Analyzing College Students' Advising Records To Improve Retention And Graduation Outcome

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***Abstract*—This full research paper studies the impact of faculty-student advising interactions over students' retention and graduation outcomes. These 3000+ students were enrolled in a community-based learning program between 2014 and 2018 at San Francisco State University, a 4-year public degree-granting university. To address the ongoing challenge of low retention and graduation rates, this program has introduced early and preventative interventions through both mandatory and voluntary advising with a team of 40+ advisors.**

We apply statistical and machine learning approaches to analyze the advising records generated over a period of 5 years. Specifically, we have addressed the following problems: (1) what is the impact of timing and frequency of advising interactions on students' retention and graduation status? (2) how effective are such interactions in helping academically at-risk students? (3) What are the common types of interactions and how are they correlated with students' academic performance? Finally, (4) how much insight can we further gain through looking into advisors' written notes?

Our results show that the current advising practice is not biased against a specific demographic group. They also show that it is important to require advising during a student's first term of her college career. Delaying such interactions to the second term, for instance, can significantly lower the likelihood to retain students in their third term and then seventh term, consequently reducing their chance to graduate within four or five years. Finally, after having applied a host of natural language processing (NLP) techniques (e.g., LDA topic modeling) to advisors' written notes, the results suggest that a more rigorous note-taking approach is needed in order for such notes to help gain broader and deeper insights into students' advising needs.

Keywords—Educational data mining, Academic advising, Retention rate, Graduation rate, Text mining

I. Introduction

One ongoing challenge faced by many higher education institutions is to devise effective mechanisms to improve their students' retention and graduation rates. In the United States, the 4-year graduation rate of first-time, full-time students who started in 2012 was 43.7% while 5-year graduation rate, including 4-year graduation, for the same group was 58.7% [1]. At the authors' 4-year degree-granting public university, these rates are even lower [2]. Specifically, the 4-year graduation rates for the cohorts beginning to seek a degree in 2009-2016 range between only 17.5% and 25.8%. For these same cohorts, their 6-year graduation rates vary from 50.00% to 55.8%.

As summarized in [3], to improve students' retention rate and subsequently graduation rate, higher education institutions have devised and implemented a variety of strategies and mechanisms. The following seven constructs have been shown to be effective at influencing the retention rate: academic advising, social connectedness, student involvement, faculty and staff approachability, business procedures, learning experiences, and student support services. The Metro College Success Program, a community-based learning program, established at the authors' public 4-year degree-granting university embodies all these above constructs [4]. Note from this point on, we will refer to this program as "the Metro" or "the Metro program".

The Metro program was created in 2007 with a mission to improve education equity and excellence. Nearly all of its students are either low-income, first-generation college-going, or underrepresented minorities. These students are enrolled in this program during their freshman and sophomore years, and continue receiving academic support after they leave the program until their graduation. The most recent data demonstrate the effectiveness of the Metro program [4]. When comparing with their peers who share similar academic, socioeconomic, and demographic background but not enrolled in this program, the retention rates are significantly higher (e.g., 73% vs. 63% for 2-year retention and 64% vs. 59% for 4-year). Furthermore, CPLB's 5-year and 6-year graduation rates are also significantly higher at 45% (vs. 41%) and 58% (vs. 49%), respectively. This study focuses on analyzing and understanding the impact of the Metro's long-standing student advising practice over retention and graduation.

We apply statistical, machine learning, and natural language processing (NLP) techniques to 3000+ students' advising records accumulated between 2014 and 2018. (Records before 2014 are not digitalized yet.) Specifically, we seek to address the following problems: (1) what is the impact of timing and frequency of advising interactions on retention and graduation? (2) how effective are such interactions in helping academically at-risk students? (3) What are the common types of interactions and how are they correlated with students' academic performance? Finally, (4) how much insight, if any, can we gain through looking into advisors' unstructured written notes?

