METHODOLOGICAL CONSIDERATIONS FOR ALCOHOL RESEARCH USING SOCIAL NETWORKS ANALYSIS

A Dissertation

by

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ABSTRACT

This research project has three goals: (1) to present an overview on the use of Amazon Mechanical Turk (MTurk) as a data collection tool in alcohol-related research, and discuss the potential impacts of important MTurk-specific methodological decisions; (2) to extend our understanding of peer influence on alcohol use among college students utilizing a social network analysis (SNA) approach; and (3) to establish best practices for operationalizing perceived peer alcohol use within SNA research.

The variety of uses for MTurk to facilitate alcohol-related investigations will be discussed. Alcohol researchers interested in collecting data using MTurk are encouraged to pay particular attention to methodological best-practices detailed in this report.

To explore the influence of peer drinking on personal behavior, the author will describe results from a comparison of two distinct assessment strategies for measuring perceptions of peer drinking: (1) perceptions of the "typical" student's drinking behaviors, versus (2) egocentric social network measures, in which respondent's report on perceptions of the drinking behaviors of personally identified peers. Overall, egocentric network measures explained markedly greater levels of variability in peer influence on personal alcohol consumption, compared to global typical student measures. Proximal peers have a greater influence on personal alcohol consumption than "typical students" at the same institution.

Finally, the author will report on whether using different strategies for measuring referent/peer alcohol use (i.e., single-item or two-item approaches versus multiple item assessments) within alcohol-related SNA research impacts study results. Commonly,

SNA research employs single-item or two-item assessments (i.e., quantity, frequency, or quantity/frequency) to measure individuals' perceptions of peer drinking. Findings suggest utilizing a minimum of three items (i.e., frequency, quantity, and frequency of heavy drinking) is necessary to provide adequate insights into alcohol consumption patterns of respondents.

Future research would benefit from utilizing an egocentric network approach to examine the complex, interpersonal nature of alcohol use among college students. Future investigations utilizing an egocentric network approach may fail to capture valuable insights if using simple quantity/frequency assessments of nominated peers' alcohol use. Moreover, this can enhance the effectiveness of programming efforts aimed at reducing heavy drinking among college students within social contexts.

DEDICATION

To my family for their unwavering support.

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CONTRIBUTORS AND FUNDING SOURCES

Contributors

This work was supervised by a dissertation committee consisting of Dr. Adam Barry [advisor], Dr. Patricia Goodson, and Dr. Megan Patterson of the Department of Health and Kinesiology, and Dr. Jamilia Blake of the Department of Educational Psychology.

Dr. Barry helped to conceptualize the research project and provided detailed feedback throughout. Dr. Patterson contributed input and feedback on methods and analyses. Drs. Goodson and Dr. Blake gave insight and guidance throughout the course of the project. All other work conducted for the dissertation was completed by myself independently.

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NOMENCLATURE

ACHA	American College Health Association
AUDIT	Alcohol Use Disorders Identification Test
AUDIT-C	Alcohol Use Disorders Identification Test – Consumption
CAPS-r	College Alcohol Problems Scale-revised
GPA	Grade Point Average
HIT	Human Intelligence Task
IRB	Institutional Review Board
MTurk	Amazon's Mechanical Turk
NIAAA	National Institute on Alcohol Abuse and Alcoholism
SAMHSA	Substance Abuse and Mental Health Services Administration
SNA	Social Network Analysis
WHO	World Health Organization

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CHAPTER I

INTRODUCTION

Amazon Mechanical Turk (MTurk; Amazon, 2018) is a crowdsourcing platform and host to over 500,000 registered *workers* who can browse and be compensated for completing tasks (e.g., surveys, experiments) created by *requesters* (Buhrmester, Kwang, & Gosling, 2011; Mason & Suri, 2012; Paolacci, Chandler, & Ipeirotis, 2010; Paolacci & Chandler, 2014). The use of MTurk as a data collection tool has become increasingly popular among social and behavioral scientists, as the platform offers a number of advantages over traditionally relied upon convenience sampling methods (i.e., college student samples; Berinsky et al., 2012; Buhrmester et al., 2011; Paolacci et al., 2010). MTurk samples are more demographically and geographically diverse (older, less white, less democratically skewed) than undergraduate college student samples, and are thus, more nationally representative (Berinsky et al., 2012; Buhrmester et al., 2011). Also, MTurk allows for rapid data collection at a relatively low cost (Buhrmester et al., 2011).

Alcohol researchers have recognized the potential for MTurk as an affordable, yet high quality source of social and behavioral data. This is evidenced by a growing number and variety of alcohol-related investigations conducted on MTurk, including cross sectional and replication studies (Morris et al., 2017; Veilleux, Skinner, Reese, & Shaver, 2014), measure development projects (Lovett, Ham, & Veilleux, 2015), longitudinal investigations (Boynton & Richman, 2014; Strickland & Stoops, 2018), and intervention development studies (Cunningham, Wild, Cordingley, van Mierlo, & Humphreys, 2009). As such, MTurk represents a valuable and appropriate data collection tool in this particular alcohol-related investigation – an examination of the effects of social influence on the drinking behaviors of college students.

The hazardous drinking behaviors of college students' and associated consequences are well-documented (National Institute on Alcohol Abuse and Alcoholism [NIAAA], 2018; Substance Abuse and Mental Health Services [SAMHSA], 2017). Public health researchers have studied extensively the perceptions of and motivations for alcohol use patterns among this population. Perceptions of peer drinking are a particularly strong contributing factor to college students' alcohol consumption patterns (Neighbors, Lee, Lewis, Fossos, & Larimer, 2007; Perkins, 2002). Specifically, students typically perceive that their college counterparts consume alcohol in larger quantities and more frequently than they actually do (Martens, 2006; Perkins, 2002). As a result, students may increase their own drinking behaviors in an attempt to match their misperceived overestimates of other students' drinking. In attempts to offset this influence, college health practitioners have developed programming efforts designed to correct students' misperceived overestimates of alcohol consumption among their peers (Wechsler et al., 2003). However, the mixed results of these programming efforts, as evidenced by the continued influence of misperceptions of peer drinking on college students' actual alcohol consumption behaviors, warrants our further attention (Wechsler et al., 2003). These findings point to the need for improvement upon current means for assessing the relationship between perceptions of peer drinking and students' own drinking behaviors and how we design, implement, and evaluate programming efforts intended to ameliorate this public health issue.

One limitation of current efforts to capture the association between students' perceptions of peer drinking behaviors and their own alcohol use is the reliance on campus-based, global measures asking about the drinking of typical students at one's respective university (American College Health Association [ACHA], 2015). Alternatively, it is crucial to tap into students' personal social environments, consisting of their closest and most influential peers. Utilizing a social network analysis (SNA; Borgatti, Everett, & Johnson, 2018; Valente, 2010) approach to assess the drinking behaviors of respondents' immediate social ties offers the means through which to improve upon traditional campus-based, global approaches.

Given this constellation of factors, this investigation has three broad goals. First, I will present an overview on the use of Amazon Mechanical Turk (MTurk) as a data collection tool in alcohol-related research and discuss the potential impacts of important MTurk-specific methodological decisions. Second, I will extend the understanding of peer influence on alcohol use among college students utilizing a social network analysis approach. Finally, I will establish best practices for operationalizing alcohol use within alcohol-related SNA research to enhance the direction of future work.

In order to accomplish these goals, the specific research objectives of the current study are: (1) To develop a review of the literature (a) outlining usages for MTurk as a data collection tool in alcohol research and (b) establishing a best practices framework for alcohol-related social science research using MTurk; (2) To compare and contrast two distinct methods for assessing the impact of perceptions of peer alcohol use on personal alcohol use (i.e., global campus-based measures seeking to elicit an individual's perceptions of the "typical" student's drinking behaviors, versus egocentric social network measures specific to actual participant-referent relationships, in which respondent's report on their perceptions of the drinking behaviors of personally identified proximal peers.); and (3) (a) To empirically test whether different strategies for measuring referent/peer alcohol use (i.e., single items, mirrored behavioral questions) within alcohol-related SNA research impact study results, and (b) to establish best practices for measuring peer alcohol use (i.e., preferred name interpreter question/s) within alcohol-related research using egocentric network analysis.

This dissertation consists of five chapters with three interconnected, yet distinct, manuscripts (Chapters 2-4). Conceptually, each manuscript will examine empirical implications associated with methodological choices in alcohol-related research. While each article is written independently, the dissertation as a whole will embody all of the necessary requirements of a traditional five-chapter dissertation. The composition and description of the dissertation is as follows:

- Chapter I: Presents a brief overview of the topic of interest, and a rationale for the project is described.
- Chapter II: The current body of literature using MTurk to conduct alcohol-related research is discussed. Usages for MTurk as a data collection tool in alcohol research are described, and a best practices framework for alcohol-related social science research using MTurk is established. This chapter will represent the first journal article.
- Chapter III: Results obtained using two distinct methods for assessing the impact of perceptions of peer drinking on personal alcohol use are compared: (1) global campus-based measures seeking to elicit individuals' perceptions of the "typical" student's drinking behaviors, versus (2) egocentric social network measures specific to actual participant-referent relationships, in which respondent's report on their perceptions of the drinking behaviors of personally identified proximal peers. This chapter will represent the second journal article.
- Chapter IV: Different strategies for measuring referent/peer alcohol use (i.e., single items, mirrored behavioral questions) within alcohol-related SNA research are tested,

and impacts on study results are detailed. Best practices for measuring peer alcohol use (i.e., preferred name interpreter question/s) within alcohol-related research using egocentric network analysis are established. This chapter will represent the third journal article.

- Chapter V: Conclusions from the project are discussed. Practical implications for the field of public health are described. Future directions for research areas are outlined.

CHAPTER II

USE OF MTURK IN ALCOHOL RESEARCH: BEST PRACTICES

Herein, I outline the utility of Amazon's Mechanical Turk (MTurk – Amazon, 2018) as a data collection tool within the social and behavioral sciences. In doing so, I will discuss the inherent strengths and weaknesses associated with the use of MTurk as a data collection tool in comparison to alternative convenience sampling approaches. As a heuristic example, I will present the body of alcohol-related research utilizing MTurk in the data collection process and describe the variety of alcohol-related investigations conducted to date. Furthermore, I will provide researchers and practitioners with a checklist of best practices for utilizing MTurk to collect data in alcohol-related studies.

MTurk: Utility as Data Collection Tool

Many common social and behavioral research sampling procedures utilizing college students (e.g., classroom convenience samples, Psych 101 studies, online surveys to subsamples of students) have significant limitations. Students recruited from undergraduate university populations differ demographically (i.e., are younger, more likely to be white, more likely to be female, and come from higher socio-economic backgrounds) from adults and students recruited from the general population (Barnes, Welte, Hoffman, & Tidwell, 2010; Gainsbury, Russell, & Blaszczynski, 2014). Similarly, small college student samples often fail to reflect the larger institution's demographic profile from which they were drawn. Thus, limited generalizability arises when relying on samples extracted from a single university or site. Amazon's Mechanical Turk (MTurk; Amazon, 2018) – a popular crowdsourcing platform – represents a social and behavioral research tool that can address many of these aforementioned limitations.

