Professors' Impact on Cybersecurity Students' Learning

Emre Tokgoz, Julissa Molina, Joel Joseph, Sergio Duarte, Alyssa Xiang, Tanvir Ahmed
State University of New York, Farmingdale, NY, tokgoze, molij17, josej18, duarsp, xiana21, ahmet9 @farmingdale.edu

Abstract **– Cybersecurity students have certain expectations from professors when it comes to conceptual learning. Such factors have not been studied pedagogically in the literature. In addition, such factors can impact the course flow and may also impact these learners' motivation and success not only in the classroom but also in their major and their future careers. In this study, we use qualitative and quantitative techniques to analyze data collected from 103 students at a university located in the Northeastern side of the United States. The study attained Institutional Review Board (IRB) approval and was conducted during a 6-month period. Quantitative data analysis applications included statistics, data distribution with model fitting, correlation with heatmap evaluation, cross-correlation, and Mann-Whitney U-test. The qualitative data analysis relied on 30-40-minute video recorded and transcribed interview responses of the participants that aimed to follow up on their research questionnaire answers; Each participant is compensated money for taking place in the video recorded interviews. The overall quantitative results indicated the ability of the professor to explain the theory, examples provided by the professor, professor's friendliness, and experiences of the professor to be the top four choices. The experiences of the professor and real-life examples given are highly cared for by the research participants. The majority of the participants indicated the importance of the lecture flow for a smooth educational experience.**

Index Terms - Cybersecurity education; Professor-based factors; Lecture flow; Pedagogical cybersecurity research.

INTRODUCTION

Careers related to technology and engineering have experienced exponential growth in the last decade, with cybersecurity roles having a predicted growth of 33% in the next decade, according to the United States Bureau of Labor Statistics [1], compared to a 25% growth expectation for software engineers. Estimates of CyberSeek and ISC2 have shown that there are between 480,000 and 570,000 unfilled cybersecurity jobs currently in the United States [2]. With the recent increases in cyber threats and vulnerabilities in many companies and technologies, there is an increasing need for cybersecurity professionals that also highlights the need for universities' and colleges' ability to properly equip students with the skills needed for the field. As such demand grows, understanding the factors and influences that can impact a student's learning experience is essential when preparing students for complex roles that are highly demanded. Our research seeks to discover whether the quality of the courses and the associated resources ensures the students to feel prepared for succeeding in this field.

Building a proper foundation for students to learn is essential, but there is limited research that can pinpoint specific professor related factors that include student input on what they believe can help them to learn better. Research indicates that effective teaching strategies and professor- or instructor-driven factors play a pivotal role in a student's engagement in coursework [3], ability to apply course concepts in practical problems or solutions, and interest in engaging in research with faculty. However, these educational models lack specified details, and there is little explanation of what specific characteristics in these course structures contribute to student preparedness and learning [4]. It has also been observed that a well-organized cybersecurity education can limit skill gaps, and an educational strategy that follows a problem-based, project-based, and hands-on learning can assist students in developing analytical skills; However, such results do not aim to cover what aspects of a course are effective for cybersecurity students' learning, nor does it present any quantitative evidence or statistical exploration to show that said frameworks or specific course flows resonate with students' learning. Furthermore, research on how various forms of course delivery such as in-person, hybrid, or online accompanied by structured course models providing flexibility and satisfaction in student learning is limited [5]. Therefore, there are hardly any research studies that offer an analysis of the effectiveness of pedagogical methods with the exploration of faculty' role in enhancing student outcomes [5,6].

Beyond the technical factors influencing the education of future professionals, interactions with instructors are an important influencing factor. Research has indicated that student-instructor correspondence shows students' willingness to participate and comfort in confiding struggles with instructors, but this has not been observed for cybersecurity students [3]. Past studies address that social settings or activities like class trips, presentations, and additional personalized support helped students while such studies also don't address instructors' educational contributions to effective student learning [5,6]. The research observations include social factors such as whether an instructor remembers a student's name as well as the instructor's friendliness both inside and outside the learning environment, and availability to meet with students outside of class hours—nuanced elements that highlight how educators can enhance students' academic experiences and connection.