We have also applied a host of NLP techniques to preprocess and characterize the written notes. For instance, we utilize simple techniques such as stemming, lemmatization, and part-of-speech tagging [5]. We have also employed the LDA (Latent Dirichlet Allocation) and LSA (Latent Semantic Analysis) topic modeling approaches [6][7] in an attempt to learn the underlying structure embedded in the written notes.

This study has resulted in several actionable findings. For example, the results suggest to implement mandatory advising during a student's very first term in their college career. Furthermore, after students have successfully completed their first year of college, advising interactions in subsequently terms do not seem to play as an important role on retention or graduation. Finally, the current written notes fall short in helping one gain broader and deeper insights into students' advising needs. As a result of this research, the Metro program has planned to require every freshman to receive advising in her first semester.

The remainder of this article is structured as follows: Section II briefly reviews the most relevant works to place this study in its proper context. Section III describes the analytic methods adopted in this study. Main results are presented in Section IV. Further discussions of these results are included in Section V. Finally, Section VI concludes this study and then identifies a few future research directions.

II. Related Work

This work falls in the general area of educational data mining. Readers are referred to [8][9][10][11] for more comprehensive reviews of this area. We next briefly review the works that are directly related to this study.

Studies in the past few decades have repeatedly demonstrate the importance of students-faculty/staff interactions in students' academic, professional, and also personal growth [2][13][14][15]. Meera *et al.* [16] argue that students-faculty interactions, when properly executed, can be crucial in developing students' academic self-concept, enhancing intellectual and professional development. A recent effort reports a strong connection between advising interactions and students' identity development in addition to retention and college success [17]. Researchers have also studied the effect of informal faculty-student interactions such as [18]. In this study, all the interactions can be categorized as formal and sometimes initiated by the advisors out of necessity, for instance, fulfilling the advising requirement for academically at-risk students.

Studies such as [19] look into the student-faculty interaction patterns at a research institution along gender and ethnicity. They found that the impact of such interactions on student outcomes vary by student gender and race but it does not by student socio-economic or first-generation status. Specifically, they notice a significantly stronger positive relationship for African American students relative to other students. We also analyze such interaction patterns, but largely focus on whether we have been unintentionally favoring one group over others. Given that the majority of the students enrolled in the Metro program are from underrepresented minority groups, we lack sufficient data to perform similar analysis as in [19]. Furthermore, recent researches also provide insights in effectively advising first-generation college students, such as [20]. This is not the focus of this study.

Finally, this study is also related to topic modeling approaches for analyzing unstructured text data. In our case, advisors' written notes are normally short in length. We apply both LSA and LDA approaches [6][7]. The former adopts the bag-of-words document representation and utilizes matrix decomposition to rank and uncover latent semantic components. The latter on the other hand adopts a generative probabilistic process by modeling each document as a finite mixture over an underlying set of topics, where each topic in turn is modeled as an infinite mixture of an underlying set of topic probabilities. Both LSA and LDA have been widely applied to learn the underlying topical structure embedded in a collection of documents. We refer readers to the following comprehensive reviews for further information: [23][24][25].

III. Method

In this section, we describe the main methods adopted to analyze the advising records. To put such methods into their proper context, we will first describe the list of attributes contained in an advising record, the list of pre-defined interaction categories, and finally a summary of the involved student cohorts.

A. *Advising Practice and Data*

The Metro program's advising team takes a proactive approach with a goal to advise a minimum of 95% of all the enrolled students in their freshman year. Each student is instructed to attend one mandatory advising each school year. Students are also encouraged to seek further advising. Finally, individual instructors are trained to identify students who may need further assistance based on their academic performance in a specific course or by observing a student's classroom behavior. These students are often referred to the advising team by the instructors. Subsequently, the advising team will initiate the first advising interactions with such students and continue until the involved advisor considers the underlying matter has been satisfactorily handled.

