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INFORMATION SYSTEMS EDUCATION JOURNAL

Editors

AI-Powered Learning Support: A Study of Retrieval-Augmented Generation (RAG) Chatbot Effectiveness in an Online Course

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Abstract

This study investigates the effectiveness of a Retrieval-Augmented Generation (RAG) chatbot to enhance learning and engagement in a self-paced, asynchronous online R programming course. To contextualize the development and potential of RAG chatbots, we conducted a literature review on existing approaches and their use in educational settings. Following this, a chatbot powered by generative artificial intelligence (GenAI) was designed to provide tailored conceptual explanations and code examples based on course materials, addressing a range of student inquiries. To evaluate its effectiveness, the study analyzed chatbot interaction logs and survey responses collected at the end of the course. Results showed that students with greater prior knowledge of the subject matter were more likely to engage with the chatbot, primarily seeking help on advanced topics not covered in the course lectures. Overall, students expressed high satisfaction with the chatbot, particularly valuing its ability to provide helpful explanations that are based on the course materials. This study highlights the potential of GenAI, and RAG chatbots specifically, to enhance online education and provides practical insights for future implementations.

Keywords: Chatbots, Retrieval-Augmented Generation (RAG), GenAI, Online Education, R Programming, AI in Education

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AI-Powered Learning Support: A Study of Retrieval-Augmented Generation (RAG) Chatbot Effectiveness in an Online Course

Guido Lang & Tan Gürpinar

1. INTRODUCTION

Online courses often face unique challenges in providing adequate support to students (Lang & D. O'Connell, 2015; Napalit et al., 2023). Unlike traditional classroom settings, students in online courses lack immediate access to instructors for real-time assistance. This can lead to delays in addressing students' questions and difficulties, potentially hampering their learning progress (Hurlbut, 2018). Additionally, the asynchronous nature of many online courses means that students may be working on course materials at different times, further complicating the provision of timely support (Varkey et al., 2023).

The role of artificial intelligence (AI) in education has grown significantly with recent research identifying it as the most mentioned technology in discussions of emerging technologies in higher education (Gürpinar et al. 2024). Generative AI (GenAI), such as ChatGPT, Copilot, Claude, and Gemini, generate responses based on proprietary data and human-reinforcement learning. These chatbots use deep learning models, particularly transformer architectures, to understand and generate human-like text (Meyer et al., 2023). They rely on patterns learned from online datasets to predict the most probable next word or phrase in a conversation. While they are effective in generating coherent and contextually relevant text, their responses are limited to the information they have been trained on and do not automatically update with new data or specific documents (Jungherr, 2023). The technology that powers AI chatbots, i.e., large language models, has been shown to have useful applications in information systems education, specifically for writing of teaching cases (Lang et al., 2024).

Retrieval-Augmented Generation (RAG) chatbots integrate retrieval mechanisms with their generation capabilities to enhance the accuracy and relevance of their responses. These chatbots first retrieve pertinent information from a predefined knowledge base or a set of documents before generating a response (Jeong, 2023; Maryamah et al., 2024). The retrieved information is then used to inform the generation process, ensuring that the responses are not only coherent but also contextually precise and up-to-date. This approach is particularly beneficial in educational settings, where the need for accurate, specific, and context-aware answers is crucial. By leveraging both retrieval and generation, RAG chatbots can provide targeted support, addressing student queries with a higher degree of relevance and precision (Pichai, 2023).

Given the distinct advantages of RAG chatbots in delivering precise and contextually relevant information, their use in educational settings presents a promising avenue for enhancing student support. This transition from general AI chatbots to more sophisticated RAG systems raises several pertinent questions regarding their effectiveness and acceptance among students. Specifically, understanding the factors that influence students' engagement with such chatbots, the reasons behind their non-usage, and the types of queries they find most helpful can provide valuable insights. Additionally, gauging students' overall perceptions and attitudes towards the chatbot can further elucidate its impact on their learning experience (Labadze et al., 2023). In this context, the current study aims to address the following research questions:

- RQ1: What factors affect students' likelihood to use a course chatbot?
- RQ2: What are the reasons why students don't use a course chatbot?
- RQ3: What do students actually use a course chatbot for?
- RQ4: What do students think of a course chatbot?

Contributions
From a theoretical perspective, this study enriches the body of knowledge on AI-enhanced learning environments by demonstrating the efficacy of RAG chatbots in delivering targeted educational support. It provides empirical evidence on how RAG chatbots, which blend retrieval and generative capabilities, can effectively address the specific needs of students in online courses. Moreover, this research offers a nuanced understanding of how advanced AI technologies can be leveraged to enhance learning experiences, thereby contributing to the theoretical understanding surrounding AI and education.

On the practical side, the findings from this study offer actionable insights for educators and educational institutions looking to integrate chatbots into their online course offerings. It highlights the practical benefits of using RAG chatbots to provide immediate and context-aware support to students, thereby reducing the instructional burden on educators and enhancing the overall student learning experience. The findings suggest that RAG chatbots can effectively assist with advanced queries and lecture-related questions, making them a valuable tool for supporting student learning.

2. RELATED LITERATURE

Several studies have explored the use of AI chatbots in educational contexts. The recent meta-study by Labadze et al. (2023) emphasize numerous benefits of integrating chatbots in teaching, as seen from both students' and educators' perspectives. They found that educators primarily save time and gain in an improved pedagogy while students see advantages in three key areas: homework and study assistance, a personalized learning experience, and the development of emerging skills. Still, there are hurdles in operationally implementing AI chatbots and not enough insights into their impact on specific skills (Labadze et al., 2023). This motivates our research to focus on the implementation of AI chatbots in connection to programming skills.

For this field, our research builds on further studies that already explore the use of chatbots in programming education. For instance, a study by Ait Baha et al. (2023) examine the integration of AI chatbots in e-learning systems designed to support students' programming skills. Conducted in a Moroccan public college where French is the primary language, the chatbot effectively enhanced students' educational experiences by guiding instead of simply delivering answers. The chatbot's interactive nature provided students with timely answers, reducing uncertainty. The study suggests that future research should involve different learning contents and contexts to determine the specific tasks for which students use the chatbot and where they benefit the most (Ait Baha et al., 2023).

Furthermore, the implementation of a chatbot assisting in Python programming further demonstrates the positive impact of AI tools in programming education. Created using the SnatchBot API, the chatbot was found to be user-friendly and effective in simplifying programming logic and enhancing students' Python skills. The tool's success during the COVID-19 pandemic underscores its potential in supporting online learning environments. Future work proposed by the authors includes the consideration of additional programming languages and tests in other universities (Chinedu & Ade-Ibijola, 2021).

In another study, Kazemitabaar et al. (2024) deploy a chatbot in a C programming course, providing valuable insights into the varying performance of different LLM models across various programming languages and their impact on student engagement and learning outcomes (Kazemitabaar et al., 2024). Drawing from expert interviews, they also develop design recommendations for chatbots to allow for transparent and controlled use, which have been considered in this research.

Lastly, a study by Vukojičić and Krstić (2023) explores the influence of ChatGPT on student work, particularly in enhancing code commenting practices and promoting uniform writing styles. This uniformity improves code readability and maintainability, fostering better comprehension and collaboration among peers and instructors. The study highlights that ChatGPT not only hones individual coding skills but also contributes to a more efficient and effective learning environment (Vukojičić & Krstić, 2023). As a result, ChatGPT helped the students to produce code that is easier to understand and modify, confirming a small scope Reddit survey that recommends ChatGPT as an effective LLM to assist in R programming (https://www.reddit.com/r/rstats/comments/1d0glz3/best_chatbot_for_r_programming/).

These studies collectively demonstrate the potential and current limitations of AI chatbots in programming education. They highlight the importance of model accuracy, the positive impact on coding practices, and the interactive support provided to students. Our research aims to build on these findings by specifically focusing on the implementation of a RAG chatbot in an online R programming course. This focus addresses the unique challenges and opportunities presented by R programming and aims to provide a more tailored and effective educational tool for students in this domain.

3. METHODOLOGY

The first author developed and implemented RAG course chatbot for use in his graduate-level, seven-week, asynchronous, online course on "Business Data Analytics with R". The course consists of video lectures, which focus on coding demonstrations in R, and hands-on assignments such as exercises and lab projects, which are based on the video lectures. The course doesn't use a textbook and all course materials were developed by the first author. The course is part of the MS in Business Analytics program offered at the authors' university. While the course doesn't have any prerequisites, it is assumed that students in the program have knowledge of undergraduate statistics.

The RAG course chatbot is a Python web application that runs on Streamlit and uses LlamaIndex (for retrieval-augmentation) and OpenAI's GPT-4 (for generation). The course chatbot was developed based on the instructions and Python source code provided by Frasca et al. (2023). All lecture materials, including the code used in the lectures and exercises, was ingested by the chatbot. By utilizing RAG, the course chatbot was able to respond using examples from the lectures, referencing exercises, and following the professor's code style. The prompt instructed the chatbot to focus on explaining R programming and statistical concepts based on the course materials, which were sufficiently encompassing since the course didn't use a textbook. The full prompt along with a screenshot of the chatbot's user interface can be found in Appendix A. The course chatbot was publicly available online without user authentication for the duration of the course. All user queries were saved verbatim in a log file in the Streamlit backend.

At the beginning of the course, students were informed of the availability of the course chatbot via a statement in the syllabus, an announcement in the first lecture, and a written announcement on the course Blackboard site. Usage of the course chatbot wasn't required nor was it promoted again throughout the course.

The logs from the course chatbot contain the verbatim queries that were entered by the students into the course chatbot. A total of 80 queries were made by the students. The logs were content-analyzed by the authors using a grounded theory approach (Strauss & Corbin, 1990). After an initial pass-through, the authors decided on a set of categories that represent all queries. The authors then collaboratively categorized each of the 80 queries into one category.

At the end of the course, students completed an anonymous survey on Qualtrics that collected demographic information and measured their use of, and attitudes towards, the course chatbot. Similar to the logs, the open-ended questions were also content-analyzed by the authors using a grounded theory approach (Strauss & Corbin, 1990). Again, after an initial pass-through, the authors agreed on a set of categories that represent all responses and subsequently categorized each response accordingly. Students were offered extra credit (worth about 1.50 % of the final grade) in exchange for participation in the survey. The full survey can be found in the Appendix B. This study was approved by [university name withheld for review]'s Institutional Review Board under protocol number 03624.

4. RESULTS

Of the 40 students enrolled in the course, 38 (95%) completed the survey. Of the 38 students that completed the survey, most (n = 27, 71.05%) are in the 18-24 years age range, followed by the age ranges of 25-34 years (n = 6, 15.79%), 35-44 years (n = 4, 10.53%), and 55-64 years (n = 1, 2.63%). The majority (n = 23, 60.53%) is female. In terms of employment status, 17 (44.74%) are employed part-time, 13 (34.21%) are employed full-time, and 8 (21.05%) are not employed. None of the demographic factors are associated with any of the following results.

What Factors Affect Students' Likelihood to Use a Course Chatbot?

Of the 38 study participants, 16 (42.10%) used the course chatbot at least once. Prior use of AI chatbots (such as ChatGPT, Copilot, Gemini, Claude) is not associated with course chatbot use ($t = -1.04$, $p = 0.31$). However, prior knowledge of R is significantly related to course chatbot use. Specifically, students that used the course chatbot had more prior knowledge of R ($M = 2.18$, $SD = 0.98$) than students that didn't use the course chatbot ($M = 1.45$, $SD = 0.67$, $t = -2.58$, $p = 0.02$). Figure 1 depicts the difference in prior knowledge of R between the groups of non-users and users.

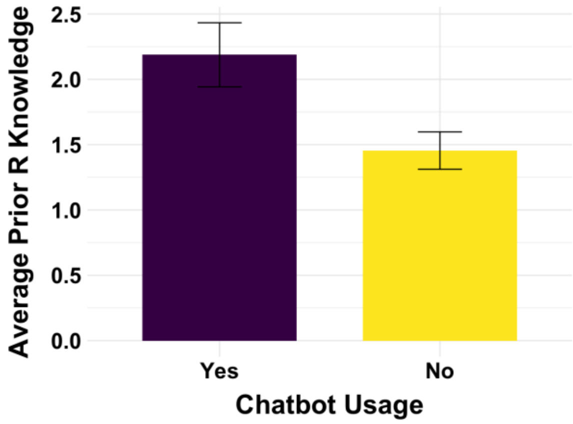

Figure 1: Average prior R knowledge by chatbot usage

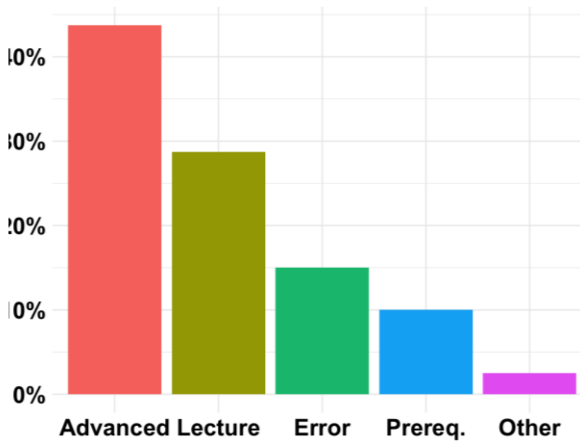

Figure 2: Distribution of query categories

What do Students Actually Use a Course Chatbot for?

Based on the log analysis of the 80 queries, it was found that almost half of the queries (n = 35, 43.75%) can be categorized as "advanced," meaning they are queries about topics that go beyond the topics covered in a lecture. An example query in this category is "*Is difftime number data type treated any differently than number data type?*" (note that this wasn't covered in a lecture). Over a quarter of the queries (n = 23, 28.75%) can be categorized as "lecture", meaning they are queries about topics that are covered in a lecture. An example query in this category is "*What functions can you use to aggregate data?*" (note that this was covered in a lecture). The third most frequent category of queries is "error" (n = 12, 15.00%), meaning they are queries about errors encountered when writing code for the lectures and/or assignments. An example query in this category is "*Explain error Quitting from lines 56-71 [unnamed-chunk-4] (Final-Project_Code.spin. Rmd)*". One tenth of the queries (n = 8, 10.00%) are part of the "prerequisite" category, which means they are queries about topics that are assumed to be prerequisite knowledge for the course. An example query in this category is "*What is a p value?*". Lastly, 2 queries (2.50%) were categorized as "other" because they're unrelated to any of the previous categories. These queries were "*How do you work as a chat bot, do you send an API request to gpt-4 or something?*" and "*Thank you!*". The distribution of number of queries per category is depicted in Figure 2.

What are the Reasons Why Students Don't Use a Course Chatbot?

Of the 22 survey participants who indicated that they didn't use the course chatbot, 16 (72.73%) provided a reason as to why they didn't use the course chatbot. The most frequent reason provided by 8 (50%) students was a lack of need for the course chatbot because the video lectures recorded by the professor were sufficient. The second most frequent reason mentioned by 6 (27.27%) students was an unawareness of the existence of the course chatbot. Lastly, 2 (12.5%) students stated they didn't use the course chatbot because they preferred to challenge and troubleshoot errors themselves. Figure 3 depicts the distribution of reasons for non-usage of the course chatbot.

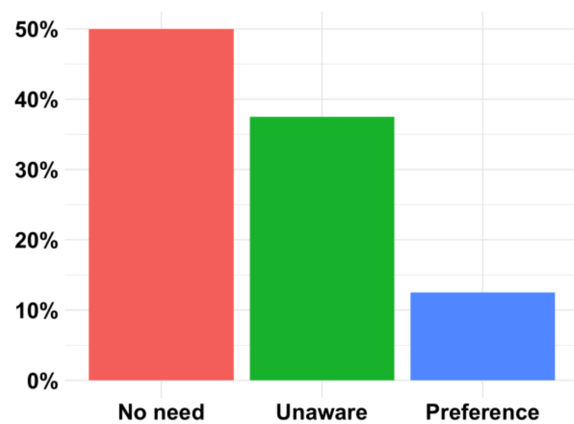

Figure 3: Distribution of reasons for non-Usage of chatbot

What Do Students Think of a Course Chatbot?

Students were asked to indicate their agreement with a statement measuring the extent to which the course chatbot enhanced their learning experience. About 87% somewhat or strongly agreed, suggesting that students felt very positively about the course chatbot. Figure 4 depicts the distribution of responses to this item.

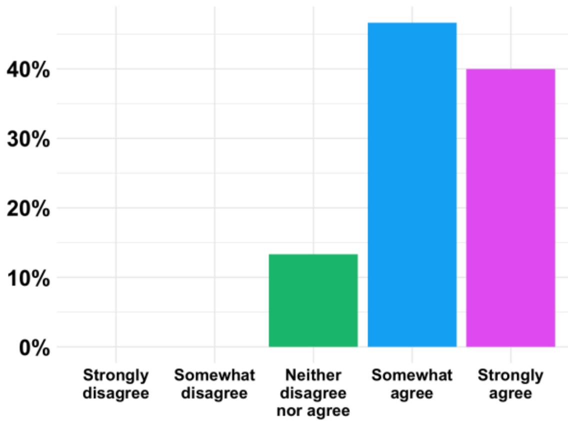

Figure 4: Responses to "The course chatbot enhanced my learning experience."

Additionally, students were asked to indicate their agreement with a statement measuring the extent to which they wished course chatbots would be used in more courses. Similarly, about 87% somewhat or strongly agreed, suggesting again that students felt very positively about the course chatbot. Figure 5 depicts the distribution of responses to this item.

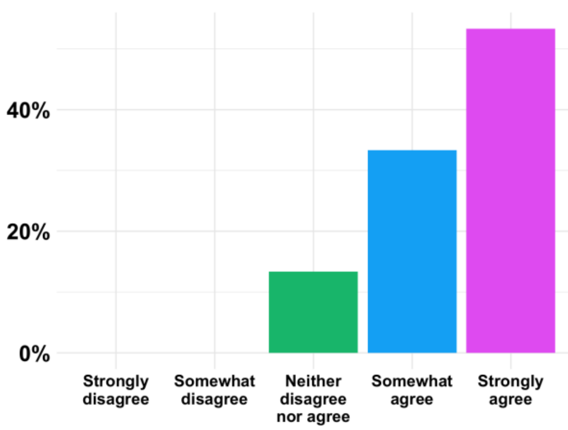

Figure 5: Responses to "I wish course chatbots would be used in more courses."

Not surprisingly, students' responses to these latter two questions were highly positively correlated ($r = .88$, $p < 0.001$). In other words, the more students felt the chatbot enhanced their learning experience, the more they wished other courses would use it, too. Lastly, 3 students (8.33%) mentioned the course chatbot positively and unprompted in the end-of-semester course evaluation, further indicating a positive reception by students.

Finally, students were asked what they liked most about the course chatbot in an open-ended question. Eleven (68.75%) students gave an answer. Among the answers given, the most frequent answer provided by 5 (45.45%) students was that the course chatbot provided helpful explanations. Three (18.75%) students each liked that the course chatbot was aligned with the course materials and that the course chatbot was easy to use. Figure 6 depicts the distribution of responses

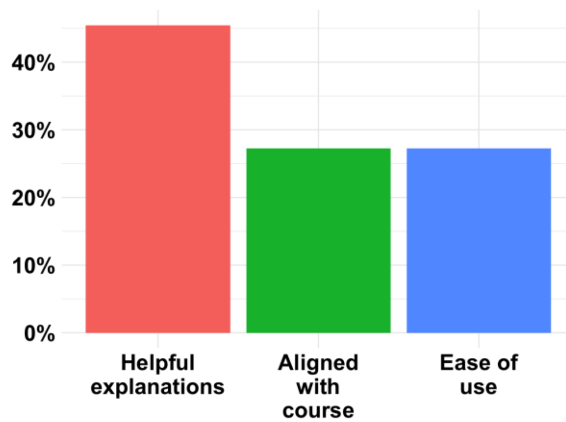

Figure 6: Distribution of responses to what students liked most about the chatbot

5. DISCUSSION AND CONCLUSION

This study examined the implementation and impact of a RAG chatbot in an online R programming course. Our findings indicate that prior knowledge of R significantly influences students' likelihood of using the chatbot. Somewhat surprisingly, students with higher prior knowledge of R were more likely to use the chatbot. Students primarily used the chatbot for advanced queries and lecture-related questions. Feedback from students was overwhelmingly positive, highlighting the chatbot's helpful explanations along with many students expressing a desire for similar chatbots in other courses.

Regarding RQ2, which asked about the reasons why students do not use a course chatbot, our results revealed that the most frequent reason for non-usage was a lack of need due to already sufficient video lectures. Unawareness of the chatbot's existence was also common. These findings underscore the importance of clear communication and possibly repeated reminders for course technology resources.