Past research findings focused on a single aspect rather than exploring various factors that our research questions, such as whether a student's learning ability is influenced by a professor's gender, experience, or ability to convey course concepts. Although there have been studies showing that the implementation of high-impact practices—such as learning communities, undergraduate research, and internships—enhances student learning, they fail to acknowledge that many of these practices involve mentors, faculty, and professors [6]. Additionally, studies sparingly mention the role of academic advising as highlighted to be a critical component in student development [6], and these studies underscore the importance of faculty, moreover a professor's involvement in a student's ability to learn and academic life.

Our research's primary objective is to assess and collect qualitative and quantitative data to determine whether coursework and experiential interactive factors with professors affect cybersecurity students; Factors that prior studies have not covered yet. Therefore, this study aims to explore whether several factors, including professor characteristics, teaching methods, and course structure, influence how effectively cybersecurity students learn in their major. This research aims to contribute to the broader, limited discourse on effectively improving cybersecurity education and analyzing specific factors affecting future cybersecurity technologists by exploring and gaining insights from participants of the study. The insights of the analyzed data are expected to support educators in creating more effective and strategic learning environments, preparing students for success in a growing, lucrative, and evolving field. For this purpose, we briefly outline the research methodology in the next section. The third section focuses on the quantitative analysis of the collected data. Qualitative data analysis is conducted in the fourth section that relies on the interview responses of the research participants. The last section contains conclusive remarks on the results of the study and future work.

RESEARCH METHODOLOGY

The findings presented in this research are derived from a research study conducted at a public university in the Northeastern region of the United States by a team of five assistant researchers and a Principal Investigator (P.I.). After obtaining Institutional Review Board (IRB) approval, the research team collected data that follows the associated protocol. Pre- and post-data collection and evaluation included two informed consent forms, a survey, and transcribed video interview recordings of the participants. For this research, the survey was deployed to 101 cybersecurity undergraduate students. The quantitative data is the statistical data attained from students based on the following research questions as a part of the survey they completed:

Which of the following factors do you believe affect your learning ability based on your interactions with the professor?

1. Professor's gender
2. Professor's experiences
3. Professor's examples
4. Professor's ability to explain the theory.
5. Professor's friendliness in and out of the learning environment
6. Professor's flexibility
7. The grades the student gets.
8. Lecture method (online, on-ground, hybrid)
9. The professor calls the student by name in the class.
10. Office hours

Does the flow of the course lectures impact cybersecurity students' learning in their major?

Our research employs quantitative and qualitative methods to analyze the data. The quantitative analysis is comprised of the statistical distributions of the data as well as numerical responses recorded from participants. The qualitative data is obtained through video recorded interviews with each participant's compensation to take place in the recorded interviews that lasted between 30-40 minutes, and sought to gain a deeper, more holistic understanding of their survey responses. These interviews help to analyze collectively to ascertain and identify any detailed insights not conveyed in the quantitative results. Participants elaborated on their choices or factors contributing in their ability to learn cybersecurity concepts from Professors during the interviews as well as the potential impact of course structure on their learning. The quantitative results to be explained in the next section are derived from statistical calculations and a variety of visuals are used for displaying the results for summarizing the results.

QUANTITATIVE RESULTS

The numerical data is collected in a way that participants can pick multiple options for the research questions that they are asked, and the associated quantitative analysis is driven by this approach that also includes the correlations between variables as well as the two research questions that the participants are asked. Therefore, the analysis that we will be outlining here relies on a cumulative look at all the responses provided. The impact of professor-based factors also relates to the flow of the lecture therefore this is one of the major correlation analyses that we will be presenting in this section. The distributions of the graphs are designed by using the statical weighted distributions of the data within the entire data set.

Part A. The factors that are believed to affect cybersecurity undergraduate students learning ability are based on interactions with the professor.

Part B. The flow of the course lectures impact cybersecurity students learning in their major.

The major contribution of Part A is to focus on the professor to understand the factors that are driven by the professor in the major and what cybersecurity students believe for such factors to impact their learning ability based on the interactions with the professor. These factors are important to understand as they are the main psychological drivers of the students to continue believe that they are impacting them. In correlation with these factors, Part B focuses on the flow of the lectures with their impact on their learning; This part correlates with Part A noting that the flow of the lecture relates to professor however there can be other factors that can impact students learning such as cell phone or laptop usage, chatting with friends etc.