TABLE I. tabulates the list of student attributes, which are further categorized into one of the following types: demographic, academic, and advising-related. Note that the term-wise retention status is a calculated attribute by examining a student's course enrollment record in a given term.

Shown in TABLE II. is the list of pre-defined interaction topics identify by the Metro advising team. An individual advising record can be labeled with more than one topic per the advisor's perception. Notice the *check-in* type, which functions as a method to nurture a student's sense of belonging and to potentially learn about individual students' specific needs.

Finally, we divide the 3000+ students into different sub-groups to facilitate the subsequent data analysis. For instance, only students entering the program in 2014 and 2015 are included to study the impact of advising over their 4-year graduation status. The rationale is straightforward as we should only consider students who were in a position to graduate at the time of this study. See TABLE III. for more details.

TABLE I. STUDENT RECORDS AND ADVISING RECORDS

Type	Attribute: the list of possible values
Demographic Attributes	*Gender:* male, female4.
	Ethnicity: African American, Asian, Hispanic/Latino, Native-Hawaiian, Two or more Races, White, Unknown
	Mother's education: Postgraduate, Four-year College Grad, Two-year College Grad, Some College, High School Grad, Some High School, No High School, Unknown
	Father's education: same as above
Academic	*Cohort year*: 2014-2018 *Preliminary choice of major* *List of term-wise GPA*: 0.00—4.00 *List of cumulative GPA*: 0.00—4.00 *Term-wise retention status:* yes, no *Graduation status*: yes/no, which term.
Advising Records	*Date of advising*: 8/2014 – 12/2019} *Method:* Email, Phone, In-Person, SMS, Video conferencing *Advisor:* a staff of the 40 members *Topics:* one or more as listed in TABLE II. *Notes:* unstructured text

TABLE II. PRE-DEFINED TOPICS OF ADVISING INTERACTIONS

Type 1. Academic Performance and Support	
Academic Performance Class scheduling Attendance Improving study skills	General student success skills GE & requirements (major or transfer) Career exploration Math Remediation
Type II. Class scheduling, program/school services	
Adjustment to college Advising/Counseling Outreach Referral to the school Student Services Financial Aid Tutoring Outreach	Dropping School Dropping program Major change Program-related Issue
Type III. Check-in, non-school related, or other	
Check-in (no issue) Outside School Issue	Other

TABLE III. STUDENT SUBGROUPS

Performance criteria	List of cohort years under consideration at the time of this study
1. Third Term Retention	[2014, 2015, 2016, 2017, 2018]
2. Fifth Term Retention	[2014, 2015, 2016, 2017]
3. Seventh Term Retention	[2014, 2015, 2016]
4. Four-year Graduation	[2014, 2015]
5. Five-year Graduation	[2014]

B. Non-Metro Prgram Participating Students for Comparative Study

To facilitate comparative study, the Metro program leadership team has also identified a group of ~2600 students who share similar demographics as the Metro students but did not participate in the program. We refer to this group as the *comparison group* in this article. Students in the comparison group were selected by matching admission term, ethnicity, level of household income, first generation college student status, starting Math and English levels, and whether their declared major was in STEM or non-STEM.

C. Advising Interactions vs. Demographic Data

We perform a series of Chi-Square goodness of fit tests [21] to learn whether the advising practice during the period of study biases against a specific demographic group. Specifically, we consider the following dimensions: gender, ethnicity, mother's education level, or father's education level.

Take the gender dimension as one example, the expected distribution is identified as the distribution of female and male students in the student body. The observed distribution is the frequency of advising interactions received by female and male students, respectively. If the resulting Chi-Square statistics has a p-value ≤ 0.05 (i.e., the significance level), we consider the advising practice unfair towards different gender, which warrants for further investigation.

D. Advising Timing/Frequency vs. Retention/Graduation

The timing of a student's advising is captured by the following two aspects: (1) *time of the first advising*, that is, the term in which she received her first advising, and (2) *only being advised in*, that is, the only term (or year) in which she received advising and she did not receive any advising in the remaining terms (or year).

