The Networks and Cultural Assets Project

SEPTEMBER 2023

CENTER FOR RESEARCH ON College-Workforce Transitions

Using Multiple Generator Random Interpreters (MGRIs) for Studying Undergraduate Student Support Networks

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RESEARCH BRIEF

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Summary

This research brief introduces the Multiple Generator Random Interpreter (MGRI; Marin & Hampton, 2007), a method for collecting personal or "ego" network data, as an alternative to traditional name generators and interpreters in social network research. Specifically, we focus on:

1. How MGRIs are different from Traditional Name Generators and Interpreters (TNGIs), and

2. What new insights can be yielded from using MGRIs when assessing college students' support networks.

We answer (1) with a review of social network literature, then focus on (2) by describing research methods and empirical evidence from two studies we have conducted of Latino/a/x/e (hereinafter "Latine") college students in two U.S. states. We conclude with insights from our analyses and links to resources for implementing MGRIs in online surveys.

Keywords (3)
social network analysis, ego network analysis, name generators, Latino/a/x/e college students

Introduction

Researchers in higher education who study *social support networks*—groups of interpersonal relationships through which individuals exchange help, advice, and guidance (Wasserman & Faust, 1994)—widely use name generators and interpreters in surveys. "Name generators" are questions that elicit the names of people with whom survey respondents exchange information or discuss certain topics. After collecting these names, surveys often include "name interpreters" that ask respondents to provide information on the people who have been listed, including, for example, each person's role in the respondent's life, their education level, how close the respondent feels affectively to each person, etc.

To reduce cognitive burden, which can exponentially grow with the number of names a respondent lists, a common practice in the field has been to cap the number of contacts that respondents are allowed to list in response to name generators (Merluzzi & Burt, 2013). We refer to this method as the **Traditional Name Generator and Interpreter (TNGI) approach.**

Evidence suggests, however, that TNGIs have limitations. The capping method often captures only a part of the social network of interest. It also tends to overrepresent people with whom the respondent has closer relationships (Peng et al., 2023).

An alternative to this capping method is the **Multiple Generator Random Interpreter (MGRI) approach** (Marin & Hampton, 2007). This method lets respondents list as many names as they wish in response to two or more name generators, then only collects further data on a randomly sampled subset of these people in subsequent name interpreter questions. Research indicates this method gathers data that more effectively represents wider personal networks, while also decreasing respondent burden (Golinelli et al., 2010; McCarty et al., 2007; Stadel & Stulp, 2022).

Although evidence has shown that this method is robust, few studies have adopted the MGRI, primarily because it is still fairly new and there is a lack of information on how to apply it in practice (Peng et al., 2023).

Study Purpose

With these gaps in mind, we aim to answer two important research questions in this brief:

1. What is the MGRI in social network analysis, and how is it different from the TNGI?
2. What new insights, if any, can be yielded from using MGRIs when measuring college students' support networks?

We focus on (1) with a review of the literature outlining the differences between MGRIs and TNGIs. In speaking to (2), we describe methods and comparative empirical evidence from two research studies we have conducted focused on Latino/a/x/e (hereinafter "Latine") college students in two U.S. states, one of which used TNGIs (N=129) and the other which used MGRIs

(N=408). We conclude with insights from our analyses and links to resources for implementing MGRIs in online surveys.

Question 1: Explaining MGRI and How It is Different from TNGI

Traditional Name Generators

Name generators have been the standard method for collecting social network information since the 1960s (Laumann, 1966). One widely used name generator question is, “With whom have you discussed important matters over the last six months?” (Campbell & Lee, 1991). Name generators are typically followed by name interpreters, a set of follow-up questions on each listed person or “alter.” Name generators and interpreters have been increasingly used in higher education research to assess students’ social connections as they relate to academic development and persistence in college (e.g., Brown, 2019).

TNGI methods often use capping techniques, where researchers limit the number of names that respondents can list in response to name generators (Burt, 1984; Merluzzi & Burt, 2013). Capping has traditionally been considered necessary to reduce the social network survey burden for participants, as well as to prevent the penalization of participants who list more contact names (McCarty et al., 2019). Still, these methods have several limitations. Because participants tend to list the names of people who are closer to them, TNGIs often generate family-centered networks, which in turn may lead to biased analyses and results (Marin & Hampton, 2007). More seriously, capped name generators may not reliably capture the true size of a network, an important measure of social resources (Perry et al., 2018).

The limitations of TNGI have critical implications for higher education research and practice. Establishing and expanding social networks has been considered an important developmental goal for college students’ academic and career success, and researchers have recommended educators support students in growing their networks beyond family and friends (Rios-Aguilar & Deil-Amen, 2021). Providing evidence-backed support requires a close examination of students’ social networks, which often necessitates the use of social network survey tools such as name generators and interpreters. The concern that the most widely used method, TNGI, is limited in capturing these networks beyond close-knit relationships, leads to another concern, namely that the empirical evidence used for supporting students might not actually be capturing the “true” or whole personal networks of college students.