MTurk is an online labor market offering a pool of over 500,000 registered *workers* from over 100 countries who can browse and be compensated for completing tasks (e.g., surveys, experiments) created by *requesters* (Buhrmester et al., 2011; Mason & Suri, 2012; Paolacci, Chandler, & Ipeirotis, 2010; Paolacci & Chandler, 2014). MTurk samples consistently perform equal to, or better than, traditionally relied upon convenience samples (e.g., college students) and are more geographically and demographically diverse (Berinsky et al., 2012; Buhrmester et al., 2011; Paolacci et al., 2010). More specifically, MTurk samples are on average older, less white, and less democratically skewed (i.e., more nationally representative) than American college samples (Berinsky et al., 2012; Buhrmester et al., 2011). Furthermore, rapid rates of data collection at relatively low cost has contributed to the recent proliferation in the use of MTurk throughout the scientific community (See Figure 1). Simply put, MTurk offers an affordable, yet high-quality source for data collection within the social and behavioral sciences (Berinsky, Huber, & Lenz, 2012; Buhrmester, Kwang, & Gosling, 2011; Kim & Hodgins, 2017; Paolacci, Chandler, & Ipeirotis, 2010).

The utility of MTurk as a data collection tool for alcohol-related research has been demonstrated throughout the recent literature (Strickland & Stoops, 2019). MTurk has been shown to be a valuable scientific resource for conducting alcohol-related cross-sectional research and replication studies (Morris et al., 2017; Veilleux, Skinner, Reese, & Shaver, 2014), measure development (Lovett, Ham, & Veilleux, 2015), longitudinal research (Boynton, M. H., & Richman, 2014; Strickland & Stoops, 2018), and intervention development (Cunningham, Wild, Cordingley, van Mierlo, & Humphreys, 2009). That said, various methodological considerations (e.g., attention/validity checks, screening questionnaires and qualification restrictions, payment schedules) concerning the use of MTurk for collecting data must be taken into account, as these methodological choices can impact study's internal and external validity(see Buhrmester, Talaifar, & Gosling, 2018; Chandler & Shapiro, 2016; Strickland & Stoops, 2019 for a review). Herein, we compose a review outlining usages and best practices for MTurk as a data collection tool in alcohol research.

Heuristic Example

Procedure

PRISMA guidelines (Moher et al., 2009) were used to guide the search of alcohol-related peer-reviewed literature employing MTurk as a data collection tool (See Figure 2). Garrard's (2013) Matrix Method was utilized to organize the literature and document vital study characteristics. Variables accounted for included: citation/author information, year of publication, alcohol use construct(s)/measure(s), other construct(s)/measure(s), study type, and reporting of MTurk methodological decisions (e.g., payment, attrition, recruitment procedures, inattention/validity checks, exclusion criteria, duplicate workers).

A computerized database search spanning six databases (ERIC (EBSCO), Google Scholar, MEDLINE (PubMed), PsycINFO, Web of Science, SCOPUS) was conducted using various combinations of relevant key terms ("amazon mechanical turk" OR "MTurk" AND "alcohol*"). In order for an article to be included in the review, the following criteria had to be met: (1) the article had to employ Amazon Mechanical Turk (MTurk) as a data collection tool to facilitate an alcohol-related investigation, and (2) the article had to be written in English. There were no restrictions based on publication date.

Our database search resulted in 5,282 total articles published between 1993 and 2019. Of these articles, 5,111 were excluded prior to abstract review based on title. These articles were excluded because it was clear they either did not consist of an alcohol-related investigation or failed to employ MTurk as a data collection tool. Another 84 articles were removed because they were duplicates. After the remaining 89 article abstracts were reviewed, 3 more articles were excluded because (a) the study was not an alcohol-related investigation, or (b) the study did not use MTurk as a data collection tool. Thus, 86 full-text articles were extracted and included in the review.

MTurk: Applications in Alcohol Research

The following section provides a narrative on existing research utilizing MTurk as a data collection to answer questions relevant to alcohol use and misuse. More specifically, the use of MTurk to conduct the following types of alcohol-related investigations will be discussed: (1) alcohol-related cross-sectional research and replication studies, (2) measure development, (3) longitudinal research, and (4) interventions development.

Cross-sectional Research and Replication Studies

A large number of MTurk alcohol-related investigations employ cross-sectional research methods to facilitate independent experiments or replication studies. In fact, one of the notable benefits demonstrated through the use of MTurk in alcohol-related investigations is the relative ease with which alcohol researchers can enhance reproducibility and generalizability of results. Alcohol researchers enhance the rigor of their work by employing MTurk to rapidly test for effects observed in laboratory settings or using other convenience sampling methods with limited generalizability (e.g., college student samples). Furthermore, Mturk has demonstrated a propensity to screen for and provide access to diverse participant pools (e.g., heavy alcohol users).

Along these lines, a large number of alcohol-related behavioral economic demand studies facilitated via MTurk have examined hypothetical consumption of alcohol products across a range of prices (Kaplan et al., 2017; Kaplan & Reed, 2018; Morris et al., 2017). The results of these studies have been similar to those observed in laboratory settings. Morris et al. (2017) validated an alcohol purchase task (APT) to provide supporting evidence for the use of crowdsourcing platforms to study behavioral economic determinants of alcohol use. Other MTurk investigations have assessed the effect of time constraints (i.e., duration of access) on the APT (Kaplan et al., 2017), whether "happy hour specials" influence self-reported consumption on the APT (Kaplan & Reed, 2018), as well as differences in alcohol demand between alcohol-only users and co-users of alcohol and cannabis. Another study examined the effects of craving on an individual's demand for alcohol (Noyes & Schlauch, 2018). The plethora of uses for MTurk in the facilitation of alcohol-related behavioral economic demand investigations are promising and speak to the potential for the crowdsourcing platform to be used to conduct a variety of alcohol-related cross-sectional and replication studies.

Measure Development

Alcohol researchers have recognized the propensity for MTurk to provide large samples with relatively diverse alcohol use histories – a vital resource for measure development and testing. There are several alcohol-related investigations to date which have used MTurk to develop and test the initial factor structure of a measure. Also, many replication studies have sought to confirm factor structures and enhance generalizability of novel alcohol-related measures.

As previously mentioned, many alcohol researchers have conducted exploratory factor analysis (EFA) on various alcohol-related measures using MTurk as a data collection tool. Many of these studies have developed and evaluated measures related to motivations for and influences on alcohol use and cravings. One study exposed MTurk workers to alcohol visual cues and examined the factor structure of a measure intended to capture alcohol craving ratings in response to these photographic stimuli (Lovett, Ham, and Veilleux, 2015). This investigation provided support for the use of these alcohol visual cues as valid and reliable stimuli for studying alcohol cue reactivity. Meisel, Colder, and Read (2016) developed and tested a novel measure of injunctive/descriptive norms and drinking/abstaining behaviors to address prior measurement issues in social norms research. Morean et al. (2018) designed and validated the Self-Report Habit Index (SRHI) to assess habitual marijuana, alcohol, cigarette, and e-cigarette use in response to environmental cues. Another investigation evaluated the psychometric properties of a measure intended to capture young adults' motivations for participating in drinking games (Zamboanga et al., 2019).

Moreover, several of these exploratory studies have examined the psychometric qualities of measures related to the effects of alcohol use (e.g., physical, psychological). Lac and Berger (2013) developed and validated a measure for alcohol myopia – the ability for alcohol to narrow attention and impair mental processes – using two independent MTurk samples. Another investigation operationalized and psychometrically evaluated a measure for eliciting "hitting bottom" in relation to seeking treatment for an alcohol use disorder (AUD; Kirouac and Witkiewitz, 2017). Lac and Donaldson (2018) used 3 MTurk samples to explore and validate the psychometric properties of the Positive and Negative Affect Schedule (PANAS) - a measure of positive and negative emotions associated with alcohol use.

Alternatively, alcohol researchers have demonstrated the capability for MTurk to provide quick, affordable replication studies, providing means to confirm factor structures and enhance generalizability of previously validated alcohol-related measures. Along these lines, one study evaluated and confirmed the three-factor structure of the Protective Behavioral Strategies Scale-20 (PBSS-20; Treloar, Martens, & McCarthy, 2015; Richards et al., 2018) – the first investigation to do so among a non-college student sample and generalize to the U.S. adult population. Campbell and Strickland (2019) used a geographically diverse MTurk sample to replicated the previously validated psychometric properties of the Brief DSM-5 AUD Diagnostic Assessment. A clear strength with regard to the use of MTurk in alcohol research centers on its allowance for rapid, affordable measurement development.

Longitudinal Research

Mturk features a unique identification component allowing for easy administration of follow-up assessment. Utilizing this feature, alcohol researchers have conducted longitudinal studies using MTurk samples. Boynton and Richman (2014) assessed alcohol consumption over a 14-day period using an online daily diary design - in which participants (N = 369) completed an average of 8.5 daily entries (60.7%) - replicating findings from similar investigations. Another study assessed alcohol consumption among 279 participants over an 18-week period by collecting weekly recordings of alcohol use, replicating expected relationships with regard to alcohol use (Strickland & Stoops, 2018). Participants completed an average of 73% of the weekly recordings, and 94% reported being satisfied with the study procedures. Though the use of MTurk to collect longitudinal data in alcohol research is in its infancy, these studies point to the initial validity and feasibility for doing so.

Interventions Development

Mturk has also been used in interventions development research and has proven a particularly valuable tool for testing Internet-based interventions. Internet-based interventions are ideal for hard-to-reach populations, such as those residing in rural areas. Numerous studies have demonstrated the capability for researchers to use MTurk to recruit hazardous drinkers for participation in internet interventions (Cunningham, Godinho, & Kushnir, 2017a; Cunningham, Godinho, & Kushnir, 2017b). However, the majority of these internet interventions facilitated through MTurk have been ineffective at reducing heavy drinking.

One study obtained 977 hazardous drinkers for participation in a randomized control trial testing for the efficacy of a smartphone-based brief intervention application for unhealthy alcohol use (Bertholet, Godinho, & Cunningham, 2019). However, results indicated the smartphone-based brief intervention was not an effective intervention due to limited application downloads. A second study demonstrated the feasibility and effectiveness of normative and personalized feedback brief interventions for at-risk drinkers aged 50 years and older (Kuerbis et al., 2017). Findings indicated the brief online feedback intervention was feasible, and the majority of participants indicated a preference for online intervention. Both types of brief intervention were moderately effective, however, normative feedback was more effective than personalized feedback with regard to motivation to reduce alcohol use. In a third study, Wittleder et al. (2019) delivered a brief, self-guided online intervention encouraging multiple health behavior changes. Participants reported an increased commitment to reduce drinking immediately after the intervention, and hazardous drinkers indicated statistically significant decreases in alcohol use at a one-month follow up. A fourth study used MTurk to conduct two randomized clinical trials aimed at reducing unhealthy alcohol use (Cunningham, Godinho, and Bertholet, 2019). While recruitment was successfully conducted rapidly and at a relatively low cost, the interventions were found to be largely ineffective. A final study used MTurk to recruit participants with an alcohol use disorder (AUD) in order to test the feasibility, acceptability, and efficacy of delivering online cognitive training interventions (Strickland, Hill, Stoops, and Rush, 2019). While response rates over the 2-week intervention period (65% of materials completed) and satisfaction with study procedures were promising (94.6%), intervention effects on participant alcohol consumption were modest. Given the propensity for MTurk to relatively easily provide access to at-risk heavy drinking populations at low cost, prevention and intervention specialists interested in alcohol use and misuse can feasibly test potentially high-impact internet interventions.

