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Investigating Relationships Between Undergraduate Engineering Students' Social Interactions and Academic Performance through Social Network Analysis

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This empirical research brief presents preliminary quantitative results from a mixed-methods study that explored relationships between the social networks of engineering undergraduates and their GPA and retention using Social Network Analysis (SNA) techniques.

Interpersonal relationships are well known to be an important part of engineering students' academic and subsequent professional success. Specific to student learning, social constructivist theories [1]-[4] consistently present that the learning of a given individual, or *ego*, is strongly influenced by their *alters,* or individuals that the ego interacts with. These alters may be a more knowledgeable other, a peer, or a less knowledgeable other [1]-[7]. In each case, a learner-ego's ability to access new knowledge, integrate new knowledge, or reinforce existing knowledge is increased by observing and/or communicating with alters [7]-[9]. Thus, engineering education research has increasingly sought to elucidate how specific types of social interactions relate to students' success in the educational context.

Among the methods to explore the relationships between student interactions and success, SNA has been adapted from general sociological research [10]-[12] as a particularly well-suited technique for quantitatively and visually considering how students' interpersonal networks relate to outcomes [13]-[15]. Studies applying SNA in the engineering education context have observed that significant, positive relationships exist between students' connectedness and course-specific grades [16]-[20]; that students often demonstrate *homophily,* or selecting alters of similar traits such as race, gender, and grades [21]-[24]; and that networks are dynamic within single semesters and over years [25]-[27]. However, we note that there is a particular focus in the relevant literature toward online student interactions [14], [15], [28] potentially due to the ease of network data collection in online environments [29]. For those studies on face-to-face or hybrid student networks, there is an additional focus on sampling within a single semester in time, a single course enrollment in participant sampling, and a single alter type such as in-class group work networks or study networks. This focus results in a gap in the literature regarding holistic student network formation, evolution, and relationship to high-level outcomes.

To address this research gap, we conducted a two-year mixed methods study of first- and second-year undergraduate engineering students at a large, public university in the Western United States [30]. The purpose of the full study was to develop a holistic understanding of the formation of students' interpersonal networks and their relationship to student outcomes measured by GPA and retention, with a particular focus on the role of students' peers. This research brief presents a subset of the findings developed to answer the Research Question (RQ): *What relationships exist between first- and second-year undergraduate engineering students' network characteristics and academic outcomes (i.e., course-specific GPA and retention in the following semester)?*

Methodology

To answer this RQ, we applied a convergent parallel mixed methods design [31], [32]. Specifically, we gathered (a) quantitative and qualitative network data to understand student networks holistically. We were particularly interested in the interplay between students' *friendship*, *informal*, and *formal* networks (we distinguish these network types in the network data collection). Concurrently, we gathered data regarding (b) student participants' outcomes including GPA and retention, where we identified retention as student enrollment in the subsequent semester. Combining the results of (a) and (b) enabled us to explore how students' interactions related to outcomes. We concurrently gathered focus group data to understand (c) the breadth of reasons students choose to, or not to interact with a given potential alter. The results of (a), (b), and (c) were combined to develop full study conclusions and recommendations. *This research brief will focus on a subset of the results from the network data relating to (a) and (b).*

Data Collection

To gather the necessary data for (a), we first required an estimate of the students' networks over time. In accordance with an approved IRB protocol, we administered open-ended name generator surveys [11], [12], [29] through Qualtrics which identified participants' friendship, formal study (i.e., course-required group work), informal study (i.e., non-course-required work), and other (i.e., any alters that provided learning support but were not other students in the friendship, informal, or formal networks) peer network members. Participants were aware that the categories may coincide for a given alter, as demonstrated by the survey provided in Appendix A. Students received an email and LMS-based invitation to the survey at the second, fifth, ninth, eleventh, and fourteenth week of the Fall 2021, Spring 2022, Fall 2022, and Spring 2023 semesters each.

To gather the relevant data for (b), we supplemented the network data with registrar queries at the conclusion of each study semester regarding participant outcomes (i.e., GPA and retention). We also identified participant demographics (i.e., age, sex, gender, ethnicity, veteran status, and major). To account for potential demographic variable changes (e.g., age), we used the demographic variable value at the end of each semester for the subsequent analyses.