Limitations
This study has several limitations that should be considered when interpreting the findings. First, the survey data and the chatbot logs were collected independently and anonymously, thus making a combined analysis impossible. As a result, this study couldn't draw inferences between actual chatbot use and attitudes about the chatbot. Second, the relatively small sample size limits the generalizability of the results. With only 38 student participants, the findings may not be representative of larger or more diverse student populations. Third, the voluntary nature of chatbot usage introduces potential self-selection bias. Students who chose to use the chatbot may have distinct characteristics or motivations compared to those who did not, which could influence the study's outcomes. This bias may affect the validity of the conclusions drawn regarding the factors influencing chatbot usage and the types of queries submitted. Fourth, the absence of a control group and objective measures of performance (e.g., test scores) prevents isolating the chatbot's direct impact on learning. Lastly, the study was conducted within a single course at a specific institution, which may limit the applicability of the results to other courses, institutions, or educational contexts.

Future Research
Future research should address these limitations by exploring the impact of RAG chatbots and other forms of GenAI in more diverse and larger student populations across various educational contexts and disciplines. In particular, future studies might incorporate a control group or additional courses to strengthen causal inferences, and they could collect objective measures of learning outcomes such as test scores or final grades. Longitudinal studies could provide insights into the long-term effects of chatbot usage on student learning outcomes, engagement, and satisfaction. Additionally, research could also examine the effectiveness of different chatbot design features and interaction modalities to identify best practices for maximizing their utility and acceptance among students. By addressing these areas, future studies can contribute to a more robust and generalizable body of knowledge on the use of AI technologies in education.

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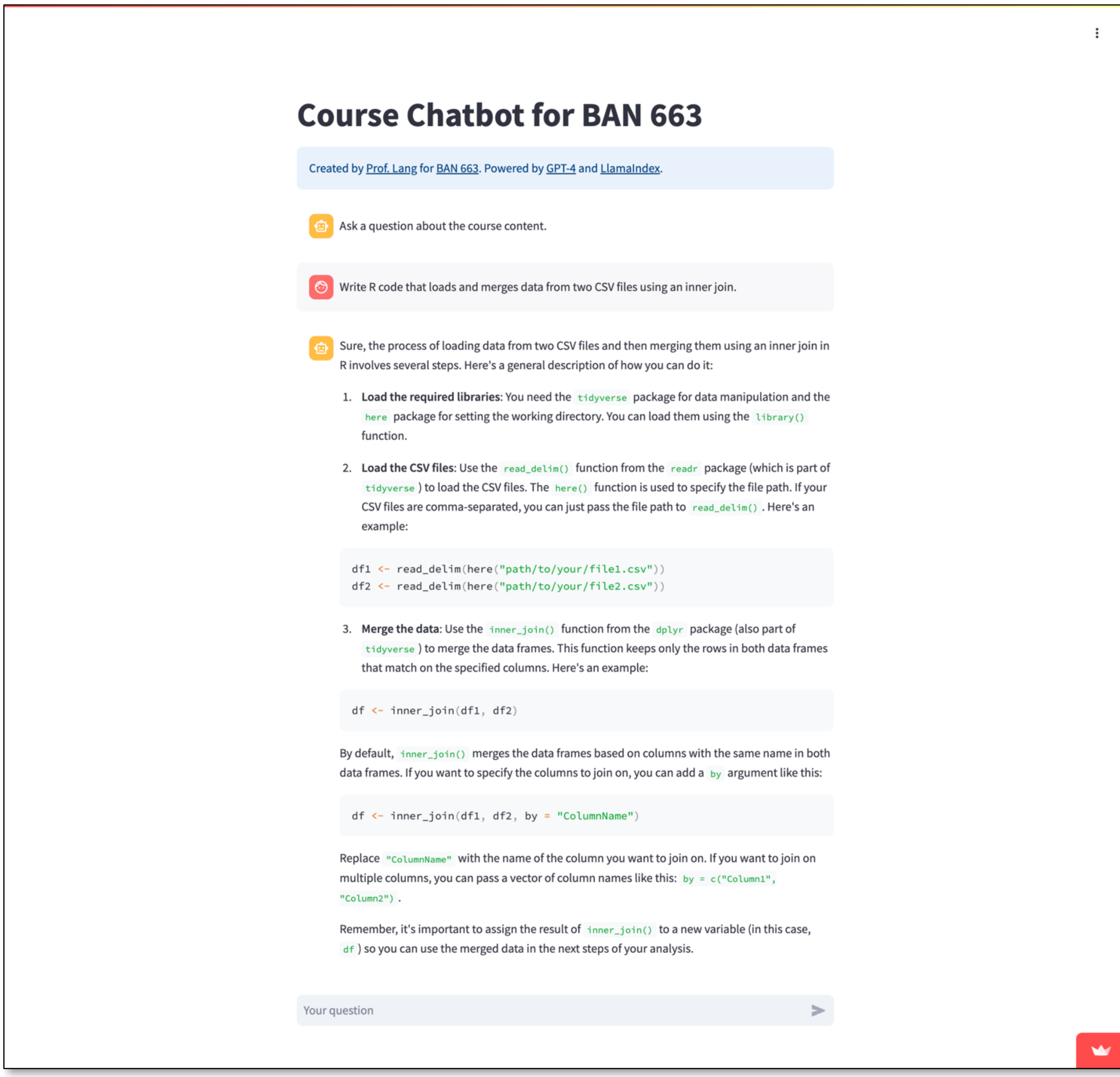
APPENDIX A: RAG CHATBOT PROMPT AND USER INTERFACE

"You are a course chatbot for BAN 663 (Business Data Analytics with R) taught by Prof. Guido Lang at Quinnipiac University. You were created by Prof. Lang and you are powered by GPT-4 and LlamaIndex. Your task is exclusively to answer questions related to R programming and statistics. When faced with inquiries, your responses should be confined to explaining, clarifying, and discussing aspects of R code and related statistical concepts based on the course materials given to you. Your objective is to encourage learning and comprehension. While you may provide R code snippets, you should never offer direct code solutions. Instead, focus on explaining the functionalities of R programming and the use of statistics in plain language to help users understand the underlying concepts. Refer to the course materials whenever possible. Lastly, never address queries outside the realm of R programming and statistics."



APPENDIX B: SURVEY ITEMS

1. What is your age range? (Under 18, 18-24, 25-34, 35-44, 45-54, 55-64, 65 or older)
2. What is your gender? (Male, Female, Non-binary/Third gender, Prefer not to say)
3. What is your current level of employment? (Full time, Part time, Not employed)
4. What was your knowledge of R prior to this course? (Likert scale: 1 – None at all, 5 – A great deal)
5. How much experience with AI chatbots (such as ChatGPT, Copilot, Claude, or Bard) did you have prior to this course? (Likert scale: 1 – None at all, 5 – A great deal)
6. Have you used the course chatbot for this course? (Yes, No)
    a. If No: Why didn't you use the course chatbot? (Open answer)
7. To what extent do you agree with the following statements? (Likert scale: 1 – Strongly disagree, 5 – Strongly agree):
    a. The course chatbot enhanced my learning experience.
    b. I wish course chatbots would be used in more courses.
8. What did you like most about the chatbot? (Open answer)

Training Data-Savvy Managers: An Analysis of Graduate Business Analytics Programs

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Abstract

The purpose of this study is to investigate the current state of graduate level business analytics education in the United States. The goal of this research is twofold. The first goal is to understand how higher education institutions are addressing the growing demand for analysts and data-savvy managers in the job market. To achieve this aim, the researchers carried out a detailed investigation of 82 programs focused on graduate business analytics education. Using publicly available curricula, they collected data and performed thematic and statistical analysis on topics covered, formats, tools, and techniques. The study found that programs related to training data-savvy managers exhibit a high degree of variability. This variability can manifest in various ways, such as the course content, program structures, required credits, and the tools and techniques being used.

The second goal of this research is to provide a competency framework for data-savvy managers and a blueprint for those institutions looking to create a graduate BA program to train technically proficient and analytically skilled managers. As such, based on current program offerings and anticipated industry demand, a model BA graduate program curriculum is developed and provided.

Keywords
Business Analytics Education, IS Education, Graduate Programs, Data-Savvy Managers, Data-Driven Decision Making, Technology-Savvy Managers

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Training Data-Savvy Managers: An Analysis of Graduate Business Analytics Programs

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1. INTRODUCTION

In today's fast-paced digital era, businesses are focusing on the intersection of technology and operations to remain competitive. The integration of business analytics (BA) into corporate strategy has become crucial for companies to leverage data for their advantage. The significance of data analysis and information management in contemporary business strategy and operations cannot be overstated. The ability to gather, interpret, and use data effectively is no longer a specialized skill but a fundamental requirement for managers across various sectors. This has led to an increased demand for managers who can analyze complex information sets and make strategic decisions based on them. As this demand grows, educational institutions are feeling the pressure to adapt and innovate their graduate programs to meet this need.

The issue posed for higher education institutions interested in offering programs at the graduate level in business analytics (BA) is what is the status of existing programs and what are the next steps to take? Our investigation seeks to shed light on the current state and future trends of graduate programs in BA education in the United States.

The goal of this research is twofold and includes two research questions. First, we will be focusing on how BA graduate programs are adapting to meet the needs of the modern job market. Are current BA graduate programs covering the appropriate topics such as tools, techniques, skills and knowledge? Both the US Bureau of Labor Statistics and the World Economic Forum show strong demand for job seekers with BA skills (BLS 2023, World Economic Forum, 2020). In the next section we will list some of the specific industry skills in demand. Our aim is to provide a comprehensive overview of the educational landscape in this critical field and identify how academic programs are responding to the industry's demand for technically proficient and analytically skilled managers.

The second goal of this research is to provide a competency framework for data-savvy managers and a blueprint for those institutions looking to create a graduate BA program to train managers and domain experts in analytical skills. What competencies are required for analytically skilled managers? What should the format and curriculum of a graduate BA program look like? It is our hope that the findings of this research can help guide those institutions looking to embark on the journey to create a graduate BA program.

2. LITERATURE REVIEW

2.1. Industry Demand for Analytics Skills

In the USA, the projected job market for business analytics related occupations remains stronger than average well into the future, according to US Bureau of Labor Statistics (BLS) (*Employment Projections*, 2023). BLS data shows both statisticians and data scientists occupations (with a median income of 95k and 100K in 2021, respectively) are expected to be in the top ten of fastest growing jobs through 2031. This trend is not isolated to the US and is also expected at a worldwide level (World Economic Forum, 2020).

According to the World Economic Forum (WEF), Data Analysts and Scientists, Software and Applications Developers, and E-commerce and Social Media Specialists are set to experience increasing demand enhanced by the use of technology; and there is an accelerating demand for emerging specialist roles in: AI and Machine Learning Specialists, Big Data Specialists, Process Automation Experts, Information Security Analysts, User Experience and Human-Machine Interaction Designers, Robotics Engineers, and Blockchain Specialists.

2.2. Skills Required for Analytics Roles

There is a substantial body of literature (both academic and occupational based) detailing what specific BA related skills are currently in demand now as well as predicting into the future. A recent report by Harvard Business Analytics Program (2023), emphasizes the necessity for a combination of hard and soft skills for every business analytics professional, including analytical capabilities, business acumen, and interpersonal skills, to effectively harness data for strategic advantage.

O'Connor (2020) lists seven must-have skills for data analysts. Those skills include Structured Query Language (SQL), Microsoft Excel, critical thinking, R or Python statistical programming, data visualization, presentation skills, and machine learning. According to O'Connor, SQL is the ubiquitous industry-standard database language that is most important for data analysts to know. The author notes that although programming languages like R or Python are better at handling large data sets, advanced Excel methods such as Macros and VBA lookups are commonly used for quick analytics.

Southern (2020) underscores the increasing demand for data-centric professions, reflecting the transformative impact of technology on the contemporary labor market. The research identifies key roles, including data analysts and data specialists, as essential components in navigating the complexities of decision-making processes across various industries. This shift towards data-driven positions is indicative of a broader trend where the integration of technology and data analytics plays a pivotal role in organizational strategy and operational efficiency. As such, the findings underscore the critical need for a workforce equipped with the necessary skills to adapt to this evolving landscape. Stanton and Stanton (2020) complement this view by examining the essential skills required for business students to succeed in analytics-related careers. Their comprehensive industry assessment identifies practical competencies, such as data visualization, statistical analysis, and critical thinking, which are highly valued by employers. Together, these works underline the necessity of aligning educational programs with industry needs to equip students for analytics-driven roles.

2.3. Emerging and Disruptive Trends and Skills In Business Analytics

Markow and Sederberg (2020) at Burning Glass Technologies analyzed over 17,000 unique skills demanded among over one billion historical job listings in their database to identify "disruptive technology skills," which include those emerging skills that would have the most disruptive impact on an organization's workforce. The authors detailed those skills in AI and Machine Learning, Cloud Technologies, Connected Technologies, Fintech, IT Automation, Natural Language Processing (NLP), Parallel Computing, Proactive Security, Quantum Computing, and Software Development Methodologies, with many of those seeing triple digit growth in job openings.

Recent reports and analyses highlight key developments in the field of business analytics. According to the World Economic Forum (2023), analytical thinking, creative thinking, and proficiency in AI and big data are expected to remain top in-demand skills by 2027. Similarly, McKinsey & Company (2023) emphasize the growing demand for machine learning practitioners, data scientists, and professionals skilled in natural language processing, citing a significant gap between industry needs and workforce capabilities.

Emerging job roles such as AI and machine learning specialists are highlighted by IABAC (2023) and Analytics Insight (2023), with these roles being central to transforming business processes. DataCamp (2024) further identifies essential technical skills like statistical analysis, data visualization, and Python programming, alongside critical soft skills such as communication and teamwork.

Forbes Technology Council (2023, 2024) explores the integration of composable analytics and the transformative impact of AI on analytics roles. These shifts emphasize the need for continuous learning to adapt to changing technological landscapes. The International Institute of Business Analysis (2023) adds that the global state of business analysis requires a balance of technical expertise and domain knowledge to address evolving market demands.

Educational institutions are responding to these changes by integrating cutting-edge technologies and practical applications into their curricula. MIT Sloan School of Management (2023) emphasizes the importance of equipping students with a blend of technical and interpersonal skills to drive data-driven decision-making.

2.4. Curriculum Development for Analytics Education

According to the WEF, there will be a significant gap between analytics skills required by industry and the skill set of the current workforce (World Economic Forum, 2018). Paul and MacDonald (2020) also identify this gap in the realm of analytics skills and present analytics curricula to close the gap. Stanton and Stanton (2020) conclude that developing curriculum that addresses specific industry skill set requirements combined with opportunities for students to gain industry experience and certifications may present the best path for preparing students for future industry needs.

Mills, Chudoba and Olsen (2016) gathered data in 2011, 2015, and 2016 from randomly selected AACSB undergraduate programs in US universities, based on course catalogs and interviews with academic advisors. Most of the programs had added data science-related courses during the period surveyed; specifically, there was a 583% increase in big data analytics, a 300% increase in visualization, a 260% increase in business data analytics and a 236% increase in business intelligence. The authors noted the 2011 International Conference on Information Systems (ICIS) Panel Report, which found a disconnect between academia and industry needs and called for additional coursework in business analytics, data mining, SQL, and big data. Based on recent studies, the authors also noted the increase in industry demand over one year in 2014, for employees with these skills, which was nearly 90%; accordingly, there is a projected shortage of 1.5 million managers with big data experience.

Kang, Holden and Yu (2015) designed a master's degree program based on the four pillars of analytics: 1) Data Preprocessing, Storage & Retrieval, 2) Data Exploration, 3) Analytical Models & Algorithms, and 4) Data Products. Prerequisites for the program, provided through bridge courses, if necessary, included skills in object-oriented programming, database theory, web concepts and statistics. The three core required courses in the curriculum focused on projects which required students to apply what they learned in their classes to real-world problems of practical significance. For example, a student used natural language processing (NLP) to create an information retrieval system for searching holiday destinations based on specified criteria. After completing foundation and concentration coursework, students were required to produce a thesis, a project, or enroll in a capstone course.

Wilder and Ozgur (2015) provided a model identifying the "output of business analytics programs," i.e. industry needs for personnel in the field. They identified the data scientist, the data specialist, and the data-savvy manager as potential graduates of business analytics programs. While a data scientist requires a foundation in mathematics and computer science, a data specialist functions more as a traditional information technology (IT) worker and a data-savvy manager must know how to identify suitable questions to be answered through data analysis and how to frame these questions. Based on this research, they proposed six required courses: Data Management (tools such as SQL), Descriptive Analysis (statistics), Data Visualization (key indicators, scorecards, dashboards), Predictive Analytics (advanced statistics), Prescriptive Analytics (Spreadsheet Models), and Data Mining (CRISP-DM).

Meyer (2015) stated that there was no defined curriculum for data analytics. He described the subject as multi-disciplinary and developed a cross-college program with the potential to earn a degree in either the College of Arts and Sciences or the College of Business. Meyer concluded that the elements of data analytics are: data/database, statistics, operations research, computer science, and managerial strategy. Because these courses already exist, it is only necessary to add courses such as Data Visualization, Programming in R, or Customer Sentiment Analysis to initiate a program in data analytics.

Burns and Sherman (2019, 2022) reviewed numerous undergraduate BA programs and subsequently developed a model curriculum for a BA minor. That curriculum included prerequisite courses that covered statistics, IT foundations, and Excel, required courses that covered BA foundations and management science, and a buffet of electives that include options for marketing-based courses, econometrics, or technology specific courses such as data visualization, statistical programming, database management, or specific BA applications.

The skills mentioned above are often not covered in traditional curricula for managers and industry specialists. Graduate programs such as Business Analytics can equip managers and analysts with the necessary skills to work with data effectively and can fulfill the demand for managers capable of analyzing intricate data sets and making strategic decisions based on their insights.

3. RESEARCH METHODOLOGY

This research was conducted using a "grounded theory" approach. Grounded theory was developed by the sociologists Barney Glaser and Anselm Strauss in the 1960's. In the grounded theory approach, conclusions are drawn and theories are produced by analyzing a body of data. In essence, the theories that are produced are "grounded" in the data (Glaser & Strauss, 1967).

For this project, the Graduate Management Admission Council (GMAC)'s program finder tool was used to identify the body of data whereby the grounded theory would be applied. The tool was used to search for non-MBA graduate programs in business analytics in the US, yielding an initial count of 192 programs. However, some of them were duplicates since some universities offer similar online and on-campus programs separately. We examined the websites of each program and removed duplicates and programs that were not relevant to this study.

The investigation focused on graduate programs in business schools that aimed to train managers and analysts with expertise in data. Therefore, any program that only focused on a specific area of analytics such as marketing, healthcare, supply chain, etc., was excluded from the investigation. Additionally, the study's scope was limited to programs that connected data science or analytics with business applications; as the GMAT tool also returned some non-business programs, programs exclusively focused on data science or analytics were not included. Furthermore, programs with limited data available on their public websites were also eliminated as required information could not be obtained. A total of 82 graduate programs in the United States that emphasize business analytics were examined. Appendix A shows a list of schools that were included in the study. During the grounded theory analysis, the researchers visited the website of each program and noted down the number of prerequisites, required courses, elective courses, and the total number of credits. They also took note of the class style and delivery mode. Whenever possible, the researchers recorded the required and elective courses, tools, and techniques taught in each program.

4. FINDINGS

In our investigation of 82 business analytics graduate programs, we found a wide range in the number of required courses. Figure 1 provides a detailed analysis of the total credits, required credits, and elective credits in these programs. While the total credits varied from 30 to 52, the most common range was 30-34 credits. The number of required and elective credits showed even greater variation, with the number of required courses ranging from six to 46 credits. However, the most common range of required credits was 26-31. Finally, Figure 1 shows that the total elective credits ranged from 2 to 25, with 6 to 11 electives being the most frequent category.

