



Examining perceived adolescent socioemotional development and repeated camp experiences using a planned missing data design

Ryan J. Gagnon

To cite this article: Ryan J. Gagnon (2020): Examining perceived adolescent socioemotional development and repeated camp experiences using a planned missing data design, Journal of Leisure Research

To link to this article: <https://doi.org/10.1080/00222216.2020.1787803>



Published online: 20 Jul 2020.



Submit your article to this journal [↗](#)



View related articles [↗](#)



View Crossmark data [↗](#)



Examining perceived adolescent socioemotional development and repeated camp experiences using a planned missing data design

Ryan J. Gagnon 

Clemson University

ABSTRACT

In questionnaire-based research, leisure investigators must balance the need for comprehensive measurement with participant fatigue associated with lengthy questionnaires. Planned missing data designs (PMDD) offer a solution to reduce survey length while maintaining precision in measurement. This study introduces PMDD through an examination of the influence of parental years of camp experience as a child ($M = 2.54$ years) and their child's level of camp experience ($M = 1.39$ years) on parental perceptions of developmental outcomes (PPDO) associated with camp participation. Data were collected from a cross-sectional sample of 699 parents via an online survey examining the influence of repeated camp experiences on adolescent socioemotional development following their child's (M age = 12.25 years) participation in a residential summer camp experience. Utilizing a structural equation model in combination with the PMDD, the results indicated neither parent nor child level of camp experience influenced PPDO score.

KEYWORDS

Missing Data; planned missingness; structural equation modeling; camp; youth development

Those responsible for the design, administration, facilitation, and assessment of recreation and leisure programs are faced with increasing pressure(s) to demonstrate evidence of programmatic efficacy, particularly those charged with serving youth in out-of-school-time (OST) programs and summer experiences (Bialeschki & Sibthorp, 2011; Roth & Brooks-Gunn, 2016). From the perspective of program funders, administrators, and in many cases parents, it is no longer enough for a young person to simply participate in an OST program, these programs must also demonstrate growth in a range of socioemotional skills. Indeed, in response to these escalating pressures, many programs have begun regular assessment to determine if and how they are achieving targeted outcomes, to demonstrate proper stewardship of often scarce resources, and to identify areas in need of programmatic improvement (Durlak et al., 2010; Roth & Brooks-Gunn, 2016). This increasingly normative focus toward the evaluation of OST programs and summer camp experiences has also led to tensions between researchers and practitioners (Henderson et al., 2006; Sibthorp et al., 2013). Specifically, leisure researchers are often faced with challenges between research and practice where researchers charged with assessing a program, exploring a question, or testing a theory often have more questions

than are feasible for a practitioner to implement as a questionnaire in the programs they offer.

The strain between the need for adequate measurement (e.g., sufficient number of questions within a survey to acceptably measure a targeted outcome) and asking too many questions of survey respondents, potentially introducing fatigue, is also an ongoing problem within the broader social sciences (Harel et al., 2015; Rutkowski, 2017). Given the likely sustainment of evidence-based programing and assessment in youth-serving programs (Mihalic & Elliott, 2015), the present study explores a strategy to mitigate the strain between programmers' need for brevity in their measures of program outcomes and researchers' need for depth to accurately capture a leisure phenomenon, a planned missing data approach (Enders, 2010). Utilizing a planned missing data approach, the present study examines two potential influences on the achievement of targeted socioemotional outcomes associated with residential summer camp attendance: (1) the value of repeated parent camp experiences as a child and (2) the value of repeated child camp experiences. Put differently, is more camp better to achieve targeted socioemotional development? Importantly, the overarching intent of the study is to illustrate an applied example of a planned missing data design (PMDD) to those interested in understanding the role and potential of contemporary missing data management within the recreation and leisure sciences. Below, residential summer camp as a developmental context is presented, challenges with missing data are shared, and the current study is introduced.

Residential summer camp as a developmental context

Residential summer camp is a well-established out-of-school-time (OST) context for the development, and/or improvement of socioemotional development, physical health, and relationship skills (Gillard & Watts, 2013; Henderson, Thurber, et al., 2007; Sibthorp et al., 2013). For example, Garst and Gagnon (2016) illustrated in a study of 2952 parents, that as a result of their child attending camp, parents observed significant development across five targeted socioemotional outcomes: communication, responsibility, self-regulation, attitude, and exploration. For many campers and their families, the benefits of attending camp are longstanding and substantial (Dawson, 2017). At a broad level, camp research indicates the relationships, growth, and development campers associate with their camp experience(s) has led to improved long term readiness for both academic experiences (i.e., college) and positive growth in later career preparedness (Whittington & Garst, 2018; Whittington et al., 2017; Wilson & Sibthorp, 2018).

Despite the seeming breadth of evidence demonstrating the positive relation between camp attendance and outcome achievement, residential summer camps, and other OST programs are facing escalating pressures to demonstrate programmatic efficacy, with often declining resources to do so (Bialeschki et al., 2007; Sibthorp et al., 2013). In response to these demands, research exploring how to best maximize programmatic benefits for youth has greatly expanded (Bialeschki et al., 2007; Roth & Brooks-Gunn, 2016). Indeed, within broader OST contexts, a central question relates to "when and how does participating ... matter" (Simpkins, 2015, p. 121). More specifically, an understanding of the factors that allow for the most potential to be squeezed out of OST

experiences like summer camp could facilitate more youth and young people to be served by these same programs.

Specifically, within the camp research context, a longstanding question is how much of camp is necessary to achieve targeted outcomes, with conventional wisdom suggesting that more camp (e.g., repeat attendance) is better (Thurber et al., 2007). More simply, if a child attends camp over multiple years they should achieve iteratively higher rates of targeted outcomes. Crucially, this “conventional” wisdom does not always bear out in the literature. For instance, in a review of the relation between OST program participation and outcome achievement, Roth et al. (2010) noted no systematic relation between repeated participation and enhanced outcome scores. Conversely, both Simpkins et al. (2004) and Tiffany et al. (2013) demonstrated a positive relation between repeated participation in OST programs and increased rates of outcome achievement. Further, in a study of camp alumni and positive youth development, Garst et al. (2016) demonstrated positive associations among repeated camp attendance, positive youth development, physical wellbeing, and self-determinate behaviors. In brief, the link (or lack thereof) between rates of OST program attendance and outcomes is somewhat contradictory in the broader OST literature (Eisman et al., 2018), and even less so in residential summer camp contexts (Gagnon, 2019). Thus, an understanding of how outcomes may relate to repeated camp experiences may provide researchers and practitioners with additional evidence on whom (and perhaps whom not) to serve given limited resources.

There appears to be a relatively well developed body of literature examining the potential influence(s) of child participation levels on OST program outcomes (Roth & Brooks-Gunn, 2016; Simpkins, 2015). However, there is less clarity regarding parental influences on the quantity of their OST program participation and the corresponding outcomes achieved by their child in OST programs. As suggested by Bohnert et al. (2010) and Gagnon (2019), other factors such as a family’s resources, perceptions of OST programs, and their own level of prior experiences in similar settings may not only influence their child’s rate of participation but also the value the parent(s) perceive from their child’s participation in a particular activity. In a study exploring parent anxiety associated with camp, Kingery et al. (2012) demonstrated lower rates of camp experience were associated with higher rates of child and parent anxiety. Camp alumni research also illustrates the potential connection between camp attendance and outcome achievement, where former campers associate their camp experience with a wide range of positive emotional, economic, and career outcomes (Brandt & Arnold, 2006; Whittington et al., 2017; Whittington & Garst, 2018); thus, there could be links between parents level of camp experience as a child themselves (or lack thereof), and the value and/or developmental outcomes they associate with their child also attending camp (Garst et al., 2016; Henderson, Scheuler-Whitaker, et al., 2007).