An Alternative Technique

The MGRI approach has been recognized as one of the most promising alternatives to capped TNGIs (Peng et al., 2023). After allowing respondents to list all those in their lives who meet the name generator criteria, MGRIs then use only a randomly selected subset of those names for subsequent name interpreter questions (Marin & Hampton, 2007). Participant burden for those who list more alters is diminished, and researchers are able to gather data on a more unbiased subgroup of network alters. Indeed, studies have found that MGRIs better capture the characteristics of “true” or whole personal networks (e.g., Golinellil et al., 2010; Stadel & Stulp, 2022). For instance, Stadel and Stulp (2022) compared using capped TNGI and MGRI with a sample of 701 Dutch women. The results showed that MGRI yields information closer to the true network values (e.g., size, density) than capped TNGI. Although the benefits of MGRI are supported by empirical evidence, the method has been largely underutilized (Peng et al., 2023).

While the underuse of the MGRI approach can partly be explained by its more recent introduction to social network analysis, it has also been underutilized because it is difficult to implement in online survey settings, where much new social network research originates (e.g., Perry et al., 2018). MGRIs require respondent-specific, in-survey alter randomization for those listing more than a small number of names, and automated, online settings introduce a number of programming complications. Most studies using MGRIs thus far have collected social network data through personal interviews, perhaps for this reason (e.g., Peng et al., 2023). Although interviews continue to be considered an effective method for implementing complex survey tools like the MGRI, they are also time-consuming and costly, limiting researchers' ability to gather data from larger samples. These issues are critical, particularly for researchers and practitioners with limited resources.

Question 2: Studying the Use of MGRIs to Measure College Students' Support Networks

In order to adopt MGRIs while controlling study costs, we have developed an online survey tool using this more robust social network data gathering method. Herein, we introduce descriptive findings from a pair of studies comparing a TNGI survey tool with our MGRI tool to discuss the MGRI approach's significance in social network research in higher education.

Study Methods

Data Sources

This brief consists of two studies that the authors conducted between 2021 and 2023. Study 1 used a TNGI to assess the networks of Latine college students of all majors at a regional college in the state of Wisconsin. Study 2 used a MGRI to assess the networks of Latine STEM college students at seven universities in the state of Texas. Table 1 displays the demographic information of each study sample.

Table 1. Respondent Demographic Characteristics

	Study 1 (TNGI) N=129		Study 2 (MGRI) N=408	
Measure	**Frequency**	**Percent**	**Frequency**	**Percent**
Gender				
Cisgender Man	55	42.6	163	40.0%
Cisgender Woman	70	54.3	210	51.5%
Transgender Woman/Man	0	0.0	2	0.5%
Non-binary	4	3.1	10	2.5%
Not listed	N/A	N/A	8	2.0%
Prefer not to reply	N/A	N/A	15	2.0%
Racial identity (Multichoice)				
American Indian or Alaska Native	2	1.6	8	2.0%
Asian or Asian-American	2	1.6	6	1.4%
Black or African American	1	0.8	6	1.4%
Hispanic or Latina/o	129	100.0	408	100.0%
Native Hawaiian or Pacific Islander	0	0.0	1	0.2%
White or Caucasian	40	31.0	51	12.5%
Other	N/A	N/A	1	0.2%
Identified Hispanic/Latino Origin				
Mexican/Mexican American/Chicano/a	108	83.7	375	91.9%
Cuban	3	2.3	2	0.4%
Puerto Rican	10	7.8	9	2.2%
Other	15	11.6	26	6.1%
Major				
Arts and Humanities	10	7.8	N/A	N/A
Biological/Life Sciences	7	5.4	171	41.6%
Business	49	38.0	N/A	N/A
Education	20	15.5	N/A	N/A
Engineering	1	0.8	209	51.2%
Health Professions	2	1.6	N/A	N/A
Math and Computer Science	11	8.5	11	2.7%
Physical Science	0	0	17	4.2%
Social Science	22	17.1	N/A	N/A
Other Majors	2	1.6	N/A	N/A
Not listed	2	1.6	N/A	N/A

Study 1 used one name generator following TNGI capping methods. This prompt, which we refer to as the “academic and career matters” generator, asked students to “list the first name or initials of up to six people with whom [they] have discussed academic or career matters during the last 6 months.” Students were presented with six empty boxes in total on one screen and could list no more than six names in response.

Study 2 followed an MGRI approach using two name generators. The first name generator presented to students in this study was the most commonly used “important matters” prompt.