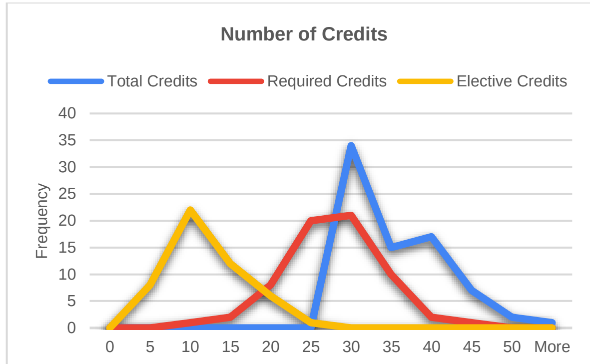

Figure 1 - Counts of Total, Required, and Elective Credits in BA Graduate Programs

Graduate programs in BA cover a range of topics. To determine the areas of coverage, the course titles and descriptions were analyzed using thematic analysis. A researcher analyzed the frequency of topics in each area across the BA programs. The results showed that the most common prerequisite course required was statistical analysis. The top five required courses are capstone project/practicum, database/data management, various analytics techniques, business analytics/data science, and data mining/machine learning. Figure 2 summarizes the top ten required courses and the top three elective courses in BA graduate programs based on the frequency of occurrence and classification in the programs

In most BA graduate programs (83%), students are required to complete a capstone project. Additionally, analytics techniques are covered in one or more specific courses in the majority of BA programs (73%). These analytics techniques include exploratory data analytics, predictive analytics, prescriptive analytics, probability and data modeling, forecasting, optimization, risk management and simulation, spreadsheet modeling, time series modeling, decision modeling, multivariate data analytics, and data streams analytics.

The required courses had less diversity and repetition compared to the elective courses. As illustrated in Figure 2, the most commonly offered electives were focused on specific applications of analytics, courses on particular data mining or machine learning algorithms, and visualization and storytelling with data. While specific applications of analytics were the most frequently offered elective course, programs provided a broad range of analytics applications, such as supply chain analytics, marketing analytics, accounting analytics, financial analytics, healthcare analytics, data analysis for security, government data and analysis, transportation informatics, climate and ecosystem monitoring, sports analytics, management analytics, data-driven quality management, HR and people analytics, game data analytics, fraud analytics, entertainment analytics, internet customer analytics, customer relationship management analytics, and competitive analytics, based on their program's focus and faculty specialties.

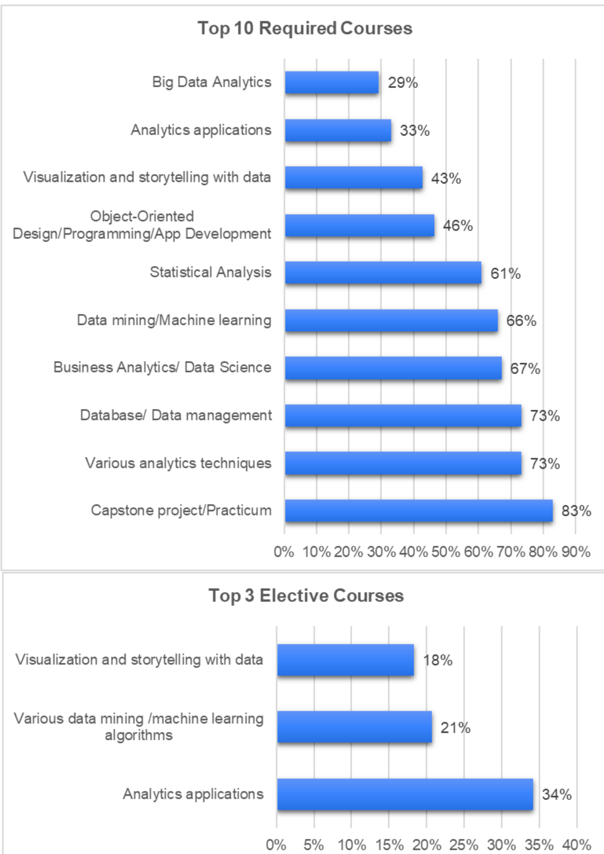

Figure 2 - Top Required and Elective Courses in BA Graduate Programs

In the investigation conducted, it was found that only 60% of the programs examined stated their program format. Of the 50 programs that did list their program format, the online format was the most common with a percentage of 41%, while the on-campus format was the least common with a percentage of 21%. Furthermore, only 56% of the programs mentioned the tools and platforms that they cover. Python and R were the most frequently mentioned tools/platforms, however, other tools such as SQL, Tableau, SAS, SPSS, and Excel were also utilized in different programs as either an elective or a required course. Figure 3 provides a comparison of the percentage of different program formats and the usage of tools in BA programs.

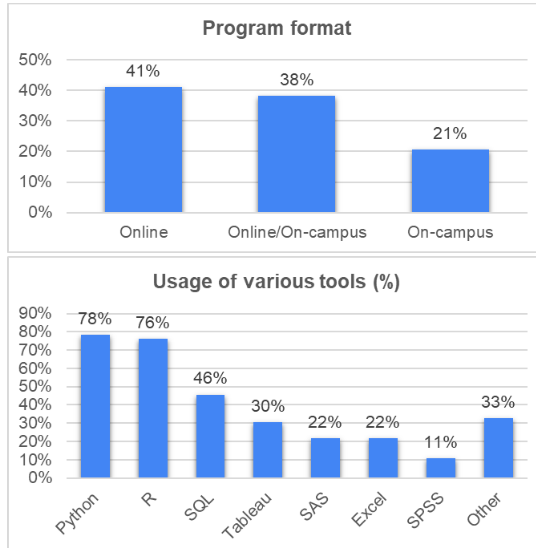

Figure 3 - Program Format and Usage of Tools of BA Graduate Programs Who Listed This Information

5. A COMPETENCY MODEL FOR DATA-SAVVY MANAGERS

The first goal of this research is to review the current state of BA graduate programs and to determine if they are, in general, competent and meeting the needs of industry. Hindle et al, define the field of Business Analytics as "the intersection of a variety of disciplines" including Information Systems (Hindle et al 2020). In addition, the Business Analytics discipline is frequently housed with and taught in conjunction with Information Systems. For this reason, a tool that can be used to test the competency of BA graduate programs is the ACM/AIS Competency Model. Appendix B shows the ACM/AIS Competency Model (Leidig and Salmela, 2020). The model was developed to "provide guidance regarding the core content of the curriculum". Here, the model is applied to the findings of the research in order to gauge the aggregate competency of the programs.

Figure 4 shows the percentage of programs that cover different areas of the ACM/AIS Competency Model. Not surprisingly, all programs cover Data, while most programs cover Integration and Foundation. However, Technology and Organizational Domain were the least covered competencies. Appendix C provides more details on the topics covered by BA graduate programs and the frequency of them.

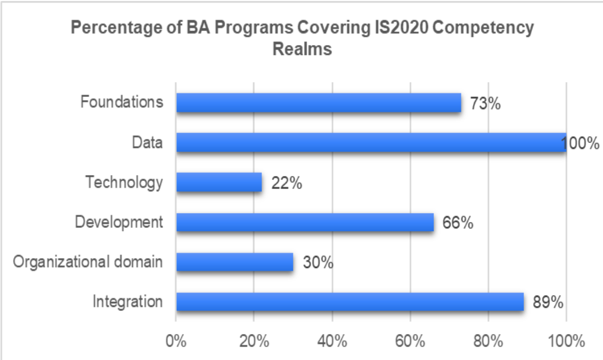

Figure 4 - ACM/AIS Competency Model Area Coverage by BA Graduate Programs

Some observations can also be made when comparing the material covered by graduate BA programs to the current and projected needs of industry. Comparing industry needs to the typical curriculum can give us a measure of how well BA programs are doing in preparing students for careers in the workforce. It appears that most programs are doing satisfactory performance in preparing students for current high-demand jobs, with most programs covering foundational analytics, data, and integration topics in the BA arena. These are all important skills currently high on the list of industry needs. However, the research shows that there may be a shortage of coverage of topics and skills needed for new and advancing technologies such as AI, machine learning, process automation, user experience and human-machine interaction, robotics, and blockchain.

In pursuit of the second goal of this research, Figure 5 illustrates a BA competency framework tailored for technically proficient and analytically skilled managers. The framework draws inspiration from the high-level ACM/AIS Competency Model and encompasses six main competency areas: foundation, data, technology, development, organizational domain, and integration. However, the details of each area have been customized and expanded to encompass specific competencies for data-savvy managers.

Each competency area aligns with key industry needs identified in Section 2. For example, the Foundation area emphasizes critical thinking and statistical analysis, which are among the most sought-after skills as reported by O'Connor (2020) and Southern (2020). Similarly, the Technology area incorporates advanced roles like AI and machine learning specialists, as highlighted by Markow and Sederberg (2020). The Integration competency supports cross-functional skills such as data storytelling and communication, aligning with industry demands for versatile managers (Stanton & Stanton, 2020).

Figure 5 - Competency Model for Data-Savvy Managers

This framework not only informs curriculum design but also ensures alignment with evolving industry needs. For instance, the inclusion of courses like 'AI for Business' and 'Machine Learning for Managers' directly addresses the Technology and Development areas, while electives in marketing analytics and visualization connect to the Integration competency. By tying competency areas to practical applications, this model supports the development of a future-ready workforce.

6. A MODEL GRADUATE CURRICULUM IN BUSINESS ANALYTICS

To complete the second goal of this research, Figure 6 presents a model curriculum for a graduate BA program. The model curriculum is a 30-credit program comprised of seven required courses and three electives. The model also includes an additional six credits of prerequisite foundation courses that can be waived based on the background of the student. The program is intended as a standalone Master of Science (MS). The purpose of the model is to introduce a curriculum that prepares the student for the job market needs outlined previously in the literature review. The model is meant to represent the ideal graduate BA program based on what the programs included in the study are doing.

6.1. Prerequisite Courses

The role of the prerequisite courses would be to prepare the student for the program. The prerequisites include Basic Statistics, and Data & Technology Literacy. The Basic Statistics course would cover statistical theories and techniques commonly used in the analysis of business data. Emphasis is on descriptive measures, probability theory, estimation techniques and forecasting methods, hypothesis testing, and time series analysis. The Data & Technology Literacy course is designed to cover basic IT foundational topics for students with no academic or experiential technology experience. Topics would include computer hardware and software architecture, fundamental data concepts including organizing data and database management systems, telecommunications and networks, types of systems and their development, and the role of information technology in business and society. This course introduces students to fundamental database theories and data organization, which are essential for analyzing and managing business data effectively. By integrating database management at this stage, students gain the skills required to navigate database systems and prepare for advanced coursework. In addition, students will learn to navigate Microsoft Excel software and become familiar with Excel's features and capabilities.

Once students have fulfilled the prerequisites, the model curriculum suggests seven required courses: Business Analytics Foundations, Business Analytics Advanced, Machine Learning/Data Mining for Managers, AI for Business, Management Science, Ethical Considerations Related to Analytics, and a capstone course.

6.2. Business Analytics (Foundations and Advanced Courses)

The Business Analytics Foundations course would provide students with the fundamental concepts and tools needed to understand the emerging role of business analytics in organizations. The course would cover managerial statistical tools in descriptive analytics and predictive analytics, including probability distributions, sampling and estimation, statistical inference, and regression analysis. Students would also learn how to communicate with analytics professionals using basic data visualization techniques to effectively use and interpret analytic models and results for making better business decisions.

The second required course, Business Analytics Advanced, would provide students with advanced concepts and tools needed to understand the role of data analytics in organizations. Topics would include forecasting, risk analysis, simulation, data mining, and decision analysis. Emphasis is on applications, concepts and interpretation of results as well as conducting statistical analyses.

6.3. Machine Learning/Data Mining for Managers

The third required course, Machine Learning/Data Mining for Managers, covers two important topics for BA graduate students. Data mining involves analyzing large blocks of information to identify meaningful patterns and trends. Those patterns and trends are then used to provide valuable insights. Machine learning techniques can play a key role in data mining when used to identify patterns and trends. This course would cover the various machine learning techniques and how they can be applied to data mining in order to recognize important insights into large datasets.

6.4. AI for Business

The fourth required course, AI for Business covers the fundamentals of AI and its various subfields. Students will also gain insight into real-world applications of AI in different industries and functional areas. Furthermore, students will develop the ability to formulate AI strategies for organizations, including selecting appropriate AI technologies and implementation approaches. They will learn how to collect, clean, and preprocess data for AI projects and gain practical experience building AI models and algorithms.

Prerequisites

(Entry requirements or foundation courses for students lacking the knowledge)

- Data and Technology Literacy
- Basic Statistics

Core

(Seven Required Courses)

- Business Analytics Foundations
- Business Analytics Advanced
- Machine learning/Data Mining for Managers
- AI for Business
- Management Science
- Ethical Considerations Related to Analytics
- Capstone

Electives

(Choose Three)

- Database Management Systems
- Visualization and Storytelling with Data
- Statistical Programming or Software (R or Python)
- Analytical Tools (SAS, SPSS, Tableau, etc.)
- Various Analytics Techniques
- Various DM/ML Algorithms
- Analytics Applications
- Various Analytics Techniques
- Business Intelligence/Decision Support
- Secure Computing
- Cloud Computing
- Emerging Technologies

Figure 6 - A Model Curriculum for a Graduate BA Program

6.5. Management Science

The fifth required course, Management Science, involves strategic conceptualization, decision-making and analysis of processes within the business and its environment. This course introduces quantitative and computing techniques that contemporary managers use to create models representing the business problems they need to solve. The emphasis of this course will be on the integration and development of modeling skills including problem recognition, data collection, model formulation, analysis, and communicating the results. Building logical thinking and quantitative skills are among the objectives of this course.

6.6. Ethical Considerations Related to Analytics

The sixth course, Ethical Considerations Related to Analytics, would cover the ethical implications of business analytics. Using the ethical frameworks of utilitarianism, deontological ethics and virtue ethics, students will investigate some of the more common areas in which ethical conflicts arise in the business analytics setting and propose a number of methodologies for addressing them.

6.7. Capstone

The final required course is a capstone course. This would be a project-based course. Alternative capstone projects could include research papers, case studies, creative works, internships, and field placement projects. The projects are designed to challenge students to think critically, solve complex problems, and demonstrate their readiness for work in the BA field.

6.8. Elective Courses

The elective courses in the model curriculum help the students develop skills that increase their knowledge of a specialized area within their field. The model curriculum suggests three electives, many of which are "technology based". These courses help to define the utilization of analytical tools. For instance, Statistical Programming (R or Python), Database Management Systems, SQL, Machine Learning, Data Mining, Data Visualization (any effort to help people understand the significance of data by placing it in a visual context), and Statistical Software are all courses that help the student understand technologies important to the analytics process. Additional technology-based courses such as Secure Computing, Cloud Computing, and Emerging Technologies could also be included.

The model curriculum also suggests that application-based courses should be included as electives. Appendix D provides a list of potential application courses. Appendix D is not intended to be exhaustive given the pervasive nature of analytics. However, some examples of such courses would include marketing-based courses, such as e-commerce or e-marketing, financial based courses such as Econometrics , healthcare analytics, sports analytics, security analytics, etc. The list is endless given that analytics can be applied to potentially any discipline.

7. CONCLUSION

The purpose of this study was to investigate the current state of graduate level business analytics education in the United States by presenting how higher education institutions are addressing the growing demand for analysts and data-savvy managers in the job market. A detailed investigation of 82 programs focused on graduate business analytics education was conducted and the findings were subsequently reported. The study found that programs related to training data-savvy managers exhibit a high degree of variability and that this variability can manifest in various ways, such as the course content, program structures, required credits, and the tools and techniques being used. The findings were summarized and tabulated to show the typical number of credits, the typical required courses, and the typical electives included in a graduate business analytics program.

The findings were then analyzed through the scope of the ACM/AIS Competency Model (Leidig and Salmela, 2020). That analysis showed that the while some core competencies (data, integration, foundation) are typically covered, other areas such as technology and organizational domain were covered less often. The findings were also compared to the literature review on current and projected needs of industry. This exercise showed that most programs are doing a decent job of preparing students for current high-demand jobs by covering foundational analytics, data, and integration topics in the BA arena. However, the research showed that there may be a shortage of coverage of topics and skills needed for new and advancing technologies such as AI, machine learning, process automation, user experience and human-machine interaction, robotics, and blockchain. Based on these results, a competency model was created for comparative and evaluative purposes concerning BA graduate programs aimed at preparing data-savvy managers.

Finally, a model BA graduate program curriculum was developed. The model suggests two prerequisite courses, seven required courses, and three electives. The model was developed based on the research data collected and subsequent findings. The model is presented in order to inform and guide institutions looking to develop a BA graduate program to train technically proficient and analytically skilled managers. It should be noted that how an academic unit goes about designing the graduate BA program that best fits its institution will be subject to many variables such as workforce needs, faculty expertise, student demographics and backgrounds, institutional resources, and industry collaborations. Ultimately, the goal of a graduate degree, to prepare students for a career in their chosen field, must serve as a driving force in curriculum development.

As the field of Business Analytics continues to expand and the demand for skilled workers in the discipline grows, it is expected that more and more institutions will introduce graduate programs in BA. It is the hope of these researchers that this project will aid in that effort.

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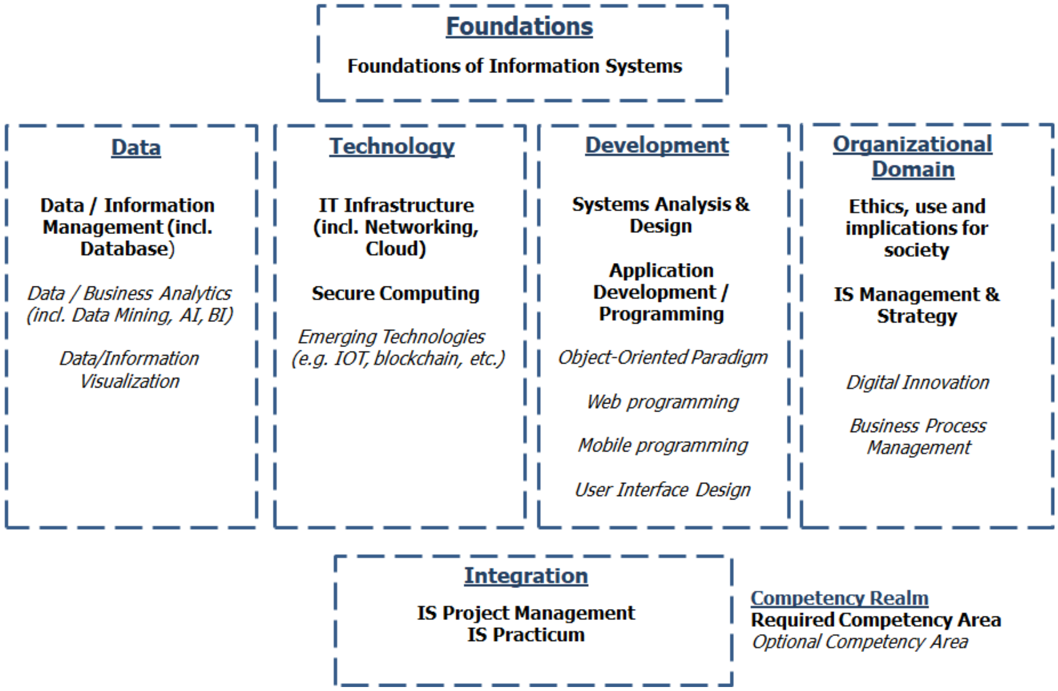
Appendix A - Schools Included in the Study

American University Arizona State University Babson College Bentley University Boston University Brandeis University California Polytechnic State University - San Luis Obispo Carnegie Mellon University College of William & Mary Columbia University Drexel University Duke University Emory University Fairfield University Florida State University George Washington University Georgetown University Georgia College Georgia Institute of Technology Hult International Business School Iowa State University Kent State University Loyola Marymount University Loyola University of Chicago Mercer University Montclair State University New Jersey City University New York University North Carolina State University Northeastern University Northwestern University Pennsylvania State University - Great Valley Purdue University Rochester Institute of Technology Rutgers University Saint Joseph's University Saint Mary's College of California San Francisco State University Santa Clara University Seattle University	Seton Hall University Shepherd University Southern Illinois University St. Peter's University Stevens Institute of Technology Syracuse University Tufts University Tulane University University of Alabama-Huntsville University of California - Davis University of California - Irvine University of California - Los Angeles University of Colorado Boulder University of Connecticut University of Dallas University of Hartford University of Illinois at Chicago University of Illinois at Springfield University of Indianapolis University of Iowa University of Louisville University of Maryland University of Massachusetts - Amherst University of Massachusetts - Lowell University of Miami University of Michigan - Dearborn University of Minnesota University of North Carolina - Charlotte University of San Diego University of Southern California University of Texas at Dallas University of Tulsa University of Utah University of Washington - Seattle University of Washington - Tacoma University of Wisconsin - Superior Villanova University Virginia Polytechnic Institute and State University Washington University in St. Louis West Virginia University William Paterson University Yeshiva University

Appendix B - ACM/AIS Competency Model (Leidig and Salmela, 2020)