Pivoting to this study’s intent, applying a PMDD, seems particularly appropriate given the heavy reliance on questionnaire-based research within residential summer camps. These relatively normative questionnaire-based studies include the examination of the influence(s) of parental behaviors on camp outcomes (Gagnon, 2019), camp as a context for positive youth development (Sibthorp et al., 2013; Thurber et al., 2007), and camp as a mechanism to improve autonomy, relatedness, and competencies associated with chronic illness (Hill et al., 2015). While these survey-based approaches are

relatively normative within camp settings (Garst & Gagnon, 2016; Henderson, Thurber et al., 2007; Sendak et al., 2018; Sibthorp et al., 2013), so are the broader concerns about research negatively impacting the camp experience itself. As noted by Henderson, Bialeschki, et al. (2007), "... camp directors and staff are busy people who invest great energy in planning and implementing quality camp programs, leaving little time for conducting rigorous research and evaluation" (p. 757). Thus, the reductions in survey length that may be realized with the application of planned missing data designs, offer those concerned with reducing the intrusiveness of research, a tool to mitigate this important concern.

Unplanned missing data: Some basics

Prior to examining the methodological focus of the present study, planned missingness, it is useful to examine "unplanned missingness." Unplanned missingness within leisure research is typically represented by incomplete questionnaires and skipped questions. How this missing information is managed represents a common challenge facing leisure researchers in understanding why a particular question may have been skipped and/or omitted (Freire & Caldwell, 2013; Whitehead, 1994). The causes of this missing information are generally multidimensional (e.g., uncomfortable questions, survey fatigue, unplanned survey outages), and are represented by one of three "missing" mechanisms. Ideally, data are missing completely at random (MCAR), where the missing data are entirely unrelated to the observed or missing variables (i.e., there is no quantifiable systematic cause of missingness; Rhemtulla & Little, 2012). In a MCAR scenario, the data are missing due to chance events (e.g., a participant's cell phone battery dying while they complete a questionnaire), are not systematic in nature, and typically represent a small proportion of the total sample (Buuren, 2018).

The second mechanism of missingness occurs when data are missing at random (MAR), where the missing data are related to observed variables, potentially allowing for the researcher allowing for the researcher to mitigate possible causes of missingness and/or confounds to their research question (Little & Rhemtulla, 2013). For instance, respondents without internet access could be less likely to provide social media preferences, suggesting the missing data are related to rates of internet connectivity; this is of course predicated on the researcher having data regarding rates of internet connectivity. Importantly, while MAR data are less desirable than MCAR data, they also represent an additional research question, where the systematic cause is known, and thus investigable. Moreover, in scenarios with MAR data, there is a robust suite of tools to manage, explore, and potentially mitigate the covariates and/or predictors of missingness (Enders, 2010; Buuren, 2018).

The third mechanism of missingness occurs when data are missing not at random (MNAR). In MNAR scenarios, the missing data are dependent on other missing values (Ludtke et al., 2017). Put differently, the reason for the missing data is unknown(able) to the research team. For example, persons who have lower reading ability may skip more complex questions; however, without collecting information on reading levels from respondents, the research team may be unable to determine why a sub-sample skipped certain questions (Buuren, 2018). In this instance, there is typically not an

approach to predict or recover the missing information as the missing data is generally unavailable to the researcher (Rhemtulla & Little, 2012).

Beyond the primary mechanisms of missing data (i.e., MCAR, MAR, and MNAR), how missing data are managed is also multifaceted. Across the social and behavioral sciences, common approaches to the management of missing data reflect techniques, that while relatively pervasive, are also severely problematic (Newman, 2010). Seemingly, the most common approaches are deletion-based techniques, where a respondent is removed from the data set if they fail to complete all questions. In an extreme case, deletion based techniques effectively treat a respondent who completed 99 of 100 questions as identical to a respondent who completed 50 of 100 questions, both ending in their removal from proceeding analyses. Deletion based approaches require assumptions that are untenable for nearly all social science research and likely lead to increased rates of Type II error and biased study results, due to inaccuracy in standard errors and corresponding changes in estimates of effect size (Enders, 2010; Newman, 2010). Despite these limitations, deletion-based approaches remain as the default option in many software packages utilized by social scientists (e.g., SPSS, Lavaan, EQS), conceivably perpetuating their use (Field, 2018; Jamshidian & Jalal, 2010; Rosseel, 2012).

Beyond deletion-based approaches, a family of imputation based techniques has also emerged to address missing data (e.g., mean, regression, stochastic regression, hot deck), where a value is generated based on some available information and entered into missing cells, which also can harm the veracity of study results (Silvia, et al., 2014). Indeed, simulations under ideal missing data conditions (i.e., MCAR) comparing these approaches to modern techniques (e.g., multiple imputation, full information maximum likelihood) typically result in inflated rates of Type 1 error, biased parameter estimates, and problematic standard errors (Enders, 2010). While these approaches remain common in some sectors of leisure and recreation research and the broader social sciences, they diminish the support and validity of a particular study's results, perpetuate outdated techniques, and advance theories that could otherwise be discounted (Appelbaum et al., 2018; Freire & Caldwell, 2013).

How should missing data be managed?

In ideal circumstances, the researcher would not have missing data. Indeed, the use of “forced choice” options in online questionnaires have emerged as a response to prevent missing data, where the respondent is required (i.e., forced) to reply to an item in order to proceed through the questionnaire. However, it has also been demonstrated that the use of forced choice techniques can harm data quality and increase rates of careless responders (see Curran, 2016; Décieux et al., 2015). Put differently, missing data is likely to occur, even in a well-designed questionnaire. In recognition of the limitations associated with forced response survey designs and parallel problems with deletion based and many imputation approaches, two “modern” techniques are available to manage missing data, full information maximum likelihood (FIML) and multiple imputation (MI) (For a detailed description and tutorial of these techniques in practice see Buuren, 2018; Enders, 2010). In FIML approaches, all observed parameters, (hence “full information”) are utilized to estimate missing values and errors within the data set, and then these

estimates are utilized in parallel analyses (e.g., confirmatory factor analysis) (Cham et al., 2017; Enders, 2001). Conversely in MI approaches rather than estimating missing values, the “values are generated for each missing value in the data set... the results are combined... to achieve parameter estimates and standard errors...” (Rhemtulla & Little, 2012, p. 427), and depending on the software package, values based on these analyses are imputed into the previously blank cell, over several iterations, creating multiple data sets, which are then merged for later analyses. In both the FIML and MI estimation techniques, the results are typically statistically equivalent (Bentler, 2006; Newman, 2010) and in simulated studies, generally as accurate as those with complete data available.

Planned missingness

With the emergence of FIML and MI estimation techniques, there is also a relatively recent shift in some social science research from reacting to unplanned missing data, to a more intentional strategy which capitalizes on the strengths of FIML and MI techniques, planned missing data designs (Graham et al., 2006). Rather than reacting to reductions in item variance due to survey length and/or reducing the number of items within a questionnaire, thus reducing potential research quality, a planned missingness approach mitigates challenges with missing data by reducing the overall length of a questionnaire (Jorgensen et al., 2014). Beyond the utilization of planned missing designs for issues relating to fatigue, they may also be applicable for measures requiring additional resources (e.g., biomarker tests), those of a sensitive nature (e.g., illicit drug use), and longitudinal designs (Décieux et al., 2015; Enders, 2010; Harel et al., 2015).