Data Analysis

Prior to conducting statistical analysis, we required an accurate matrix representation of the student networks through time [12], [33]. However, the open-ended survey data included misspellings, incomplete entries, and similar issues which complicated connecting participant provided names to each other, and to the registrar data. There were 3055 valid survey responses which each contained 0-20 unique name entries. Matching these response values to true names manually would be infeasible. Fortunately, this issue is a common problem in data science referred to as *entity resolution* [34]-[36]. To resolve our data, we ran the open-source GitHub repository EntityRAID [37] and supplemented those results with time-aggregated network proximity metrics [38] as described in [30]. With a final matrix representation developed from these algorithms, we linked available participant registrar data to the graph objects from the entity resolution and imported the final graph objects into Gephi [39] and RStudio for visual and statistical analysis respectively.

For comparing participant network traits to outcomes, we estimated participants' connectedness through measures of *out-degree*, the number of alters the participant ego identified; *in-degree*, the number of alters who identified the participant ego; and *total degree*, the sum of in- and out-degrees for a participant ego. Due to the likely skewness and non-normality of the GPA and connectedness measure data residuals, we applied Spearman Rank correlations of participants' connectedness measures to the continuous dependent variable of GPA to contrast student connectedness with a GPA. Similarly, we applied Mann-Whitney U-tests to contrast the connectedness of retained and attritted participant groups. We determined significance at the p-value ≤ 0.05 and tests were two-tailed to first identify if there were significant differences.

Informed by a prior pilot study [40], the name generator surveys included a section for participants to identify alters who were not other students but were a part of their study network (e.g., work associates, romantic partners, etc.). To capture these non-student peer interactions, the final question in the name generator survey asked participants to identify all non-student alters they interacted with for the purpose of studying engineering course material (Appendix A). A pair of coders inductively developed a codebook of non-student alter types then consolidated these responses to consensus. The final 14 non-student alter types identified in this study with relevant codebook including descriptions and examples are provided in Appendix B. We also applied Mann-Whitney U-tests to contrast the distributions of participants' GPAs according to participants whose network included alters of specific non-student alter types.

Results and Discussion

In total, 947 unique participants completed the survey and consented to the collection of their registrar data. Semester-aggregated participation rates were 32%, 18%, 29%, and 21% in the Fall 2021, Spring 2022, Fall 2022, and Spring 2023 semesters respectively. Within that sample, most participants were white (97.2%), male (78.6%), and 23 years old or younger (92.7%). Further details, including full available demographic data, are provided in Appendix C. While we did not collect data on participant religious affiliation, a potentially important characteristic of the sample population is its location in the Mormon Culture Region [41].

Student Connectedness and Academic Outcomes

As expected, the residuals for participant GPAs and connectedness measures were not normally distributed. So, we conducted non-parametric Spearman Rank Correlation tests to determine if a change in participants' connectedness related significantly to a change in participants' GPA. The results for each network type, connectedness measure, and semester are summarized in Table 1. All significant results showed a positive relationship between GPA and connectedness.

Table 1. Summary of results regarding participants' GPA vs. connectedness measures.

Outcome	Semester	Network Type	Out-degree	In-degree	Total-degree
GPA	**Fall 2021 (n=446)**	Full	**	**	**
		Friend			
		Informal		*	
		Formal			
	Spring 2022 (n=217)	Full	*		
		Friend			
		Informal	*		**
		Formal			
	Fall 2022 (n=354)	Full	**		**
		Friend	**		**
		Informal	**	**	**
		Formal			*

	Spring 2023 (n=235)	Full	**		**
		Friend			
		Informal			
		Formal			

**p≤0.05, two-tailed. **p≤0.01, two-tailed.*

To further explore the relationship between academic outcomes and connectedness, we also contrasted the distribution of connectedness measures for retained vs. attritted participants. The connectedness measure distributions were non-normal, and as a result, we applied Mann-Whitney U-tests to determine if the distributions of the connectedness measures for retained participants were significantly different from the distributions of connectedness measures for attritted participants. The results of these tests are also summarized in Table 2. All significant results showed a positive relationship between retention and connectedness.