The quantitative techniques that are employed for the analysis of the data included the following:

- Statistical data distribution equation
- Correlation analysis
- Mann-Whitney test
- Kruskal-Wallis Test
- Heatmap analysis of cross-correlation between the parts.

The following subsections focus on the interpretations of these quantitative results with figures and tables to demonstrate a comprehensive understanding of the collected large data set.

I. Statistical Data Distributions

In this section we focus on distributions of the data collected for Parts A and B. These distributions nature relied on the collective data for both parts with the associated percentages of each factor.

The statistical distribution for Part A is demonstrated in Figure 1 with the best fitting model is determined to be a linear regression with an R^2 value of 94.39%.

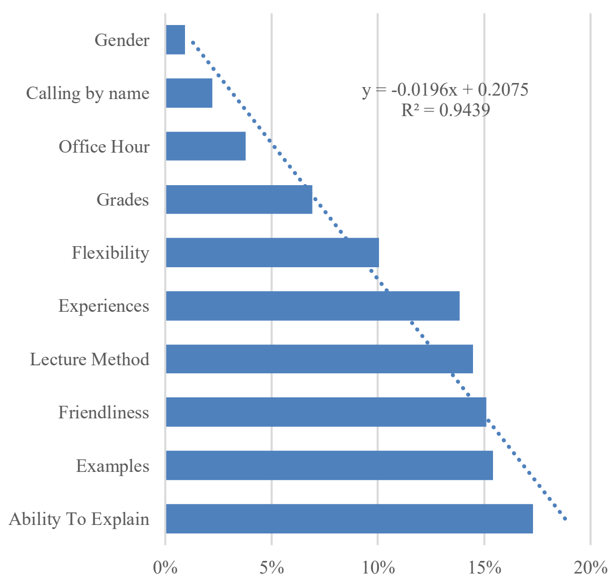

FIGURE I
DATA DISTRIBUTION OF PARTICIPANT CHOICES FOR PART A

In this figure,

- The ability of the professor to explain the theory received the highest percentage of 17.3% of the data as the top choice of the participants.
- Examples provided by the professor had the second highest rate of 15.41%.
- Friendliness of the professor is determined to be the top third option at a rate of 15.1 %.
- Professor's experiences are identified to be the fourth highest option with a rate of 10.1%.
- The lowest percentage selected was the professor's gender with a rate of 0.94%.

Figure II below displays an overview of the responses to Part B of the research that focused on the course flow. About 77% of the participants mentioned that the flow of the lecture impacts them while about 20% of the participants mentioned the lecture flow to be impacting on occasions. About 3% of the participants mentioned that the lecture flow does not bother them when it comes to learning course concepts in cybersecurity.

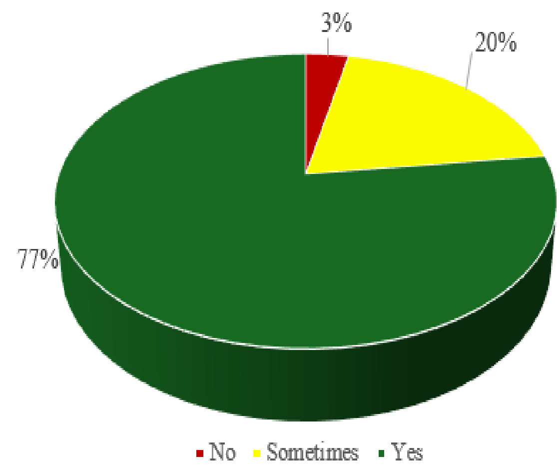

FIGURE II
IMPACT OF LECTURE FLOW ON STUDENTS' LEARNING CONCEPTS

II. Selected Options' Cross-Correlations of Part A

Correlation of the options selected Part A is important to be addressed given that one choice's selection in relation to another one signifies how much these coupled options valued by the participants. Figure III displays the heatmap of the relative correlation values between all variables that are organized according to the column variable selections. This relative correlation is driven by the number of choices for the column and the overlapping row option. The asymmetric nature of this heat map is a result of differences in selections for each column option. As an example, relative to the participants who selected "Experience" of the professor, there is an 88.89% correlation between "Experiences" and "Examples" while the correlation between these two variables is 80% relative to the "Examples" option.