As noted by Little and Rhemtulla (2013) there are several formats to implement PMDD. For instance, in longitudinal studies (e.g., those with multiple time-points), a wave design is frequently implemented where participants are randomly assigned to be excluded from particular waves (e.g., time points) over the duration of a study. Similarly, in a cross-sectional study (e.g., a single period of data collection) respondents are randomly assigned to a panel of questions that include a specific set of items and exclude others (Enders, 2010). Importantly, in both wave and panel designs a set of common items proceeds the planned missingness. For instance, as presented in Table 1 and illustrated in Figure 1, all respondent panels complete block A, and then are randomly assigned to either blocks 1, 2, or 3. The information collected within block A is typically a combination of demographic information (i.e., gender, race, SES) and some information relating to key dimensions of the study (i.e., attitudinal and behavioral measures), acting as auxiliary variables for later missing data

Table 1. Simple three-form design.

	Block A	Block 1	Block 2	Block 3
Form X	X	X	X	●
Form Y	X	●	X	X
Form Z	X	X	●	X

Note. ● Indicates missing data; X indicates complete data.

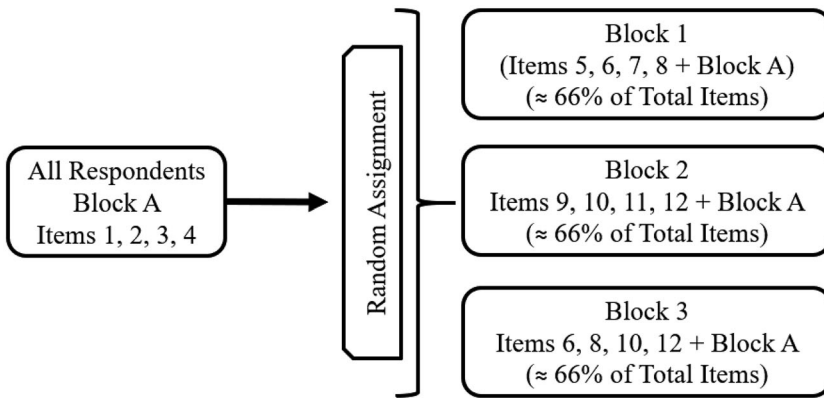


Figure 1. Visualization of example planned missingness flow. 12 possible items in the illustrated example, with each respondent completing all of block A items (items 1–4) and then randomly assigned to either Block 1, 2, or 3 to complete an additional 4-items, totaling 8 of 12 possible items.

management. With the simple panel design presented in [Table 1](#), respondents complete about 66% of total questions.

As described earlier, there are multiple approaches to manage missing data (deletion, imputation) and the more empirically appropriate maximum likelihood based techniques such as MI and FIML. Preceding the management of missing data, investigating the mechanism(s) of missingness are a necessary condition. To understand if the cause of missingness is known (e.g., males tended to skip a question about political views at greater rates than females) or if the reason for the skipped question is unknown to the researcher (e.g., respondents with poorer reading levels skipped more lengthy questions), the researcher must test the missing data mechanism(s) to determine if they are MCAR. If the MCAR threshold is not met, the researcher must identify and (where possible) address the mechanism(s) of missingness (Kim & Bentler, 2002; Little, 1988). Critically, as noted by Newman (2010), while MCAR is typically the most desirable mechanism of missing data, it may rarely appear in practice. However, in the case of a planned missing design, the systematic cause of the missing data is random, and by definition MCAR (Little & Rhemtulla, 2013).

The present study

This study was guided by two goals: (1) to illustrate and apply a relatively new approach to quantitative research examining the potential socioemotional benefits of leisure and recreation experiences like summer camp, a planned missing data design, and (2) to examine the potential effect(s) of repeated summer camp experiences on socioemotional outcomes. Consequently, the study was guided by two primary hypotheses: Parents of campers with higher rates of camp attendance will report higher rates of perceived developmental outcomes in their child (H1). Similarly, parents with greater levels of parent camp experience as a child themselves will report higher rates of perceived developmental outcomes in their child (H2).

Method

Sample and Procedures

As part of a larger study exploring the potential benefits of structured OST programs and parental influences on these programs, the present study took place over the summer of 2018 with two nonprofit camp organizations located in the southeast United States. These organizations were selected for inclusion in the current study due to their robust history of program assessment and well-established parental communication channels via electronic messaging (e.g., email and social media). Camp sessions at both organizations were co-educational residential (i.e., overnight on-site) experiences typically lasting between 5 and 7 days (4–6 nights). The organizations shared similar targeted outcomes for participants including the development and/or improvement of socioemotional skills (i.e., attitude, responsibility, exploration) through a diverse array of intentionally-designed activities and programs including shooting sports, environmental sciences, and wilderness exploration.

Upon institutional review board approval, data were collected from 726 parents of campers. Specifically, parents were sent an email from their corresponding camp organization 1 week after the completion of their child's camp attendance with instructions to complete the embedded Qualtrics questionnaire link. One-week later parents were sent a reminder to complete the questionnaire if they had not already done so. To incentivize participation, entry to win one of six \$50.00 gift cards was offered to respondents. After data diagnostics and testing for multivariate outliers, 27 respondents were removed from the data set (described below), leading to a final sample of 699. The combination of emails and the gift card drawing led to an overall response rate of 37.90% to the questionnaire (699 respondents/1844 potential respondents = 37.90%).

Parent respondents were primarily female (87.8%; Male = 12.2%). As compared to the state where the camps were located, respondents were relatively affluent (Average Household Income = \$135,964, $SD = \$74,505$, $Mdn = \$125,000$; 2018 state median income = \$48,781) and educated, with 78% of the sample reporting a current education level of a bachelor's degree or greater (2017 state percent with bachelor's degree = 27%) (U.S. Census Bureau, 2019). Parent respondents identified primarily as white, not Hispanic or Latino (87.8%; 2018 state average = 63.7%), with African American (5.7%; 2018 state average = 27.1%), Hispanic or Latino origin (2.6%; 2018 state average = 5.8%), multiple race (2.3%; 2018 state average = 1.9%), Native American (0.9%; 2018 state average = 0.5%), Indian or Arabic origin (0.4%), and Asian origin (0.3%) (2018 state average "Asian alone" = 1.8%) representing the remainder of the study sample (U.S. Census Bureau, 2019). Parents reported an average of 2.54 years ($SD = 2.82$ years, range = 0–17 years) of attending camp when they were a child.

Children, about whom parents were reporting, were primarily male (52.4%; female = 47.6%) with two children identified as non-binary. Children were on average 12.24 years of age ($SD = 2.59$ years) and had attended camp for an average of 1.39 years ($SD = 0.82$ years; range = 1–7 years). As with parents, children were primarily identified as white, not Hispanic or Latino (84.4%), with African American (6.3%), multiple race (5.3%), Hispanic or Latino (2%), Asian origin (0.9%), Native American (0.7%), and Indian or Arabic origin (0.4%) representing the remainder of the sample.

Table 2. Missing data patterns.

Factor/item	Sample size	Percent missing (%)	Missing data condition
Responsibility			
... takes responsibility for their own actions	698	0.14	None
... takes care of their own things	698	0.14	None
... can be trusted to do what needs to be done	698	0.14	None
... follows through when asked to do something	698	0.14	None
... follows directions	695	0.57	None
Attitude			
... doesn't get frustrated easily●	450	35.62	B
... has a good mental attitude	463	33.76	A
... has a generally "positive" view on life	458	34.48	C
... shows a positive attitude when around others	450	35.62	B
Exploration			
... participates in new learning experiences	453	35.19	C
... is curious about new topics and subjects	442	36.77	B
... seeks challenges beyond their comfort zone	457	34.62	A
... is willing to try new experiences	453	35.19	C

Note. ● Indicates item removed from analyses after measurement model testing; numbers and percentages are at post analyses levels.