Table 2. Summary of results regarding participants' retention vs. connectedness measures.

Outcome	Semester	Network Type	Out-degree	In-degree	Total-degree
Retention	**Fall 2021 (n=446)**	Full		**	*
		Friend			
		Informal			
		Formal		*	
	Spring 2022 (n=217)	Full			
		Friend			
		Informal			
		Formal			
	Fall 2022 (n=354)	Full	**	**	**
		Friend	**		**
		Informal	**	**	**
		Formal		*	

**p≤0.05, two-tailed. **p≤0.01, two-tailed.*

These results include several interesting findings. In all, there were many observations suggesting student participants' connectedness related to both a higher overall GPA, and a higher likelihood of retention. These findings reinforce prior observations from smaller samples [16], [18], [42], [43]. Interestingly, these observations were more prevalent during the fall semesters, particularly during the Fall 2022 semester, which we are not aware of in prior studies. We also note that the formal network connectedness measures showed significance only for in-degree connectedness. Formal networks are fixed in size, and we expect that this result is likely due to students nominating those peers they seek help from or recognize as high performing [44], [45].

The friendship network result, however, is surprising. Prior studies have noted significant, positive relationships between students' friendship network connectedness and academic outcomes [22], [25]-[27], [46], [47]. This suggests that further research regarding the evolution and influence of friendship networks on academic outcomes is needed. These findings are also supplemented by the discussion in the next section.

Another important consideration in these data is the fact that Covid-19 restrictions remained in full effect during the Fall 2021 semester and decreased thereafter. The network results showed that connectedness, estimated by degree measures, demonstrated more significant results after the pandemic restrictions were lifted (starting in the Spring 2021 semester). This is seemingly opposite the observations of studies focused on students' general peer networks in the Covid-19 pandemic, which suggest that social support was likely to be more important during mandatory isolation [48]. We propose that the conflicting results may be due to the use of only network size to measure connectedness in this study, and that interaction quality may conflate the simple relationships of network size vs. outcomes.

Other Student Support Types and Academic Outcomes

We also observed in the pilot of this study that participants felt there were several other peer alter types (i.e., not other engineering students) who were important to their learning. To capture this potential, we gathered non-student alters in the survey instrument as elaborated in Appendix A. To identify those non-student alter types which related to increased student outcomes, we conducted pairwise Mann-Whitney U-test contrasts of the distribution of GPAs for participants whose networks included each alter type. A summary of these results is provided in Table 3. An important note, that repeated observations per participant are included in these analyses, challenging the assumption that the GPA distributions are independent.

Table 3. Mann-Whitney U test p-values from contrasting distributions of GPAs according to participants whose networks include a given non-engineering-student alter type.

Alter Type: Median GPA, n=Sample Size	**A) Job Supervisor: 3.5, n=20**	**B) Teaching Assistant: 3.63, n=42**	**C) Spouse: 3.35, n=28**	**D) Parent: 3.54, n=162**	**E) Neighbor: 3.44, n=8**	**F) Professor: 3.73, n=108**	**G) Coworker: 4.0, n=17**	**H) Sibling: 3.66, n=110**	**I) External Friend: 3.40, n=104**	**J) Roommate: 3.43, n=32**	**K) Dating Partner: 3.12, n=26**	**L) Non-Parent/sibling family: 3.48, n=54**	**M) Online Connection: 2.79, n=4**	**N) Religious Leader: 4.0, n=3**
A)	1	0.69	0.23	0.44	0.59	0.70	0.41	0.91	0.15	0.20	0.02*	0.41	0.41	0.18
B)	-	1	0.46	0.70	0.69	0.21	0.15	0.64	0.16	0.28	0.03*	0.67	0.57	0.16
C)	-	-	1	0.49	0.83	0.09	0.08	0.21	0.99	0.97	0.33	0.61	0.67	0.13
D)	-	-	-	1	0.81	0.02*	0.07	0.22	0.17	0.35	0.02*	0.89	0.58	0.12
E)	-	-	-	-	1	0.31	0.30	0.50	0.83	0.84	0.26	0.83	0.67	0.17
F)	-	-	-	-	-	1	0.30	0.29	0.00**	0.02*	0.00**	0.07	0.41	0.29
G)	-	-	-	-	-	-	1	0.17	0.02*	0.05*	0.01**	0.10	0.30	0.56
H)	-	-	-	-	-	-	-	1	0.01**	0.09	0.01**	0.33	0.49	0.20
I)	-	-	-	-	-	-	-	-	1	0.96	0.14	0.34	0.76	0.08
J)	-	-	-	-	-	-	-	-	-	1	0.19	0.48	0.69	0.08
K)	-	-	-	-	-	-	-	-	-	-	1	0.07	0.98	0.04*
L)	-	-	-	-	-	-	-	-	-	-	-	1	0.65	0.13
M)	-	-	-	-	-	-	-	-	-	-	-	-	1	0.36
N)	-	-	-	-	-	-	-	-	-	-	-	-	-	1