	Experiences	Examples	Ability To Explain	Friendliness	Flexibility	Grades	Lecture Method	Calling by name	Office Hour	Gender
Experiences		80.00%	71.43%	77.55%	75.76%	72.73%	70.21%	71.43%	91.67%	100%
Examples	88.89%		80%	85.71%	93.94%	72.73%	89.36%	85.71%	75.00%	100%
Ability To Explain	88.89%	90.00%		93.88%	100.00%	68%	95.74%	100.00%	100.00%	100%
Friendliness	84.44%	84%	82.14%		87.88%	90.91%	85.11%	100.00%	100.00%	100%
Flexibility	55.56%	62.00%	58.93%	59.18%		68.18%	59.57%	57.14%	66.67%	66.67%
Grades	35.56%	32.00%	26.79%	41%	45.45%		36.17%	71.43%	58.33%	66.67%
Lecture Method	73.33%	84.00%	80.36%	82%	84.85%	77.27%		85.71%	75.00%	100.00%
Calling by name	11.11%	12.00%	12.50%	14%	12.12%	22.73%	12.77%		25.00%	0.00%
Office Hour	24.44%	18.00%	21.43%	24%	24.24%	31.82%	19.15%	42.86%		33.33%
Gender	7%	6%	5%	6%	6%	9%	6%	0%	8%	

FIGURE III
HEAT MAP OF PART A DATA OPTIONS' CROSS-CORRELATIONS

This heatmap structure tells us the highest correlation values for professor's ability to explain, examples given by the professor, experiences of the professor, the friendliness of the professor, and the lecture method in relation to the other variables. This is a clear indicator that the participants who selected these options also picked other options at high percentages, typically greater than 80%. Calling by name, office hour, and gender have the lowest three percentages of correlations with the other options.

Just like the values themselves, the correlation, and standard deviations of the cross-correlations matter. Figure IV below demonstrates the average and standard deviation values for the column values in Table III. The highest averages are attained for calling by name and gender are due to the lowest percentages of selections while the office hour had a high range of data values that attained both 100% and 0%. The lowest standard deviation is attained for the grades option indicating that the lowest deviation in the column values occurred within the associated column data.

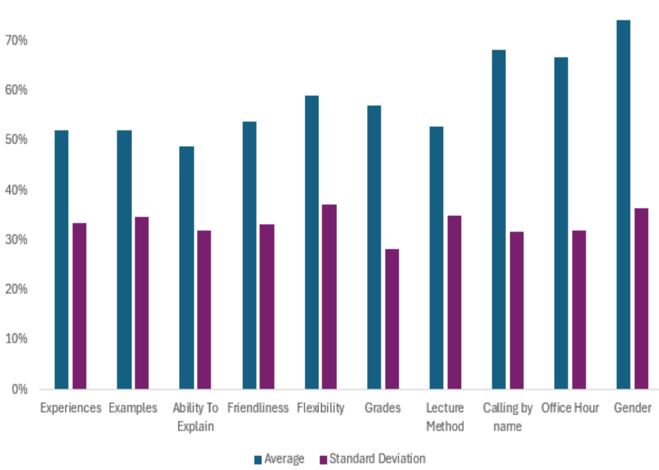

FIGURE IV
AVERAGE AND STANDARD DEVIATIONS OF PART A'S DATA CORRELATIONS

The numerical values of averages and standard deviations attained for Figure IV are displayed in Table I. Noting that cross-correlation is an indicator of the participants agreed selections to the given question, the highest correlations indicate the highest overlap with other options while the higher standard deviation indicated higher levels of variation within the column from the other options. Gender is an exceptional item in this case due to the low number of selections attained for this option.

The cross-correlation average values ranged between 57 and 77% with the highest average of 76.79% identified for calling by name option while the lowest average of 54.24% is found for professor's ability to explain the theory. The lowest standard deviation value of 20.11% for professor's calling the students by name while the highest average of cross-correlation standard deviation value of 36.43% was determined for gender.