Missing data procedures

Upon opening the link to the questionnaire, parent respondents provided basic demographic information regarding themselves and their child attending camp. Next as illustrated in Table 2, all respondents completed the items within the responsibility factor. Upon completion of these items, respondents were then randomly assigned to one of three conditions (i.e., condition A, B, or C), which consisted of the additional item sets. This planned missingness design is based upon the simple three-panel approach described in Enders (2010). Importantly, this approach reduces the participant number of items approximately 33%, while the embedded MCAR conditioning of the data does not introduce undue bias into later analyses.

Measures

Parental perceptions of developmental outcomes

To assess parent perceptions of developmental outcomes (PPDO), a modified version of the PPDO was utilized in the present study due to its previously established psychometric properties (Garst & Gagnon, 2016; Gagnon & Garst, 2019) and alignment with the targeted outcomes of the study sites. The PPDO was initially designed with five factors measured on a 1 (Strongly Disagree) to 5 (Strongly Agree) scale. The five factors exhibited acceptable levels of internal consistency (communication $\alpha = .88$; responsibility $\alpha = .85$; self-regulation $\alpha = .84$; attitude $\alpha = .89$; exploration $\alpha = .82$) in prior applications (e.g., Garst & Gagnon, 2016). The initial PPDO was orientated toward parental observations of socioemotional skills resulting from structured out-of-school-time (OST) experiences, where higher scores indicate improvement or change in a desired socioemotional skill. Due to evidence of ceiling effects presented in Garst and Gagnon (2016) (e.g., participant scores clustering toward the high end of the scales), the PPDO was adapted to a 1 (strongly disagree) to 7 (strongly agree) Likert scale where higher values also suggest improvement in the measured socioemotional skill within the present study. Additionally, due to misalignment with the study site targeted outcomes, the self-

Table 3. Descriptive and confirmatory statistics.

Factor/item	<i>M</i> ♦ (<i>SD</i>)	λ	α	AVE
Parent perceptions of developmental outcomes**			.77	.52
<i>Responsibility*</i>		.75		
<i>Attitude*</i>		.69		
<i>Exploration*</i>		.73		
Responsibility*			.90	.64
... <i>takes responsibility for their own actions</i>	5.67 (1.068)	.73		
... <i>takes care of their own things</i>	5.52 (1.123)	.78		
... <i>can be trusted to do what needs to be done</i>	5.84 (1.005)	.87		
... <i>follows through when asked to do something</i>	5.45 (1.019)	.81		
... <i>follows directions</i>	5.78 (0.939)	.79		
Attitude*			.91	.77
... <i>has a good mental attitude</i>	5.91 (0.98)	.92		
... <i>has a generally "positive" view on life</i>	5.93 (1.06)	.90		
... <i>shows a positive attitude when around others</i>	6.06 (0.88)	.81		
Exploration*			.87	.62
... <i>participates in new learning experiences</i>	6.34 (0.72)	.79		
... <i>is curious about new topics and subjects</i>	6.30 (0.81)	.76		
... <i>seeks challenges beyond their comfort zone</i>	5.70 (1.18)	.79		
... <i>is willing to try new experiences</i>	6.12 (0.94)	.82		

Note. Parental Perceptions of Developmental Outcomes is a 2nd order factor reflecting three 1st order factors treated as items (indicated by *); ♦ Means (*M*) are based upon Full Information Maximum Likelihood (FIML) Values; λ : standardized coefficient (factor loading); AVE: Average Variance Extracted; α : Cronbach's alpha.

regulation and communication factors were not utilized in the present study. Additionally, Gagnon and Garst (2019) suggested the PPDO had unacceptably high between factor correlations ($r > .70$), describing the necessity of examining alternative factor structures (e.g., 2nd order factor) to mitigate challenges with this potential collinearity (Brown, 2015; Byrne, 2006). Consequently, in the present study, the PPDO was modeled as a second-order factor (i.e., common cause) of three respective first-order factors, comprised of 13-items in total (see Table 2 for complete list of items and factors). As indicated in Table 3, all factors exhibited acceptable levels of internal consistency in the present study (e.g., $\alpha = .77$ –.91), paralleling results of past studies using the selected scales.

Data diagnostics and planned analyses

After collection, the data were screened in SPSS 24 for multivariate outliers using a combination of the Chi-square distribution function ($p < .001$) and Mahalanobis distance (Field, 2018), which indicated 27 respondents exceeded these criteria, and were removed from subsequent analyses. Next, the data were transferred to RStudio (version 1.2.5042) and screened for multivariate normality utilizing the MissMech package (version 1.0.2), as this package allows for tests of normality with missing data (Jamshidian & Jalal, 2010). Specifically, the multivariate normality and homoscedasticity function was utilized, which demonstrated non-normal distributive properties in the data set (i.e., Hawkins test, $p < .001$; Anderson-Darling nonparametric k -sample test, $p < .001$) (Jamshidian & Jalal, 2010). Given the evidence of non-normality, a robust maximum likelihood estimation technique with Huber-White standard errors (MLR) was utilized for assessment of model fit quality, parameter estimation, and hypotheses testing (Bentler, 2006; Rosseel, 2012).

Prior to testing of the study hypotheses with a structural equation model, the measurement properties of the scales were assessed utilizing Confirmatory Factor Analyses (CFA) and corresponding statistical criteria in the Lavaan package (version 0.6–5) (Rosseel, 2012). Specifically, both the measurement model and structural equation model fit was examined, employing the robust versions of two relative indexes of fit, the Tucker-Lewis Index (TLI) and Comparative Fit Indices (CFI). In both the CFI and TLI levels closer to one (e.g., CFI > .900) illustrate how the tested model is an improvement over the baseline model (Kline, 2016). Additionally, the robust version of the Root Mean Square Error of Approximation (RMSEA) and its 90% confidence interval was utilized to assess absolute goodness of fit, where levels closer to zero [e.g., RMSEA = .070, (90% CI .060–.080)] indicate better model fit (Brown, 2015; Rosseel, 2012). Importantly, these conventional model fit cutoff points were used only as reference points, not rigid thresholds to be passed (Hu & Bentler, 1999; Marsh et al., 2004). More specifically, model fit and supporting statistical analyses were contextualized based on prior published analyses utilizing the selected measures, rather than arbitrary cutoff criteria (e.g., CFI = .90 being acceptable, CFI = .89 being unacceptable) (See also Brown, 2015; Kline, 2016; Marsh et al., 2004).

Beyond fit indices assessing the measurement model fit, the convergent validity of the scale was examined utilizing a combination of Cronbach's Alpha ($\alpha > .60$) to assess internal consistency within factors, standardized factor loadings (i.e., pattern coefficients; $\lambda > .50$) to assess the relative associations between observed items and corresponding latent factor(s), and Average Variance Extracted scores (AVE > .50) to assess the level of explained versus unexplained variance accounted for by unique factors (Brown, 2015; Fornell & Larcker, 1981; Kline, 2016).

Missing data analyses

Prior to testing of the measurement model, the data were examined for potential systematic causes of missingness. As noted earlier, respondents completed approximately 66% of total items (i.e., questions) as part of the planned missing design, which bears out upon examination of the missing data patterns, where the three largest patterns of missingness were reflected in the missing data pattern matrix; that is, a respondent's randomly assigned missing data condition (i.e., condition A, B, or C) are reflected in the percent of total questions completed (see Table 2). Importantly, this random assignment should lead to non-significant ($p > .001$) tests of MCAR, which indicates the causes of missingness are nonsystematic. As noted by Jorgensen et al. (2014) "by randomly assigning participants to conditions in which they do not respond to certain items... the mechanism is by definition MCAR, which is the ideal mechanism because it is ignorable" (p. 398).