**p≤0.05, two-tailed. **p≤0.01, two-tailed.*

Considering the results in Table 3, several interesting trends emerge. To begin, it is notable to consider the distribution of non-student study partners identified by the survey participants. Specifically, with a sample of 947 student participants, these data demonstrate a wide breadth of likely study supports used by the students in the large undergraduate engineering context.

Considering the pairwise contrast results, the median GPA for participants who reported studying with a dating partner who was not a fellow engineering student was 3.12 (n=26), and this value was significantly lower than those participants whose study network included a job supervisor (3.50, n=20), teaching assistant (3.63, n=42), parent (3.54, n=162), professor (3.73, n=108), coworker (4.00, n=17), sibling (3.66, n=110), or religious leader (4.00, n=3). Similarly, those participants who reported studying with friends who were not other students had a median GPA of 3.40 (n=104) and had significantly lower GPAs than those participants whose study networks included a professor, coworker, or sibling. Student participant networks which included a roommate who was not a fellow student also demonstrated a significantly lower median GPA (3.43, n=32) than participants whose networks included professors and coworkers.

Together, these results demonstrate that institutional and professional supports overall related to higher student academic performance than external peer supports. Prior studies [22], [25], [26], [44], [47], [49] suggest that friendship integration into the institutional context is important for student success, and these observations may add that beneficial social integration includes student help-seeking from institutional-specific alters.

Conclusion

Several key findings are presented in this research brief. First, relating holistic student-peer networks to high-level academic outcomes including GPA and retention demonstrated that students' connectedness significantly related to increased GPA and likelihood of retention across several observations. These significant observations were more prevalent during fall than spring semesters. Second, analyzing student study supports outside of other engineering students demonstrated several sources of learning support, including familial, institutional, professional, and external peer sources. Third, among the other student support types, institutional and professional supports related to significantly higher GPAs overall than external study support networks which included friends, dating partners, and roommates.

While this study was conducted on a large scale (n=947), the findings remain limited in several areas. The study context was a single institution, and the resulting sample primarily consisted of white males under 23 years of age. This limits generalizability as family structures, help-seeking behaviors, and other cultural or regional influences may mediate the observed relationships. The analyses are also simplified due to their scale and neglect several items. For example, there is likely a limit to the number of effective study partners as observed across smaller scale studies [50]-[52], and simple in-, out-, and total degree neglect this potential. Further, the simple statistical tests applied do not consider potential directionality and inter-dependence of network and outcome measures. Future work, including the extension of this mixed-methods study, will include qualitative data to supplement the *why* behind many of the observations here. Mixed analysis of the quantitative and the qualitative data will enable researchers to inform interventions targeting how to influence interactions which relate positively to student outcomes.