Appendix C – Percentage of Topics Covered With At Least One Course

Category	Topic	Pre-Req.	Req.	Elec.
Foundations	Statistical Analysis	6%	61%	2%
	IS Intro/Managing Digital Organizations/MIS	1%	11%	2%
Data	Business Analytics/ Data Science		67%	
	Database/ Data management		73%	4%
	Data mining/Machine learning		66%	6%
	Various DM/ML algorithms		16%	21%
	AI		6%	6%
	BI/Decision support		12%	5%
	Knowledge management		1%	1%
	Visualization and storytelling with data		43%	18%
	Big Data Analytics		29%	12%
	Various analytics techniques		73%	13%
	Analytics applications		33%	34%
	Special Topics in Data Analysis		7%	12%
Technology	Infrastructure (network)		4%	
	Cloud computing		4%	10%
	Secure computing		2%	9%
	Emerging technologies (IoT, Blockchain, etc.)		4%	5%
Development	System analysis & design		7%	1%
	Enterprise systems		2%	7%
	Object-Oriented Design/Programming/App Dev.	2%	46%	7%
Organizational Domain	Ethics, use & implications for society		17%	6%
	Management & strategy		1%	
	Digital innovation			
	Business process management		5%	4%
Integration	Project management		11%	12%
	Capstone project/Practicum		83%	2%
Others	Mathematical Modeling		1%	
	Operations Research		2%	1%
	Special Topics in IS			1%
	E-Commerce			2%
	Leadership and change management		13%	5%
	Strategy and analytics		16%	6%
	System Administration/IT operations		1%	1%
	Research Methods		4%	6%
	Communications		18%	1%
	Experimental Design		2%	1%
	Cognitive Computing			1%
	Data and Information Quality		1%	2%
	Multivariate Statistics		5%	2%
	Game Theory and Strategic Decision Making		1%	4%
	Operation Management	1%	9%	9%
	Accounting	4%	7%	9%
	Economics or Finance	5%	12%	13%
	Economics Models		6%	10%
	Organizational Behavior		4%	2%
	Marketing	5%	6%	5%
	Business Essentials/Fundamentals	2%	2%	
	Negotiation		1%	

Appendix D – Potential Analytics Application Based Electives

Accounting Analytics
Climate and Ecosystem Monitoring
Competitive Analytics
Customer Relationship Management Analytics
Data Analysis for Security
Database Marketing
Data-driven quality management
Entertainment Analytics
Financial Analytics
Fraud Analytics
Game data analytics
Government Data and Analysis
Healthcare Analytics
HR and People analytics
Internet Customer Analytics
Management Analytics
Marketing Analytics
Social Network Analytics
Sport Analytics
Supply Chain Analytics
Transportation Informatics

Using LEGO® Brick Data to Teach SQL and Relational Database Concepts

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Abstract

This paper introduces the LEGO® Database, a large natural dataset that can be used to teach Structured Query Language (SQL) and relational database concepts. This dataset is well-suited for introductory and advanced database assignments and end-of-semester group projects. The data is freely available from Kaggle.com and contains eight tables with 633,250 rows of data on 11,673 LEGO® sets sold between 1950 and 2017. As a guiding example, I introduce an example group project assignment designed to provide students hands-on experience with database management and SQL queries. I also discuss tips, suggestions, and lessons learned from using the data for group projects over the past five years. While LEGO® bricks have been widely used in educational settings, including college and computer classrooms, this is the first work to discuss the use of LEGO® data in a college database course.

Keywords: Database Education, Structured Query Language (SQL), Real-World Datasets, Project-based learning, LEGO® for Education, Database Projects

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Using LEGO® Brick Data to Teach SQL and Relational Database Concepts

James Wolf

1. INTRODUCTION

There is significant debate among IT educators regarding the best type of database needed to teach Structured Query Language (SQL) and relational database concepts. Some point out that small, simplified databases make it easier for students to grasp fundamental database concepts and SQL syntax without getting overwhelmed (Miao et al., 2019). However, many educators are concerned that "toy" databases may not fully prepare students for the challenges they will face after graduation (Jukic & Gray, 2008; Wagner et al., 2003; Yue, 2013).

Smaller datasets allow students to manually inspect the data and verify the accuracy of their queries (Taipalus et al., 2023). This practice is particularly beneficial for novices as it helps them identify logical errors in their SQL statements and understand the relationship between the query and its output (Miao et al., 2019; Taipalus et al., 2023).

However, these small and simple databases may fail to adequately prepare students for the complexities of real-world database systems, which typically involve large datasets (Yue, 2013). For this reason, many database educators now advocate using large, real-world data in database courses to better prepare students for the complex database systems they will encounter once they enter the workforce (Jukic & Gray, 2008; Wagner et al., 2003; Yue, 2013). As a result, these natural datasets tend to be much larger and more complex than the simplified examples in textbooks. They may provide more realistic learning experiences.

This work introduces database instructors to the Kaggle.com LEGO® database and demonstrates how it can be used to teach database concepts (especially SQL skills) in a college classroom. The data are appropriate for all phases of database instruction but especially well-suited for a semester-long group project. As a guiding example, I introduce a group project assignment designed to provide students with hands-on experience in database management. The detailed project helps students develop SQL and database management technical skills as well as soft skills, such as teamwork and problem-solving.

I have successfully used variations of the detailed LEGO® Database Project in graduate and undergraduate database courses. In addition to describing the LEGO® Database and an example group project assignment, I also discuss teaching tips, suggestions, and lessons learned from using the LEGO® data for group projects over the past five years.

2. LITERATURE REVIEW

Database management and SQL are among IT professionals' most important and sought-after skills. While NoSQL databases have increased in usage, relational databases remain more widely used, and database management and SQL skills continue to be in high demand for IT professionals and a growing number of fields that employ artificial intelligence (AI), business analytics, and data analysis. Recent studies on the required skills for IT professionals show that relational database skills remain in high demand. One of the most important of these skills is the ability to query relational databases using SQL. (Cummings & Janicki, 2021, 2020; Gurcan & Sevik, 2019; Halwani et al., 2022; Li et al., 2021; Radovilsky et al., 2018; Yin & Zhang, 2023)

Database skills are included in approved computing curricula and mandated by computing accrediting bodies. Both ABET's Computing Accreditation Commission and the ACM-AIS IS2020 Task Force model curriculum emphasize the importance of database management in Information Systems degree programs (ABET, 2023; Leidig & Salmela, 2022). The IS2020 report, produced by the Joint Task Force of the Association for Computing Machinery (ACM) and the Association for Information Systems (AIS), is the latest in a series of model curriculum recommendations and guidelines for undergraduate degrees in Information Systems (IS). IS2020 lists the ability to query a relational database as a required competency for Information Systems graduates, specifying that graduates should be able to "*translate user* *stories to SQL statements using (SELECT, FROM, WHERE, ORDER BY, DISTINCT, LIKE, BETWEEN, IN, JOIN, GROUP BY, HAVING, sub-queries, ANY, ALL, UNION)* (Leidig & Salmela, 2022)."

Database Education Challenges

Several studies have found that students find computing boring (Bellino et al., 2021; Biggers et al., 2008; Giannakos et al., 2017; Yardi & Bruckman, 2007; Zaharias, 2009) and unconnected to the world outside of the classroom (Anderson et al., 2008; Bellino et al., 2021). Students often feel that the exercises and assignments from their computing classes are irrelevant to situations encountered in their daily lives (Bellino et al., 2021).

LEGO® Bricks in the College Classroom

Educators from all disciplines have attempted to make learning fun and more hands-on by using LEGO® Serious Play (LSP) exercises in their classes. LEGO® bricks have been employed in a wide array of college classrooms, most often in STEM courses, but also in business and arts classrooms (Benesova, 2023; Geithner & Menzel, 2016; Jensen et al., 2018; Martin-Cruz et al., 2022; Warburton et al., 2022; Wengel, 2020).

LEGO® Bricks in College Computer Classes

LEGO® brick activities have been widely used in computer education. For example, Kurkovsky (2018) highlighted the use of LEGO® bricks in teaching software interface design. Zhang (2016) detailed 12 years of employing LEGO® Robotics to introduce Artificial Intelligence. Lindh and Holgersson (2007) examined the impact of LEGO® Serious Play (LSP) on students' problem-solving in mathematics and technology. Steghöfer et al. (2017) described LEGO®-based workshops for teaching the agile software engineering process and scrum. Morales-Trujillo (2021) described KUALI-Brick as a LEGO® activity for teaching software quality assurance.

Similarly, Kurkovsky (2016) introduced the use of LEGO® bricks to teach test-driven development. Kurkovsky (2015) explored the use of LEGO® Serious Play for teaching software engineering. Fronza et al. (2022) reported a remote coding camp for high school students, adapting LEGO® activities for online engagement. Walsman et al. (2022) employed LEGO® bricks in a virtual learning environment for structural understanding.

Using LEGO® bricks in the computer classroom can create a playful and imaginative atmosphere that many students enjoy. For example, students in Kurkovsky et al. (2019) reported that the LEGO® activities allowed them to understand software development from a different perspective and helped them to visualize and further develop their ideas.

Similarly, student feedback from Kurkovsky (2015) suggested that LEGO® helped improve teamwork and oral communication. Students indicated LEGO increased motivation, promoted creativity, and improved information retention. Many students enjoyed LEGO and looked forward to using them more.

While LEGO® bricks have been widely used in computing education, this is the first paper to discuss the use of LEGO® brick data in database education.

Relevance, not fun, changes perspectives

Fun activities, like those that utilize LEGO® Serious Play, may not be enough to change student attitudes toward computing. Bellino et al. (2021) note that most "fun" interventions are not very useful and do not have a lasting impact on student perceptions. Bellino et al. (2021) noted that students enjoy "fun" interventions but that these interventions did not change students' perceptions of computing as boring/fun. However, Bellino et al. (2021) did find that relevant interventions changed student perceptions of computing as boring/fun.

Students want their studies to feel relevant to their lives, careers, and the world outside the classroom (Bellino et al., 2021). Several studies have found that students do not find computing classes relevant to the real world (Barker et al., 2009; Bellino et al., 2021; Biggers et al., 2008; Kafura & Tatar, 2011; Kapoor & Gardner-McCune, 2018; Yardi & Bruckman, 2007).

Real-World Problems

One of the most effective ways to make learning relevant and connect student learning with the outside world is by having students work on real-world problems (Hsu et al., 2018). Real-world problems can help students develop their problem-solving skills, learn to think critically and develop their ability to collaborate with others. Additionally, real-world problems can help students see the relevance of computational thinking in their own lives and future careers (Hsu et al., 2018). Similarly, using a real-world dataset with a well-known domain (e.g., LEGO® bricks) could provide a connection to everyday life that students feel is often missing from computing classes (Bellino et al., 2021; Jukic & Gray, 2008).

Education research shows that a problem-solving curriculum based on real-world settings can lead to better intellectual curiosity and attitudes toward education (Bellino et al., 2021). Students are more motivated to learn when the subject matter is relevant to their personal lives (Ormrod & Davis, 2004) and learn more when the material is interesting (Ormrod & Davis, 2004).

The Declarative Nature of SQL

Novice SQL programmers have difficulty with SQL queries that require GROUP BY with and without HAVING, NATURAL JOINS, simple subqueries, correlated subqueries, and self-joins (Ahadi et al., 2015, 2016; Miedema et al., 2023; Migler & Dekhtyar, 2020; Taipalus et al., 2018).

Sadiq et al. (2004) suggested that these difficulties stem from the declarative nature of SQL. SQL requires that students think in terms of sets rather than step-by-step procedures. Echoing this, Celko (2008) believes that a procedural programming mindset keeps SQL novices from taking full advantage of the power of SQL and other declarative languages. This mindset poses a hurdle for many beginners. Ahadi et al. (2015) suggest that novices might make errors due to a procedural approach to constructing queries rather than embracing the set-based logic of SQL.

To affect the needed change in mindset, novice SQL programmers need both instruction and opportunities for practice. The LEGO® Database combines the fun of LEGO® bricks and the relevance of a large database of real-world data with a well-known domain.

The LEGO® Group was founded in Billund, Denmark, in 1932 by Ole Kirk Kristiansen and is now one of the world's largest manufacturers of toys (LEGO.com, 2024a). The LEGO® name derives from the Danish words *Leg* and *Godt*, which means "Play Well" (LEGO.Com, 2024a). The company is best known for its LEGO® bricks. LEGO® bricks are small, interlocking plastic blocks in various shapes, sizes, and colors. LEGO® bricks can be connected to create countless models and structures. LEGO® bricks are typically sold in sets that allow builders to build a specific object (LEGO.Com, 2024a). The most popular sets are a mix of homegrown themes LEGO® Icons, a range for older builders, LEGO® City and LEGO® Technic™, and entertainment IPs like Star Wars™ and Harry Potter™ (LEGO.Com, 2024b).

3. THE LEGO® DATABASE

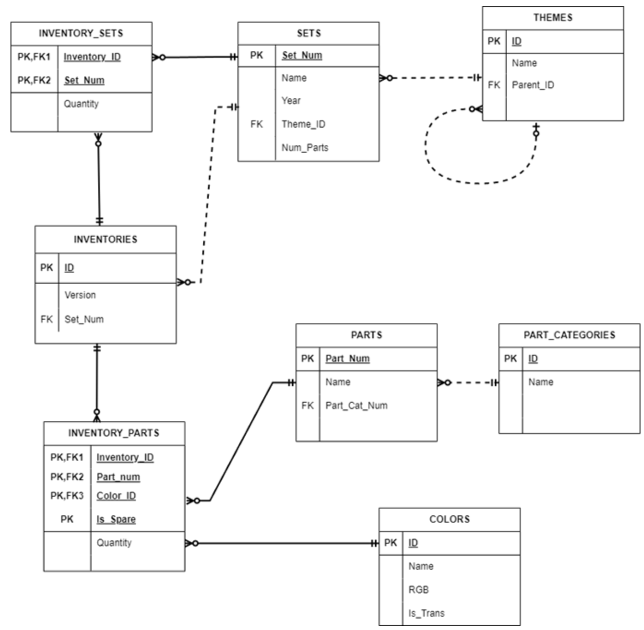

Figure 1: A Basic Entity Relationship Diagram of the LEGO Database

The LEGO® database has eight tables with 633,250 rows of data on 11,673 LEGO® sets sold between 1950 and July 2017. Please see Appendix A for more details.

Table	Rows	Columns
Sets	11,673	5
Colors	135	4
Themes	614	3
Inventories	11,681	3
Inventory_Parts	580,251	6
Inventory_Sets	2,846	3
Part_Categories	57	2
Parts	25,993	3
Total	**633,250**	**29**

Table 1: List of Tables in the LEGO® database

LEGO bricks have become a global phenomenon, and several online sites cater to LEGO fans. One of the best of these sites is Rebrickable.com (Brick Land, 2022). Rebrickable.com allows owners of LEGO sets to see the other LEGO sets they can build from the sets and parts they already own (https://rebrickable.com/about/). The database contains information on which parts are included in different LEGO® sets (*LEGO Database*, 2017). The data for the Kaggle.com LEGO® Database was obtained from Rebrickable.com and uploaded to Kaggle.com by Rachael Tatman, a language technology educator who previously worked as a developer advocate and data scientist at Kaggle.com (*Tatman*, 2024).

4. AN EXAMPLE ASSIGNMENT

To illustrate the LEGO® database's classroom potential, I present and discuss a hands-on database assignment. Please see Appendix B for the full text of the assignment. The LEGO® Database Project has six parts and seven deliverables, each with unique requirements and point values. This project typically accounts for 10% of the overall course grade.

Section 1. Group Contract: The project begins with team formation and the completion of a Group Contract. This contract delineates the team's roles, responsibilities, and expectations, thus ensuring a unified approach.

The instructor assigned all groups, and no formal roles were assigned. Students determined formal or informal roles after posting the assignment and after a lecture on group work. In addition to a lecture on *Building an Effective Team*, teams were required to prepare and assent to a group contract outlining modes of communication, expectations, and a conflict resolution framework.

Section 2. Data Model: Using the LEGO® dataset from Kaggle, students analyzed the data and created an Entity-Relationship Diagram (ERD) employing the crow's foot notation based on the provided crude ERD. This task aimed to develop skills for understanding data relationships and schema design.

Section 3. Creating and Loading Kaggle Data: Students employ Data Definition Language (DDL) and Data Manipulation Language (DML) to create database tables according to the ERD, load data, and establish key relationships. This phase offers practical experience in database creation and management.

Section 4. Querying the Data: This section challenges students to write SQL queries for data extraction, ranging from basic retrieval to complex queries involving aggregate functions and subqueries. It tests proficiency in data retrieval using SQL commands and functions.

Section 5. Entering New Data: Students manually input data for a specific LEGO® set (e.g., a Pirate Ship) to simulate real-world database updating scenarios. This tests students' understanding of the existing database structure and helps develop integration skills.

Section 6. Feedback: The project concludes with reflective feedback. Students write statements outlining their contributions and evaluating their peers, fostering self-awareness and peer evaluation skills.

Assessment is based on participation, submission quality, and peer feedback and is aimed at promoting engagement and a deeper understanding of database concepts. The methodology emphasizes practical application, collaborative learning, and reflective practice within a structured educational framework, bolstering technical and soft skills, such as teamwork and critical thinking.

5. TEACHING TIPS

Group projects and collaborative assignments are common in collegiate database courses. If done well, group work can enhance student enjoyment, engagement, and learning (Johnson & Johnson, 2008; Murphy et al., 2020). However, if done poorly, group work can add to student frustration, disengagement, and group failure (Thiemann, 2022; Wolf, 2011).

Group Formation

Given the importance of getting groups right, group formation has been widely studied. While some studies report the advantages of homogeneous groups (Müller et al., 2024) or even that group diversity does not impact results (Horwitz & Horwitz, 2007), most research suggests that diverse groups outperform non-diverse groups (Chen et al., 2019; Cheng et al., 2008; Horwitz & Horwitz, 2007; Summers & Volet, 2008; Yang et al., 2022).

It is important to prioritize building teams for success. I typically create teams of three or four students. For a class of 24, I create eight groups of three. Strategically, I distribute the strongest SQL programmers and students who might need more team support. I place the remaining students randomly or based on stated student preferences. Before team formation, I solicit student input on desired teammates.

My experience shows that placing all high performers together or all those who struggle together leads to uneven outcomes. By mixing skill levels, I find that all groups are more likely to complete the project successfully.
To promote problem-solving within teams, I encourage students to ask their teammates for help before contacting me with project difficulties.

I recently implemented a policy where students must copy their teammates on any questions sent via email. This fosters transparency and potentially allows teammates to solve the problems among themselves. Additionally, I often delay before responding to a team member's question, giving their peers a chance to offer solutions and reinforcing a sense of team responsibility.

Encouraging Teamwork

Following Johnson and Johnson's (2008) advice, I have built in interdependence, time for teamwork skills, and individual accountability in the group project. I have created interdependence by providing each student group with group-specific Oracle credentials. All group members have access to the same Oracle account, and all SQL-related group work must be completed using the group account. Also, the assignment focuses on interdependence. The tables must be created before the data can be loaded. The data must be in place before the queries in section 4 can be completed or before the new set's data can be loaded in section five.

I devote time to teamwork in several ways. First, before assigning the project, I lecture on teamwork in class. I also incorporate several strategies for mitigating negative group aspects. Each team must create a group contract that spells out expectations and how to handle group conflicts.

To encourage teamwork and team bonding, I have students complete in-class assignments together and establish team contracts outlining communication expectations, conflict resolution protocols, and project roles. Once the group project is assigned, teams must sit together during class meetings and work collaboratively on in-class assignments and project components.

The project's deliverables are staggered over several weeks, and I check in with each team during each class meeting after the project is assigned.

Finally, I build individual accountability into the assignment by requiring each team to summarize each member's contribution. Each student must complete an individual learning reflection and a post-project survey asking them to rate their group members and themselves on several aspects of group interactions.

Tools and Technologies Used

For this assignment, students used Oracle 19c and SQL developer. These tools were already used throughout both the undergraduate and graduate courses. In addition, the SQL developer has easy-to-use import functionality, which allows the students to import the Kaggle LEGO® data directly into Oracle. Throughout the courses, students use individual Oracle accounts. All group members were given access to a group account on the university server for the group assignment. Another benefit of using SQL Developer is that it allows for command echoing via the SET ECHO utility. This allows students to submit a single plain text file showing both SQL and query results.

Assessment Criteria

Learning outcomes and assignment grades were assessed through direct and indirect measures. The direct measures included the evaluation of the technical correctness of all deliverables—the ERD, SQL scripts, and reflective feedback. The indirect measures involved self-assessments and peer evaluations, which were measured using online surveys.