Limitations of MTurk Research

There are several inherent limitations associated with the use of MTurk as a data collection tool for alcohol research. First**,** Mturk samples are limited with regard to external validity and generalization to the national population. MTurk samples represent nonprobability samples of the general population (i.e., convenience samples) and are not to be presented as nationally representative. For example, MTurk workers are younger and more educated than the general population (Paolacci & Chandler, 2014). This finding notwithstanding, MTurk samples have consistently performed equally to, or better than, traditionally relied upon convenience sampling methods (e.g., college student samples) with regard to accuracy in representing the U.S. population. Thus, although alcohol researchers using MTurk as a data collection tool must consider limitations associated with generalizability, these concerns are similar to those present in commonly utilized sampling approaches.

A second limitation linked with the use of MTurk in alcohol research is the inability to biologically validate self-report alcohol use data. Alcohol researchers relying on self-report data – regardless of data collection procedures (e.g., online v. face-to-face) – have the potential to encounter biases related to under- and over-reporting of alcohol use. However, several studies have shown participants are more likely to be honest about sensitive information (i.e., less underreporting of alcohol use) with online – as opposed to in-person – data collection (Kim & Hodgins, 2017; Strickland & Stoops, 2018; Strickland, Hill, Stoops, & Rush, 2019). Also, attention and validity checks can be utilized in order to enhance data quality. For example, qualification restrictions (i.e., restricting participation to MTurk workers with a 95% approval rating on at least 100 HITs) have been linked to decreases in failing attention checks and lower rates of socially desirable responses (Peer, Vosgerau, & Acquisti, 2014).

A third limitation associated with the use of MTurk to collect data relates to the experience of research participants. MTurk workers with a great deal of experience on the platform may have previously been exposed to similar procedures or task. Previous exposure to a task or procedure can influence future behavior with regard to a similar task. Thus, it is important to account for the number of HITs a worker has completed as a potential confounder for any analyses to be conducted.

MTurk: Best Practices

A number of seminal works on the effective use of MTurk as a data collection tool have outlined best practices for conducting behavioral research using MTurk (Buhrmester et al., 2018; Chandler & Shapiro, 2016). In particular, this body of literature outlines several noteworthy issues MTurk researchers should consider, including but not limited to, inattention, nonnaiveté and dishonesty, and attrition (See Table 2.1 for further descriptions). To offset against inattention, clearly communicate instructions and time requirements, include unobtrusive attention-check questions, and consider restricting participation in your study to MTurk workers with a high reputation (i.e., 95% or higher approval rating on at least 100 tasks; Buhrmester et al., 2018; Peer et al., 2014). To minimize nonnaiveté, ensure to take measures to prevent duplicate workers from completing a task more than once, use prescreening items to assess participants' familiarity with study topics and measures, and monitor cross-talk among potential participants while the study is being conducted (Buhrmester et al., 2018; Chandler, Mueller, & Paolacci, 2014). Systematic attrition can be minimized by accurately estimating the time required for participation and monitoring and reporting attrition rates (Buhrmester et al., 2018; Chandler & Shapiro, 2016). Similarly, ethical considerations must be made in order to ensure participants are treated fairly. For instance, pay participants a fair wage ($0.10 per minute or higher is recommended; Chandler & Shapiro, 2016). In reporting the methodological steps taken in their published research, MTurk users are advised to report all methodological decisions made, as these decisions are likely to impact study results and represent key contextual and limiting factors.

Alcohol researchers interested in collecting data using MTurk are encouraged to do the following when appropriate: (1) pay a fair wage; (2) disguise the purpose of the study until it is accepted; (3) measure and report study attrition; (4) prescreen unobtrusively; (5) prevent duplicate workers; (6) avoid obtrusive attention checks; (7) use novel research materials when appropriate; (8) pilot test studies; and (9) transparently report methods and results (See Table 2.2 for best-practices guidelines; Chandler & Shapiro, 2016). Alcohol researchers who intend to use MTurk to facilitate future investigations should make concerted efforts to adhere to these best practices where appropriate. If used properly, the potential uses for MTurk in conducting rigorous alcohol-related research are extensive.

Future Directions

While the recent proliferation in the use of MTurk to conduct alcohol research is noteworthy, there is a dire need for new studies to continue to evaluate the validity and reliability of MTurk. MTurk alcohol-related investigations to date have largely been cross-sectional or replication studies. There is a need to continue to expand research centered on more complex designs (e.g., longitudinally-oriented designs, interventions development) in order to better inform the scientific community as to the realities – good or bad – associated with using MTurk to conduct alcohol research. Furthermore, systematic reviews of MTurk alcohol research can provide valuable assessments of the extent to which MTurk-specific methodological choices (e.g., payment variations, attention/validity checks, qualification restrictions) can impact study results. Such reviews can also serve to evaluate the current published alcohol literature's adherence to MTurk methodology-related best practices. Ultimately, increased knowledge and understanding of how to best leverage MTurk to complement existing methods for conducting alcohol research (e.g., clinical trials, community interventions, epidemiological studies) can lead to enhancements in the rigor and reproducibility of research conducted within the field of alcohol use and misuse.

Table 2.1

Important issues when conducting research on MTurk

Issue	Description
Inattention	Not paying particularly close attention when completing a task (e.g., speeding through a survey)
Nonnaiveté	MTurk workers can complete as many tasks as they want, and experienced workers can become familiar with study materials (e.g., scales, measures) producing biased data
Dishonesty	Dishonest responses can occur if participants believe it will help them to meet study inclusion criteria
Attrition	Participant drop-out rate, or number of participants lost during an experiment

Adapted from (Buhrmester et al., 2018)

Table 2.2

MTurk best practices checklist

(1) Pay a fair wage – at least $0.10 cents per minute
(2) Disguise the purpose of the study until it is accepted – To avoid selection bias, only include payment amount, a time estimate, and description of type of task (e.g., survey). Include details on the topic of the study in the informed consent form hosted on the survey platform.
(3) Measure and report study attrition – Create a priori rules concerning missing data and keep track of attrition rates, as selective attrition can impact study results. Also, to offset attrition make sure to accurately estimate time needed to complete the study, so that participants have accurate expectations.
(4) Prescreen unobtrusively – Only prescreen if necessary to gain access to a hard-to-reach desired population. Otherwise, allow participants to complete survey and remove unwanted participants after completion. When prescreening for desired participant characteristics, do so with an initial questionnaire and restrict access to longer survey for participants who meet selection criteria.
(5) Prevent duplicate workers – Use the MTurk feature, which utilizes worker identification numbers to prevent workers from completing the same task more than once.
(6) Avoid obtrusive attention checks – Instead, limit participation to workers who have successfully completed at least 100 tasks with a 95% or higher approval rating.
(7) Use novel research materials when appropriate – To avoid participant nonnaiveté, use novel measures and experimental tasks when possible. If using more common measures, make sure their use is theoretically justified.
(8) Pilot test studies – In order to avoid costly mistakes in the case that the study is not running properly, pilot test all tasks on a small worker sample. In the pilot test, include an open-response item, in which participants can provide feedback on how study design and materials can be improved.
(9) Transparently report methods and results – Clearly describe methods and other pertinent information, such as recruitment procedures, sample demographic characteristics, attrition rates, measures of participant nonnaiveté or inattention, and MTurk's qualification features used to restrict worker eligibility (e.g., geographical restrictions, worker approval ratings).

Adapted from (Buhrmester et al., 2018; Chandler & Shapiro, 2016)

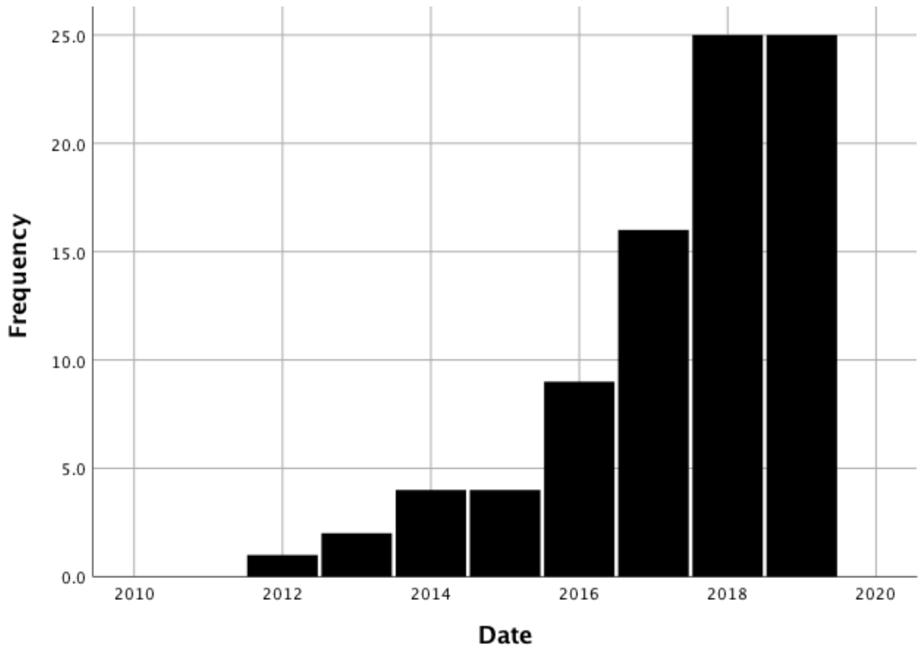

Figure 2.1. Alcohol-related peer-reviewed publications using Mturk (2010-2019)

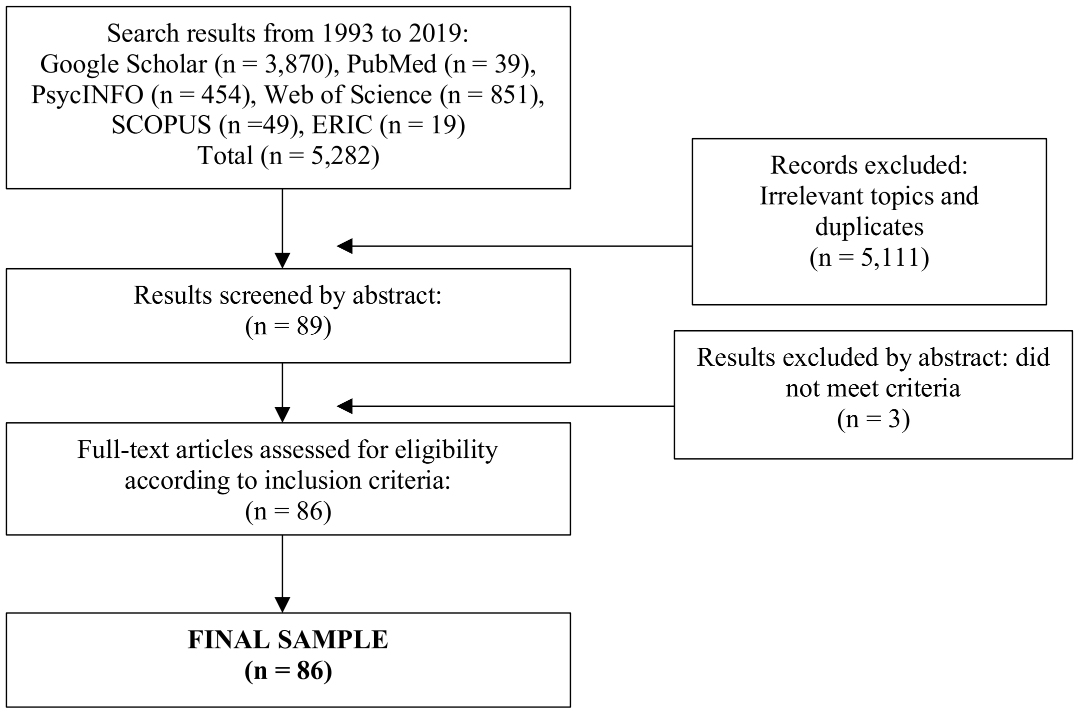

Figure 2.2. PRISMA flow diagram of alcohol-related studies employing MTurk to collect data.