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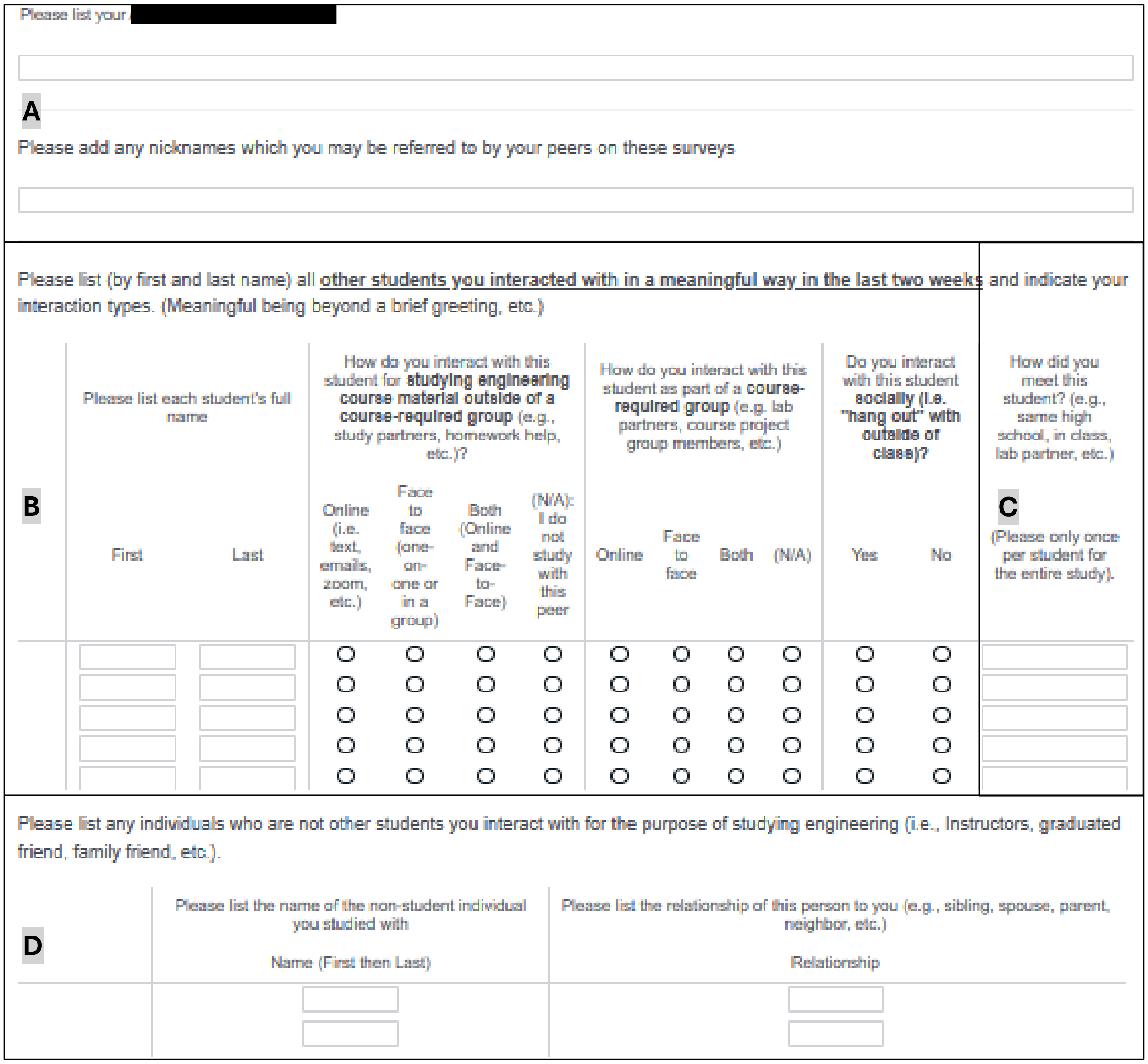
Appendix A

The full name generator survey that was implemented through Qualtrics.



Please list your [redacted]

A

Please add any nicknames which you may be referred to by your peers on these surveys

Please list (by first and last name) all **other students you interacted with in a meaningful way in the last two weeks** and indicate your interaction types. (Meaningful being beyond a brief greeting, etc.)