TABLE I
A SUMMARY OF AVERAGE & STANDARD DEVIATIONS OF CHOICES

	Option	(Average, Standard Deviation) in %
1	Experiences	(57.78,30.88)
2	Examples	(57.75, 32.22)
3	Ability to Explain	(54.24, 29.36)
4	Friendliness	(59.69, 30.01)
5	Flexibility	(65.53, 33.66)
6	Grades	(63.07, 23.36)
7	Lecture Method	(58.51, 32.35)
8	Calling by Name	(76.79, 20.11)
9	Office Hour	(73.96, 24.98)
10	Gender	(74.07, 36.43)

Looking at the overall analysis of the data collected for this section, professor's ability to explain, examples given by the professor and friendliness of the professors are the top three choices as displayed in Figure I with the same participants choosing these three options together at a high percentage as indicated by the cross-correlation analysis.

III. Cross Correlation Analysis of Part A and B Data

The correlation between the factors that affect cybersecurity undergraduate students learning ability based on interactions with the professor and the flow of the course lectures that may impact cybersecurity students learning in their major will be analyzed in this section. Figure V demonstrating the percentages of the cross correlations between Part A and Part B responses. It is evident that the displayed linear regression model is a decent fit to the data as proven by the R^2 value of 96.94%. Both flexibility and professor's ability to explain the concepts are cross correlated with Part B at a rate of 11.95% that placed these two options in top four of the choices for cross correlation between responses to Parts A and B while lecture method with 14.15% and professor's calling the students by name with 12.26% are the other two of the top four options unlike Figure I results. This indicates that participants with these four choices had the strongest belief of the flow of the lecture impact their learning. The lowest cross-correlation occurred for the Gender with course flow importance at a rate of 0.94%.

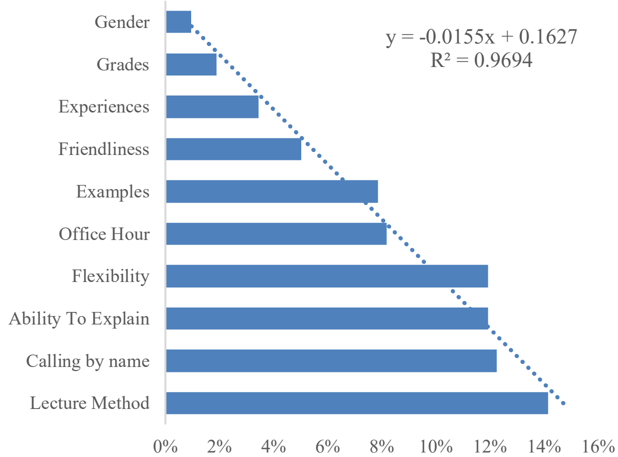

FIGURE V
CROSS CORRELATION BETWEEN THE DATA ATTAINED FOR PARTS A AND B

IV. Mann-Whitney and Kruskal-Wallis Tests

Mann-Whitney U and Kruskal-Wallis Tests are Chi-square evaluation methods used for data sets without normal distribution nature to identify the significance levels of the categorized data. We use two different categorizations of the collected data to apply the Kruskal-Wallis test while a single categorization of the data is used for Mann-Whitney test.

The Mann-Whitney test is applied to Part A and Part B data as two independent sets as the choices made for the two groups. The results indicated the two groups to have statistically insignificant differences therefore the two groups have similar nature.

The Kruskal-Wallis is applied twice based on the following data classification:

- Classification 1: Each one of the options of Parts A and B are considered as one group, therefore each option is assumed to be an independent group.
- Classification 2: The grouping of the data is based on the following:
  - Group 1. Consisted of professor's experiences and examples given.
  - Group 2. Consisted of friendliness, flexibility, and ability to explain.
  - Group 3. Designed by using lecture method, office hour, lecture flow, and lecture method.
  - Group 4. Consisted of grades attained by the student.

The second classification's Kruskal-Wallis test resulted in statistically significant results with a p-value of 19.81%, hence there is a significant difference between the groups designed that also indicates a major difference in the grouping. Category 1 on the other hand a statistically significant results with a p-value of 2.17×10^{-6}. This result indicates the significance of the difference in each option's averages of the ranked categories.