CHAPTER III

A COMPARISON OF APPROACHES FOR ASSESSING PEER ALCOHOL USE

Despite persistent efforts to address alcohol misuse across college campuses, hazardous drinking among college students persists as a major public health concern (Substance Abuse and Mental Health Services [SAMHSA], 2017). Approximately 35% of college students report binge drinking over the previous 30 days (i.e., consuming 5 or more drinks on a single occasion for men or 4 or more drinks on an occasion for women), and 10% report heavy drinking over the same time period (binge drinking on 5 or more days in the past month) (National Institute on Alcohol Abuse and Alcoholism [NIAAA], 2018). College student alcohol use is associated with a litany of negative physical and environmental health risks, ranging from vandalism to physical and sexual assaults (NIAAA, 2018).

Numerous etiological factors have been linked to unhealthy alcohol consumption patterns among college students. A prominent factor identified throughout the literature – social, or peer influence (i.e., peer alcohol use and perceptions of peer alcohol use) – has been demonstrated as a particularly strong predictor for heavy drinking among college students (Neighbors, Lee, Lewis, Fossos, & Larimer, 2007; Perkins, 2002). Peer influence on drinking behaviors includes both descriptive and injunctive norms (Berkowitz, 2004). Descriptive norms capture an individual's perceptions of frequency and quantity of peer alcohol use. Injunctive norms, alternatively, refers to the perceived peer approval of alcohol use. The combination of an individual's descriptive and injunctive norms serve to establish their perception of what may be deemed socially acceptable or unacceptable (i.e., social norms) with regard to drinking behaviors.

On average, college students tend to overestimate the alcohol use levels of their peers

(Martens, 2006; Perkins, 2002). In other words, college students generally believe their college counterparts consume alcohol more frequently and at higher quantities than they actually do. In turn, these students may increase personal alcohol use in an effort to mirror their overestimates of peers' drinking. Consequently, public health practitioners across campuses nationwide have implemented social norms programming geared to correct students' misperceptions of peers' actual levels of alcohol consumption. These efforts have produced mixed results, in terms of effectiveness, in reducing alcohol use and warrant further examination and refinement (Wechsler et al., 2003).

Common strategies for measuring college students' perceptions of peer alcohol consumption often rely on items meant to capture individuals' perceptions of the global student body (i.e., drinking of a typical student at their respective university). This approach is flawed because all individuals in a given global network are treated equally in terms of social influence on an individual's personal drinking behaviors. Such an approach overlooks the true social contexts of college students, who exist within a more nuanced, uniquely defined social network personal to each individual. Simply put, persons most likely to influence an individual's behavior are his/her closest, most proximal peers.

Social networks analysis (SNA; Borgatti, Everett, & Johnson, 2018; Valente, 2010) offers an alternative measurement approach allowing for examinations into how composition and structure of students' personal social networks influence their alcohol-related behaviors. SNA allows for the explication of the effects of social norms on personal alcohol use by accounting for relationships between individuals throughout a social network – directly informed by respondents - and in which students report on the influence and behaviors of proximate, meaningful social ties (Patterson & Goodson, 2019). SNA consists of two broadly distinct analytical approaches (i.e., egocentric and whole network; Borgatti, Everett, & Johnson, 2018; Valente, 2010). The egocentric approach focuses on the perspective of the respondent, or ego, and attempts to elicit a deeper understanding of that focal individual's personal social environment consisting of their closest, most personal ties. An ego may be asked to identify 5-10 individuals, or alters, he/she feels most close to, as well as the type and strength of each relationship. Then, the ego is asked to report on their own behaviors, as well as the behaviors of the alters they nominated. Alternatively, a whole network approach attempts to account for all connections between individuals within a given social environment (e.g., college dormitory, office work setting). Within the whole network approach, all members of a particular network are asked to report on their own behaviors, as well as their connections to and behaviors of any of the other members located within the whole network.

Scholars have already leveraged network analysis to explore social norms and alcohol use. For instance, Kenney et al. (2017) compared how misperceptions of peer alcohol use were related to students' personal drinking behaviors using normative data collected via global campus-based surveys and questions specific to actual participant-referent relationships. While the students overestimated alcohol use of their residence hall peers when questioned in a global manner ("When a college student in your residence hall drinks, how much does s/he drink?"), they accurately perceived the drinking behaviors of peers nominated as close friends. The difference between students' perceptions of their nominated peers' alcohol use and the actual self-reported drinking behaviors of their peers was not statistically significantly different. Moreover, overestimating nominated peers' alcohol use – as opposed to global overestimation – held a stronger association with personal alcohol use.

Kenney et al. (2017) utilized a whole network approach to study the influence of misperceptions of peer alcohol use on students' personal drinking behavior. Opting to use a whole network approach, student respondents were asked to identify their ten closest social ties living in their residential dormitory. Thus, these students were limited in who they could identify as social contacts. It is likely that some of the respondents may have developed other close friendships with students enrolled in the same courses or participating in the same social organizations but did not reside in their given dormitory. Given the restriction on who respondents could identify as social ties, it is possible this approach did not accurately capture all of the respondents' closest, most influential peers. Given the strong association between the alcohol use behaviors of an individual's immediate, most proximal peers and their own alcohol use patterns, it would seem an egocentric network approach would provide additional, novel insights. To our knowledge, investigations examining the influence of social norms on alcohol use via egocentric network analysis are limited.

Thus, the purpose of this investigation is to examine the relationship between college students' personal alcohol consumption patterns and the drinking behaviors of their personally identified close peers using egocentric network data. In doing so, I will compare and contrast the results obtained using two distinct methods for assessing the impact of perceptions of peer drinking on personal alcohol use: (1) global campus-based measures seeking to elicit individuals' perceptions of the "typical" student's drinking behaviors, versus (2) egocentric social network measures specific to actual participant-referent relationships, in which respondent's report on their perceptions of the drinking behaviors of personally identified proximal peers.

Methods

Participants and Procedures

Data was collected via Amazon's Mechanical Turk (MTurk; Amazon, 2018) in January and February 2020. Via MTurk, a link for a Human Intelligence Task (HIT) was provided to any participants/workers meeting the specified eligibility criteria. After informed consent was given, participants completed an online survey consisting of demographic, personal and peer alcohol use, and egocentric network questions. MTurk enlists a feature enabling requesters the option to limit task viewability to those who meet predetermined eligibility criteria. This feature serves as a screening method to prevent unwanted and/or duplicate participation. Participants in this study were limited to current college-enrolled individuals residing in the United States between the ages of 18-26 with MTurk reputations of 95% or higher on a minimum of 100 HITs (Peer, Vosgerau, & Acquisti, 2014).

Upon clicking the link and accepting the task, workers were directed to a survey (and informed consent) hosted on *Qualtrics*. Approximately 309 individuals completed and were compensated for the HIT. Sample size was determined based on the number of items included in the survey. In order to enhance the generalizability of results, a ratio of 5 to 10 participants per survey item is suggested for samples of up to 300. For samples of more than 300, this ratio is less important, as item and test parameters start to stabilize (Tinsley & Tinsley, 1987). Survey respondents were compensated in an ethical manner (i.e., \$5; \$0.10 per minute or higher is recommended by Chandler & Shapiro, 2016). Study protocols were vetted and approved by the university's institutional review board prior to data collection.

Measures

Demographics. Demographic items assessed participant age, gender, race/ethnicity, sexual orientation, year in school, type of institution, visa status, relationship status, Greek-life affiliation, living arrangements, GPA, and participation in athletics.

Alcohol use. Personal alcohol use was measured using the consumption version of the

Alcohol Use Disorders Identification Test (AUDIT-C; Bush, Kivlahan, McDonell, Fihn, & Bradley, 1998). Adapted from the original ten-item AUDIT (Saunders, Aasland, Babor, De la Fuente, & Grant, 1993), the AUDIT-C is a three-item questionnaire intended to screen for hazardous drinking behaviors. The first item assesses frequency of alcohol consumption ("How often do you have a drink containing alcohol?"). Response options were: (0) never, (1) monthly or less, (2) 2-4 times a month, (3) 2-3 times a week, or (4) 4 or more times a week. The second item presents respondents with a standard drink definition and attempts to capture quantity of alcohol consumed on a typical drinking day ("How many standard drinks containing alcohol do you have on a typical day"). Response options were: (0) 1 or 2, (1) 3 or 4, (2) 5 or 6, (3) 7 to 9, or (4) 10 or more. Finally, the third item measures frequency of binge drinking ("How often do you have six or more drinks on one occasion?"). Response options were: (0) never, (1) less than monthly, (2) monthly, (3) weekly, or (4) daily or almost daily. All items are summed up to establish a total score ranging from 0-12. Generally, the higher an individual scores, the more hazardous their drinking. Typically, scores of 4 or more for men, and 3 or more for women, are used to identify hazardous drinkers. DeMartini and Carey (2012), however, suggest higher scores for college students, contending 7 for males and 5 for females is most appropriate to identify at-risk drinkers in college settings. The psychometric qualities of the AUDIT-C have been tested with college student populations, consistently demonstrating valid and reliable scores (Barry, Chaney, Stellefson, & Dodd, 2015; DeMartini, & Carey, 2012).

Global Perceptions of Peer Alcohol Use. Three items adapted from the National College Health Assessment (ACHA, 2015) were utilized to measure perceptions of "typical" students' alcohol use. The first item seeks to account for perceptions of typical students' frequency of alcohol consumption ("Within the last 30 days, how often do you think the typical student at your school used alcohol (beer, wine, liquor)"). Responses options were: (0) Never used, (1) Have used, but not in last 30 days, (2) 1-2 days, (3) 3-5 days, (4) 6-9 days, (5) 10-19 days, (6) 20-29 days, and (7) Used daily. The second item is designed to measure perceptions of typical students' quantity of drinking on a typical drinking day, and responses are open-ended ("How many drinks of alcohol do you think the typical student at your school had the last time he/she "partied"/socialized? (If you think the typical student at your school does not drink alcohol, please enter 0) ______ Number of Drinks"). Lastly, a third item assessed perceptions of typical students' frequency of binge drinking ("Over the last two weeks, how many times do you think the typical student at your school had five or more drinks of alcohol at a sitting?"). Response options were: (0) N/A, don't drink, (1) None, (2) 1 time, (3) 2 times, (4) 3 times, (5) 4 times, (6) 5 times, (7) 6 times, (8) 7 times, (9) 8 times, (10) 9 times, (11) 10 or more times.

Egocentric network variables.

Identification of important peers. Respondents were asked to identify up to five college peers (i.e., individuals currently enrolled at the same academic institution) who they felt closest to. After a list of alters was generated for an ego, interpreter questions were employed to systematically evaluate the following: (a) the nature of the social tie between the ego and alter (i.e., type of relation), and (b) the characteristics of the alter (i.e., demographics, fraternity/sorority involvement, alcohol use behaviors) (Borgatti, 2018; Valente, 2010). Lastly, inter-relator questions asked the ego to report on the social ties between alters (e.g., Does person A consider person B a personal friend?).

Nominated peer drinking. After egos nominated up to five alters, they were asked to report on the drinking behaviors of each alter. The items used to assess alters' alcohol consumption behaviors mirrored the global perceptions of peer alcohol use items (ACHA, 2015).

The phrase “typical student at your school” was replaced with “this person” in each of the three items (e.g., “(“Within the last 30 days, how often do you think ‘this person’ used alcohol (beer, wine, liquor”).