B

Please list each student's full name		How do you interact with this student for **studying engineering course material outside of a course-required group** (e.g., study partners, homework help, etc.)?				How do you interact with this student as part of a **course-required group** (e.g. lab partners, course project group members, etc.)				Do you interact with this student **socially (i.e. "hang out" with outside of class)?**		How did you meet this student? (e.g., same high school, in class, lab partner, etc.) C (Please only once per student for the entire study).
First	Last	Online (i.e. text, emails, zoom, etc.)	Face to face (one-on-one or in a group)	Both (Online and Face-to-Face)	(N/A): I do not study with this peer	Online	Face to face	Both	(N/A)	Yes	No	

Please list any individuals who are not other students you interact with for the purpose of studying engineering (i.e., Instructors, graduated friend, family friend, etc.).

D

Please list the name of the non-student individual you studied with	Please list the relationship of this person to you (e.g., sibling, spouse, parent, neighbor, etc.)
Name (First then Last)	Relationship

Figure A1. The name generator survey instrument which gathered a) participant egos by their university identification number and any nicknames the participant may be referred to by others, b) participants' alters in the formal, informal, and friendship networks, c) how interactions with each alter began, and d) participants' study network alters which are not captured by (c).

Appendix B

The full codebook that was used to identify non-student alter types.

Table 2. Non-student alter types identified in the open-ended name generator survey questions.

Non-Student Alter Type	***Description*** • **Example Excerpt**
Job Supervisor	*The alter is identified as the participant's supervisor at work.* • Site supervisor • Internship supervisor
TA	*The alter is identified as a Teaching Assistant for a course the participant enrolled has taken.* • Physics TA • Lin/diff TA
Spouse	*The alter is identified as the participant's spouse.* • Wife • Spouse
Professor	*The alter is identified as an institutional professor/instructor for a course the participant has taken.* • Instructor • [Specific course name] Professor
Neighbor	*The alter is identified as living in proximity to the participant and does not meet other categories (e.g.., roommate).* • Neighbor • Neighbor back home
Parent	*The alter is identified as the parent/caretaker of the participant.* • Parent • Mother
Coworker	*The alter is identified as working at the same location as the participant.* • Recent [study university] grad, mechanical engineer/co-worker • Internship coworker
Sibling	*The alter is explicitly identified as a sibling of the participant.* • Sister • Big brother
Roommate	*The alter is identified as the roommate of the participant.* • Roommate/sorority sister • Roommate

External Friend	*The alter is identified as a friend of the participant, external to the friends identified as other students in the prior survey questions.* • Family friend • High school friend
Dating Partner	*The alter is identified as dating the participant and is external to the alters identified as other students in the prior survey questions.* • Girlfriend • Partner
Non-Parent/Sibling Family	*The alter is identified as a member of the participant's family, but not a sibling or parent.* • Uncle Cousin-in-law
Online Connection	*The alter is identified as meeting the participant through online media.* • Engineering discord server • A Youtuber
Religious Leader	*The alter is identified as meeting the participant through the alter's role as a religious leader.* • Pastor • Church leader

Appendix C

The summary of survey participant registrar-identified demographics according to registrar descriptions.

Table 3. Study participant registrar-provided demographics.

Primary Category	Observed Sub-Categories*	Count	Fraction (%**)
All	Count of unique survey participants with outcomes	947	100.0
Gender	Binary-Male	743	78.6
	Binary-Female	200	21.2
	Non-Binary	2	0.2
Ethnicity	Not Hispanic or Latinx	876	96.6
	Hispanic or Latinx	31	3.4
Race	White (Non-Hispanic)	927	97.2
	Asian	19	2.0
	Black (Non-Hispanic)	3	0.3
	American Indian Alaskan Native	3	0.3
	Pacific Islander	2	0.2
Veteran	Non-Veteran	936	98.8
	Veteran	11	1.2
Age at First Semester of Study Participation	18	126	13.3
	19	156	16.5
	20	164	17.3
	21	198	20.9
	22	149	15.8
	23	84	8.9
	24	30	3.2
	25	14	1.5
	≥26	25	3.0
Major (Engineering)	Mechanical	534	59
	Civil	130	14
	Biological	85	5
	Electrical	86	9
	Computer	43	9
	Environmental	16	2
	General	15	2

*Note *Registrar data is verbatim except for the authors' choice to adjust from "Latino" to "Latinx" for the purpose of removing potentially incorrect grammatical gender.*
***Due to incomplete registrar records, percentages are calculated using available count, not study total (947).*