QUALITATIVE ANALYSIS AND RESULTS

The immense value of the qualitative results cannot be underestimated to be used research participants opinions on cybersecurity education. The qualitative results are attained by following the IRB approved guidelines of this study: Participants voluntarily participated in video recorded follow-up interviews to further explain their responses to the research questions and the video recordings are transcribed for furthermore analysis. Each participant is compensated with money for participating in the 30–40-minute video recorded interview by the Principal Investigator (PI). The qualitative results are matched with the quantitative results to have a better conclusion of the participants view of the research questions. What follows next are samples of the collected qualitative data for both parts of the research.

There are certain factors that impact psychological states and well-being of students that we need to pay as educators and researchers as they will also become educators, professionals, and researchers in the society that would impact others as well. The factors we cover in this work can be the ones that the professors can pay attention to and aim to change in a positive trajectory in alignment with possible interest of students. A simple example is the monotonicity of the lecture flow that may have a tremendous impact on some students understanding while it may not have impact on others; The ideal approach would be to target the best possible flow of the lecture for all students to be able to make the best out of the course for a successful learning experience. Given the options that the professor can make changes such as experiences, examples, method of explaining the theory, level of friendliness in and out of the learning environment, flexibility calling students by their names in the class, office hours, and lecture flow, what can professor improve for improving cybersecurity education? The following qualitative results are some of the participants' reflections to partially answer this question.

For instance, the following participant cares about the lecture method, and friendliness and experiences of the professor to explain the theory while lecture flow does not bother the research participant (RP).

Interviewer. *Which of the factors do you believe affect your learning ability based on your interactions with Professor?*

RP 1. *Lecture method, friendliness, ability to explain the theory, and I guess the professor's experiences. When they are able to share their perspective from the industry, you know, different situations that they've worked in, it gives a lot of good contexts on work experience and career opportunities.*

Interviewer. *The flow of the course lectures impacts my learning.*

RP 1. *Hmm. I do not think so. I have never had the flow of a course really stand out to me as an issue.*

Just like RP 1, the following RP also cares about the experiences of the professor the most who also cares about the flow of the lecture.

Interviewer. *Looking at these factors, which ones do you believe affect your learning ability based on your interactions with the professor.*

RP 2. *I would say the professor's experience is the biggest factor for me. Professors who have a lot of real-world experience really make a difference in how we learn. They know what is happening out there in the industry and what we, as students, need to focus on. For example, I once had a professor who shared* *stories from their own career and even brought real-life data into class. They explained, this is what happens in real scenarios and broke down everything in a way that made it super easy to understand. That kind of teaching really sticks with you because it connects what we are learning in class to what we will face in the real world. When professors use their experience to give us real-life examples, it makes the lessons so much more meaningful. It helps me see what is coming and really keeps me engaged. Because it makes the class more interesting and gets me more involved. When a professor shares their real-world experience, it just grabs your attention and makes you want to participate more. That is why the professor's experience is the most important.*

Interview. *Does the flow of the lecture course lectures impact your learning?*

RP 2. *Oh yeah, it definitely does. Like, if today we are learning the basics of cybersecurity and then next class, we dive into something that builds on that, like cryptography, it makes a lot of sense. It feels connected, and it helps me expand my knowledge step by step. But when the flow is all over the place—like one day it is cybersecurity, and the next day it is something totally unrelated, like Java programming—it just feels disconnected. It is harder to stay engaged because the topics do not tie together. So yeah, the flow of the lectures really matters.*

Unlike the other two RPs, the following RP cares about the office hours the most while caring about the flow of the lectures for a comprehensive understanding of the course concepts and psychological well-being.

Interviewer. *Which of the following factors do you believe affect your learning ability based on your interactions with the professor?*

RP 3. *Yeah, I think office hours is a big one.*
Knowing that if I don't have enough time to answer my questions, my schedule is busy. I can just always look for the office hours and talk. With the professor, if I am struggling, or if I did this and I'm letting him know. So, communication with the professor in that way is very nice. The professor's ability to explain the theory.
I have never had a problem because I ask too many questions, so I get a grasp of it based on the questions that I asked to help me. So, I would say just the communication with the professor.
Professor's friendliness does help if the professor is more open to answering questions and known is there rather than just doing the lecture. And again, I never experienced this, but maybe in the other classes the prerequisites. There are some professors that just want to be there and leave, and nothing wrong with that.
It just does not help. And the lecture method I prefer on-ground and hybrid, but if needed online I think piggybacking on the question before that communication with the professor would be nice.