As for advising frequency, we identify the advising frequency that a student received in a given term. Following the suggestion of our Metro program collaborators, these frequencies are discretized as follows: none (0 interaction), low (1-3 times), medium (4-7 times), and high (>7 times).

We then perform the Chi-Square independence test [21] to accept or reject whether advising timing/frequency is correlated with one of the following outcomes: third-term retention, fifth-term retention, seventh-term retention status, 4-year graduation rate, and 5-year graduation rate. We set the significance level at 0.05, that is, we accept the presence of a statistically significant correlation if the resulting p-value is ≤ 0.5.

In addition to performing Chi-Square independence tests, we also perform the Z-test to confirm whether two proportions are significantly different [22]. For example, let p_1 be the portion of students who received zero advising interactions and persisted in Term 3, p_2 be the portion of students who received >7 advising interactions and persisted in Term 3. We perform the Z-test to find out whether $|p_1 - p_2|$ is statistically significant at the significance level of 0.05.

E. At-risk Students vs. Advising Frequency/Advising Topics

This task assesses whether advising could potentially help improve at-risk students' academic performance. We first categorize students according to their cumulative GPA after each term (namely, term 1, term 2, term 3, and term 4) to one the following three groups:

- Good standing: GPA>2.5
- At risk: 2.0≤GPA≤2.5
- Probation: GPA < 2.0

We then examine how advising frequency within a term affects a student's at-risk/probation status by the end of the term. A series of Z-tests are performed to verify whether such status changes are significant.

We also examine the distribution of advising topics (TABLE II.) at the type level and individual topic level with respect to students' GPA status. This allows us to gain insights in the types of advising needs required from each of these three groups.

F. Unstructured Written Notes Analaysis

The Metro program has accumulated a large quantity of written notes over the years. This task aims to gain a deeper understanding of the underlying reasons behind each type of advising. For example, it is of great interest to learn the common reasons that lead a student to consider dropping out of college or the Metro program. We apply the aforementioned LDA and LSA topic modeling approaches for this purpose. (See Section II.)

Before we perform topic modeling, we first perform several basic NLP techniques to characterize the notes: the distribution of the length of such notes measured in words and sentences; and the list of common nouns, verbs, adjectives and adverbs used in such notes. Such NLP techniques include tokenization, sentence segmentation, and part-of-speech tagging [5].

Before applying the LDA and LSA algorithms to learn the underlying topics associated with each type of advising, we preprocess the notes to remove stop words. We also perform stemming and lemmatization. The NLTK Toolkit [27] is used to perform all the NLP-related tasks in this study.

IV. RESULTS

We report and discuss the main results and their corresponding implications in this section.

A. Fairness of the Current Advising Practice

TABLE IV. tabulates the actual gender distribution in the "Expected" column, and the number of advising interactions received by each gender in the "Observed" column. The Chi-Square goodness of fit tests render the following p-values for all the students, students in Term 1, and students in Term 2 are: 0.98, 0.71, and 0.95, respectively. This is a strong indication that the advising distribution agrees with the gender distribution of the student body. In other words, *the advising practice is fair w.r.t. gender.*

We also look into whether the advising distribution agrees with the distribution of one's mother's or father's education background, as parents' education level is directly related to a student's socioeconomic status. We are pleased to find out that *the current advising practice is also fair in this regard.*

TABLE IV. ADVISING VS. GENDER

Gender	Overall Students		Term-1 Students		Term-2 Students	
	Expcted	Observed	Expected	Observed	Expected	Observed
Male	1315	1302	1002	1749	768	1399
Female	2335	2334	993	1759	770	1398

TABLE V. ADVISING VS. ETHNICITY

Ethnicity	Overall Students		Term-1 Students		Term-2 Students	
	Expected	Observed	Expected	Observed	Expected	Observed
Hispanic	2145	2157	1621	1655	1622	1291
Black	445	467	150	345	312	256
Asian	721	709	538	524	576	446
White	69	72	53	44	53	41
Two or More	103	104	76	68	82	59
Other	77	78	62	57	58	42