Analysis

Egocentric data was input using E-Net (Borgatti, 2006) - a software platform specifically designed to produce standard ego network measures. In our investigation, we were interested in social homogeneity, or how ego’s alcohol use behaviors were affected by their perceptions of alters’ drinking behaviors (Borgatti, 2018). Thus, measures of central tendency – or network composition (i.e., average of an egocentric network variable, or proportion of network on a given variable) were explored (Borgatti, 2018; Valente, 2010). Network composition variables were calculated based on alters’ gender, race, Greek-life affiliation, frequency of alcohol consumption, typical quantity consumed, and frequency of binge drinking. Specifically, the average frequency of alcohol use, typical quantity consumed, and frequency of binge drinking was calculated for each egocentric network.

After ego network measures were calculated, data was exported to SPPS 26.0 (IBM, 2019), where descriptive statistics and hierarchical linear regression analyses were computed. Hierarchical linear regression analyses were conducted to evaluate whether egocentric network variables explained individual variations in egos’ alcohol use (i.e., AUDIT-C scores) over and above global perceptions of peer alcohol use (i.e., respondent’s perceptions of the typical college students’ drinking), after controlling for age, gender, race/ethnicity, year in school, and Greek-life affiliation. Thus, the first block of covariates included only individual level characteristics (i.e., age, gender, race/ethnicity, year in school, and Greek-life affiliation). The second block of predictors added global perceptions of peer alcohol use. The third block included network composition variables for gender, race, and Greek-life affiliation. Finally, compositional variables based on alters' drinking behaviors were added to the model in the fourth block.

Results

Descriptive Statistics

The sample consisted of 309 participants (i.e., egos) with an average age of 21.76 years (SD=2.19; see Table 3.1). Nearly 53% of the sample were female. The majority of participants were White (58.4%; n=181), 14.5% (n=45) were Asian or Pacific Islander, 12.9% (n=40) were Black or African American, 6.8% (n=21) were biracial or multiracial, and 5.8% (n=18) were Hispanic or Latino/a. Approximately 92% (n=285) of the participants were current undergraduate students, and the other 8% (n=25) were graduate students. The sample largely consisted of students at four-year public universities (66.2%; n=204), while 17.2% (n=53) were enrolled at four-year private universities, 14.6% (n=45) were enrolled at community or junior colleges, and 1.9% (n=6) were enrolled at vocation-technical colleges. Most of the participants were enrolled as full-time college students (83.8%; n=258) – as opposed to part-time – and 6.8% (n=21) were international students. About 13% (n=41) were currently involved in Greek-life on campus (i.e., currently active in a fraternity or sorority). The average AUDIT-C score for the sample was 4.88 (SD=2.88; range=0-12). Over half of egos (54.9%; n=168) scored five or higher, and 26.5% (n=81) scored 7 or higher (scores of 4 or more for men, and 3 or more for women, are used to identify hazardous drinkers; scores of 7 for males and 5 for females used to identify at-risk drinkers in college settings) (Barry, Chaney, Stellefson, & Dodd, 2015; DeMartini, & Carey, 2012). Almost all egos (97.4%; n=302) nominated at least one alter who consumed alcohol in the previous 30 days, and 41.9% (n=130) of egos indicated that their entire network consumed alcohol in the last month. A vast majority of egos (88.1%; n=273) nominated at least one alter who binge-drank once or more in the previous two weeks, and 15.5% (n=48) of egos indicated that their entire network participated in binge-drinking at least once over the previous two weeks.

Hierarchical Linear Regression

The first block of the regression model (see Table 3.2), including only individual level variables (i.e., age, gender, race/ethnicity, year in school, and Greek-life affiliation) to predict egos' alcohol use (AUDIT-C scores), produced statistically significant results [$F(10,289)=3.524$, $p < .001$]. Block one of the model accounted for 10.9% (Adjusted $R^2=0.078$) of the variance in egos' AUDIT-C scores.

For the second block of the regression model, global perceptions of peer alcohol use were added to the model as predictors. Block two of the model produced statistically significant results [$F(13,286)=5.406$, $p < .001$] and accounted for 19.7% (Adjusted $R^2=0.161$) of the variance in egos' alcohol use. Global perceptions of peer alcohol accounted for 8.9% of the variance in egos' alcohol use over and above age, gender, race/ethnicity, year in school, and Greek-life affiliation, which is statistically significant [$F(3,286) = 10.517$, $p < 0.001$].

Block three of the regression model added network composition variables for gender, race, and Greek-life affiliation as predictors; this model also produced statistically significant results [$F(16,283)=5.079$, $p < .001$] and accounted for 22.3% (Adjusted $R^2=0.179$) of the variance in egos' alcohol use. Network composition variables for gender, race, and Greek-life affiliation accounted for 2.6% of the variance in egos' alcohol use over and above age, gender, race/ethnicity, year in school, Greek-life affiliation, and global perceptions of peer alcohol use, which is statistically significant [$F(3,283) = 3.139$, $p < 0.001$].

Finally, the fourth block of the regression model added compositional variables based on egos' perceptions of alters' drinking behaviors as predictors; this model also produced statistically significant results [$F(19,280)=6.954$, $p < .001$] and accounted for 32.1% (Adjusted $R^2=0.274$) of the variance in egos' alcohol use. Network composition variables based on egos' perceptions of alters' drinking behaviors accounted for 9.7% of the variance in egos' alcohol use over and above age, gender, race/ethnicity, year in school, Greek-life affiliation, global perceptions of peer alcohol use, and network composition variables for gender, race, and Greek-life affiliation, which is statistically significant [$F(3,280) = 13.391$, $p < 0.001$]. In the final model, being a current member of a sorority or fraternity ($\beta=.115$, $t=2.091$, $p=.037$) and egos' global perceptions of typical quantity of alcohol consumed by other students at their school ($\beta=.128$, $t=2.106$, $p=.036$) were the only individual-level variables significantly related to egos' AUDIT-C scores. Of the compositional egocentric variables, only egos' perceptions of typical quantity of alcohol consumed by nominated alters ($\beta=.317$, $t=3.558$, $p<0.001$) was significantly associated with egos' AUDIT-C scores.

Discussion

This investigation sought to juxtapose the association of personal alcohol use and perceptions of peer drinking established using two distinct methods: (1) global campus-based measures seeking to elicit individuals' perceptions of the "typical" student's drinking behaviors, versus (2) egocentric social network measures specific to actual participant-referent relationships, in which respondent's report on their perceptions of the drinking behaviors of personally identified proximal peers. Results from hierarchical regression analyses demonstrated that egocentric network variables (i.e., network composition) accounting for egos' perceptions of nominated alters' alcohol consumption explained a significant portion of variance in egos' alcohol use behaviors over and above individual-level predictors, global perceptions of peer alcohol use, and network composition variables for gender, race, and Greek-life affiliation. Consistent with previous findings (Kenney et al., 2017), results demonstrate the enhanced capability for egocentric social network measures – as opposed to global campus-based measures – to explain peer influence on personal alcohol consumption. Moreover, it is clear that close personal social ties have a greater impact on personal alcohol use than “typical students” attending the same institution. Global perceptions of peer alcohol use among students at one’s school or university (i.e., broader social norms) significantly influence the alcohol use behaviors of college students. However, accounting for the influence of the drinking behaviors of one’s nominated, proximal peers offers a deeper understanding of peer influence on personal alcohol consumption among the college student population. Such an approach to the influence of social norms on personal alcohol use behaviors can serve to better inform and enhance the effectiveness of normative feedback-based alcohol interventions.

Attribute Variables

Block one of the regression model served to control for individual-level predictors commonly associated with personal alcohol consumption throughout the literature. Though model one produced statistically significant results, only two individual-level variables (i.e., Greek-life affiliation; egos’ global perceptions of typical quantity of alcohol consumed by other students at their school) were significantly related to egos’ AUDIT-C scores in the final model. It is not surprising that being a current member of a sorority or fraternity is associated with higher levels of alcohol consumption, given “Greek members comprise a subgroup that consumes alcohol in greater quantities, underscores and misperceives the risks of alcohol abuse, and emulates a social environment and culture in which drinking alcohol is a key part of life” (Barry, 2007, p. 307).

In the second block of the regression model, global perceptions of peer alcohol use (i.e., frequency, quantity, and binge-drinking frequency) were added to the model. This model produced statistically significant results, and global perceptions of peer alcohol accounted for a significant portion of the variance in egos' alcohol use over and above age, gender, race/ethnicity, year in school, and Greek-life affiliation. Unexpectedly, only egos' global perceptions of typical quantity of alcohol consumed by peers held a significant relationship with their own drinking. Egos' perceptions of the frequency at which their peers consume alcohol in general and the frequency at which they binge-drink were not significantly associated with their own alcohol consumption.

Network Variables

The third block of the regression model added egocentric network variables (i.e., composition) based on gender, race, and Greek-life affiliation and explained a statistically significant portion of the variance in egos' alcohol use over and above age, gender, race/ethnicity, year in school, Greek-life affiliation, and global perceptions of peer alcohol use. The fourth block of the regression model added egocentric network predictors based on egos' perceptions of alters' drinking behaviors (i.e., frequency, quantity, binge-drinking frequency) and explained a statistically significant portion of the variance over and above predictors included in block three. Thus, egos' perceptions of their close social ties' drinking behaviors added nuance in explaining their own personal alcohol consumption over and above traditional global, campus-based approaches. Whether by peer selection (i.e., surrounding oneself with peers who consume alcohol in similar patterns; McPherson, Smith-Lovin, & Cook, 2001) or peer influence (i.e., adopting drinking behaviors to match the alcohol use patterns of close social ties; Valente, 1996), results indicate that egos who partake in more hazardous drinking behaviors are more likely to operate in a social environment with higher levels of alcohol consumption. That said, of the compositional egocentric variables, only egos' perceptions of typical quantity of alcohol consumed by nominated alters was significantly related to higher AUDIT-C scores. Though it is unclear exactly why the quantity measures of peer drinking exhibited stronger relationships to personal alcohol use, this finding deserves future attention. There are many other quantity-frequency (QF) measures of alcohol use (e.g., Armor, Polich, & Stambul, 1978; Midanik,1994; Skinner & Sheu, 1982). Future investigations should seek to include several variations of QF measures to determine if this finding – perceived quantity of peer drinking being most strongly correlated to personal alcohol use - could be replicated.

Limitations

There are several inherent limitations associated with this investigation. First, this study is cross-sectional in nature, and results are to be interpreted as correlational, rather than causational. Future investigations implementing longitudinal designs to explore the impact of network structure on individuals' alcohol consumption across time are warranted. Such studies could examine whether college students self-select into social environments consistent with their own drinking behaviors, or if students engage in drinking behaviors to mirror those of their close social ties. Second, there are limitations associated with the use of MTurk as a data collection tool. Mturk samples are limited with regard to external validity and generalization to the national population. MTurk samples represent nonprobability samples of the general population (i.e., convenience samples) and are not to be presented as nationally representative. Thus, although alcohol researchers using MTurk as a data collection tool must consider limitations associated with generalizability, these concerns are similar to those present in commonly utilized sampling approaches. Another limitation associated with the use of MTurk to collect data relates to the experience of research participants. MTurk workers with a great deal of experience on the platform may have previously been exposed to similar procedures or tasks. Previous exposure to a task or procedure can influence future behavior with regard to a similar task. Future investigations could account for the number of HITs a worker has completed as a potential confounder.