This generator asked participants to “list the first name and last initial of all people with whom [they] have discussed matters important to [them] during the last 6 months” (Burt, 1984). Respondents in Study 2 were then presented with the “academic and career matters” generator. In order to assess the overlap between two networks, we asked participants in Study 2 if they had discussed academic or career matters with any of the alters listed in the “important matter” generator. Study 2 participants were first provided five boxes for listing names in response to each generator. Those who filled out all available boxes for each generator were led to another set of five boxes. Those who filled out these five boxes were led to another set of five boxes. Each of the two generators in Study 2 had a total of fifteen boxes for listing names. Therefore, students could name up to thirty names in response.

In Study 1, a set of name interpreters (follow-up questions on each listed alter) were presented for all the listed alters. In Study 2, participants who listed six or fewer names were presented with name interpreters for all listed alters. Those who listed more than six names in Study 2 were presented with name interpreters for a set of six of their alters who were randomly selected from their larger list.

In both studies, the total number of alters students listed measured “network size.” Following traditional ego network methods, Study 1 and Study 2 included interpreters asking respondents to indicate the role of each alter in their lives (family member, friend, etc.), how close they felt to each alter (otherwise known as “tie strength”), each alter’s gender identity and racial identity, and each alter’s educational level. Both studies also asked respondents to indicate whether each listed alter in their network knew other alters, results of which indicate “density,” or how interrelated one’s social network is.

Data Analysis

We compared the two datasets using descriptive statistics focusing on network size, density, tie strength, and alter characteristics. To control the effect of using two name generators in Study 2, we split the Study 2 datasets into two parts, one referred to as “whole network,” including all alter names listed from the two name generators, and one referred to as “academic and career network”. Although this treatment may have reduced bias, it is important to note that there are other demographic attributes (e.g., students of all academic majors in Wisconsin compared to students of only STEM majors in Texas) and institutional contexts (e.g., a Predominantly White Institution in Wisconsin compared with mostly Hispanic-Serving Institutions in Texas) that may introduce other biases in the comparison. These limitations should be considered when interpreting study results.

Findings

Table 2 summarizes the personal network characteristics of each Latine student sample.

Table 2. Student Respondent Network Characteristics

	Study 1 TNGI (N=129) Academic & Career Networks		Study 2 MGRI (N=408) Whole Networks		Study 2 MGRI (N=408) Academic & Career Networks	
	Range	Mean (SD)	Range	Mean (SD)	Range	Mean (SD)
Network size	0-6	2.57 (1.57)	0-20	5.09 (2.79)	0-17	3.85 (2.47)
Network Density	0-1	0.38 (0.33)	0-1	0.30 (0.27)	0-1	0.29 (0.31)
Tie Strength	1-4	3.23 (0.67)	1-4	3.32 (0.54)	1-4	3.34 (0.60)

Note: Network size (in this study): number of listed alters; Network density: proportion of the actual connections to all potential connections in a network; Tie strength: average value of closeness (1=Distant, 2=Less than close, 3=Close, 4=Very close) with all alters in each personal network.

The most notable difference across the datasets is that the average network size was larger in Study 2 (5.09) than Study 1 (2.56), even when we limited the alter sample to academic and career networks (3.85). Specifically, the average network size of academic and career networks in Study 2 was still 1.3 alters larger than Study 1's average (2.57).

Further examination of the data shows that 13% (N=53) of students in Study 2 listed more than six alters for academic and career networks. Average network density was also lower in Study 2 (0.29-0.30) as compared to Study 1 (0.38). This means that alters among respondents in the Study 2 sample were less likely to know one another than those of Study 1. Average tie strength was similar across the two studies (3.23-3.34).

We also examined listed alters' characteristics (Table 3).