Finally, TABLE V. summarizes the ethnicity-based distribution and the corresponding advising frequency. Note that we only include groups with a minimum size of 50 or more here. The Chi-Square goodness of fit tests render the following p-values for all the students, students in Term 1, and students in Term 2 are: 0.97, 0.91, and 0.80, respectively. Again, this is a strong indication that the advising distribution agrees with the ethnicity distribution of the student body. We therefore conclude that *the advising practice is fair w.r.t. ethnicity.*

B. The Impact of Advising Timing and Frequency

TABLE VI. and TABLE VII. summarize the 3rd term retention together with the corresponding advising timing. One can observe the following from these tables: First, the Metro students exhibit a significantly higher retention rate than that of comparison students (83.71%). Second, students who did not receive advising have the highest retention rate. *These two together suggest that advising is not the sole contributing factor to Metro program's overall higher retention rate. Other program-level student support services such as tutoring may also have played a positive role.*

TABLE VIII. examines the relationship between advising frequency and the 3rd term retention status. One immediately notices that students who received the most advising interactions have the lowest retention rate. These students probably were struggling the most. As a result, they had sought out for advising again and again. On the other hand, students who received 1-7 interactions had a retention rate higher than that of the comparison group (83.71%) As such, *more information is needed before one downplays the role of advising over a student's retention.*

TABLE IX. contrast the retention rate of those who received their first advising in Term 1 against those who received their first advising in Term 2. Regardless of the advising frequency range, the former is significantly higher than the latter. *This suggests that earlier advising have a higher potential in improving the retention outcome.* This makes sense considering how challenging for freshman students to maneuver and adapt to a brand-new college experience.

In contrast to advising's impact over Term 3 retention, we do not observe a similar impact over students' Term 5 and Term 7 retention status. As shown in TABLE X. , the Metro students' retention rate is still higher than that of comparison students', but when a student received her first advising does not seem to make much a difference over her 5th term retention status. *This* *indirectly suggests that advising plays a more important role in a student's first year of college.* Once a student has persisted after the first year, advising may not have as strong an impact over her future retention status. Similarly, we have not observed a significant correlation between advising frequency and a student's 5th and 7th term retention status.

TABLE VI. THIRD TERM RENTION VS. TIME OF FIRST ADVISING

Time of first advising	**Total Students**	**3rd term persistence**	**Chi-Square Test**
Term 1	1928	1739 (90.20%)	p-value = 0.02
Term 2	595	536 (90.08%)	
None	299	285 **(95.32%)**	
Comparison students	2597	2174 (83.71%)	

TABLE VII. THIRD TERM RENTION VS. ADVISING TIMING

Only-being-advised in	**Total#(Students)**	**Third Term Retention**	**Chi-Square Test**
Term 1	375	349 (93.07%)	p-value = 0.11
Term 2	595	536 (90.08%)	
Terms 1 & 2	1553	1390 (89.50%)	
None	299	285 **(95.32%)**	
Comparison students	2597	2174 (83.71%)	

TABLE VIII. THIRD TERM RENTION VS. ADVISING FREQUENCY

Advising Freq	**Total Students**	**3rd term Retention**	**Chi-Square Test**
Being Advised only in Term 1			
1 to 3	352	328 (91.05%)	p-value: 0.05
4 to 7	21	20 (91.66%)	
> 7	2	1 (50.0%)	
Being Advised only in Term 2			
1 to 3	467	424 (88.67%)	p-value: 0.06
4 to 7	99	91 (91.03%)	
> 7	29	**21 (61.31%)**	
Being Advised in Term 1 & Term 2			
1 to 3	472	447 (94.70%)	p-value: 0.001
4 to 7	571	521 (91.48%)	
> 7	510	**422 (78.83%)**	