Technical Correctness

Errors in SQL queries can be classified into four error categories: syntax errors, semantic errors, logical errors, and complications (Ahadi et al., 2015, 2016; Miedema et al., 2023; Migler & Dekhtyar, 2020; Taipalus et al., 2018). *Syntax errors* are errors in the formatting and structure of the SQL code that prevent the database management system from understanding and executing the query (Ahadi et al., 2015, 2016; Taipalus et al., 2018). *Semantic errors* are errors where the SQL code is syntactically correct but does not produce the intended results for any given data demand (Brass & Goldberg, 2006; Taipalus et al., 2018). *Logical errors* are errors where the SQL code is syntactically correct but does not produce the intended results for a particular data demand (Taipalus et al., 2018). C*omplications* are queries that return the correct result table but are unnecessarily complex in their execution (Brass & Goldberg, 2006; Taipalus et al., 2018). Taipalus et al. (2018) use the term *exemplary* to denote queries without errors or complications.

When judging the technical correctness of the SQL coding segments of the assignments, I use the following criteria. Exemplary code receives full credit, and SQL complications receive only minor deductions. Semantic and logical errors, depending on the severity of the error, receive partial credit. SQL with syntax errors usually incurs significant deductions.

Student Engagement

Student engagement is primarily measured via student self-assessments and peer evaluations. Both the self-assessments and peer evaluations were measured using online surveys. The surveys asked about leadership and participation rates in group discussions, consistency in meeting project deadlines, the level of effort, and the portion of the assignment completed.

6. DISCUSSION

There is significant debate among IT educators regarding the best type of database needed to teach Structured Query Language (SQL) and relational database concepts.

Simple Databases

Simple databases are easy for beginning students to understand and visualize (Gudivada et al., 2007). These small databases allow students to focus on concepts rather than data (Gudivada et al., 2007; Yue, 2013) and easily identify SQL mistakes (Miao et al., 2019).

Yue (2013) found that students are more engaged by databases with a readily understood business domain, a relatively simple structure, and a realistic but manageable amount of data. Miao et al. (2019) note that using large datasets to explain SQL errors is often ineffective, especially in educational settings. Instead, they suggest smaller, more focused counterexamples offer a more efficient and understandable way to illustrate the source of the error.

The databases used in most college database classes are small and almost "toy-like" (Yue, 2013). They are intentionally small to aid instruction but have a toy-like feel that adds to the disconnect between classroom exercises and real life. Utilizing the Teradata University Network's DMS to examine databases from several popular textbooks, Yue (2013) found that textbook database tables tended to be small, simple, and lacked advanced features. Confirming Wagner, Shoop, and Carlis (2003), Yue (2013) found that most textbook databases utilized the employee-department-project, student-course-enrollment, or similar domains.

Natural Databases

Natural learning environments are those that more closely resemble real-world work environments, while manufactured learning environments are more controlled and structured (Taipalus & Seppänen, 2020).

Natural learning environments may better prepare students for future work environments and help them develop problem-solving and critical-thinking skills. However, they can be more difficult for students to learn and may not provide all students with the necessary structure and support (Taipalus & Seppänen, 2020).

A Middle Ground

Taipalus and Seppänen (2020) suggest that the best approach to teaching SQL is to use a mix of natural and unnatural learning environments. This allows students to benefit from the advantages of both types of environments and helps them develop the skills they need to be successful in the workplace. One common solution is to employ small databases in the early stages of a database course and then switch to a larger, more complex database for assignments and projects after students have mastered the basics (Seyed-Abbassi et al., 2007; Wagner et al., 2003). Silberschatz et al. (2011) offer another approach, using tables with a few rows for early course examples but increasing the number of rows for more advanced exercises (Seyed-Abbassi et al., 2007; Taipalus et al., 2023; Wagner et al., 2003).

Gudivada et al. (2007) suggest what could be considered a middle ground, using a subset of a large natural database. They describe using a subset of the available product data from Amazon.com: only books within the "Computers & Internet" category for their relational database course. Gudivada et al. (2007) note that datasets used for database instruction should go beyond simple textbook examples, offering students a realistic and challenging experience that mirrors real-world database characteristics and complexities while ensuring that the scale of the project remains manageable within the timeframe of a semester-long course.

A related option, not mentioned in the literature but employed by the author, is using privileges, synonyms, and tailored views for instruction and examples. The views can be altered and increased in size and complexity once students have mastered basic concepts and syntax. This method, like Gudivada et al. (2007), has the added benefit of acquainting students with the tables and data domain before adding complexity and volume.

7. CONCLUSIONS

Educational research suggests that focusing on problem-solving in the real world may foster intellectual curiosity and motivation, attitudes toward schooling, and academic achievement (Angeli et al., 2016; Wolfe & Brandt, 1998). When solving real-world problems, students show greater curiosity, motivation, attitudes toward learning, and greater achievement. Focusing on real-world problems can make computational thinking more relevant and keep students engaged and interested in the subject (Wolfe & Brandt, 1998).

This work introduces the Kaggle.com LEGO® Database and demonstrates how it can be used to teach database concepts (especially SQL skills) in a college classroom. The LEGO® Database is a large, real-world dataset. The dataset is complex enough for advanced student assignments. However, since the domain is familiar to most students, the LEGO® Database is also appropriate for beginning exercises. Assignments using the LEGO® Database have been well received by students.

While relational database education and SQL are the focus of this work, the LEGO® Database is also useful for a wide variety of undergraduate and graduate courses, including statistics, data science, and research methods.

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APPENDIX A.

LEGO® Database Table Description

Please note that all file and attribute descriptions are from the Kaggle.com LEGO® Database site: https://www.kaggle.com/datasets/rtatman/lego-database

The LEGO® Database has eight tables, which are:

Sets: This table contains information about the LEGO sets, such as their name, year, number of parts, and theme.

The sets.csv file has 11,673 rows and five columns. Each column represents a different attribute of a LEGO set. Here is a brief description of each column:

- set_num: The unique identification number of the set, consisting of letters and numbers.
- name: The set's name, such as "Fire Truck" or "Batwing Battle Over Gotham City".
- year: The year when the set was released, ranging from 1950 to 2017.
- theme_id: The identification number of the theme the set belongs to, such as "City" or "Batman".
- num_parts: The number of parts the set contains, ranging from 1 to 5922.

Colors: This table contains information about the LEGO colors, such as their name, RGB value, and whether they are transparent.

The file colors.csv has 135 rows and four columns. The columns are:

- id: a unique identifier for each color (integer)
- name: the name of the color (string)
- rgb: the hexadecimal code for the color (string)
- is_trans: a boolean value indicating whether the color is transparent or not (string)

Themes: This table contains information about the LEGO themes, such as their name and parent theme.

- themes.csv: This file contains 614 rows and three columns. It lists the theme names, theme IDs, and parent theme IDs of the LEGO themes.

id: Theme unique ID. (integer)
name: Name of the theme. (string)
parent_id: Unique ID for the larger theme, if there is one. (integer)

Inventories: This table contains information about the inventories of the LEGO sets, such as their set number, version, and number of parts.

The file inventories.csv in the LEGO database has 11,681 rows and three columns. The columns are:

- id: The unique identifier of the inventory (integer)
- version: The version of the inventory (integer)
- set_num: The set number of the

inventory (string)
id: Unique ID for this inventory entry.
version: Version number.
set_num: Set number (form `sets.csv`).

Inventory_Parts: This table contains information about the parts in each inventory, such as their part number, color, quantity, and whether they are spare or not.

The file inventory_parts.csv has 580,251 rows and six columns. The columns are:

- inventory_id: The ID of the inventory the part is in (integer)
- part_num: The ID of the part (string)
- color_id: The ID of the color of the part (integer)
- quantity: The quantity of the part in the inventory (integer)
- is_spare: Whether the part is a spare or not (string)

inventory_id: Unique ID for the inventory this part is appearing in. This is the same as the id value in `inventories.csv.`
part_num: Unique ID for the part, as per `parts.csv.`
color_id: Unique ID for the color, as per `colors.csv.`
quantity: The number of copies of this part included in the set!
is_spare: Whether or not this is a spare part. Spare parts are additional parts not needed to finish the set.

Inventory_Sets: This table contains information about the sets in each inventory, such as their set number, quantity, and whether they are spare or not.

The file inventory_sets.csv has 2,846 rows and three columns. The columns are:
- inventory_id: The ID of the inventory the set belongs to (integer)
- set_num: The set number (string)
- quantity: The quantity of the set in the inventory (integer)

inventory_id: Unique inventory ID from `inventories.csv.`
set_num: Unique set ID from `sets.csv.`
quantity: The quantity of the inventory included.

Part_Categories: This table contains information about the categories of the LEGO parts, such as their name and ID.

The part_categories.csv file has 57 rows and two columns. The columns are:
- id: contains the unique identifier for each part category (integer).
- name: contains the name of each part category (string).

Parts: This table includes information on Lego parts, including a unique ID number, the name of the part, and what part category it is from.

The file parts.csv has 25,993 rows and three columns. The columns are:
- part_num: Unique ID for the part (string).
- name: Name of the part (string).
- part_cat_id: Part category unique ID (integer) (from `part_categories.csv`).

part_cat_id: the part category from `part_categories.csv.`

APPENDIX B.

Group Project Instructions

- For this assignment, use your Group Oracle Account. Each team member will have access to this account.
- There are seven deliverables for this project

Part 1 Group Contract (5 Points)

1. Complete and submit the Group Contract by 04/20 @ 11:55 PM via the course management system. An example Group Contract is attached. You may use the example or make one of your own.

Submit the group contract via the course management system. This is deliverable #1

Part 2 The Data Model (10 Points)

2. Go to https://www.kaggle.com/rtatman/LEGO-database and download the data.

3. There is much information about this data on this webpage. Please take the time to use the view information about each file in the dataset.

4. The Kaggle site has a rudimentary Entity Relationship Diagram ERD of the LEGO® dataset (https://www.kaggle.com/datasets/rtatman/LEGO-database?select=downloads_schema.png). Using any application you want, recreate the ERD using the crow's foot method we discussed in the first half

of the course. Include all attributes, primary keys, foreign keys, maximums, and optional/mandatory indicators.

Submit a PDF of your group's ERD. This is deliverable #2

Part 3 Creating and Loading the Kaggle Data (35 Points)

5. Drop all the tables mentioned in the above ERD (in case you already have tables with these names) EXCEPT inventory_sets. We will not be using inventory_sets for this project.
6. Use DDL to create the inventories, inventory_parts, parts, and sets tables
7. Load the data from Kaggle.com into the inventories, inventory_parts, parts, and sets tables
8. Write the DDL needed to create the colors, part_categories, and themes tables.
9. Load the data from Kaggle.com into the colors, part_categories, and themes tables.
10. Write the SQL needed to create the primary keys for each table.
11. Create all needed foreign keys. Please note that EVERY relationship in your ERD represents a foreign key.
12. SET ECHO ON and Run DESCRIBE on each table created for this project
13. Run SELECT * on each table created for this project. Show only the first ten rows from each table.

Submit a single file (plain text) showing the SQL and results for questions 5-13. This is deliverable #3

Part 4 Querying the Data (10 Points)

14. Query the proper systems/dictionary table to show all constraints on each table you created. Only show the tables you created for this assignment—order tables in ascending order by name. Use FORMAT and SET PAGESIZE as needed to improve the appearance of the results.
15. Create the query to answer: How many red parts are in the LEGO® data? Count all parts with red anywhere in the color name.
16. Create the query to answer: What are the Parts Categories with the highest percentage of spare parts compared to non-spare parts? Show the top 5 in descending order. Order by column number. Do not order by column name or alias.
17. Create the query to answer: What is the parent theme with the most "children" themes?
18. Find the average number of pieces in each LEGO® set (by year). Give the average number of pieces a meaningful alias. Order the results from highest to lowest using the alias for the average number of pieces. Show only the top 8 years.
19. Create the query needed to answer: Which set has the most unique spare parts?
20. Create the query to answer: Which theme has the most total parts across all sets? Show the name and the number of pieces. Show only the top theme (or themes if there is a tie) – not all.
21. What is/are the oldest sets in the LEGO® data WITH a Guardians of the Galaxy theme? Show only the oldest set (or sets if there is a tie) – not all. You must use a NATURAL JOIN for this question.

Submit a single file (plain text) showing both the SQL and results for questions 14-21. This is deliverable #4

Part 5 Entering New Data (30 Points)

22. Enter all data for LEGO® set 11966-1: (Pirate Ship) into your tables. More information about LEGO® set 11966-1: (Pirate Ship) can be found here: https://brickset.com/sets/11966-1
Enter all data via INSERT statements.
23. You must enter the set into the set table and populate all other tables as needed. There are 33 parts, but some are duplicates. Some may already exist in the data, but others must be added. This part may be the assignment's most time-consuming (and difficult) part. Please plan accordingly.
24. SET ECHO ON and Run the needed SELECT statements to show that you have loaded the data correctly. SHOW ALL DATA from #22/#23. Only show the data related to the Pirate Ship set. Use FORMAT and SET PAGESIZE if needed to improve the appearance of the results.

Submit a single file (plain text) showing the SQL to answer questions 22-24. This is deliverable #5

Part 5.a. – for graduate student teams only
You must also enter all data for an additional LEGO® set -- https://brickset.com/sets/11961-1/Helicopter

Repeat steps 22-24 for this LEGO® set -- include with deliverable #5

Part 6 Feedback (10 Points)
25. Write a short statement describing each member's contribution to the project. This is deliverable #6 (5 points)

26. Each group member must complete a survey on team member contributions. This is an individual assignment.

I will post the survey during Week 15. This is deliverable #7 (5 Points).

A UTAUT-based analysis of the Adoption Factors of Student Evaluations of Teaching

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Abstract

Student Evaluations of Teaching are an essential component of educational assessment that provides valuable feedback to instructors and their institutions. Indeed, their effectiveness depends on students' active participation and engagement with the assessment process itself. Identifying the factors that influence students' adoption of teaching evaluation systems is crucial for increasing response rates, which ultimately leads to better validity and utility of the assessment. However, adoption dynamics of course evaluations received little attention, especially in computer science disciplines. This paper presents the findings of a study aimed at identifying the factors that motivate and hinder students from participating in the course feedback process. To this end, we designed a survey using the Unified Theory of Acceptance and Use of Technology and distributed it among college students to assess their experiences with the current evaluation system. Our findings show that while students perceive the importance of providing professors with feedback to improve their teaching performance, other extrinsic aspects, such as effort and facilitating conditions, together with the uncertainty of whether their input is acknowledged and acted upon, hinder them from filling out Student Evaluations of Teaching. Based on these insights, we offer actionable recommendations for improving SET.

Keywords: Student Evaluation of Teaching (SET), Educational assessment, Unified Theory of Adoption and Use of Technology, UTAUT Model.

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A UTAUT-based analysis of the Adoption Factors of Student Evaluations of Teaching

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1. INTRODUCTION

The significance of student feedback in shaping instructional quality, with specific regard to higher education, has been acknowledged in a large body of scholarly literature (Okogbaa, 2016). Given its effectiveness in decision-making on important issues, such as teaching quality, course organization, assessment, and learning resources (Okogbaa, 2016), different types of Student Evaluation of Teaching (SET) systems have been designed to capture the value of ongoing, constructive feedback, which not only informs teachers about their practice but also stimulates reflection and dialogue between all stakeholders, including students, educators, and administrators (Mandouit, 2018). In fact, SET serves multiple purposes that contribute to the overall quality of teaching and learning, including providing faculty with useful feedback to improve their pedagogy (Boysen, 2016), supporting administrators in their annual faculty performance evaluations when making merit pay, promotion, and tenure decisions (Jaquett et al., 2017; Terry et al., 2017), and assisting students in course and instructor selection decisions, thanks to the possibility to provide students with information about the perceived teaching styles and course demands of different instructors (Stroebe, 2020).

Previous research explored instructors' perceptions of and reactions to SET based on various aspects of teaching. Several studies found that formal evaluations, particularly those using standardized instruments with multiple dimensions, raise awareness among teachers and encourage them to tailor their pedagogy and course design and delivery to meet students' preferences (Boysen, 2016). In the context of the review and tenure process, untenured instructors are more likely to use SETs to inform their teaching practice compared to tenured instructors (Omer et al., 2023). Also, previous studies found that, as instructors' practices are shaped by their beliefs about students' needs and capabilities, SET can be useful in reframing teachers' perspectives to align with their students better (Lee et al., 2016). However, the validity and reliability of SETs are subjects of ongoing debate due to their susceptibility to numerous factors beyond teaching quality. For instance, previous research identified significant variance in SETs attributable to differences among teachers, courses, and individual student perceptions (Feistauer, 2016; Quansah, 2024). This variability is further complicated by disciplinary differences, as (Yu et al., 2022) noted that students in STEM fields generally provide higher ratings compared to their peers in non-STEM disciplines. Consequently, instructors in non-STEM fields, who are more likely to face harsher evaluations, tend to view SETs more negatively than their STEM counterparts (Omer et al., 2023).

While extensive research has examined instructors' perspectives on SET, there remains a gap in studies exploring students' perceptions. Previous studies found that students perceive teaching evaluation as an important process for improving teaching and giving them a voice (Sullivan et al., 2024). Also, regardless of the type of institution, academic discipline, class standing, and respondent gender, students generally hold positive views about the evaluation process (Kite et al., 2015) and see themselves as qualified to assess teaching performance (Huxam et al., 2017; Suárez et al., 2022). Simultaneously, several studies reported overall low completion rates (Brown & Kosovich, 2015). Specifically, the factors motivating students' engagement with SET and preventing them from providing their teachers with feedback have received less attention. Indeed, understanding students' adoption of teaching evaluation systems is especially crucial to enhancing the quality of teaching and adapting to the evolving needs of students.

In addition to traditional official SET tools, third-party review platforms and websites offer students a more informal and, in many cases, anonymous means of sharing their feedback. For instance, RateMyProfessors.com (RMP) is a popular website where students can anonymously rate professors on difficulty, clarity, and overall quality. In addition, students can leave public reviews about their experiences on this platform. RMP, active in the United States, Canada, and the United Kingdom, has quickly become a popular resource with millions of user-generated ratings and comments. RMP evaluations can significantly shape students' perceptions and self-efficacy in courses. For example, by accessing reviews from peers who have taken the course, students may rely on RMP to bridge an information gap, especially when official SETs are unavailable or difficult to access (Boswell, 2020). Therefore, addressing the lack of research on the adoption factors that motivate and prevent students from filling out SETs also involves a closer examination of the reasons why students engage with alternatives to official SETs.

While previous studies have highlighted various factors influencing students’ participation in SET and suggested strategies to increase completion rates, it is important to acknowledge that students’ adoption of SET is not only influenced by student motivations but also by a range of other factors, including institutional policies, faculty engagement, and administrative support. This, in turn, requires a comprehensive evaluation of intrinsic and extrinsic factors impacting students’ adoption of the system. For instance, intrinsic factors may include students’ perceptions of the relevance and usefulness of SET feedback and their understanding of how their input contributes to improving teaching quality. Extrinsic factors, on the other hand, could encompass institutional incentives or rewards for participation, the clarity of communication regarding the purpose and use of SET data, and the ease of access to evaluation platforms.

To this end, theoretical frameworks such as the Unified Theory of Acceptance and Use of Technology (UTAUT) model (Venkatesh, 2003) provide a structured approach to highlight the multifaceted adoption factors of SET. This model identifies various dimensions, including performance expectancy, effort expectancy, social influence, facilitating conditions, and intrinsic motivation, which influence individuals’ behavioral intention to use any technology. As SET mostly rely on digital evaluations, by applying the UTAUT framework, institutions can gain deeper insights into the motivations and hindrances of students’ adoption of SET and tailor interventions accordingly.

In this paper, we present the findings of a study in which we leveraged the UTAUT to survey students’ adoption of SET and develop actionable recommendations for enhancing the SET process. By leveraging UTAUT’s established constructs, including performance expectancy, effort expectancy, social influence, facilitating conditions, and intrinsic motivation, this study aims to provide a nuanced understanding of the intrinsic and extrinsic factors influencing students’ acceptance and utilization of course evaluation mechanisms. Utilizing this model could also provide comprehensive recommendations to improve the adoption and effectiveness of SET systems, ultimately enhancing teaching and learning experiences, especially in Computer Science. Based on our results, our recommendations include refining communication strategies to emphasize the importance of student feedback, providing training or support resources to faculty members to effectively utilize SET data for instructional improvement effectively, and enhancing transparent communication.

2. RELATED WORK

The significance and impact of SET have been extensively studied in various disciplines. For example, in medical sciences, SET reports influence teaching and administrative practices, with lecturers actively responding to student feedback (Safavi et al., 2012). Similarly, in engineering education, SET is linked to students’ perceptions of faculty expertise and teaching abilities (Fawad, 2014).