Given the structural multivariate nonnormality of the data (e.g., Hawkins test, $p < .001$; Anderson-Darling nonparametric k -sample test, $p < .001$), non-parametric tests of MCAR were applied in the present study, to account for this non-normality (Jamshidian & Jalal, 2010; Kim & Bentler, 2002). More specifically, three Generalized Least Squares (GLS) tests of MCAR were examined, which build upon Little's (1988) test of MCAR (Kim & Bentler, 2002) in EQS 6.3 software. The non-significant results of the GLS test of homogeneity of means [$\chi^2_{(108)} = 125.97$, $p = .113$], GLS test

of homogeneity of covariance matrices [$\chi^2_{(245)} = 215.57, p = .914$], and GLS combined test of homogeneity of means/covariances [$\chi^2_{(353)} = 341.35, p = .662$] indicate the patterns of missingness within the data set are nonsystematic and thus MCAR (Bentler, 2006; Byrne, 2006). Correspondingly, a Full Information Maximum Likelihood (FIML) technique was utilized to estimate missing values and errors within the data set for testing of the measurement model and study hypotheses.

Measurement model

Given the evidence the missing data were MCAR, the measurement model was tested through a confirmatory factor analysis (CFA) in RStudio utilizing the Lavaan package and robust estimation techniques (i.e., Satorra Bentler; [S/B]; Maximum Likelihood Robust, MLR; Bentler, 2006; Satorra & Bentler, 1988; 1994). The preliminary measurement model demonstrated acceptable fit: $S/B\chi^2_{(62)} = 242.13, p < .001, TLI = .92, CFI = .94, RMSEA = .06$ (90% CI .05–.07). However, inspection of the factor loadings indicated an unacceptable level in one item within the first order attitude factor: *my child... doesn't get frustrated easily* ($\lambda = .40$). As such the measurement model covariances and were explored for potential solutions to realign this item, but this inspection did not yield acceptable alternative specification (Bentler, 2006). Consequently, the poor-performing item was removed, and the CFA was repeated, which indicated acceptable model fit: $S/B\chi^2_{(51)} = 201.97, p < .001, TLI = .93, CFI = .95, RMSEA = .07$ (90% CI .06–.07). As illustrated in Table 3, the final 12-item measure exhibited acceptable levels of internal consistency both at the first-order level ($\alpha = .87$ –.91) and second-order level ($\alpha = .77$) and acceptable factor loadings (i.e., pattern coefficients) across all factors and items (i.e., $\lambda > .60$).

Results

Given the acceptable measurement properties of the scale, a structural equation model (SEM) was conducted to test the study hypotheses. Similar to the CFA results, the SEM illustrated acceptable fit given the established criteria: $S/B\chi^2_{(73)} = 245.75, p < .001, TLI = .93, CFI = .94, RMSEA = .06$ (90% CI .05–.07). As evidenced in Figure 2, there was no significant effect of prior child camp experience on PPDO score (H1; $\beta = -.07, SE = .06, p = .13, R^2 = .006$), nor was there a significant effect of prior parent camp experience as a child on PPDO score (H2; $\beta = .03, SE = .02, p = .45, R^2 = .006$).

Discussion

The present study applied a relatively new method for the management of missing data, to an often-asked question within leisure and recreation programs serving youth: if some of a program is good, is more better? The study results indicated that within the present study sample, the hypothesized positive effects of repeated child camp attendance or parent experience as a camper on outcomes were not statistically significant or practically meaningful. While the lack of effect was potentially unsurprising considering the lack of effects demonstrated in some prior OST research (Gagnon, 2019; Roth et al., 2010), the causes of outcomes are likely more multifaceted than simply years of

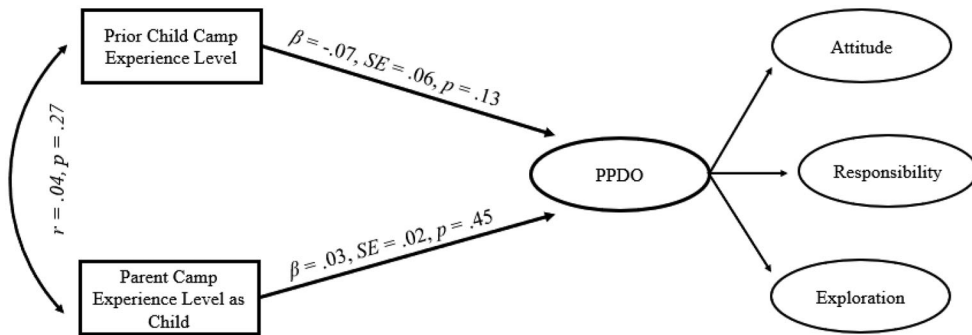


Figure 2. Illustration of SEM Results. β : standardized regression coefficient; SE : robust standard error; p : probability value; r : Pearson's correlation; Missing data constant, error terms, error covariances, and individual items excluded for parsimony of presentation. PPDO: Parent Perceptions of Developmental Outcomes; PPDO is a second order factor.

attendance alone. As suggested by Henderson, Bialeschki et al. (2007), structural components (e.g., session length, day or residential structure, staff training, and budgetary differences) all also likely play a role in the achievement (or lack thereof) of programmatic outcomes. Thus, future assessment of the relation between participation quantity and outcomes should also include assessments of participation quality (Tiffany et al., 2013). Among these participation focused measures, Bohnert et al. (2010) recommend capturing the breadth of participation (e.g., total OST programs), the intensity of participation (e.g., average weekly hours participated relative seasonality of OST activity), engagement (e.g., level of behavioral and emotional attachment to OST activities), and as measured in the present investigation, duration (e.g., number of years participated). The addition of these assessments would likely tell a more complex story of the value of repeated OST experiences on program outcomes. Put differently, a parsimonious explanation may be desirable regarding the linear influence of attendance on outcomes (e.g., more of program X leads to better outcome Y); however it is more likely this relation is influenced by multiple components and systems rather than simply raw years of attendance (Arnold, 2018). Indeed, while the addition of these assessments may cause a researcher to avoid them due to the potential for overextending their measures, a PMDD could reduce the burden on participants and also provide more detail on the relations between the multiple dimensions of participation advised here and assessed outcomes.

Beyond, the additional measurement of how both quantity and quality of participation influence outcomes, nonlinear approaches to explain these relations likely also play a role in understanding how and for whom outcomes are best achieved. For instance, prior research on the influence of OST activity participation levels on outcomes (Knifsend & Graham, 2012) has suggested moderate (versus high or low) levels of participation in OST activities led to the most “optimal” outcomes. Thus, in future investigations, the use of both traditional linear approaches should be combined with curvilinear assessments to determine if and for whom, outcomes are achieved as a result of repeated camp experiences. Importantly, uncovering the ideal level(s) of participation to achieve desired outcomes can allow those charged with resource allocation to make better informed decisions about how and for whom to “resource” when allotting limited opportunities (e.g., scholarships, cabin slots, etc.).

While the hypothesized effects were not detected in the present study, the planned missingness approach appears to have been successfully implemented as evidenced by the non-significant MCAR tests, the consistency of responses over the length of the questionnaire (e.g., Tables 2 and 3), and similar levels of measurement quality to prior studies implementing the PPDO in a non-planned missing approach. The relative success of this approach in a leisure context also provides more evidence on the potential of leisure and recreation contexts not only for research into the benefits and consequences of participation in our subfield, but also illustrates how these same contexts may act as “labs” to improve and/or innovate research methods. For instance, it remains unclear how “unplanned” missingness within PMDD conditions may bias parameter estimates; furthermore, the research in this area is primarily confined to simulations versus real-world applications (Enders, 2010; Rhemtulla & Hancock, 2016; Silvia et al., 2014). This gap offers recreation and leisure researchers an opportunity to not only innovate within their selected subfield(s), but also to contribute to the larger community of social scientists.