TABLE IX. THIRD TERM RENTION VS. ADVISING TIMING/FREQUENCY

Advising Frequency	**3rd Term Retention Rate if first advised in Term 1** (Total # of students: 1,928)	**3rd Term Retention Rate if first advised in Term 2** (Total # of Students: 595)
>2	1704 (81.60%)	356 (72.88%)
>3	1392 (81.08%)	198 (71.45%)
>4	1104 (80.52%)	128 (70.31%)
>5	876 (80.11%)	82 (67.73%)
>6	682 (79.51%)	54 (64.15%)
>7	512 (78.77%)	29 (61.31%)
>8	398 (78.17%)	21 (61.11%)
>9	307 (77.41%)	12 (60.00%)
>10	244 (77.19%)	7 (50.00%)

TABLE X. FIFTH TERM RENTION VS. ADVISING TIMING/FREQUENCY

First Being Advised In	Total Students	5th Term Retention	Chi-Square
Term 1	922	855 (92.73%)	p-value= 0.73
Term 2	285	266 (93.33%)	
Term 3	117	112 (95.73%)	
Term 4	40	38 (95.00%)	
None	69	63 (91.30%)	
Comparison students	1513	1322 (87.38%)	

We next examine whether the timing of first advising interaction has a long-lasting impact over the 7th term retention status. One observes from 0that *being advised in the first term is associated with a higher 7th term retention rate regardless of advising frequency*. On the other hand, if a student persists college without being advised during the first college year, advising seems to have little influence on her 7th term retention status.

TABLE XI. SEVENTH TERM RENTION VS. ADVISING TIMING/FREQUENCY

Advising Frequency	**7th Term Ret. Rate if first advised in Term 1**	**7th Term Ret. Rate if first advised in Term 2**	**7th Term Ret. Rate if first advised in Term 3**	**7th Term Ret. Rate if first advised in Term 4**
Total Num of Students	715	209	90	37
>2	668 (72.21%)	171 (64.05%)	72 (91.46%)	16 (88.33%)
>3	598 (71.55%)	129 (62.25%)	40 (92.47%)	8 (91.67%)
>4	529 (71.00%)	94 (60.30%)	23 (95.14%)	5 (100%)
>5	443 (70.44%)	70 (57.47%)	15 (96.67%)	3 (100%)

TABLE XII. 4-YEAR GRADUATION VS. ADVISING TIMING/FREQUENCY

Advising Frequency	**4-Year Grad Rate if first advised in Term 1**	**4-Year Grad Rate if first advised in Term 2**	**4-Year Grad Rate if first advised in Term 3**	**4-Year Grad Rate if first advised in Term 4**
Total Num of Students	429	126	80	35
>2	394 (9.79%)	107 (8.29%)	64 (16.23%)	15 (29.17%)
>3	348 (8.80%)	80 (7.79%)	33 (11.94%)	7 (33.33%)
>4	309 (8.50%)	58 (6.17%)	20 (9.71%)	4 (33.33%)
>5	262 (7.69%)	44 (3.48%)	13 (5.00%)	2 (50%)

The positive impact of being advised in the first term is also noticeable when considering such students' 4-year and 5-year graduation status. In TABLE XII. , we observe a similar phenomenon as for the 7th term retention rate, where students received their first advising in Term 1 show a higher 4-year graduation rate than those who received their advising in Term 2. This positive effect becomes even more prominent when examining the 5-year graduation rate (TABLE XIII.). Here, students who received advising in Term 1 outdo all the other groups. Even more noticeable is the sharp contrast between students who received advising in Term 1 and those in Term 2. The odds for the former group to graduate in 5 years is 5 to 1. This once again suggests the importance of advising students in their first term.