Table 3. Characteristics of Student Respondent Alters by Study

	Study 1 TNGI (N=332)	Study 2 MGRI (N=2077; sampled N=1800)	Study 2 MGRI (N=1,572; sampled N=1,360)
	Academic & Career Networks	Whole Networks	Academic & Career Networks
		Frequency (Percentage)	
Gender Identity			
Cisgender Man	131 (39.5%)	701 (38.94%)	526 (38.68%)
Cisgender Woman	199 (59.9%)	915 (50.83%)	710 (52.21%)
Transgender Woman/Man	0 (0.0%)	13 (0.72%)	11 (0.81%)
Non-binary	2 (0.6%)	25 (1.39%)	15 (1.10%)
Not listed	N/A	72 (4.00%)	48 (3.53%)
Don’t know	N/A	74 (4.11%)	50 (3.68%)
Racial Identity (Multichoice)			
American Indian or Alaska Native	2 (0.6%)	21 (1.17%)	17 (1.25%)
Asian or Asian-American	11 (3.3%)	80 (4.44%)	60 (4.41%)
Black or African American	15 (4.5%)	51 (2.83%)	37 (2.72%)
Hispanic or Latina/o	152 (45.8%)	1,437 (79.83%)	1079 (79.34%)
Native Hawaiian or Pacific Islander	1 (0.3%)	4 (0.22%)	3 (0.22%)
White or Caucasian	173 (52.1%)	336 (18.67%)	264 (19.41%)
Other	N/A	45 (2.50%)	32 (2.35%)
Relationship with Ego			
Spouse or significant other	30 (9.0%)	136 (7.56%)	126 (9.26%)
Family	149 (44.9%)	666 (37.00%)	485 (35.66%)
Friend	83 (25.0%)	806 (44.78%)	601 (44.19%)
College Student	27 (8.1%)	468 (26.00%)	364 (26.76%)
College Educator	55 (16.6%)	120 (6.67%)	105 (7.72%)
Co-worker	18 (5.4%)	104 (5.78%)	84 (6.18%)
Spiritual Advisor	2 (0.6%)	26 (1.44%)	15 (1.10%)
Other	40 (12.0%)	56 (3.1%)	36 (2.65%)
Education			
Less than high school	28 (8.4%)	112 (6.22%)	65 (4.78%)
High school diploma or GED	124 (37.3%)	708 (39.33%)	521 (38.31%)
Associate degree	44 (13.3%)	262 (14.56%)	198 (14.56%)
Bachelor’s degree	72 (21.7%)	134 (27.83%)	389 (28.60%)
Master’s or Professional degree	48 (14.5%)	134 (7.44%)	117 (8.60%)
Doctorate degree	16 (4.8%)	76 (4.22%)	66 (4.85%)

We find that a larger proportion of Study 2 alters were identified as Hispanic or Latina/o (79% versus 45% in Study 1), and a smaller proportion were identified as White or Caucasian (19% versus 52%). This difference may very well be caused by regional and institutional differences between the study samples, though this is a promising area of future research.

It is also notable that family members make up a smaller proportion of examined alters in the MGRI study (Study 2) than in the TNGI study (Study 1). Another interesting finding is that Study 2 networks have larger proportions of friends (25% in Study 1, 44-45% in Study 2) and college students (8.1% in Study 1, 26-27% in Study 2). The proportion of college educators in the network also decreased among respondents in the MGRI study (17% in Study 1, 7-8% in Study 2), while the educational level of alters did not vary noticeably when comparing Study 1 to Study 2, except Bachelor's and Master's or Professional degrees: a larger proportion of Study 2 alters had Bachelor's degrees (27-29%) than Study 1 alters (22%), while a smaller proportion of Study 2 alters had Master's or Professional degrees (7-9%) compared to Study 1 alters (15%).

Discussion

The comparison of the two personal network datasets indicates that MGRI better captures information on students with larger personal networks. The finding that 13% of the respondents in Study 2 listed more than six people as academic and career discussants suggests that TNGI (which typically caps the number of alters between four and six; Merluzzi & Burt, 2013) may not capture as accurate a network size measure. We also found that networks captured by MGRI were less kin-centered, which aligns with previous studies suggesting that TNGI tends to yield more family-centric networks (Marin & Hampton, 2007). Aside from our empirical findings, we note that MGRI enabled us to expand the scope of our network survey. Because MGRI diminishes respondent survey burden during the name interpreter stage, we could use multiple name generators (i.e., important matters, academic and career matters) that yielded richer insights from the data in Study 2. Comparing "important matters" and "academic and career" networks showed the overlap and uniqueness of each type of relational compilation. Higher education researchers who aim to examine different types of student networks (e.g., financial support networks, academic support networks, mental health support networks) could greatly benefit from this method without overly burdening survey participants. The scholarship on social network analysis, as well as our study findings, therefore lead us to conclude that MGRI can help researchers capture more accurate data on larger and increasingly diverse college student networks.

Toolkit for Adopting MGRI in Online Surveys

We have developed an open-access toolkit for adopting MGRI in online surveys, which can be accessed through our website at https://ccwt.wisc.edu/mgri-toolkit/. This toolkit includes a handbook, a sample survey in Qualtrics, and R scripts for data cleaning. Researchers with a basic understanding of Qualtrics and R will be able to adopt MGRI in an online survey with this toolkit.

Resources

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The Networks & Cultural Assets (NCA) Project is based in the University of Wisconsin-Madison's Center for Research on College-Workforce Transitions (CCWT).

The NCA Project is funded by the National Science Foundation and the Bill & Melinda Gates Foundation.

Suggested citation:
Jang-Tucci, K., Benbow, R. J., & Bañuelos, N., (2023). *Using Multiple Generator Random Interpreters (MGRIs) for Studying Undergraduate Student Support Networks.* Networks & Cultural Assets Project. Center for Research on College-Workforce Transitions. University of Wisconsin–Madison, Division of Continuing Studies.

Keywords:
Social network analysis, ego network analysis, name generators, Latino/a/x/e college students

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