Importantly, while planned missingness offers a solution to mitigate fatigue on participants and potential reductions in resources necessary to conduct a study, there remains a fundamental responsibility on the part of the researcher(s) to design studies that are both conceptually appropriate and visually engaging to potential respondents, so they participate fully in the process (Ruel et al., 2015). Crucially, researchers must also commit to appropriate sampling and recruiting techniques, to ensure the respondents who reply accurately reflect the research purpose. Indeed, intentional design of both the esthetic components and study procedures may yield more precise study results (Fielding et al., 2017). Otherwise, the planned missingness approach could fail to accurately reflect the data of the respondents it is intending to.

Planned missing data designs also offer more than a simple strategy to reduce survey length as indicated in the present study. The approach reflected in planned missingness offers researchers the ability to introduce more expensive measurements (e.g., biomarkers, experience sampling) where a respondents “missing” data can be generated, a strategy to reduce the exposure of participants to psychologically challenging questions (e.g., adverse childhood experiences), and an approach to mitigate the sample attrition often associated with longitudinal designs (Enders, 2010; Little, 2013). The science underpinning missing data analysis continues to evolve, with the seeming (re)introduction of Bayesian statistics to latent modeling, the use of paid panel survey “takers” (e.g., MTurk), the growing normativity of latent analytical techniques as part of standard training for many social scientists, “big” data analytics, and increasing access to open source software (e.g., R) for conducting more advanced analyses, previously only accessible to those with the resources to access more economically demanding software packages (Finch & French, 2015; Kline, 2016; Muthen & Asparouhov, 2012; Ophir et al., 2020).

Limitations

While some study limitations have been previously described, a few warrant additional exploration. The cross-sectional design of the study limits the inferences about change associated with repeated camp experiences. A design with multiple waves of data may capture changes in slopes associated with repeated camp experience over time, that

were not reflected in the present study design. At the parent level of data, the sample was relatively homogenous, parent respondents were primarily female, white, educated, and affluent. While these sample limitations are seemingly normative within camp research (e.g., Garst & Gagnon, 2016; Henderson, Scheuler-Whitaker, et al., 2007), it is possible with a more diverse sample, the analyses may have yielded differing results dependent on the subgroups of interest.

Additionally, the measure of participation within the present study, years of camp attendance, is notably coarse. More in depth aspects of participation within the camps (e.g., quality, intensity, depth, relevance) may yield differing results (Hirsch, et al., 2010; Masten & Cicchetti, 2010; Simpkins et al., 2004). Further, the compounding influences of other OST experiences (e.g., sports, afterschool academic workshops) may more wholly explain the benefits (or lack there of) of OST programs like camp (Simpkins, 2015), and adding this information to future studies may illustrate how differing combinations of OST activities facilitate better outcome achievement. Another measurement issue was presented within the PPDO itself. Specifically, in spite of the PPDO's past levels of psychometric acceptability in camp research, an item was dropped from the present study (e.g., My child ... doesn't get frustrated easily). This item was demonstrated as a poor fit within the model, potentially due to a double-barreled meaning (i.e., "doesn't" and "easily"). Future research could benefit from an assessment of the PPDO scale validity to including determining how and if wordings could be improved, and if alternative scale structures could improve its measurement properties (e.g., satisfaction and frustration of socioemotional skills; see also Chen et al., 2015).

Conclusion

For those relying on quantitative data to understand, examine, test, and explore within leisure and recreation sciences, the contemporary management of missing data is a necessary skillset, one that is complex, challenging, and for the nerdiest of nerds even "fun". Indeed, as noted by Enders (2010) "missing data analyses are difficult because there is no inherently correct methodological procedure" (p. 344). However, it does seem that in nearly all sufficiently powered studies, maximum likelihood techniques such as FIML and Multiple Imputation are preferable to the deletion based and simpler imputation approaches of the twentieth century (Baraldi & Enders, 2010). Those responsible for the training of the next crop of social scientists should carefully reflect on the perpetuation of outdated techniques and in some cases the eminent works which utilized them. It may be no surprise when these same eminent studies utilizing outdated approaches fail to replicate, reflecting the broader replication crisis in the psychological and social sciences (Lilienfeld, 2017). Importantly, PMDD offer another tool for leisure researchers, both potentially to mitigate deleterious effects on participants, but perhaps more notably, these approaches may influence the intentionality behind a studies design, where sampling, missingness, and analyses converge, leading to iterative improvements in the rigor and inferences available to social, behavioral, and leisure scientists and those we serve.

ORCID

Ryan J. Gagnon  <http://orcid.org/0000-0002-0338-6370>

References

- Appelbaum, M., Cooper, H., Kline, R. B., Mayo-Wilson, E., Nezu, A. M., & Rao, S. M. (2018). Journal article reporting standards for quantitative research in psychology: The APA publications and communications board task force report. *The American Psychologist*, 73(1), 3–25. <https://doi.org/10.1037/amp0000191>
- Arnold, M. E. (2018). From context to outcomes: A thriving model for 4-H youth development programs. *Journal of Human Sciences and Extension*, 6(1), 141–160.
- Baraldi, A. N., & Enders, C. K. (2010). An introduction to modern missing data analyses. *Journal of School Psychology*, 48(1), 5–37. <https://doi.org/10.1016/j.jsp.2009.10.001>
- Bentler, P. M. (2006). *EQS 6 structural equations program manual*. Multivariate Software, Inc.
- Bialeschki, M. D., & Sibthorp, J. (2011). Celebrating the camp experience through eighty years of camp research. *Taproot Journal*, 20(2), 13–24.
- Bialeschki, M. D., Henderson, K. A., & James, P. A. (2007). Camp experiences and developmental outcomes for youth. *Child and Adolescent Psychiatric Clinics of North America*, 16(4), 769–788. <https://doi.org/10.1016/j.chc.2007.05.011>
- Bohnert, A., Fredricks, J., & Randall, E. (2010). Capturing unique dimensions of youth organized activity involvement: Theoretical and methodological considerations. *Review of Educational Research*, 80(4), 576–610. <https://doi.org/10.3102/0034654310364533>
- Brandt, J., & Arnold, M. E. (2006). Looking back, the impact of the 4-H camp counselor experience on youth development: A survey of counselor alumni. *Journal of Extension*, 44(6), Article 6RIB1.
- Brown, T. A. (2015). *Confirmatory factor analysis for applied research* (2nd ed). Guilford Press.
- Buuren, S. (2018). *Flexible imputation of missing data* (2nd ed.). Taylor and Francis Group.
- Byrne, B. M. (2006). *Structural equation modeling with EQS: Basic concepts, applications and programming* (2nd ed.). Routledge.
- Cham, H., Reshetnyak, E., Rosenfeld, B., & Breitbart, W. (2017). Full information maximum likelihood estimation for latent variable interactions with incomplete indicators. *Multivariate Behavioral Research*, 52(1), 12–30. <https://doi.org/10.1080/00273171.2016.1245600>
- Chen, B., Vansteenkiste, M., Beyers, W., Boone, L., Deci, E. L., Van der Kaap-Deeder, J., Duriez, B., Lens, W., Matos, L., Mouratidis, A., Ryan, R. M., Sheldon, K. M., Soenens, B., Van Petegem, S., & Verstuyf, J. (2015). Basic psychological need satisfaction, need frustration, and need strength across four cultures. *Motivation and Emotion*, 39(2), 216–236. <https://doi.org/10.1007/s11031-014-9450-1>
- Curran, P. G. (2016). Methods for the detection of carelessly invalid responses in survey data. *Journal of Experimental Social Psychology*, 66, 4–19. <https://doi.org/10.1016/j.jesp.2015.07.006>
- Dawson, S. (2017). Social inoculation and the extinguishing effects of pediatric medical camps: Proposing a framework for the other 51 weeks. *Recreation, Parks, and Tourism in Public Health*, 1, 5–20. <https://doi.org/10.2979/rptph.1.1.02>
- Décieux, J. P., Mergener, A., Neufang, K., & Sischka, P. (2015). Implementation of the forced answering option within online surveys: Higher response rates at the expense of validity? *Psihologija*, 48(4), 311–326. <https://doi.org/10.2298/PSI1504311D>
- Durlak, J. A., Weissberg, R. P., & Pachan, M. (2010). A meta-analysis of after-school programs that seek to promote personal and social skills in children and adolescents. *American Journal of Community Psychology*, 45(3–4), 294–309. <https://doi.org/10.1007/s10464-010-9300-6>
- Eisman, A. B., Stoddard, S. A., Bauermeister, J. A., Caldwell, C. H., & Zimmerman, M. A. (2018). Organized activity participation and relational aggression: The role of positive youth development. *Violence and Victims*, 33(1), 91–108. <https://doi.org/10.1891/0886-6708.33.1.91>
- Enders, C. K. (2001). A primer on maximum likelihood algorithms available for use with missing data. *Structural Equation Modeling: A Multidisciplinary Journal*, 8(1), 128–141. https://doi.org/10.1207/S15328007SEM0801_7
- Enders, C. K. (2010). *Applied missing data analysis*. The Guilford Press.
- Field, A. (2018). *Discovering statistics using IBM SPSS statistics* (5th ed.). SAGE.
- Fielding, N. G., Lee, R. M., & Blank, G. (2017). *The SAGE handbook of online research methods* (2nd ed.). SAGE.