TABLE XIII. FIVE-YEAR GRADUATION VS. ADVISING TIMING/FREQUENCY

Advising Frequency	5-Year Grad Rate if first advised in Term 1	5-Year Grad Rate if first advised in Term 2	5-Year Grad Rate if first advised in Term 3	5-Year Grad Rate if first advised in Term 4
Total Students	715	209	90	37
>2	169 (49.21%)	37 (13.38%)	40 (42.81%)	6 (33.33%)
>3	142 (49.79%)	29 (12.22%)	21 (46.11%)	2 (50.00%)

C. *Impact of Advising on At-risk Students & Common Advising Topics*

TABLE XIV. reports the proportions of probationary students changing or continuing to stay in probation after one semester's study. TABLE XV. concerns at-risk students in their 4th term. Overall, the Metro students fare better than the comparison group; however, the sample size is too small to draw meaningful conclusion in regard to the effect of advising over at-risk and probationary students.

TABLE XVI. reports the distribution of advising topics as labeled by the advisors with respect to the three groups of students in their 4th term. It is a positive sign that a higher percentage of probationary and at-risk students received advising concerning academic performance. It is however also interesting to observe that around 70% or more students in each group have checked in (i.e., no need to seek advising) with their advisor. *This may help explain to an extent just being there for the students may have already made a positive influence on students*.

TABLE XIV. ADVISING VS. PROBATIONARY STUDENTS IN TERM 4

Received Advising	Total Students	Still on probation	Out of probation
Yes	47	32 (68.09%)	15 (31.91%)
No	11	6 (54.55%)	5 (45.45%)
Comparison Students	71	53 (74.65%)	18 (25.35%)

TABLE XV. ADVISING VS. AT-RISK STUDENTS IN TERM 4

Received Advising	Total Students	Went into probation	Not on probation
Yes	127	18 (14.17%)	109 (85.82%)
No	66	11 (16.67%)	55 (83.33%)
Comparison Students	231	43 (18.61%)	188 (81.39%)

TABLE XVI. ADVISING TYPES VS. TERM 4 STUDENT GPA STATUS

Advising Topic Type	On Probation	At-risk	Good-standing
Total #	47	127	669
Academic performance support	15 (33.12%	34 (27.41%)	97 (14.61%)
Scheduling and program service	8 (18.18%)	47 (37.24%)	268 (40.15%)
Check-in, other	34 (74.11%)	88 (69.46%)	506 (75.69%)

We further identify the top 5 most common advising topics. They are: academic performance, check in (no issue), other, scheduling, and attendance. The presence of "other" topic appears in the top 5 is problematic. *It suggests that the Metro program may need to either create more specific advising topics to reduce the use of "other", or to ask its advisors to be more careful at using the "other" topic.*

D. *Characteristics of Written Notes and Topic Modeling*

The advisors wrote a total of 21,335 advising notes during the period under study. Fig. 2 and Fig. 1 present the histograms of the lengths of such notes as measured by the number of words and sentences in each note, respectively. It is obvious that most notes are relatively short. Specifically, approximately 68% of the notes have few than 40 words, about 71% of the notes contain 4 sentences or less.

Upon examining each individual advisor's notetaking practice, we observe a wide spectrum of habits. Some advisors routinely write long notes at an average of more than 200 words, whereas some write very short notes at an average of 8 words. T*his suggests that the Metro program leadership team may need to introduce more standards in terms of taking advising notes.*

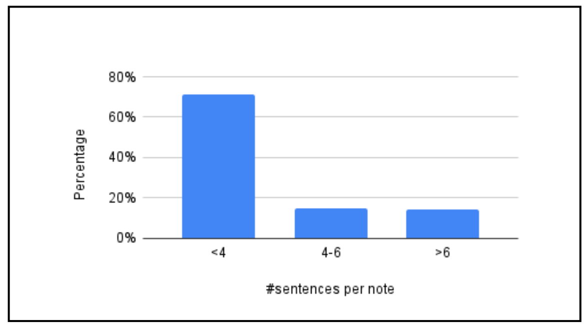

Fig. 1. Histogram of note lengths in number of words per note.