Conclusion

Commonly employed methods for capturing peer influence on personal alcohol consumption (i.e., traditional, global-based measures asking about the drinking of a “typical student” at one’s school) fail to capture the nuance associated with individuals’ perceptions of close others’ alcohol use and their own drinking behaviors. Results from this investigation demonstrate focusing on typical students, as opposed to close personal friends, would not accurately capture the magnitude of peer influence on personal drinking behaviors. This investigation outlines a novel, alternative approach (i.e., egocentric social network analysis) to study and better assess the impact of peer influence on college students’ alcohol consumption. Egocentric network composition variables based on egos’ perceptions of nominated alters’ drinking behaviors added distinction in explaining their own personal alcohol consumption when compared to traditional global, campus-based approaches. Thus, future studies would benefit from utilizing an egocentric network approach to examine the relationship between college students’ perceptions of peer alcohol use and their own drinking behaviors.

As previously discussed, respondents who demonstrated more hazardous drinking behaviors were more likely to nominate close others who exemplified similarly frequent, high quantity drinking. This finding has numerous implications for college health practitioners and researchers alike. Many traditional health programming efforts designed to combat heavy drinking in the college environment target individual-level decision-making and education (Carey, Scott-Sheldon, Carey, & DeMartini, 2007). However, findings in this study highlight the complex, interpersonal nature of alcohol use within the college student population. Thus, prevention and intervention efforts targeted at reductions in heavy drinking among college students (e.g., normative feedback interventions) may benefit from intervening within social contexts (e.g., existing peer groups, campus residence halls). Similarly, increasing offerings of alcohol-free events and programming may provide additional outlets for students to self-select into peer groups characterized by less hazardous alcohol use. Lastly, institutions of higher education should continue to devote themselves to more traditional campaigns designed to address broader alcohol-related social norms that may have a significant impact on college students' perceptions of peer alcohol use.

Table 3.1

Descriptive characteristics of the sample

Variable	N	%	M	SD
Age			21.76	2.19
Gender				
Male	146	47.2		
Female	163	52.8		
Classification				
1st year undergraduate	32	10.3		
2nd year undergraduate	74	23.9		
3rd year undergraduate	64	20.6		
4th year undergraduate	88	28.4		
5th year undergraduate	27	8.7		
Graduate student	25	8.1		
Race/Ethnicity				
White	181	58.4		
Black or African American	40	12.9		
Hispanic or Latino/a	18	5.8		
Asian or Pacific Islander	45	14.5		
American Indian, Alaskan Native, or Native Hawaiian	2	0.6		
Biracial or multiracial	21	6.8		
Other	3	1.0		
Greek-Life Affiliation				
Current member of fraternity/sorority	41	13.3		
AUDIT-C Total			4.88	2.88
AUDIT-C ≥ 5	168	54.9		
AUDIT-C ≥ 7	81	26.5		
Egocentric Network Composition Variables	302	97.4		
$\geq$1 alter that drinks (in general)	130	41.9		
100% of alters that drink (in general)	273	88.1		
$\geq$1 alter that drank 5+ drinks in one sitting (past two weeks)	48	15.5		
100% of alters drink 5+ drinks in one sitting (past two weeks)				

Table 3.2

Results from hierarchical regression analyses

Step and Variable	B	SE_B	β	R^2	Δ R^2
Block 1				0.109***	n/a
Age	0.218	0.095	0.151*		
Gender (female)	-0.610	0.327	-0.106		
Race (compared to white)					
Black or African American	-0.375	0.515	-0.043		
Hispanic or Latino/a	0.108	0.688	0.009		
Asian or Pacific Islander	-1.044	0.476	-0.128*		
American Indian, Alaskan Native, or Native Hawaiian	-1.229	1.982	-0.035		
Biracial or multiracial	0.242	0.644	0.021		
Other	-2.562	1.635	-0.088		
Grade level	0.072	0.134	0.035		
Greek-life (current member)	1.639	0.482	0.191***		
Block 2				0.197***	0.089***
Global Alcohol Frequency	-0.051	0.151	-0.020		
Global Alcohol Quantity	0.274	0.059	0.277***		
Global Alcohol Binge	0.115	0.083	0.082		
Block 3				0.223***	0.026*
Network composition					
Gender	0.010	0.008	0.089		
Race	0.008	0.006	0.092		
Greek-life	0.018	0.008	0.144*		
Block 4				0.321***	0.097***
Network composition					
Alter Alcohol Frequency	0.160	0.198	0.069		
Alter Alcohol Quantity	0.405	0.114	0.317***		
Alter Alcohol Binge	0.045	0.122	0.026		

*p ≤ 0.05, **p ≤ 0.01, *** p ≤ 0.001

CHAPTER IV

STRATEGIES FOR MEASURING PEER ALCOHOL USE WITHIN EGOCENTRIC NETWORK ANALYSIS

The use of social network analysis (SNA; Borgatti, Everett, & Johnson, 2018; Valente, 2010) to study the effects of peer influence on college students' personal drinking behaviors offers added nuance compared to commonly used global measures, which attempt to capture the influence of social norms on personal alcohol use by asking about the drinking of *typical* students at a respective university (Kenney et al., 2017). That said, there are inherent methodological considerations when using SNA to study peer influence on alcohol use – which, if properly addressed – can enhance the quality of future SNA research on drinking norms. Much of the current SNA literature seeking to capture the drinking behaviors of nominated alters do so by relying on single-item (e.g., typical quantity; Kenney et al., 2017) or two-item (e.g., typical quantity/frequency; Rosenquist, Murabito, Fowler, & Christakis, 2010) assessments of peer alcohol use. These measurement strategies for peer alcohol use fail to capture the totality of one's alcohol consumption patterns (e.g., infrequent episodes of consuming very large quantities). Both the National Institute on Alcohol Abuse and Alcoholism's Task Force on Recommended Alcohol Questions (NIAAA, n.d.) and the World Health Organization (World Health Organization [WHO], 2000) suggest asking a minimum of three types of questions (i.e., frequency of alcohol use, typical quantity of alcohol use, and frequency of heavy drinking) in order to adequately assess alcohol consumption patterns. Though recommended when assessing self-reported personal drinking behaviors, investigation into whether these methodological considerations apply to assessments of peer drinking is warranted. For instance, there is a paucity of investigations exploring whether results of SNA research would be impacted by expanding the assessment of perceived peer drinking beyond one to two quantity/frequency measures.

The purpose of the current investigation, consequently, was to empirically test whether the use of different strategies for measuring referent/peer alcohol use within alcohol-related SNA research impacts study results. More specifically, we examined which approach to gathering peer alcohol data via name interpreter questions accounted for more variance in the ego's drinking behavior. This article serves to establish best practices for measuring peer alcohol use (i.e., preferred name interpreter question/s) within alcohol-related research using egocentric network analysis.

Methods

Participants and Procedures

Amazon's Mechanical Turk (MTurk; Amazon, 2018) was utilized as a data collection tool, delivering an online informed consent *Qualtrics* survey. Eligible participants who chose to accept the Human Intelligence Task (HIT) were asked to answer questions on demographic, personal and peer alcohol use, and egocentric network characteristics. Only individuals who were currently enrolled college students in the United States, between the ages of 18-26, and who have an MTurk worker reputation of 95% or higher on a minimum of 100 HITs were eligible to participate (Peer, Vosgerau, & Acquisti, 2014). The final sample included 309 participants. Sample size was determined based off of Tinsley and Tinsley's (1987) recommended ratio of 5 to 10 participants per survey item. Ethical considerations were made to ensure payment amounts ($5) for participation were fair ($0.10 per minute or higher is recommended by Chandler & Shapiro, 2016). Study protocols were approved by the institutional review board prior to data collection.

Measures

Demographics. Respondents were asked to report on age, gender, race/ethnicity, sexual orientation, year in school, type of institution, visa status, relationship status, Greek-life affiliation, living arrangements, GPA, and participation in athletics.

Alcohol use.

AUDIT-C. Alcohol use was assessed with the three-item version of the Alcohol Use Disorders Identification Test (AUDIT-C; Bush, Kivlahan, McDonell, Fihn, & Bradley, 1998). The AUDIT-C examines frequency of alcohol use ("How often do you have a drink containing alcohol?"), typical amount of alcohol consumed on a drinking day ("How many standard drinks containing alcohol do you have on a typical day"), and frequency of binge drinking ("How often do you have six or more drinks on one occasion?"). Each item is scored on a 5-point Likert-scale ranging from 0-4. Scores for each item are added to create a cumulative AUDIT-C score between 0-12, with higher scores indicating more severe drinking. Typically, scores of 4 or more for men and 3 or more for women are used to identify hazardous drinkers. DeMartini and Carey (2012) suggest optimal cut-off scores of 7 for males and 5 for females to identify at-risk drinkers in college settings. The psychometric qualities of the AUDIT-C have been tested with college student populations, consistently demonstrating valid and reliable scores (Barry, Chaney, Stellefson, & Dodd, 2015; DeMartini, & Carey, 2012).

NIAAA Recommended Alcohol Questions. The NIAAA's Task Force on Recommended Alcohol Questions (NIAAA, n.d.) suggests asking a minimum of three types of questions (i.e., frequency of alcohol use, typical quantity of alcohol use, and frequency of heavy drinking) in order to adequately measure alcohol consumption patterns. Moreover, they make recommendations for three- and four-item assessments of alcohol use. We adapted the three item set to account for past-month level of alcohol consumption and drinking patterns by asking respondents to report on frequency of alcohol use (“During the last month, how often did you usually have any kind of drink containing alcohol?”), number of drinks consumed on a typical drinking day (“During the last month, how many alcoholic drinks did you have on a typical day when you drank alcohol?”), and frequency of binge drinking (“During the last month, how often did you have 5 or more (males) or 4 or more (females) drinks containing any kind of alcohol in within a two-hour period?”). For the four-item assessment, an additional item asked about past-month maximum number of drinks during a 24-hour period (“During the last month, what is the largest number of drinks containing alcohol that you drank within a 24-hour period?”). All items were scored on a 10-point Likert-scale.

Egocentric network variables.

Identification of important peers. Name generator questions requested for each respondent, or ego, to list five college peers (i.e., individuals currently enrolled at the same academic institution) with whom they feel closest to. Next, interpreter questions were utilized in order to better understand the nature of each social tie between an ego and alter (i.e., type of relation), as well as to elicit information with regard to alters’ characteristics (i.e., demographics, fraternity/sorority involvement, alcohol use behaviors) (Borgatti, 2018; Valente, 2010). Finally, inter-relator questions provided information on the existence/absence of social ties between alters (e.g., Does person A consider person B a personal friend?).

Nominated peer drinking. Egos reported on the drinking behavior of each nominated peer, or alter. In order to assess alters’ alcohol use behaviors, the items from the AUDIT-C (Bush et al., 1998) and NIAAA Recommended Alcohol Questions (NIAAA, n.d.) were adapted by replacing the phrase “you” with “this person” (e.g., “How often does *this person* have a drink containing alcohol?”).

Analysis

E-Net software (Borgatti, 2006) was used to aggregate data to the ego level and to calculate standard ego network measures. Network composition variables (i.e., average of an egocentric network variable, or proportion of network on a given variable) were computed (Borgatti, 2018; Valente, 2010). Compositional measures based on alcohol use behaviors (i.e., average alcohol use score for alters in a network) using varying measures for alcohol use (i.e., single-item assessment, two-item assessment, recommended four-item assessment, AUDIT-C) were calculated for each ego network.