- Finch, W. H., & French, B. F. (2015). *Latent variable modeling with R*. Routledge.
- Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, 18(1), 39–50. <https://doi.org/10.2307/3151312>
- Freire, T., & Caldwell, L. L., (2013). Afterthoughts on leisure and future research directions. In T. Freire (Ed.), *Positive leisure science: From subjective experience to social contexts* (pp. 213–223). Springer. https://doi.org/10.1007/978-94-007-5058-6_12
- Gagnon, R. J. (2019). Examining overparenting, socioeconomic status, and parental out-of-school time experience: Does socioeconomic status and out-of-school-time experience matter? *Children and Youth Services Review*, 101, 181–189. <https://doi.org/10.1016/j.childyouth.2019.04.003>
- Gagnon, R. J., & Garst, B. A. (2019). Research and practice: An applied examination of the parental perceptions of developmental outcomes scale. *Journal of Outdoor Recreation, Education, and Leadership*, 11(1), 3–20. <https://doi.org/10.18666/JOREL-2019-V11-I1-9070>
- Garst, B. A., & Gagnon, R. J. (2016). A structural model of camp director practices and outcomes: Does intention toward program outcomes matter? *Journal of Park and Recreation Administration*, 34(4), 51–65. <https://doi.org/10.18666/JPRA-2016-V34-I4-7293>
- Garst, B. A., Gagnon, R. J., & Whittington, A. (2016). A closer look at the camp experience: Examining relationships between life skills, elements of positive youth development, and antecedents of change among camp alumni. *Journal of Outdoor Recreation, Education, and Leadership*, 8(2), 180–199. <https://doi.org/10.18666/JOREL-2016-V8-I2-7694>
- Gillard, A. & Watts, C. E. (2013). Program features and developmental experiences at a camp for youth with cancer. *Children and Youth Services Review*, 35, 890–898. <https://doi.org/10.1016/j.childyouth.2013.02.017>
- Graham, J. W., Taylor, B. J., Olchowski, A. E., & Cumsille, P. E. (2006). Planned missing data designs in psychological research. *Psychological Methods*, 11(4), 323–343. <https://doi.org/10.1037/1082-989X.11.4.323>
- Harel, O., Stratton, J., & Asepline, R. (2015). Designed missingness to better estimate efficacy of behavioral studies-application to suicide prevention trials. *Journal of Medical Statistics and Informatics*, 3(1), 2–7. <https://doi.org/10.7243/2053-7662-3-2>
- Henderson, K. A., Bialeschki, M. D., Scanlin, M. M., Thurber, C., Scheuler-Whitaker, L., & Marsh, P. E. (2007). Components of camp experiences for positive youth development. *Journal of Youth Development*, 1(3), 1. <https://doi.org/10.5195/jyd.2007.371>
- Henderson, K. A., Scheuler-Whitaker, L. S., Bialeschki, M. D., Scanlin, M. M., & Thurber, C. (2007). Summer camp experiences: Parental perceptions of youth development outcomes. *Journal of Family Issues*, 28(8), 987–1007. <https://doi.org/10.1177/0192513X07301428>
- Henderson, K. A., Thurber, C. A., Whitaker, L. S., Bialeschki, M. D., & Scanlin, M. M. (2006). Development and application of a camper growth index for youth. *Journal of Experiential Education*, 29(1), 1–17. <https://doi.org/10.1177/105382590602900103>
- Henderson, K. A., Bialeschki, M. D., & James, P. A. (2007). Overview of camp research. *Child and Adolescent Psychiatric Clinics of North America*, 16(4), 755–767. <https://doi.org/10.1016/j.chc.2007.05.010>
- Hill, E., Gagnon, R., Ramsing, R., Goff, J., Kennedy, B., & Hooker, T. (2015). Measuring the impact of a medical specialty camp: Using self-determination theory. *Therapeutic Recreation Journal*, 49(4), 310–325. <https://doi.org/10.18666/TRJ-2015-V49-I4-6308>
- Hirsch, B. J., Mekinda, M. A., & Stawicki, J. (2010). More than attendance: The importance of after-school program quality. *American Journal of Community Psychology*, 45(3–4), 447–452. <https://doi.org/10.1007/s10464-010-9310-4>
- Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal*, 6(1), 1–55. <https://doi.org/10.1080/10705519909540118>
- Jamshidian, M., & Jalal, S. (2010). Tests of homoscedasticity, normality, and missing completely at random for incomplete multivariate data. *Psychometrika*, 75(4), 649–674. <https://doi.org/10.1007/s11336-010-9175-3>