SETs are particularly crucial in computer science disciplines where the rapid advancement of technology and evolving demands of the job market present significant challenges for educators and institutions. The introduction of new systems, languages, and innovations requires curricula to adapt and remain current. Also, educators face the constant challenge of identifying and addressing the changing needs of their students. In this scenario, although prior research has emphasized the need for a more integrated, relevant, and innovative approach to evaluating teaching, several studies found that even skill-oriented CS curricula often lack connection to real-world challenges students face after graduation (Weymouth et al., 2021) and computer science instructors struggle to continually adapt their course content and delivery with respect to a technological scenario evolving quickly (Hai-zhe, 2014). To this end, SETs and other types of evaluations, including mid-semester ones, can effectively address these challenges by providing valuable feedback to educators, enabling them to identify areas for improvement (Sozer et al., 2019).

Student teaching evaluations are crucial in computer science education, offering insights into course effectiveness and faculty performance. Research highlights that computer science courses often receive lower evaluations compared to other disciplines, underscoring the need for tailored teaching strategies (Wang et al., 2023). These evaluations, however, are subject to various influences such as course characteristics, level, and size (Wang et al., 2023). Additionally, in computer science departments, teaching-track faculty positions often heavily depend on student evaluations for career advancement, despite concerns about the inherent biases of these assessments (Glebova et al., 2024). Biases, including those related to gender, can skew evaluations, as found by (Santiesteban et al., 2022). Despite these issues, integrating evaluation practices with research in computing education is crucial for validating claims and strengthening empirical approaches in the field (Decker et al., 2018). As computer science education evolves, it is essential to develop more comprehensive and unbiased evaluation methods to ensure fair assessments and continuous improvement in teaching quality.

A study evaluated students' understanding of teaching quality and their assessment criteria, which can inform the design of SET tools and systems. Their findings revealed that most students recognize the importance of teaching quality evaluation and prioritize factors such as learning outcomes, teacher attitudes, and teaching ability. However, several other studies have raised concerns about the validity of SET, as the questions used in the evaluation are often teaching-oriented, non-specific, and satisfaction-based (Borch et al., 2020). Additionally, the accuracy of student evaluations in higher education is dubious due to multiple sources of measurement error (Quansah et al., 2024). To address this, researchers proposed a questionnaire that considers specific factors of teaching quality, such as the ability to transfer knowledge, instructor accessibility, and social skills, to obtain a more accurate and comparable assessment of teaching quality across universities (Vevere & Kozlinkis, 2011). Moreover, the study found that official course evaluations, which are typically conducted at the end of the term or semester, are not conducive to realizing immediate improvements. Thus, a comprehensive evaluation system that integrates multiple sources, such as student feedback, self-assessment, peer review, and teaching portfolios, is needed (Constantinou & Wijnen-Meijer, 2022).

Another concern is the effectiveness and outcome of SET. Student evaluations alone are insufficient for evaluating teaching effectiveness, and a refocus on outcome-based academic standards is needed (Cui et al., 2022). Therefore, SETs should be used cautiously to prove teaching effectiveness (Ali et al., 2021). Data generated by student evaluation systems should lead to genuine and lasting improvements in teaching quality and student learning (Palmer, 2012). They suggest making course evaluation outcomes publicly available to ensure the long-term impact of the evaluation process. Despite ongoing debates about whether SET results should be shared publicly, there is currently little evidence of implementing these suggestions and a lack of studies evaluating whether public availability of SET outcomes leads to better teaching and learning outcomes. However, several studies reported poor engagement with and participation in SET (Chapman & Joines, 2017).

In contrast to official course evaluations, platforms like Rate My Professors (RMP) offer publicly accessible ratings and potentially serve as a feedback loop between student opinions and academic performance. According to previous studies, exposure to positive RMP evaluations leads to higher ratings of instructor competence, increased student engagement, and better quiz performance compared to negative evaluations (Reber et al., 2017). Nevertheless, the influence of RMP on students' course selection decisions has been underscored: positive comments about professors on RMP can positively influence students' evaluations (Scherr et al., 2013), and students show a greater tendency to enroll in course sections taught by instructors with higher ratings (Brown et al., 2015). Considering the significant impact of RMP on students' decision-making, understanding the factors that incentivize their participation in the evaluation process could enhance the SET system, improving its validity, representation, and sustainability.

Whether through official SETs or alternative systems, understanding the factors that motivate or hinder students from contributing their feedback is key to identifying strategies that can drive engagement. In (Chapman & Joines, 2017), the authors surveyed faculty members to discover approaches for incentivizing students and increasing SET response rates. The study revealed three key tactics: (1) emphasizing the importance of class evaluations during lectures, (2) cultivating a classroom atmosphere of mutual respect between instructor and students, and (3) informing students about how their feedback contributes to course modifications. For instance, previous research suggests that faculty members should review past evaluation results and highlight any changes to show students that their feedback is valued (Medina et al., 2019). This approach may motivate students to participate in future evaluations. Specifically, the study found that response rates increase when instructors demonstrate a strong interest in receiving evaluations (Young et al., 2019). Several studies emphasize the importance of continuous monitoring and communication with students throughout the evaluation process to motivate their participation. In particular, Gordon (Gordon et al., 2018) found that rewarding students with additional points toward an assignment or test can be an effective strategy.

While these studies have identified specific strategies to improve student participation in teaching evaluations, focusing on isolated factors may not be sufficient to fully address low response rates, especially considering that SET is a complex process influenced by multiple interrelated elements. Therefore, a more comprehensive, holistic approach is needed to understand and effectively improve SET adoption among students.

Researchers have suggested extending the Technology Acceptance Model (TAM) to gain a deeper understanding of the factors influencing students' intention to participate in computer-based or online course evaluations. Previous research found that perceived usefulness is a key factor driving individuals' intention to use technology, while perceived ease of use can affect intention directly and indirectly by shaping perceptions of usefulness (To & Tang, 2019). The study further enhances the original TAM by incorporating additional factors such as subjective norm—students' perceptions of whether their teachers, classmates, or parents expect them to participate in evaluations—and perceived relevance, which refers to the extent to which students view participation as important and relevant to their overall academic experience. However, this area remains underexplored in educational research, and to the best of our knowledge, this is the only paper that has applied the Technology Acceptance Model (TAM) to understand the factors influencing course evaluation. While TAM has been widely used to examine technology adoption, it primarily focuses on perceived usefulness and ease of use, which may not fully capture the broader range of factors influencing SET. To address this limitation, we propose using the Unified Theory of Acceptance and Use of Technology (UTAUT) model (Venkatesh, 2003) in this paper, as it provides a more systematic and comprehensive framework for identifying key determinants of students' acceptance and use of tools for SET. UTAUT integrates multiple theoretical perspectives, including social influence, facilitating conditions, and performance expectancy, which makes it a more robust model for understanding technology adoption in educational settings. Despite its strengths, there remains a significant gap in the literature regarding the application of UTAUT in SET research, as no prior studies, to the best of our knowledge, have employed this model to examine students' acceptance of course evaluation tools. This study, therefore, aims to bridge this gap and provide new insights into the factors shaping students' engagement with SET technologies.

3. MATERIALS AND METHODS

The goal of our work is to provide an in-depth understanding of the specific adoption factors of SETs to ultimately aid the development of more effective strategies to incentivize students' participation in the evaluation process. Specifically, we are interested in the aspects that motivate students to fill out course evaluations as well as the factors that hinder them from participating in this process.

To this end, we utilized the UTAUT model (Venkatesh, 2003), a widely recognized theoretical framework for evaluating an individual's willingness to adopt new technology. This model has been extensively applied within educational contexts to analyze the adoption of various types of innovative systems in higher education, from social networking to communication tools and platforms (Lewis et al., 2013). Although it can be applied to evaluate students' willingness to engage with SETs, it has not been utilized for this purpose before. The UTAUT model characterizes user adoption using the following dimensions, described in Figure 1. The model dimensions can be categorized into extrinsic and intrinsic elements. The extrinsic elements include:

- *Performance Expectancy (PE)* indicates the degree to which an individual believes that using a particular technology will help them achieve gains in performance or accomplish specific tasks effectively. In the context of SET, performance expectancy relates to students' perceptions of how effective the evaluation process is in providing valuable feedback to instructors and improving the overall quality of teaching and learning. Therefore, they may assess the usefulness of SET based on their expectations of how their feedback can enhance teaching practices and academic outcomes.

- *Effort Expectancy (EE)* refers to individuals' perceptions of how effortless it is to interact with SET tools. The goals are to (1) assess the perceived ease or difficulty of filling our course evaluation based on factors such as the accessibility of the evaluation platform, the user interface design, and the simplicity of the evaluation process and (2) discover if they influence students' willingness to engage with the system.
- *Social Influence (SI)* encompasses external factors, such as peer recommendations and social norms, that impact individuals' acceptance and adoption of technology. Given that students' decisions to participate in the evaluation process can be influenced by social factors, including reminders from instructors and peer interactions, they have the potential to shape students' attitudes toward SET participation.
- *Facilitating Conditions (FC)* focuses on the availability of resources, support, and infrastructure that facilitate the adoption and usage of a technology or system. In the case of SET, incentives (e.g., extra credits) provided by the instructors as well as clear instructions and guidance on how to navigate the system, can enhance students' participation in the evaluation process.
- *Intrinsic Motivation (IM)* is the component that is often fueled by individuals' inherent interest and enjoyment in the task. Some students might derive intrinsic satisfaction from the act of providing feedback and making a meaningful contribution to the academic community. They see value in the process itself, regardless of external or incentives. Unlike extrinsic dimensions, intrinsic factors in the context of SET emphasize the perceived impact of the importance of providing feedback per se, rather than because of its value or consequences. This distinction is crucial, as students generally have a positive perception of the value of their feedback.

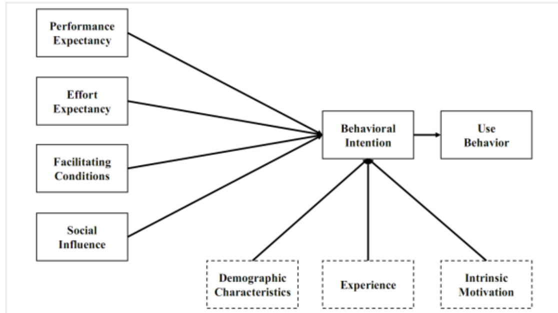

Figure 1 The UTAUT framework

We utilized the UTAUT model to design a survey consisting of 18 questions organized as follows. Questions 1-2 involved demographic and screening questions. We did not include questions about race and gender as they were deemed irrelevant descriptors for the objective of our study based on previous literature. Instead, we focused on factors such as class standing and GPA levels. Questions 3-5 indicated factors influencing their course selection process for both required and elective courses. Questions 6-10 asked participants to share factors influencing their adoption of SET and their preference for accessing SET results (Table 1).

In questions 11-16, participants were presented with a series of visualizations aimed at determining the types of information they wished to gain from SET and the preferred visual presentation methods. Questions 17-18 involved open-ended questions that enabled respondents to share additional thoughts, with the option for voluntary participation in follow-up interviews. The survey was disseminated via email and social media to over 500 students primarily enrolled at one university in the United States, though respondents were invited to share the questionnaire with their contacts.

4. RESULTS AND ANALYSIS

A total of 228 community college students from the Southeastern region of the United States, across various disciplines and primarily from undergraduate teaching populations, completed the survey in Spring 2024. The survey was self-reported. This school only uses online (computer-based) student teaching evaluations, which are sent out only at the end of the course to collect student responses. Responses from a number of students (i.e., 76) who completed less than 47% of the survey were excluded from the analysis. Most participants were juniors (35.57%), sophomores (30.20%), and seniors (22.15%), with the remaining 12.08% being freshmen, as shown in (see Figure 2). In terms of GPA level, 43.62% reported that their GPA was higher than 3.75 on a scale of 4.0, 20.13% had a GPA from 3.50 to 3.74, 20.81% had a GPA from 3.00 to 3.49, whereas 7.33% reported that they had a GPA from 2.50 to 2.99. Two participants had a GPA below 2.50, and ten reported that they either did not know or did not want to share their GPA.

Our results are summarized in Figures 3 and 4, which show the ranked UTAUT factors facilitating and hindering adoption of SET, respectively. Our findings do not indicate a specific preference in terms of overall adoption. This is due to our discovery that specific dimensions of the UTAUT model act as opposing forces. Some dimensions, such as performance expectancy and social influence, positively contribute to students' willingness to fill out teaching evaluations. However, others, including effort expectancy, facilitating conditions, and intrinsic motivation, act as hindering factors.

4.1 Motivating factors

Subsequently, we analyzed individual responses to reconcile them with the UTAUT dimensions in order to categorize the adoption factors that motivate students to complete course evaluations. Specifically, respondents were asked to rank possible options that engaged them with SETs. The respondent's top choice was given the highest weight (i.e., 5), while their least preferred choice was assigned a weight of 1. Our analysis indicated that the strongest motivating factor for completing course evaluations is the belief that providing feedback will enhance the course, with a weighted average ranking of 3.65. This finding aligns with previous research (Chapman & Joines, 2017) highlighting students' motivation coming from the potential impact of their feedback on course improvement (i.e., performance expectancy). Following closely behind is the incentive to fill out evaluations (i.e., 3.13), suggesting that external rewards or recognition also play a significant role in motivating students. Additionally, the ease of completing evaluations and the sense of responsibility to provide feedback to instructors resulted in moderately influential factors, scoring 3.01 and 2.62, respectively. These findings underscore the importance of streamlining the evaluation process and students' perceived obligation to contribute constructively to instructional improvement. Finally, factors related to social influence, including the instructor prompting for their feedback and whether other students participate in SET, appear to have the least impact on the motivation to complete evaluations. This implies either a lack of effective influence from instructors, which was also emphasized in previous studies (Young et al., 2019) or that such encouragement does not impact student behavior significantly.

4.2 Hindering factors

We analyzed the factors that represent a barrier to the adoption of SET. A significant portion (32.11%) highlighted aspects related to time constraints (i.e., effort expectancy), the non-mandatory nature of evaluations (i.e., facilitating conditions), or that SET was not a priority for them (i.e., intrinsic motivation). This was followed by 22.63% of students citing a perceived lack of impact or importance attributed to the evaluations (i.e., performance expectancy), signaling a potential gap in understanding the value of feedback and its potential influence on instructional improvement. Additionally, 18.96% of respondents expressed disinterest in providing feedback (i.e., intrinsic motivation), while 14.07% mentioned the absence of encouragement from professors or peer influence as barriers to participation (i.e., facilitating conditions and social influence), further underscoring the role of instructor engagement in fostering student involvement, but also partially in contrast with our previous findings. Usability concerns regarding the evaluation form (i.e., effort expectancy) were identified by a relatively smaller percentage of students (7.34%).

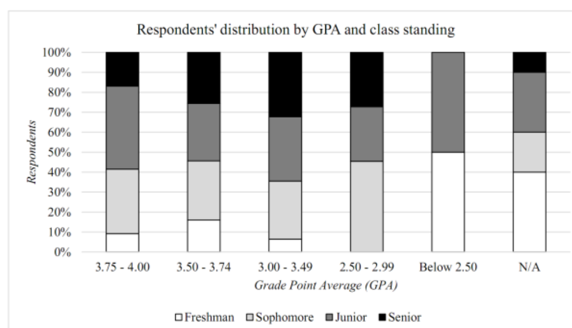

Figure 2 Distribution of respondents across class standings and GPA

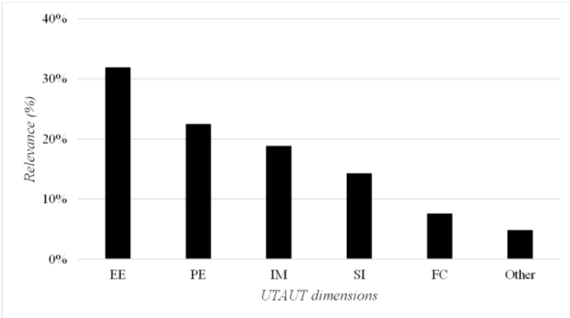

Figure 3 Ranking of factors facilitating the adoption of SET

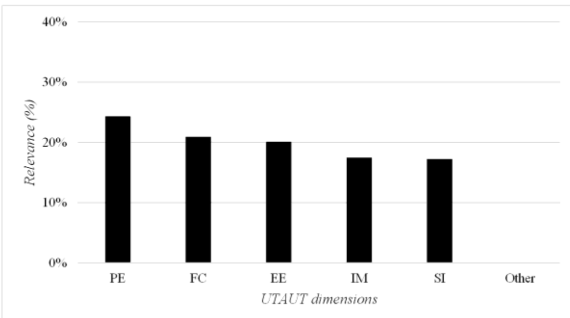

Figure 4 Factors hindering SET adoption

4.3 Behavioral intention model

After analyzing the factors that motivate and hinder students' adoption of SET, we used our results to create a behavioral intention model as specified by the UTAUT framework. Specifically, we utilized quantitative data from participants to estimate the sentiment and magnitude of each of the five UTAUT dimensions. The results are shown in Figure 5, where each latent construct is associated with its corresponding positive and negative sentiment, where the arithmetic sum yields a measure of the overall sentiment. In addition, the Figure also provides insight into the overall impact of each dimension on behavioral intention. This can be calculated by considering the absolute value of the positive and negative component of each latent construct and then by normalizing the results over a scale from 0 to 1, which can be interpreted as how each dimension impacts behavioral intention percentwise. Facilitating conditions, performance expectancy, and effort expectancy were assigned normalized weights of 0.25, 0.23, and 0.20, respectively. Intrinsic motivation and social influence scored 0.17 and 0.15, respectively.

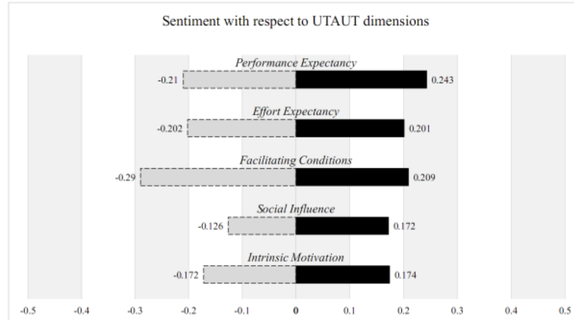

Figure 5 Factors facilitating (right) and hindering (left) SET adoption.

Performance expectancy, which reflects students' belief in the potential impact of their feedback on course improvement, plays the most significant role in driving adoption. With facilitating conditions having the second highest weight, this suggests that incentives that facilitate the participant process, such as the provision of extra credits, also play a crucial role in encouraging engagement with SET. Effort expectancy, ranking third, includes factors such as system accessibility, user interface design, and the simplicity of the evaluation process. Intrinsic motivation ranks slightly higher than social influence, indicating its relatively minor impact on adoption. While intrinsic motivation, which includes aspects such as making a meaningful contribution and perceiving value in the evaluation process itself, is present, it is not as pronounced as other factors. Finally, social influence was reported to play a minimal role in adoption, with participants mentioning factors such as reminders from instructors and peer interactions. While peer and instructor influence may serve as reminders, they are not significant drivers of student engagement with SET.

5. EXTRINSIC AND INTRINSIC FACTORS

In this section, we provide a detailed analysis of each of the extrinsic and intrinsic factors contributing to SET's low adoption level.

5.1 Performance Expectancy

While most participants reported that providing feedback will contribute to course improvement, our data shows a prevalent skepticism regarding the actual utilization of feedback results. Many participants expressed disillusionment, stating that they have never witnessed course improvements despite completing course evaluations. Moreover, the survey results indicated the importance of perceived faculty quality in students' decision-making processes. A significant majority (42.28%) cited the perceived quality of the faculty as the most crucial factor influencing their choice of courses to enroll in, surpassing other considerations such as instructor difficulty (9%). However, concerns about course quality emerged as a significant deterrent for students when considering specific classes, underscoring students' expectations that course evaluations should serve as a mechanism for enhancing educational offerings. Importantly, participants expressed a desire for greater transparency regarding the utilization of evaluations by institutions and whether feedback is acted upon. This sentiment reflects students' skepticism about the efficacy of the feedback process and their desire for more information on its outcomes. This indicates a need for institutions to provide more information and demonstrate the value placed on student feedback.

5.2 Effort Expectancy

Effort expectancy emerged as the third important determinant shaping students' motivation towards embracing SET systems, a conclusion drawn from examining survey responses employing quantitative and qualitative methodologies. Our data showed the presence of a pattern where many students perceived completing SET evaluations as straightforward, thus confirming the simplicity of the process. Our findings reveal that only 7.34% of respondents considered platform usability as a potential hindrance. This observation not only highlights the positive sentiment among students regarding the user-friendliness of SET platforms but also hints at the efficacy of their design in facilitating accessibility. The data suggests that, from a usability standpoint, the SET systems are largely well-crafted and user-friendly, creating an accessible environment for student engagement.