After ego network measures were calculated, data was exported to SPPS 26.0 (IBM, 2019). Descriptive statistics for demographic and alcohol use variables and linear regression analyses were computed. Two models (using varied measures for alter alcohol use) were constructed to assess the effects of the network homophily and composition variables on egos’ alcohol use, controlling for age, gender, race/ethnicity, and Greek-life affiliation.

Model one employed items from the NIAAA Recommended Alcohol Questions (NIAAA, n.d.) to measure alter alcohol consumption. In model one, we sought to test whether a recommended set of four alcohol items (NIAAA, n.d.) explained individual variations in egos’ alcohol use (i.e., AUDIT-C scores) over and above commonly employed single-item or two-item assessments for alter alcohol consumption. Thus, hierarchical linear regression analyses were employed. The first block of predictors for model one included individual level characteristics (i.e., age, gender, race/ethnicity, year in school, and Greek-life affiliation). The second block of predictor variables added network composition variables for gender, race, and Greek-life affiliation. In block three, a network composition variable accounting for alters' frequency of alcohol use was added. The fourth block added a network composition variable measuring alters' quantity of alcohol consumed on a typical drinking day. Finally, block five included compositional variables measuring alters' binge drinking frequency and past-month maximum number of drinks during a 24-hour period.

Model two used AUDIT-C (Bush, Kivlahan, McDonell, Fihn, & Bradley, 1998) items to account for alter alcohol consumption. Hierarchical linear regression analyses were conducted in order to determine the amount of unique variance in egos' alcohol use (i.e., AUDIT-C scores) explained by alter AUDIT-C composition variables, controlling for age, gender, race/ethnicity, and Greek-life affiliation. The first block of predictors for model two included only individual level characteristics (i.e., age, gender, race/ethnicity, year in school, and Greek-life affiliation). The second block of predictors included network composition variables for gender, race, and Greek-life affiliation. Finally, block three included compositional variables measuring alters' alcohol use frequency, typical quantity consumed, and binge-drinking frequency (i.e., AUDIT-C total score).

Results

Descriptive Statistics

The final sample consisted of 309 respondents (i.e., egos) with an average age of 21.76 years (SD=2.19; see Table 4.1). The majority of participants were female (53%; n=163) and White (58.4%; n=181). A vast majority of the sample (92%; n=285) were current undergraduate students, enrolled full-time (83.8%; n=258), and primarily attended four-year public universities (66.2%; n=204). Approximately 13% (n=41) were currently members of a fraternity or sorority on campus. The sample scored an average of 4.88 on the AUDIT-C (SD=2.88; range=0-12;

scores of 4 or more for men, and 3 or more for women, are used to identify hazardous drinkers; scores of 7 for males and 5 for females used to identify at-risk drinkers in college settings; Barry, Chaney, Stellefson, & Dodd, 2015; DeMartini, & Carey, 2012). Over half of egos (54.9%; n=168) scored five or higher on the AUDIT-C, and 26.5% (n=81) scored 7 or higher. A vast majority of respondents (97.4%; n=302) nominated at least one alter who consumed alcohol in the past month, and 41.9% (n=130) of egos indicated their entire network consumed alcohol at least once in the previous month. Also, 88.1% (n=273) of respondents nominated at least one alter who participated in binge-drinking once or more in the previous two weeks, and 15.5% (n=48) indicated their entire network binge-drank at least once over the previous two weeks.

Hierarchical Linear Regression

Model One - NIAAA Recommended Questions

Block one of the regression model (see Table 4.2), including only individual level variables (i.e., age, gender, race/ethnicity, year in school, and Greek-life affiliation) to predict egos' alcohol use (AUDIT-C scores), produced statistically significant results [$F(10,292)=3.642$, $p < .001$]. Block one accounted for 11.1% (Adjusted $R^2=0.080$) of the variance in egos' AUDIT-C scores.

For the second block of the regression model, network composition variables for gender, race, and Greek-life affiliation were added to the model as predictors. Block two produced statistically significant results [$F(13,289)=4.219$, $p < .001$] and accounted for 16.0% (Adjusted $R^2=0.122$) of the variance in egos' alcohol use. Network composition variables for gender, race, and Greek-life affiliation accounted for 4.9% of the variance in egos' alcohol use over and above age, gender, race/ethnicity, year in school, and Greek-life affiliation, which is statistically significant [$F(3,289)=5.573$, $p=0.001$].

The third block of the regression model added a network composition variable accounting for alters' frequency of alcohol use as a predictor; this model also produced statistically significant results [$F(14,288)=6.560$, $p < .001$] and accounted for 24.2% (Adjusted $R^2=0.205$) of the variance in egos' alcohol use. The network composition variable for egos' perceptions of alters' frequency of alcohol use accounted for 8.2% of the variance in egos' alcohol use over and above age, gender, race/ethnicity, year in school, Greek-life affiliation, and network composition variables for gender, race, and Greek-life affiliation, which is statistically significant [$F(1,288)=31.251$, $p < 0.001$].

The fourth block of the model added a network composition variable accounting for alters' typical quantity of alcohol consumed on a drinking day as a predictor; this model also produced statistically significant results [$F(15,287)=7.142$, $p < .001$] and accounted for 27.2% (Adjusted $R^2=0.234$) of the variance in egos' alcohol use. The network composition variable for egos' perceptions of alters' typical quantity of alcohol consumed on a drinking day accounted for 3.0% of the variance in egos' alcohol use over and above age, gender, race/ethnicity, year in school, Greek-life affiliation, and network composition variables for gender, race, Greek-life affiliation, and alters' frequency of alcohol use, which is statistically significant [$F(1,287)=11.835$, $p=0.001$].

Finally, the fifth block of the regression model added compositional variables measuring alters' binge drinking frequency and past-month maximum number of drinks during a 24-hour period; this model also produced statistically significant results [$F(17,285)=7.271$, $p < .001$] and accounted for 30.3% (Adjusted $R^2=0.261$) of the variance in egos' alcohol use. Network composition variables based on egos' perceptions of alters' binge drinking frequency and past-month maximum number of drinks during a 24-hour period accounted for 3.1% of the variance in egos' alcohol use over and above age, gender, race/ethnicity, year in school, Greek-life affiliation, and network composition variables for gender, race, Greek-life affiliation, alters' frequency of alcohol use, and alters' typical quantity of alcohol consumed on a drinking day, which is statistically significant [$F(2,285) = 6.274$, $p=0.002$]. In the final model, being a current member of a sorority or fraternity ($\beta=.147$, $t=2.652$, $p=.008$) was the only individual-level variable significantly related to egos' AUDIT-C scores. Of the compositional egocentric variables, only egos' perceptions of binge-drinking frequency by nominated alters ($\beta=.288$, $t=2.998$, $p=0.003$) was significantly associated with egos' AUDIT-C scores.

Model Two – AUDIT-C

The first block of the regression model (see Table 4.3), including only individual level variables (i.e., age, gender, race/ethnicity, year in school, and Greek-life affiliation) to predict egos' alcohol use (AUDIT-C scores), produced statistically significant results [$F(10,292)=3.642$, $p < .001$]. Block one accounted for 11.1% (Adjusted $R^2=0.080$) of the variance in egos' AUDIT-C scores.

For the second block of the regression model, network composition variables for gender, race, and Greek-life affiliation were added to the model as predictors. Block two produced statistically significant results [$F(13,289)=4.219$, $p < .001$] and accounted for 16.0% (Adjusted $R^2=0.122$) of the variance in egos' alcohol use. Network composition variables for gender, race, and Greek-life affiliation accounted for 4.9% of the variance in egos' alcohol use over and above age, gender, race/ethnicity, year in school, and Greek-life affiliation, which is statistically significant [$F(3,289)=5.573$, $p=0.001$].

The third block of the regression model added a compositional variable measuring alters' alcohol use frequency, typical quantity consumed, and binge-drinking frequency (i.e., AUDIT-C total score) as a predictor; this model also produced statistically significant results [$F(14,288)=9.259$, $p < .001$] and accounted for 31.0% (Adjusted $R^2=0.277$) of the variance in egos' alcohol use. The network composition variable for alters' AUDIT-C scores accounted for 15.1% of the variance in egos' alcohol use over and above age, gender, race/ethnicity, year in school, Greek-life affiliation, and network composition variables for gender, race, and Greek-life affiliation, which is statistically significant [$F(1,288)=63.011$, $p < 0.001$]. In the final model, being a current member of a sorority or fraternity ($\beta=.125$, $t=2.320$, $p=.021$) was the only individual-level variable significantly related to egos' AUDIT-C scores. Of the compositional egocentric variables, only egos' perceptions of nominated alters' alcohol use frequency, typical quantity consumed, and binge-drinking frequency (i.e., alters' AUDIT-C total score; $\beta=.619$, $t=7.938$, $p < 0.001$) was significantly associated with egos' AUDIT-C scores.

Discussion

This study sought to establish best practices for measuring peer alcohol use (i.e., preferred name interpreter question/s) within alcohol-related research using egocentric network analysis. In doing so, we empirically tested the ability of varying measurement strategies for referent/peer alcohol use (i.e., single-item assessments, two-item assessments, AUDIT-C, NIAAA recommended 4-item set) to predict egos' drinking behaviors. Results from hierarchical regression analyses indicated that more comprehensive measurement approaches to egos' perceptions of nominated alters' drinking (i.e., AUDIT-C, NIAAA recommended 4-item set) offer significant advantages over oft-used one-item and two-item assessments (e.g., frequency of alcohol use and/or typical quantity consumed on a drinking day) in terms of explaining egos' alcohol consumption patterns.

In the final model one, egos' perceptions of nominated alters' binge-drinking frequency and past-month maximum number of drinks during a 24-hour period explained a significant amount of variance in egos' alcohol use patterns over and above individual-level predictors (i.e., age, gender, race/ethnicity, year in school, Greek-life affiliation), network composition demographic variables (i.e., gender, race/ethnicity, Greek-life affiliation), and network composition variables for egos' perceptions of nominated alters' frequency of alcohol consumption and typical quantity consumed on a drinking day. Being a current member of a sorority or fraternity was the only individual-level variable significantly associated with egos' AUDIT-C scores – a finding that was expected and consistent with prior research demonstrating the propensity for Greek-life to be characterized by heavy drinking social environments (Barry, 2007). Of the compositional egocentric variables, only egos' perceptions of binge-drinking frequency by nominated alters was significantly related to egos' AUDIT-C scores. Neither egos' perceptions of nominated alters' frequency of alcohol use nor their perceptions of alters' typical quantity consumed on a drinking day were significantly linked with egos' personal alcohol consumption in the final model. This finding – though peculiar – is not surprising. We were interested in explaining egos' alcohol consumption patterns as an outcome variable, including infrequent episodes of consuming very large quantities of alcohol. Consistent with suggestions by the World Health Organization (WHO, 2000) and National Institute on Alcohol Abuse and Alcoholism (NIAAA, n.d.), utilizing a minimum of three items (i.e., frequency of alcohol use, typical quantity of alcohol use, and frequency of heavy drinking) was necessary to provide adequate insights into the alcohol consumption patterns of respondents.

Model two further validated this finding. In the final model two, the network composition variable for egos' perceptions of alters' AUDIT-C total scores (i.e., alcohol use frequency, typical quantity consumed, and binge-drinking frequency) explained a significant amount of variance in egos' alcohol use patterns over and above age, gender, race/ethnicity, year in school, Greek-life affiliation, and network composition variables for gender, race, and Greek-life affiliation. As in model one, being a current member of a sorority or fraternity was the only individual-level variable significantly related to egos' AUDIT-C scores. Also, egos' perceptions of nominated alters' AUDIT-C total score (i.e., alcohol use frequency, typical quantity consumed, and binge-drinking frequency) was significantly associated with egos' AUDIT-C scores. As previously demonstrated in model one, model two further conveyed the need to utilize at least three items assessing frequency of alcohol use, typical quantity consumed on a drinking day, and binge-drinking frequency in order to adequately account for the influence of nominated alters' alcohol use behaviors on egos' own alcohol consumption patterns.