- Jorgensen, T. D., Rhemtulla, M., Schoemann, A., McPherson, B., Wu, W., & Little, T. D. (2014). Optimal assignment methods in three-form planned missing data designs for longitudinal panel studies. *International Journal of Behavioral Development, 38*(5), 397–410. <https://doi.org/10.1177/0165025414531094>
- Kim, K. H., & Bentler, P. M. (2002). Test of homogeneity of means and covariance matrices for multivariate incomplete data. *Psychometrika, 67*(4), 609–624. <https://doi.org/10.1007/BF02295134>
- Kingery, J., Peneston, K. R., Rice, S. E., & Wormuth, B. M. (2012). Parental anxious expectations and child anxiety predicting homesickness during overnight summer camp. *Journal of Outdoor Recreation, Education, and Leadership, 4*(3), 172–184. <https://doi.org/10.7768/1948-5123.1116>
- Kline, R. B. (2016). *Principles and practices of structural equation modeling* (4th ed.). The Guilford Press.
- Knifsend, C. A., & Graham, S. (2012). Too much of a good thing? How breadth of extracurricular participation relates to school-related affect and academic outcomes during adolescence. *Journal of Youth and Adolescence, 41*(3), 379–389. <https://doi.org/10.1007/s10964-011-9737-4>
- Lilienfeld, S. O. (2017). Psychology's replication crisis and the grant culture: Righting the ship. *Perspectives on Psychological Science: A Journal of the Association for Psychological Science, 12*(4), 660–664. <https://doi.org/10.1177/1745691616687745>
- Little, R. J. A. (1988). A test of missing completely at random for multivariate data with missing values. *Journal of the American Statistical Association, 83*(404), 1198–1202. <https://doi.org/10.1080/01621459.1988.10478722>
- Little, T. D. (2013). *Longitudinal structural equation modelling*. The Guilford Press.
- Little, T. D., & Rhemtulla, M. (2013). Planned missing data designs for developmental researchers. *Child Development Perspectives, 7*(4), 199–204. <https://doi.org/10.1111/cdep.12043>
- Ludtke, O., Robitzsch, A., & Grund, S. (2017). Multiple imputation of missing data in multilevel designs: A comparison of different strategies. *Psychological Methods, 22*(1), 141–165. <http://dx.doi.org/10.1037/met0000096>
- Marsh, H. W., Hau, K., & Wen, Z. (2004). In search of golden rules: Comment on hypothesis-testing approaches to setting cutoff values for fit indexes and dangers in overgeneralizing Hu and Bentler's (1999) Findings. *Structural Equation Modeling: A Multidisciplinary Journal, 11*(3), 320–341. https://doi.org/10.1207/s15328007sem1103_2
- Masten, A. S., & Cicchetti, D. (2010). Developmental cascades. *Development and Psychopathology, 22*(3), 491–495. <https://doi.org/10.1017/S0954579410000222>
- Mihalic, S. F., & Elliott, D. S. (2015). Evidence-based programs registry: Blueprints for healthy youth development. *Evaluation and Program Planning, 48*, 124–131. <https://doi.org/10.1016/j.evalproplan.2014.08.004>
- Muthen, B., & Asparouhov, T. (2012). Bayesian structural equation modeling: A more flexible representation of substantive theory. *Psychological Methods, 17*(3), 313–335. <https://doi.org/10.1037/a0026802>
- Newman, D. A. (2010, April). Missing data: Problems and prospects [Paper presentation]. Consortium for the Advancement of Research Methods and Analysis, Detroit, MI, USA.
- Ophir, Y., Sisso, I., Asterhan, C. S. C., Tikochinski, R., & Reichart, R. (2020). The turker blues: Hidden factors behind increased depression rates among amazon's mechanical turkers. *Clinical Psychological Science, 8*(1), 65–83. <https://doi.org/10.1177/2167702619973>
- Rhemtulla, M., & Little, T. D. (2012). Planned missing data designs for research in cognitive development. *Journal of Cognition and Development, 13*(4), 425–438. <https://doi.org/10.1080/15248372.2012.717340>
- Rhemtulla, M., & Hancock, G. R. (2016). Planned missing data designs in educational psychology research. *Educational Psychologist, 51*(3–4), 305–316. <https://doi.org/10.1080/00461520.2016.1208094>
- Rosseel, Y. (2012). Lavaan: An R package for structural equation modeling. *Journal of Statistical Software, 48*(2), 1–36. <https://doi.org/10.18637/jss.v048.i02>

- Roth, J. L., & Brooks-Gunn, J. (2016). Evaluating youth development programs: Progress and promise. *Applied Developmental Science, 20*(3), 188–202. <https://doi.org/10.1080/10888691.2015.1113879>
- Roth, J. L., Malone, L. M., & Brooks-Gunn, J. (2010). Does the amount of participation in after-school programs relate to developmental outcomes? A review of the literature. *American Journal of Community Psychology, 45*(3–4), 310–324. <https://doi.org/10.1007/s10464-010-9303-3>
- Ruel, E., Wagner, W. E., & Gillespie, B. J. (2015). *The practice of survey research: Theory and applications*. SAGE.
- Rutkowski, L. (2017). Design considerations for planned missing auxiliary data in a latent regression context. *Psychological Test and Assessment Modeling, 59*(1), 55–70.
- Satorra, A., & Bentler, P. M. (1988). Scaling corrections for chi-square statistics in covariance structure analysis. *Proceedings of the American Statistical Association, 36*, 308–313.
- Satorra, A., & Bentler, P. M. (1994). Corrections to test statistics and standard errors in covariance structure analysis. In A. von Eye & C. C. Clogg (Eds.), *Latent variables analysis: Applications for developmental research* (pp. 399–419). SAGE.
- Sendak, M. D., Schilstra, C., Tye, E., Brotkin, S., & Maslow, G. (2018). Positive youth development at camps for youth with chronic illness: A systematic review of the literature. *Journal of Youth Development, 13*(1–2), 201–215. <https://doi.org/10.5195/JYD.2018.551>
- Sibthorp, J., Bialeschki, M. D., Morgan, C., & Browne, L. (2013). Validating, norming, and utility of a youth outcomes battery for recreation programs and camps. *Journal of Leisure Research, 45*(4), 514–536. <https://doi.org/10.18666/jlr-2013-v45-i4-3897>
- Silvia, P. J., Kwapil, T. R., Walsh, M. A., & Myin-Germeys, I. (2014). Planned missing-data designs in experience-sampling research: Monte Carlo simulations of efficient designs for assessing within-person constructs. *Behavior Research Methods, 46*(1), 41–54. <https://doi.org/10.3758/s13428-013-0353-y>
- Simpkins, S. D. (2015). When and how does participating in an organized after-school activity matter. *Applied Developmental Science, 19*(3), 121–126. <https://doi.org/10.1080/10888691.2015.1056344>
- Simpkins, S. D., Little, P. M., & Weiss, H. B. (2004). Understanding and measuring attendance in out-of-school programs. *Issues and Opportunities in out-of-School Time Evaluation, 7*, 1–12. <https://doi.org/10.18666/jlr-2013-v45-i4-3897>
- Thurber, C. A., Scanlin, M. M., Scheuler, L., & Henderson, K. A. (2007). Youth development outcomes of the camp experience: Evidence for multidimensional growth. *Journal of Youth and Adolescence, 36*(3), 241–254. <https://doi.org/10.1007/s10964-006-9142-6>
- Tiffany, J. S., Exner-Cortens, D., & Eckenrode, J. (2013). Longitudinal associations between HIV risk reduction and out-of-school time program participation. *The Journal of Adolescent Health: Official Publication of the Society for Adolescent Medicine, 52*(6), 795–797. <https://doi.org/10.1016/j.jadohealth.2013.01.011>
- United States Census. (2019). *Quick facts: South Carolina*. <https://www.census.gov/quickfacts/SC>
- Whitehead, J. C. (1994). Item nonresponse in contingent valuation: Should CV researchers impute missing values for missing independent variables? *Journal of Leisure Research, 26*(3), 296–303. <https://doi.org/10.1080/00222216.1994.11969961>
- Whittington, A., & Garst, B. A. (2018). The role of camp in shaping college readiness and building a pathway to the future for camp alumni. *Journal of Youth Development, 13*(1–2), 105–125. <https://doi.org/10.5195/JYD.2018.519>
- Whittington, A., Garst, B. A., Gagnon, R. J., & Baughman, S. (2017). Living without boys: A retrospective analysis of the benefits and skills gained at all-female camps. *Journal of Experiential Education, 40*(2), 97–113. <https://doi.org/10.1177/1053825916689266>
- Wilson, C., & Sibthorp, J. (2018). Examining the role of summer camps in developing academic and workplace readiness. *Journal of Youth Development, 13*(1–2), 83–104. <https://doi.org/10.5195/JYD.2018.563>