Interviewer. *Does the flow of the course lectures impact your learning?*

RP 3. *If the class is disorganized, the learning management system design is weird, you have to constantly ask the professor. Where is this located? Why is this located here? Is this in there? I think the LMS has to be organized and that helps with the flow. Also, if there's random quizzes, some professors do random quizzes. That's fine, but I feel like there should be some consistency with the with the learning and like knowing when it's gonna be what next week you're gonna be learning on this and in two weeks you can be that and basically like a nice syllabus to give. You a whole pathway of how the class is gonna be.*

The qualitative results indicated a strong trend in relation to the professors' ability to explain the theory, giving examples and experiences of the professor similar to the quantitative results attained in Figure I. An area where students appear to not distinguish is the real-life experience and examples given; The expected examples to be given in the classroom appeared to be also in relation to the professor's real-life experiences. The flow of the course with the ease of following the lectures and course management are the key points of the qualitative data collected.

Conclusions and Future Work

The focus of this study was on some of the factors that may impact undergraduate cybersecurity students learning as well as some of the other factors that they care about such as the grades that they get and the lecture method (that may also relate to the professors' approach depending on the design of the course.) The data is collected at a university located in Northeast side of the United States with a total of 103 students' participation in this research; money compensation is provided for participating in the video recorded interviews with the PI and the qualitative analysis relied on these transcriptions to better understand the participants prior responses to the research questions. The quantitative analysis relied on statistics, distribution fitting to the data, correlation and heatmaps of cross-correlation, and Mann-Whitney and Kruskal Wallis tests. Part A part of the research focused on the professor-based factors while Part B focused on the lecture flow's impact on the students' learning. A summary of the statistics and categories that the cybersecurity students chose for Part A are provided in Figure VI below.

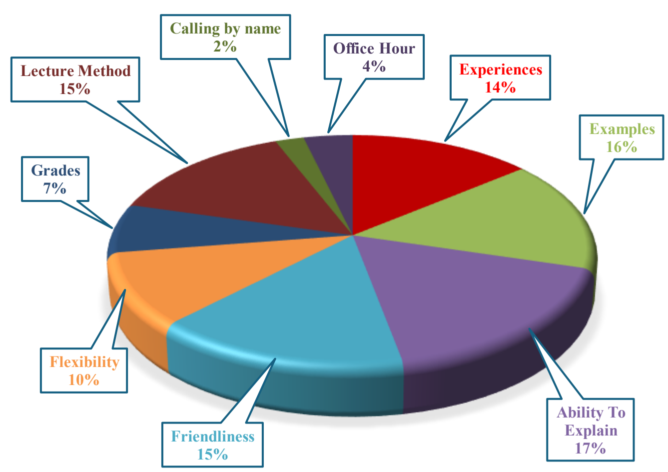

FIGURE VI
DATA DISTRIBUTION OF PART A CHOICES OF THE PARTICIPANTS

In summary, the following observations are derived:

- The RP response analysis to Part A indicated the importance of the ability of the professor to explain the theory that received the highest percentage of 17.3% of the data while examples provided by the professor had the second highest rate of 15.41%, and professor's friendliness is determined to be the top third option at a rate of 15.1%. Experiences of the professor is identified to be the fourth highest option with a rate of 10.1% while the lowest percentage was attained for the professor's gender with a rate of 0.94%.