These findings carry implications with regard to future social network research centered on the influence of social norms on personal alcohol consumption. As evidenced by prior research (Kenney et al., 2017), the drinking behaviors of nominated, proximal social ties (e.g., alters) hold a particularly strong influence on personal alcohol use among college students. Thus, accurately measuring the alcohol consumption patterns of nominated alters is crucial for social network research interested in accounting for the relationship between peer influence and personal alcohol consumption. Ensuring effective measurement of alters' drinking behaviors offers a more detailed understanding of their influence on egos' alcohol use. In turn, a more accurate measurement of alter drinking behaviors can serve to better inform and enhance the effectiveness of prevention and intervention efforts within social contexts intended to reduce heavy drinking in the college environment by providing corrective normative feedback with regard to peer perceptions of alcohol use.

Limitations

Limitations associated with this study include the cross-sectional design. Larger, longitudinal designs examining the effects of peer influence on prospective drinking behaviors of college students are warranted. These studies could examine whether students opt into social environments consistent with their own alcohol use behaviors (i.e., peer selection), or if they engage in alcohol use behaviors to match those of their proximal social ties (i.e., peer influence).

Another limitation of the current study is the use of MTurk as a data collection tool. MTurk samples utilize nonprobability convenience sampling methods and are thus limited with regard to external validity and generalization to the national population. That said, MTurk samples consistently perform equal to, or better than, traditionally relied upon convenience samples (e.g., college students) and are more geographically and demographically diverse (Berinsky et al., 2012; Buhrmester et al., 2011; Paolacci et al., 2010). Samples extracted from MTurk may also contain more experienced research participants. If these participants have been previously exposed to a similar task or procedure, this could influence study results. Future investigations could examine whether prior alcohol research experience among MTurk workers (i.e., number of HITs) is a potential confounding variable.

Conclusion

This study aimed to establish best practices for measuring peer alcohol use (i.e., preferred name interpreter question/s) within alcohol-related research using egocentric network analysis. Results indicated that utilizing more comprehensive measures to capture egos' perceptions of nominated alters' drinking (i.e., AUDIT-C, NIAAA recommended 4-item set) – as opposed to simple one- and two-item assessments (e.g., frequency of alcohol and/or typical quantity consumed on a drinking day) – offers significant improvement in explaining egos' alcohol use behaviors. In line with recommendations from NIAAA and WHO for measuring self-report alcohol use, results from this investigation point to the need to use a minimum of three items (i.e., frequency of alcohol use, typical quantity of alcohol use, and frequency of heavy drinking) to measure peer alcohol use within alcohol-related research using egocentric network analysis. Future investigations utilizing an egocentric network approach to studying the influence of social norms on personal alcohol use within the college environment may fail to capture valuable insights if using simple quantity/frequency assessments of nominated peers' alcohol use. Using more comprehensive measures to account for alters' alcohol consumption patterns offers more nuance in explaining the relationship between close others' alcohol use behavior and one's own personal alcohol consumption. Moreover, this can ensure prevention and intervention efforts targeted at reductions in heavy drinking among college students within social contexts (e.g., existing peer groups, campus residence halls) are better informed, and in turn, more effective.

Table 4.1

Descriptive characteristics of the sample

Variable	N	%	M	SD
Age			21.76	2.19
Gender				
Male	146	47.2		
Female	163	52.8		
Classification				
1st year undergraduate	32	10.3		
2nd year undergraduate	74	23.9		
3rd year undergraduate	64	20.6		
4th year undergraduate	88	28.4		
5th year undergraduate	27	8.7		
Graduate student	25	8.1		
Race/Ethnicity				
White	181	58.4		
Black or African American	40	12.9		
Hispanic or Latino/a	18	5.8		
Asian or Pacific Islander	45	14.5		
American Indian, Alaskan Native, or Native Hawaiian	2	0.6		
Biracial or multiracial	21	6.8		
Other	3	1.0		
Greek-Life Affiliation				
Current member of fraternity/sorority	41	13.3		
AUDIT-C Total			4.88	2.88
AUDIT-C ≥ 5	168	54.9		
AUDIT-C ≥ 7	81	26.5		
Egocentric Network Composition Variables	302	97.4		
≥1 alter that drinks (in general)	130	41.9		
100% of alters that drink (in general)	273	88.1		
≥1 alter that drank 5+ drinks in one sitting (past two weeks)	48	15.5		
100% of alters drink 5+ drinks in one sitting (past two weeks)				

Table 4.2

Model one results from hierarchical regression analyses

Step and Variable	B	SE_B	β	R^2	ΔR^2
Block 1				0.111***	n/a
Age	0.216	0.095	0.149*		
Gender (female)	-0.596	0.324	-0.103		
Race (compared to white)					
Black or African American	-0.358	0.506	-0.041		
Hispanic or Latino/a	0.118	0.685	0.010		
Asian or Pacific Islander	-1.032	0.474	-0.126*		
American Indian, Alaskan Native, or Native Hawaiian	-1.219	1.975	-0.034		
Biracial or multiracial	0.254	0.642	0.022		
Other	-2.550	1.628	-0.088		
Grade level	0.071	0.134	0.034		
Greek-life (current member)	1.673	0.475	0.197***		
Block 2				0.160***	0.049***
Network composition					
Gender	0.014	0.008	0.122		
Race	0.006	0.006	0.072		
Greek-life	0.026	0.007	0.207***		
Block 3				0.242***	0.082***
Network composition					
Alter Alcohol Frequency	0.543	0.097	0.325***		
Block 4				0.272***	0.030***
Network composition					
Alter Alcohol Quantity	0.527	0.153	.273***		
Block 5				0.303***	0.031**
Network composition					
Alter Alcohol Binge	0.506	0.169	0.288**		
Alter Alcohol Maximum	0.262	0.180	0.152		

*$p \leq 0.05$, **$p \leq 0.01$, *** $p \leq 0.001$

Table 4.3

Model two results from hierarchical regression analyses

Step and Variable	B	SE_B	β	R^2	Δ R^2
Block 1				0.111***	n/a
Age	0.216	0.095	0.149*		
Gender (female)	-0.596	0.324	-0.103		
Race (compared to white)					
Black or African American	-0.358	0.506	-0.041		
Hispanic or Latino/a	0.118	0.685	0.010		
Asian or Pacific Islander	-1.032	0.474	-0.126*		
American Indian, Alaskan Native, or Native Hawaiian	-1.219	1.975	-0.034		
Biracial or multiracial	0.254	0.642	0.022		
Other	-2.550	1.628	-0.088		
Grade level	0.071	0.134	0.034		
Greek-life (current member)	1.673	0.475	0.197***		
Block 2				0.160***	0.049***
Network composition					
Gender	0.014	0.008	.122		
Race	0.006	0.006	0.072		
Greek-life	0.026	0.007	0.207***		
Block 3				0.310***	0.151***
Network composition					
Alter AUDIT-C Total	0.619	0.078	0.437***		

*p ≤ 0.05, **p ≤ 0.01, *** p ≤ 0.001

CHAPTER V

CONCLUSION

This research project had three overarching goals: (1) to present an overview on the use of Amazon Mechanical Turk (MTurk) as a data collection tool in alcohol-related research, and discuss the potential impacts of important MTurk-specific methodological decisions; (2) to extend our understanding of peer influence on alcohol use among college students utilizing a social network analysis (SNA) approach; and (3) to establish best practices for operationalizing perceived peer alcohol use within SNA research.

MTurk has been used to conduct a variety of alcohol-related investigations, including alcohol-related cross-sectional research and replication studies, measurement development, longitudinal research, and interventions (See Chapter II). Alcohol researchers interested in collecting data using MTurk are encouraged to pay particular attention to the following best-practices: (1) pay a fair wage; (2) disguise the purpose of the study until it is accepted; (3) measure and report study attrition; (4) prescreen unobtrusively; (5) prevent duplicate workers; (6) avoid obtrusive attention checks; (7) use novel research materials when appropriate; (8) pilot test studies; and (9) transparently report methods and results (See Table 2.2 for best-practices guidelines; Chandler & Shapiro, 2016). MTurk proved to be a valuable data collection tool in this particular alcohol-related investigation – an examination of the effects of social influence on the drinking behaviors of college students. Moreover, the best-practices highlighted above served to guide the methodological decisions made in subsequent investigations.

In exploring the influence of peer/social drinking on personal behavior, the author compared two distinct assessment strategies for measuring perceptions of peer drinking: (1) perceptions of the "typical" student's drinking behaviors, versus (2) egocentric social network measures, in which respondent's (i.e., egos) report on perceptions of the drinking behaviors of personally identified peers (i.e., alters). Overall, egocentric social network measures explained markedly greater levels of variability in peer influence on personal alcohol consumption, compared to global typical campus student measures. Specifically, egos' perceptions of nominated alters' drinking behaviors accounted for 9.7% of the variance in egos' alcohol use beyond demographics, global perceptions of peer alcohol use, and network composition demographics, which was statistically significant [$F(3,280) = 13.391$, $p < 0.001$]. Proximal, personally identified peers have a greater influence on personal alcohol consumption than perceptions of "typical students" at the same institution. Consequently, future initiatives and programmatic efforts seeking to understand or leverage peer influence should ground their efforts in those peers personally closest to the target audience.

To further extend the need for more nuanced assessments of perceived peer drinking, the author empirically tested whether different strategies for measuring referent/peer alcohol use (i.e., single-item or two-item approaches versus multiple item assessments) within alcohol-related SNA research would impact study results. Commonly, SNA research employs single-item or two-item assessments (i.e., quantity, frequency, or quantity/frequency) to measure individuals' perceptions of peer alcohol use. Thus, the author sought to determine whether the one-item or two-item measure status quo provided comparable insights to multiple item assessments, such as those recommended by the National Institute of Alcohol Abuse and Alcoholism. In sum, more comprehensive measures of an egos' perceptions of nominated alters' drinking offered significant advantages over one- and two-item assessments. Specifically, egos' perceptions of nominated alters' binge-drinking frequency and past-month maximum number of drinks during a 24-hour period explained a significant amount of variance in egos' alcohol use, over and above perceptions of nominated alters' frequency/typical quantity of alcohol consumption and important demographic covariates. Findings suggest that utilizing a minimum of three items (i.e., frequency, quantity, and frequency of heavy drinking) is necessary to provide adequate insights into the alcohol consumption patterns of respondents. Implementing these minimum requirements in egocentric network research can enhance programming efforts targeted at reductions in heavy drinking among college students within social contexts (e.g., existing peer groups).

Future research would benefit from utilizing an egocentric network approach to examine the complex, interpersonal nature of alcohol use among college students. Future investigations utilizing an egocentric network approach to study the influence of social norms on personal alcohol use within the college environment may fail to capture valuable insights if using simple quantity/frequency assessments of nominated peers' alcohol use. Thus, more comprehensive measures to account for alters' alcohol consumption patterns offers more nuance in explaining the relationship between close others' alcohol use behavior and one's own personal alcohol consumption. Moreover, this can ensure prevention and intervention efforts targeted at reductions in heavy drinking among college students within social contexts (e.g., existing peer groups, campus residence halls) are better informed, and in turn, more effective.

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