5.3 Social Influence

Reminders from instructors and peer interactions were mentioned as factors influencing participation in the SET process but not as significant drivers. This suggests that while social influence may encourage students to complete evaluations, they are not the primary motivators for engagement. On the other hand, the data revealed interesting patterns when examining factors influencing students' choices in selecting classes. Only a modest percentage (12.75%) cited friend recommendations or enrolling in sections with recommended instructors as influential factors for required classes. However, the landscape shifts when considering elective courses. Positive feedback from other students emerged as the most influential factor, surpassing the reputation of the instructor and the course format in importance. Despite the reported insignificant role of social influence in adoption, students consistently expressed the importance of making evaluation results available in their open-ended comments. Additionally, a high percentage (91.78%) indicated varying degrees of perceived helpfulness of course evaluations. This disparity in the influence of social factors underscores a complex interplay between individual decision-making and collective feedback. While students may not be socially influenced to fill out evaluations per se, they are influenced by the feedback of their peers in making course choices. Therefore, it is important to consider both individual motivations
and social dynamics in designing effective evaluation systems and increasing student engagement.

5.4 Facilitating Conditions

Facilitating Conditions resulted the UTAUT dimension with the highest weight and, thus, playing the most important role in students' adoption of SET. Specifically, our findings indicate that facilitating conditions had the most negative impact on adoption (-0.081) compared to other dimensions that hinder adoption. This suggests that the absence of facilitating conditions poses a significant barrier to student engagement with course evaluations. To compensate for the perceived lack of student incentives, encourage student participation, and enhance the quality and quantity of responses, instructors should provide tangible benefits such as extra credits, recognize participation with some form of acknowledgment or feedback, and allocate class time for students to fill out SET forms could increase response rates. Furthermore, 32.11% of students reported a lack of time and availability as their primary concern. The timing of course evaluations, typically distributed at the end of the semester, coincides with the busiest period for students. This poses challenges for students in prioritizing the task of completing evaluations among their other end-of-semester commitments. To address the challenge of time constraints, institutions could explore flexible scheduling options for evaluations, allowing students to complete them at a time that better aligns with their availability. Also, allocating class time for students to fill out SET forms could increase response rates.

5.5 Intrinsic Motivation

Intrinsic factors accounted for a relatively minor impact on adoption. Only 18.96% of respondents expressed disinterest in providing any feedback. However, students reported a high sense of personal responsibility to provide feedback to instructors. Analyzing open-ended comments revealed that the reasons for this disinterest vary among respondents. Some expressed contentment with either the course content or the instructor's performance, feeling no imperative need to provide feedback; others indicated a sense of dissatisfaction or disinterest, leading to a reluctance to offer constructive input. Although intrinsic motivation may not be the primary driver for providing feedback, it still shapes respondents' attitudes toward providing feedback. Our findings show that students prioritize their intrinsic motivations, such as personal satisfaction or a genuine desire to contribute to the improvement of the course. As a result, external factors alone are insufficient to compel students to engage in course evaluations, except for receiving assurance that their feedback is read and taken action upon. Regarding students' sentiments toward sharing SET results with future students while maintaining anonymity, the majority (61.64%) expressed being moderately to highly willing to fill out course evaluations, whereas a high proportion (32.19%) indicated that this would not impact their behavior, as reported in Figure 8. In contrast, when questioned about the perceived helpfulness of accessing course evaluation results before enrolling in a course, the responses leaned significantly toward positive sentiments. Approximately 91.78% of participants indicated varying degrees of perceived helpfulness, ranging from moderately helpful (21.23%) and slightly helpful (27.4%) to extremely helpful (43.15%). These results, shown in Figure 7, underscore a strong endorsement of the publication of course evaluation results. Furthermore, the disparity between the two scenarios highlights the importance of perceived personal benefit in shaping students' attitudes toward evaluation processes. While the potential impact on future students may motivate some students to participate more actively, the direct benefits of accessing evaluation results for informed decision-making appear to resonate more strongly with most students.

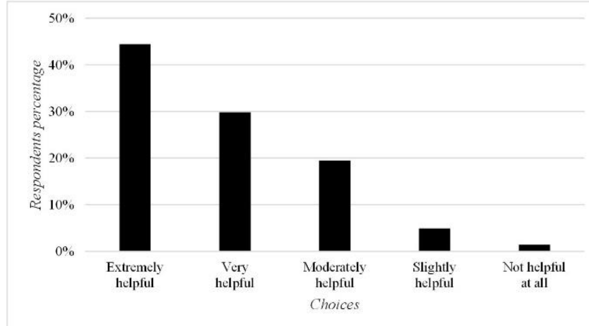

Figure 7 Perceived sentiment towards making the results of SET publicly available.

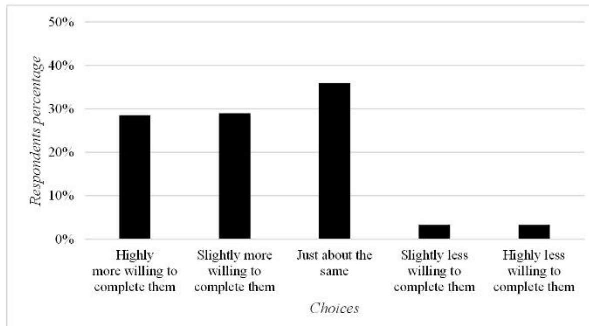

Figure 8 Perceived impact of SET's public availability on students' adoption.

6. DISCUSSION AND RECOMMENDATIONS

Our study suggests that targeted interventions are necessary to improve students' sentiment toward SET and, consequently, their behavioral intention to adopt feedback collection tools. To this end, we analyzed specific responses, comments, and motivations from participants. In this section, we present detailed feedback garnered from students via 90 responses to the open-ended question "What is missing or could be improved in teaching evaluations?" along with recommendations on addressing the dimensions that act as opposing forces hindering course evaluation adoption.

6.1 Performance Expectancy

Students reported high skepticism on how their feedback is used. R1 questioned whether "*[SET feedback] is actually used or considered*". Transparency regarding the feedback process and its outcomes is crucial to enhance students' trust in the effectiveness of SET. This is confirmed by R2 and R3, who stated "*I wish there was more transparency that the professors actually read and use the evaluations*", and "*Overall, I feel like I do the evaluations, but my* *voice is not heard*", respectively. Institutions should address students' skepticism by showing examples of how evaluations have led to improvements in courses. One recommendation, also highlighted in a student's comment, could be to publish reports summarizing student feedback and subsequent actions taken by the department.

6.2 Effort Expectancy

Students generally find the evaluation process straightforward, yet they offered suggestions for enhancing its user-friendliness, such as more concise questions and optional sections. Also, several aspects could be refined, including the format and length of the evaluation (two comments), the rating system (two comments), and visualization (three comments). For instance, R4 suggested adding "*a more visual way of representing evaluations*", while R5 advocated for "*more charts and fewer words*". Additionally, two respondents referenced RateMyProfessors, a popular website where students can anonymously rate professors, as a preferred format for course evaluations.

6.3 Facilitating Conditions

Noticeably, 16.7% (16/90) of the responses indicate a desire for the results to be published, particularly to assist with class enrollment. According to R6, "*students should be able to see [the evaluations] when enrolling in their classes. We are blindly choosing which classes to enroll in, specifically with a teacher that may just read off a Power-Point when some need more than that*". In accordance with previous literature, respondents suggested that institutions should consider publishing the results of SET to provide prospective students with information for enrollment purposes. By making evaluation results accessible, students can make more informed decisions about their course selections. Also, tangible incentives should be implemented to encourage student participation in SET. Offering extra credit or acknowledgment of participation can motivate students to engage with the evaluation process. R7 suggested providing "*incentives to fill out optional boxes. Most of the time, people just skip all optional parts*", whereas R8 noted that "*only people with highly positive or highly negative opinions are likely to fill out SET*" without incentives.

Additionally, some students raised concerns that SET questions are often "*too similar and repetitive or don't really apply to the course*". R9 suggested adding "*specific questions about [the instructor's] teaching abilities*". This indicates a need to develop a set of SET questions that are more relevant, specific, and comprehensive.

6.4 Social Influence

Among those respondents who demanded course evaluation results to get published, the majority of them also wanted future students to have access to the evaluations and "*include advice for future students*" (R10). When students know that their evaluations will be visible to their peers, they may feel a greater sense of responsibility and motivation to provide honest and constructive feedback. This social visibility can act as a powerful motivator, encouraging students to engage more actively in the evaluation process.

6.5 Intrinsic Motivation

Although intrinsic factors appear to have a relatively minor impact on adoption, enhancing these factors is crucial due to the statistically significant relationship between SET scores and students' perceived value of SET practice (Spooren, 2017). Students are more likely to engage seriously with SET if they believe their evaluations will lead to tangible improvements in teaching quality and their overall learning experience. By effectively communicating the value of SET in improving course quality, institutions can enhance students' sense of responsibility. This approach not only increases the fill-out rate but also boosts the validity of SET.

7. CONCLUSION AND FUTURE WORK

In this paper, we utilized a novel approach to understanding the key adoption dynamics of SETs. Specifically, we applied the UTAUT model, which is widely utilized in many different contexts, to identify factors that influence the willingness of individuals to engage with any product or system. The model, which has not been employed before in this context, can provide additional insight into the adoption factors of SET. By leveraging UTAUT's established constructs, including performance expectancy, effort expectancy, social influence, facilitating conditions, and intrinsic motivation, this study aimed to offer a more in-depth understanding of the specific dimensions of adoption influencing students' willingness to participate in the evaluation of teaching. Our results do not indicate a specific preference in terms of overall adoption. This is because our findings show that specific dimensions of the UTAUT model act as opposing forces, with some (i.e., performance expectancy and social influence) positively contributing to students' willingness to fill out teaching evaluations and others (i.e., effort expectancy, facilitating conditions, intrinsic motivation) acting as hindering factors. Therefore, our study suggests that specific interventions are needed on the latter dimensions to skew students' behavioral intention toward the positive side of the adoption spectrum.

Our findings reveal that while students generally recognize the importance and relative ease of completing course evaluations, they remain skeptical about the actual utilization of their feedback by faculty and institutions. This, coupled with a lack of incentives and transparency, negatively impacts students' motivation to engage meaningfully with SET. On the other hand, factors such as perceived helpfulness of SET results for future course selection and the potential for social influence through peer interactions positively contribute to students' willingness to participate in evaluations. These answers align with the Facilitating Conditions, Performance Expectancy, and Intrinsic Motivation of the UTAUT model. Based on these insights, we recommended several actionable strategies, including (1) increasing transparency by communicating how student feedback is utilized and sharing examples of course improvements resulting from SET, (2) providing tangible incentives, such as extra credit or acknowledgment of participation, to boost response rates and engagement, (3) refining SET questions to be more relevant, specific, and comprehensive for each course, (4) considering publishing SET results to assist students in making informed decisions about course enrollment and to encourage a sense of social responsibility among students, and (5) effectively communicate the value of SET in improving course quality to enhance students' intrinsic motivation. The insights gained from this model can help develop comprehensive strategies to enhance student participation and improve the overall effectiveness of SET. Our future work will address the limitations of our study. Specifically, we will collect additional data to avoid unequal representation among students' class standing and GPA.

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Questions	**Options**	**UTAUT**
For a REQUIRED course offered in multiple sections, rank the factors you use to choose which section to enroll in.	Perceived instructor quality	PE
	Perceived instructor difficulty	EE
	Course environment and requirements (e.g., attendance, group projects, class activities, atmosphere, etc.), if the information is available	FC
	Flexibility of course format and schedule (e.g., lecture, seminar, online, AP, etc.)	FC
	Friends recommending the instructor or enrolling in that section	SI
Pick the FIVE most important factors when enrolling in a course section (whether required or elective).	The reputation of the professor	SI
	How much I expect to learn about the topic	PE
	Previous experience with the instructor or similar courses	EE
	Positive feedback from other students	SI
	My friends are taking the same class	SI
	Favorable course structure and material (e.g., presence of projects, discussions, additional activities, etc.), if the information is available	FC
	Flexibility and convenience of the course format/schedule (e.g., online, time matches my schedule, attendance is not required, etc.)	FC
	I believe the course will help me get a job in that field	PE
	Strong interest in the subject matter	IM
	Perceived "easiness" of the professor (e.g., they are friendly, approachable, responsive, offer extra credit, are an easy grader, etc.)	PE
	Perceived easiness of the course in general (e.g., assignments, exams)	PE
Rank the following factors based on how much they discourage you from enrolling in a course section. (1 being the most important and 6 being the least important)	Concern about the quality of the course and experience of the professor	PE
	Lack of previous experience with the instructor or similar courses	EE
	None of my friends are taking or recommending the professor/course	SI
	The course does not have a convenient format, does not match my schedule, or has limited activities	FC
	I have little interest in the course subject or it's useless jobwise	IM
	Perceived difficulty of the course/professor (e.g., assignments, exams, etc.)	EE

Questions	Options	UTAUT
What motivates you the most to fill out course evaluations? Rank the following factors (1 being the most important and 5 being the least important)	Providing feedback will improve the course	PE
	It’s easy to fill out the evaluations	EE
	I will receive an incentive for filling them out (extra credit, rewards, etc.)	FC
	My instructor asked me to fill them out or other students are also doing it	SI
	It's my responsibility to provide the instructor with feedback	IM
What usually prevents you from filling out teaching evaluations? (Check all that apply)	Lack of perceived impact or importance	PE
	Usability of the evaluation form	EE
	Lack of time/ it's not mandatory/ it's not a priority	FC
	The professor didn't mention it, or nobody else completed it	SI
	Disinterest in providing feedback	IM

Table 1. The list of the survey questions associated with the UTAUT dimension.

The Use of Competency-Based Statements in Assessing Student Knowledge, Skills, and Abilities: A study in a Network Security Class

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Abstract

Cybersecurity content is typically taught and assessed using Bloom's Taxonomy to ensure that students acquire foundational and higher-order knowledge. In this study we show that when students are given the objectives written in the form of a competency-based statements, students have a more clearly defined outcome and are be able to exhibit their knowledge, skills, and abilities that are being measured with higher accuracy. Students also are able to demonstrate a higher level of both knowledge and confidence in describing their skills. An experiment with two sections of a network security class compared student performance on assessments, with one group receiving Bloom's Taxonomy objective statements and the second group receiving competency-based statements. The results of this study show an increase in performance on the instructional topic, and support applying the approach to cybersecurity workforce development.

Keywords: Competency-based Statements, ABCD model, Computer Science Education, Security+, Cybersecurity education

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The Use of Competency-based Statements in Assessing Student Knowledge, Skills, and Abilities:| A study in a Network Security Class

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1. INTRODUCTION

According to the (ISC)² Cybersecurity Workforce Study (2022), a global cybersecurity workforce gap of 3.4 million people exists. Knowledgeable and skilled workers are needed to adequately fill those vacancies. One method to assess a person's knowledge is by administering a certification exam, of which there are many. Most certification exams are vendor-neutral and vendor-specific, centered on knowledge, skills, and abilities necessary for a job in the information technology (IT) industry, including cybersecurity. These certifications have a set of specific objectives focused on computer and cybersecurity concepts, which are written in the form of traditional Bloom's Taxonomy statements. We believe providing students with competency-based statements would be more effective in helping students know more specifically what skills they need to be proficient in to not only pass exams, but also to be competent in the workplace. Competency is broadly defined as being able to perform a specific task, or being able to demonstrate a skill. The goal of this study was to explore the use and effectiveness of competency-based learning in relation to student exam success rates and to measure improvement in performance when using said statements.

There were two directly related motivations for this study. The first was to observe the effect of providing students with competency-based statements on a performance assessment to determine if using competency statements in place of the traditional objective statements would have a positive impact on students' performance. Second was to compare student written responses after completing a performance assessment measuring student confidence and feelings on objectives vs. competency-based statements provided in directions and expected outcomes.

2. BACKGROUND AND LITERATURE REVIEW

History

The original Taxonomy of Educational Objectives was written by Dr. Benjamin Bloom (Bloom et al., 1956). Bloom categorized and classified the cognitive domain of learning into varying levels according to complexity and outlined six main categories: knowledge, comprehension, application, analysis, synthesis, and evaluation. When writing objectives using the Bloom's Taxonomy method, objectives contain a single verb and its object. The verb describes an observable action, and these objectives can be written at Bloom's six levels of learning, with memorization being the lowest level and creative thinking being the highest. Competency-based statements are more precise statements that define the behavior and actions needed to perform well in a particular job role.

Competency-based education (CBE) differs from the traditional education program by looking at what students learn and what skills they develop during an educational program, while not emphasizing time period restraints. CBE has been steadily gaining popularity nationwide and encompasses a range of practices and policies that vary across settings. The ideas of both CBE and outcome-based education (OBE) have existed for many years and have about as many definitions and designs. Concepts and characteristics of both CBE and OBE have continued to evolve over the years and adapt to the educational landscape, as well as become blended into very similar concepts. This literature review presents an overview of aspects and various implementations of CBE.

According to Curry and Docherty (2017), the roots of CBE can be traced to the monograph "The Principles of Scientific Management" (Taylor, 1911), in which Taylor examines work practices and details his approach to improving workplace efficiency and productivity. Taylor examined practices at a steel manufacturing plant in the early 1900's. He identified procedures that, once implemented, would improve both efficiency and productivity in industrial settings. Focusing on the end product enabled Taylor to develop key principles. One of which is the importance of providing proper training to workers to ensure they acquire the necessary skills and knowledge to perform their tasks efficiently. Taylor believed that skilled workers would be more productive and contribute to overall organizational success. The fact that Taylor focused on the output and final product of the employees forms the basis of CBE and OBE. This is seen by relating what workers needed to produce in the steel plant (the outcome of products made) to what skills students today need to possess and what they need to be able to do (the skill set).

Application in Education

Elam (1971) summarized the results of a Committee on Performance-based teacher education (PBTE) established by the American Association of Colleges for Teacher Education (AACTE). This committee was given responsibility to "study the many efforts currently taking place in the United States in the area of performance-based teacher education." Elements of PBTE as described by Elam include competencies that are characterized by the knowledge, skills, and behaviors that to be demonstrated need to include specific qualities. First, a competency needs to be derived from explicit conceptions of teacher roles. Second, a competency needs to be stated so as to make possible assessment of a student's behavior in relation to specific competencies. And third, a competency needs to be made public in advance. Assessment of the competency of the student performance is the primary source of evidence. In addition, assessment would consider evidence of the knowledge of the student relevant to planning for, analyzing, and interpreting situations. The student's rate of progress through the instructional program would be determined by competency rather than time or course completion. The learning experience would be guided by feedback, which could be from others or self-evaluative by having the student watch their own recorded performance. Elam theorized that the PBTE movement most likely was a product of the United States Federal Government's "realization that little, or no progress was being made in narrowing wide inequality gaps, and that traditional teacher education programs were not producing educators equipped to teach minority group children and youth effectively" (Elam, 1971, p. 2). Elam stated that these PBTE programs require that future educators are to be held accountable not for passing grades but attaining a given level of competency in performing essential tasks of teaching.

Structure

Over the years, several different terms have emerged in this area of education. Thus, phrases that include terms such as performance-based, competency-based, teacher education, training and vocational education are commonly used, and often used interchangeably. It is stated that an education characterized as competency-based, or outcome based, will include a variety of content items such educational objectives, outcome statements, competency frameworks, task analysis, employability skill lists, and performance and grading checklists (Curry & Docherty, 2017).

In a paper similar to Curry and Docherty (Haynes et al., 2016, p. 4) describes CBE as an "approach to instruction that places emphasis on what students learn and master rather than how much time they spend in school." This definition characterizes specific learning targets for what students should be able to do in order to earn credit. It employs "assessment, support, and monitoring of individual students' progress as they work toward meeting these targets, with requirements that students demonstrate mastery of competencies" (Haynes et al., 2016, p. 4). In addition, Haynes lists both flexible pacing and progression, both extended and accelerated, as part of CBE. The study by Haynes administered surveys to students, teachers, and school administrators to understand the impact of CBE. The goal of the study was to rigorously examine the relationship between CBE practices and changes in such learning capacities, skills, behaviors, and dispositions that enhance student capacity in school. The top practice was students helping each other with schoolwork. This strategy was reportedly used by 86% of CBE schools and 96% of comparison schools. Group work was approximately 50% for each. Haynes (2016) reported that pacing and progression varied with 50% of CBE teachers allowing students to take extra time to review and master a topic, and 29% allowing students to move ahead if they are ready before other students. This study looked at many disciplines, and only mathematics showed a positive change in learning capacities.