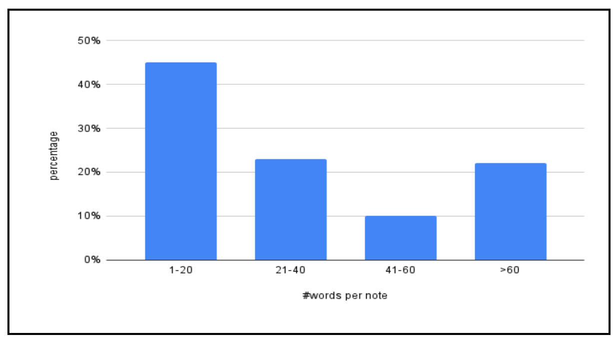

Fig. 2. Histogram of note lengths in number of sentences per note.

The efforts of learning the underlying topics using LSA and LDA topic modeling approaches, regrettably, are not fruitful. The generated topics often have very low coherence and consistency scores. We hypothesize the potential causes in the next Section.

V. DISCUSSION

One of the main findings in this study is that it is important to require new college students to receive advising in their first semester. One however needs to be careful at overgeneralizing this finding. First, nearly all the students enrolled in the Metro program are first-generation college-attending, normally from economically disadvantage underrepresented minority groups. Second, we have observed that not every student seems to benefit from this type of advising. For example, there are a group of students who never received advising, yet they achieved comparable and often higher retention/graduation rate. It is likely that these students are more resourceful, thus needing less support. This also suggests higher institutions need to first understand who their students are before designing and implementing mechanisms to support their students.

Contrary to what we may have expected to achieve, we notice that students receiving the most advising interactions in general often fare worse in terms of retention and graduation rates. Without further information, it is challenging and premature to downplay the effect of advising. For example, we do not have information to infer what would have happened to such students without these advising interactions.

At the same time, we also should not overplay the impact of advising in students' overall success. As mentioned in Section I, a student's success can be attributed to a collection of seven factors (i.e., academic advising, social connectedness, student involvement, faculty and staff approachability, business procedures, learning experiences, and student support services). The advising practice under study here is just one of the many constructs adopted by the Metro program to support its students.

Finally, to investigate the potential causes why the LDA and LSA topic modeling approaches failed to generate meaningful topics when applied to our large quantity of notes, two of the authors independently read through the notes related to a few interaction types, such as the "dropping school" type. Neither author was able to recognize the common topics. We therefore hypothesize the following two possible causes: (1) the adopted LDA and LSA algorithms are not effective at analyzing such advising notes; and (2) the written notes may be too noisy. Based on our manual inspection, we believe the latter may contribute more to this issue than the former. Furthermore, this failed attempt also points the Metro program to at least examine and evaluate their current note-taking practice, especially considering that many advisors have spent a considerable amount of time to create such notes, hoping such notes can help gain a better understanding of students' advising needs.

VI. Conclusions and Future Work

We present a comprehensive analysis of 5 years' advising records of 3000+ students at a public 4-year degree granting university. Statistical and text analytical approaches are adopted to reveal the impact of advising interactions on students' performance outcomes. We are pleased to learn that the current advising practice are fair towards different demographic groups. We also uncover the importance of early advising, especially in a student's very first term in their college career. Delaying such interventions to the second term, for instance, can significantly lower the likelihood of 5-year graduation outcome. In terms of at-risk and probationary students, the effect of advising is less conclusive due to small sample sizes. We also notice a large proportion of advising interactions that are labeled as "other". Together with the presence of large quantity of short written notes, this suggests that our community-based learning program may need to reconsider the current note-taking practice.

In the future, we plan to further characterize the students who never received advising when enrolled in this program. We also plan to explore other text analytical approaches, for instance, clustering, to analyze these advising notes. Finally, we plan to look into the tutoring service offered by this program and study how this service together with advising help students graduate with a college degree.

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