- The cross-correlation values for Part A resulted in the highest correlation values to be attained for professor's ability to explain the theory, examples given by the professor, experiences of the professor, the friendliness of the professor, and the lecture method in relation to the other variables. This is a clear indicator that the participants who selected these options also picked other options at high percentages, typically greater than 80%. Calling by name, office hour, and gender have the lowest three percentages of correlations with the other options.
- The cross-correlation between Parts A and B showed participants strongest belief of the flow of the lecture to be impacting their learning in correlation to the professor's flexibility, ability to explain the theory, lecture method and calling students by name to be top four choices of the participants. The lowest cross-correlation occurred for the Gender with course flow importance at a rate of 0.94%.
- In relation to the quantitative results, the qualitative results indicated a strong trend in relation to the professors' ability to explain the theory, giving examples and experiences of the professor. An area where students appear to not distinguish in their responses is the real-life experience and examples given by the professor; The expected examples to be given in the classroom appeared to be also in relation to the professor's real-life experiences. The flow of the course with the ease of following the lectures and course management are the key points of the qualitative data collected.
- Factors that have a strong correlation with personal traits such as friendliness of the professor and ability to explain the theory are strongly cared for by the participants.
- Professor-based experiential factors turned out to be cared highly by the students in addition to the ability of the professor to explain the theory.

The findings of this research provide valuable insight for improving teaching strategies in cybersecurity education including the following:

- It will be ideal for professors to recognize the importance of reasonable course-based expectations from students.
- Communication is an essential part of education that should be incorporated into the educational environment in a smart way regardless of the course's offering modality.
- Designs of curriculums need to have a proper structure to encourage students to learn more rather than discouraging learners through high-level challenging tasks assigned.
- Pedagogical flexibility for advancing educational needs of learners at both course and curricular levels are integral to improving and encouraging education.

Given the limited investment in pedagogical cybersecurity research literature, and as an attempt to furthermore improve cybersecurity education and increasing awareness of the professors to understand the perspectives of the students, we invite other researchers and educators to take place in this important pedagogical research area. The expansion in the need for cybersecurity professionals in the industry is also a key component in the increase of expected educators in this area, and the educators that will take place in this field can also learn the perspectives of the students.

References

[1] U.S. Bureau of Labor Statistics. (2022). Information security analysts. Occupational Outlook Handbook. [Online]. https://www.bls.gov/ooh/computer-and-information-technology/information-security-analysts.htm.

[2] Hogan, M., Lilienthal, K., Bean de Hernandez, A., McHugh, P., Arbeit, C. A., & Sullivan, P. (2025). Cybersecurity Workforce Demand and Supply: A Statistical Report. RTI International, under contract to the National Center for Science and Engineering Statistics (NCSES). Washington, DC: National Science Foundation, pp.5-6 [Online]. Available: https://ncses.nsf.gov/pubs/cybersecurity-supply-demand-report.

[3] Trolian, T. L., & Jach, E. A. (2020). Engagement in College and University Applied Learning Experiences and Students' Academic Motivation. Journal of Experiential Education, 43(3), 317-335.

[4] Mukherjee, Madhav & Le, Ngoc & Chow, Yang-Wai & Susilo, Willy. (2024). Strategic Approaches to Cybersecurity Learning: A Study of Educational Models and Outcomes. pp.8-14. 15. 117. 10.3390/info15020117

[5] Nweke, L.O., Bokolo, A., Mba, G. et al. Investigating the effectiveness of a HyFlex cyber security training in a developing country: A case study. Educ Inf Technol 27, 10107–10133 (2022). https://doi.org/10.1007/s10639-022-11038-z

[6] Payne, Brian K.; Mayes, Lisa; Paredes, Tisha; Smith, Elizabeth; Wu, Hongyi; and Xin, ChunSheng (2021) "Applying High Impact Practices in an Interdisciplinary Cybersecurity Program," Journal of Cybersecurity Education, Research and Practice: Vol. 2020: No. 2, pp.18-20.

Author Information

Dr. Emre Tokgoz, Professor, Department of Computer Security, New York State University at Farmingdale, Long Island, NY.

Julissa Molina, Research Assistant, Department of Computer Security, New York State University at Farmingdale, Long Island, NY.

Joel Joseph, Research Assistant, Department of Computer Security, New York State University at Farmingdale, Long Island, NY.

Sergio Duarte, Research Assistant, Department of Computer Security, New York State University at Farmingdale, Long Island, NY.

Alyssa Xiang, Research Assistant, Department of Computer Security, New York State University at Farmingdale, Long Island, NY.

Tanvir Ahmed, Research Assistant, Department of Computer Security, New York State University at Farmingdale, Long Island, NY.