additional training opportunities to serve their research programmes. The methodological advances described in this paper are just a few important examples of what is available for social work researchers.

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