CBE grew in popularity in the early 2000's in the health professions. This was the focus of CBE research in medicine in which CBE was identified as emerging in the field of health education to address criticisms of contemporary approaches to training (Frank et al., 2010). The goal of the paper was to provide a definition of CBE. The resulting definition became: "Competency-based Education (CBE) is an approach to preparing physicians for practice that is fundamentally orientated to graduate outcome abilities and organized around competencies derived from an analysis of societal and patient needs. It de-emphasizes time-based training and promises greater accountability, flexibility, and learner-centeredness."

As stated by Gervais (2016, p. 99) "CBE is defined as an outcome-based approach to education that incorporates modes of instructional delivery and assessment efforts designed to evaluate mastery of learning by students through their demonstration of the knowledge, attitudes, values, skills, and behaviors required for the degree sought." While this definition has some variation with previous definitions, it is consistent with the goal of having students demonstrate mastery of a desired skill set. Competencies are developed based on the feedback and contribution of all stakeholders involved, including teachers and students. Another perspective was defined as CBE settings offer students greater opportunities or personalized learning, autonomy, flexibility, and responsibility for their own learning (Patrick, et al., 2011).
The paper "Exploring secondary teachers' perspectives on implementing competency-based education" (Rogers, 2021) begins by identifying that the more traditional education systems emphasize Carnegie units, seat time, and grade averages on a 100-point scale. In contrast, CBE students must demonstrate mastery and meet specific learning targets before progressing through the curriculum. Rogers examines a five-part definition of competency-based education by the International Association for K-12 Online Learning (formally iNACOL, now the Aurora Institute). The five-part framework defines competencies as needing to include explicit, measurable, and transferrable learning objectives that empower students. The framework states "students advance upon mastery" and "assessment is meaningful and a positive learning experience for students" (Rogers, 2021, p. 2). The framework also states that "students receive timely and differentiated support based on their learning need, and that learning outcomes emphasize competencies that include application and creation of knowledge, along with the development of important skills and dispositions." (Rogers, 2021, p. 2)

An exploratory study reports that the use of CBE is expected to continue to rise (Prokes et al., 2021). This is attributed to the fact that more than 75% of institutions expected to grow CBE programs by 2024. This study describes CBE as consisting of three key elements. The first is competency statements must be tied to measurable abilities and are linked to vocational or career-oriented outcomes. The second element states that CBD requires a prescribed set of materials comprising the structure of a course. The third element focuses on the ability of the student to demonstrate mastery of competencies in multiple methods.

Forms of CBE in Computer Science and Cybersecurity Education
The National Security Agency's (NSA) National Cryptologic School manages the National Centers for Academic Excellence in Cybersecurity (NCAE-C), which creates and manages a collaborative cybersecurity educational program with community colleges, colleges, and universities. The center partners with many United States government agencies, including NICE (formally recognized as The National Initiative for Cybersecurity Education). In 2020 NICE created the Workforce Framework for Cybersecurity (Peterson, et al., 2020) which is described to be a reference for "describing and sharing information about cybersecurity work" (Wetzel, 2023, p. 4). The program and corresponding documents "express work as task statements and describes knowledge and skill statements that provide a foundation for learners including students, job seekers, and employees. The use of these statements helps students to develop skills, helps job seekers to demonstrate competencies, and helps employees to accomplish tasks" (Wetzel, 2023, p. 4).

The document lists competency areas that are defined as "a cluster of related knowledge and skill statements that correlates with one's capability to perform tasks in a particular domain" (Wetzel, 2023, p. 11). The NCWF begins by defining several cybersecurity workforce categories, broken down into 33 specialty areas. This ends up becoming approximately 1,000 tasks (actions typically performed), 630 knowledge items (what the cybersecurity professional needs to know), 370 skills, and 175 abilities. These are then used to form work roles and competency areas on which to focus. These competency areas "help learners discover areas of interest, inform career planning and development, identify gaps for knowledge and skills development, and provide a means of assessing or demonstrating a learner's capabilities in the domain" (Wetzel, 2023, p. 11). The International Atomic Energy Agency (IAEA) published "The Competency Framework, A guide for IAEA managers and staff" in 2024 in which they provide the following definition: "A competency is generally described as a combination of skills, knowledge, attributes, and behaviors that enable an individual to perform a task or an activity successfully within a given job. Competencies are observable behaviors that can be measured and evaluated, and this are essential in terms of defining job requirements and recruiting, retaining and developing staff." NICE released a new proposed list of framework competency areas for comment in 2024. This list incorporates updates from a previous draft and serves as an example of the ever-changing information on how competency areas are defined and how they can be used in preparing a job-ready cybersecurity workforce as the industry responds to the changing field.

One proposal advocates "the use of competency-based education and mastery learning (CBML) methodologies as an innovative and more effective approach than the current OBE approach" (Watkins, Tobey, O'Brien, 2018, p. 1). in cybersecurity education. The CBML approach here is defined as "a structure that creates flexibility, allows students to progress as they demonstrate master of academic content, regardless of time, place, or pace of learning" (Watkins, Tobey, O'Brien, 2018, p. 4). "This proposal is based on the set of cybersecurity tasks, knowledge, skills, and abilities defined by the job performance models produced by the National Board of Information Security Examiners (NBISE), the competency model developed by the National Institute for Science and Technology and NCWF developed by NICE." (Watkins, Tobey, O'Brien, 2018, p. 5). The proposal looks to design and build CBML curriculum materials using a bottom-up approach. First identified will be the foundational learning objectives. This places emphasis of the CBML model on learner readiness rather than completion. Once the learner has mastered the foundational skills, then they will progress to the next level. The comparison is given that most OBE learning modules might be 45 - 60 minutes long and cover multiple topics, the CBML modules are shorter, possibly 15 - 20 minutes, and focus on only one or two topics. A CBML course could have 50 - 100 learning modules. This is a similar approach to that of CBE.

The Accreditation Board for Engineering and Technology (ABET) defines student outcomes as "what students are expected to know and be able to do by the time of graduation." (ABET, 2021, p. 6). In addition to this definition, the Computing Curricula 2020 describes competency as "comprising knowledge, skills, and dispositions that are observable in accomplishing a task within a work context" (CC2020, 2020, p. 13). This report recognizes that most undergraduate computer science students will seek employment after graduation. In order to secure employment, they will need to meet "standards, practice, and real-world expectations for performance" (CC2020, 2020, p. 54). This further emphasizes the growing need for helping students to build competency in the field of computer science, of which cybersecurity is a specialized field. Raj et al., (2022) proposed that educators can address the skills gap by using a variety of methods, which can be interpreted as being competency-based. Educators can add a practicum component to required and electives courses which can count toward the final grade. Institutions can choose to move introductory courses to closed lab models, apprenticeship-style learning in courses, and require internship experience.

Alammari et al., (2022, p. 1) state that "cybersecurity competencies are a dynamic combination of knowledge, skills, and abilities and focus on performance, meaning that knowledge alone does not guarantee success." In addition, cybersecurity is a multidisciplinary field of study and a cybersecurity framework needs to accommodate different kinds of competencies. This is an affirmation that the field of cybersecurity needs to measure both student success on competencies while also building skills.

The ABCD Model

This new implementation uses terms and concepts from Bloom's create level and merges them with three elements from the book "Preparing Instructional Objectives" (Mager, 1962). Throughout his book, Mager described the importance of determining learning goals that are measurable, observable, and realistic when delivering instruction. The three elements defined are performance, condition, and criterion. This method is labeled the ABCD model and incorporates the following: A is for the audience and is used to refer to those who will be demonstrating what they learned after a period of instruction. B is for behavior, which is described as the precise and tangible evidence that will be shown by learners. C is for the condition, which refers to the circumstances under which the behavior will be done. D represents the degree, which is a standard that has to do with accuracy, or number of mistakes or kind of mistakes that learners are allowed to make before such judgement as to the learning goal not being accomplished.

The following is an example of a Bloom's Taxonomy statement being converted to a competency-based statement. The CompTIA Security+ objective document uses the following phrase: "Explain the purpose of mitigation techniques used to secure the enterprise" and one bulleted item is an access control list (ACL). The word explain is at the understand level of Bloom's

Taxonomy. A competency-based statement following the ABCD model would read as follows: "Working as a Network Security Engineer, you will need to implement an ACL on the edge router to deny all telnet connections and only allow SSH connections inbound to the router from the administrative subnet of 10.10.10.0/24 on all ingress interfaces. Use an out-of-band connection to the router interface to create and edit the ACL. The ACL will need to correctly process 100% of the data going through the router." This competency-based statement makes a reference to all four parts of the ABCD model and provides explicitly clear direction as to what job role is being performed, what needs to be done, how it will be done, and the level of accuracy required.

Literature Review Summary

The papers in the literature review show the common theme that the essence of CBE is rooted in knowledge, skills, and abilities along with competencies. The section gives an overview of different definitions and implementations of CBE. These variations show that CBE is growing and is an ever-evolving practice. There are many similarities between the many implementations of CBE, along with some differences. With this history of CBE discussed here and the benefits seen, the objective in this study was to examine how current simplistic objective statements from an industry exam can be rewritten as competency-based statements and provided to students. Next, measuring if these statements had a positive impact on the student's skills and abilities on performance activities, and ultimately leading to an improvement of scores on certification exam assessments.

3. RESEARCH DESIGN

Research Questions

We explored two questions: (1) Will students better demonstrate their knowledge, skills, and abilities when given competency-based statements than those students who are given objectives in Bloom's Taxonomy? And (2) will students be able to identify their own strengths and confidence when writing about their skills?

Research Testbed

This study used 54 students enrolled in two different sections of the same 300-level course at a four-year public University. Table 1 presents the demographic data for the two groups.

Each class met once a week for a 160-minute session on the same day each week. The 3:00 PM class was randomly chosen by the flip of a coin to serve as the competency group. Therefore, the 6:00 PM class became the control group. All students were pursuing a Bachelor of Science degree in Information Technology. Of the total number, 17 were in their junior year and 37 were in their senior year. Twenty-seven students were in group A, which was the competency group. Group B served as the control group and was also made up of 27 students.

Research Methodology

The study compared results when students are given directions based on a competency-based statement vs. students who are given objectives written in the form of Bloom's Taxonomy. It used an assessment that consisted of both quantitative and qualitative questions. Assessment results from student performance in a simulation activity were analyzed. The study also collected and reviewed quantitative data from student self-analysis through a Likert scale survey and analyzed qualitative data from an open-ended question. The assessment was administered during the eighth week of a 15-week semester course and used the program Packet Tracer (https://www.netacad.com/courses/packet-tracer) which is a network simulation tool. Packet Tracer was chosen due to its ability to simulate fundamentals of computer networks and devices and include aspects of cybersecurity. The timing was purposely selected because it allowed students time to become familiar with the Packet Tracer program, thereby eliminating the ability to use the program as influencing the quantitative results.

Group A			
	Male	Female	Total
Black	5	8	13
White	6	2	8
Hispanic	2	0	2
Asian	3	1	4
Group B			
Black	10	6	16
White	5	1	6
Hispanic	3	0	3
Asian	2	0	2

Table 1: Demographic data

Each group was provided with the same lab activity introduction. This description set the stage for the desired network that needed configuration. The starting file consisted of network devices which the students needed to configure. Successful completion of the network required the application of IP assignments including subnetting, DHCP and DNS server configuration, and wireless security to be configured. Students had the freedom to design their network however they chose, as long as it met the requirements, thus allowing the students to demonstrate their knowledge and skill set.

The topic of the assessment was a set of specific objectives identified from the CompTIA Security+ exam objectives, version SY0-701 (2023). The competency group received these objectives written out as competency-based statements following the format of the NICE Workforce Framework for Cybersecurity (2022). The Centers for Academic Excellence in Cybersecurity (CAE-C) Community in "*Evidencing Competency Oversight*" has developed a model for effectively and efficiently evidencing competency that defines how to write a competency-based statement based on the four items in Mager's ABCD model. Norwich University is the leading institution for the Evidencing Competency Oversight Project (https://www.caecommunity.org/initiative/evidencing-competency). The control group was provided the objectives directly as written by CompTIA on the exam objective document, which uses verbs and categorizations from Bloom's Taxonomy.

During the assessment students did not see any active scoring. After completion, each submission was checked individually by the principal investigator using a checklist created by identifying 40 skills that needed to be completed in order to satisfy the competencies listed in the statements. Students had flexibility with their solutions to meet the stated requirements. The investigator collected the files and analyzed the score results with the student scores on this 40-point assessment serving as the quantitative data source. Appendix A is the 40-point checklist.

After completing the Packet Tracer assessment, each group answered three survey questions regarding the activity using a five-point Likert scale. The responses were collected and analyzed quantitatively.

The final question required an open-ended written response to a prompt to describe their skills with regards to the assessment. Each group was presented with the same prompt. Student responses to this question were collected and analyzed qualitatively. Students were allotted a 45-minute session in which to complete both the Packet Trace file and answer the survey questions. Appendix B is the document provided to the control group. Appendix C is the document provided to the competency group containing all directions and questions.

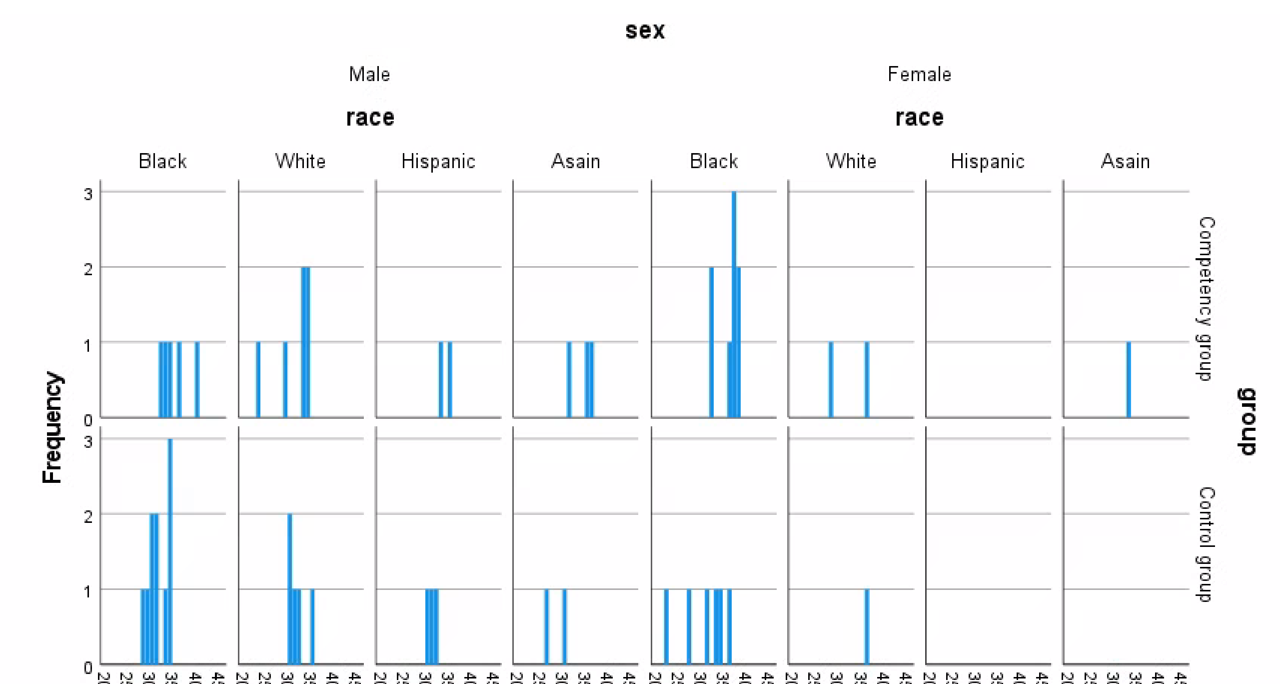

Figure 1: Packet Tracer score results based on race and sex for each of the two groups

4. EXPERIMENTAL RESULTS

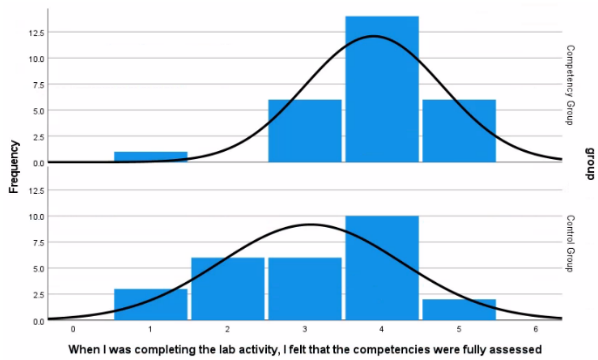

Figure 2: Frequency and normal distribution for question 1

Quantitative Data Analysis

The goal of the study was to determine the effectiveness on a performance assessment when providing students with competency-based statements for the assessment. The activity was completed by 27 students in the competency group receiving competency-based statements, and 27 students in the control group receiving objectives in the form of traditional Bloom's taxonomy statements.

The hypothesis for the quantitative portion of the study was that students will demonstrate their knowledge, skills, and abilities at a higher level of accuracy when given a competency-based statements in place of a Bloom's Taxonomy objective statement. Figure 1 charts Packet Tracer score results based on race and sex for each of the two groups. In analyzing the quantitative data by performing a t-test analysis on the scores, the results show a difference that is statistically significant between the two groups. The average score within the competency group (M=33.89, SD=3.512) is greater than the average score of the control group ($M = 31.11$, $SD = 3.117$), $t(52) = 3.074$, $p = .003$. Scores were higher in the competency-based group for both black males and females, and white females. White males in the control group scored slightly higher than the competency group white males. The significant difference between the scores persisted across both genders. The data from the Packet Tracer assessment are consistent with the hypothesis that competency-based statements positively impact student performance.

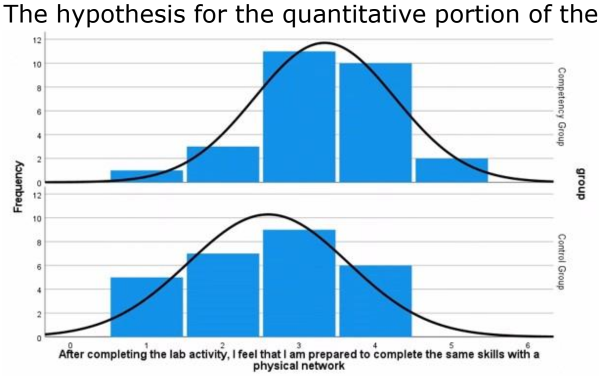

Figure 3: Frequency and normal distribution for question 2

Results from the survey questions utilizing a Likert scale were evaluated using mean and a median for central tendency and frequencies for variability (Boone & Boone, 2012). The mean and the median for questions one and two are greater for the competency group when compared to the control group. The median for question three is reported to be the same for each group at 3, while the mean for the competency group is 3.33 and for the control group it is 2.59. Further analysis using a Mann-Whitney U test on the data for question three produced a p-value of 0.02, therefore giving statistically significant evidence at $\alpha = 0.05$ to permit rejecting the null hypothesis and show that the competency group portrayed a higher level of confidence in their knowledge, skills, and abilities in each of the three questions. Figure 2 shows the frequency and normal distribution for question one.

Figure 3 shows the frequency and normal distribution results for survey question two, and figure 4 is for question three.

Appendix D lists the survey questions and the mean, median, and standard deviation Likert scale calculations for both groups.

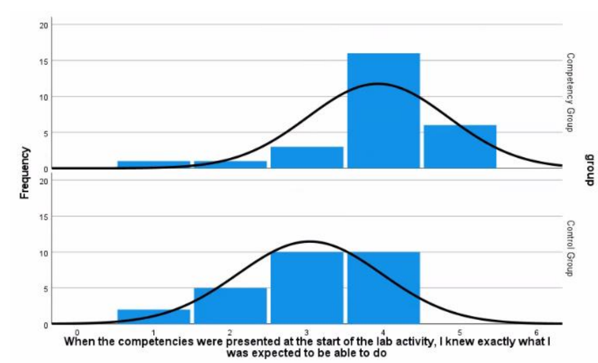

Figure 4: Frequency and normal distribution for question 3

Qualitative Data Analysis

Analysis was performed on the open-ended question following presumption-focused coding (Ado 2019). In the analysis, data relevant to this study include specific terms listed in the statements given to each group. These terms are subnetting, network, IP addresses, DNS and DHCP servers, wireless security, passwords, SSID, MAC filtering, and encryption. Coding searched for key terms and how the participant described applying the processes that included those key terms in the activity. The application of subnetting, the configuration of either or both a DNS and DHCP server, securing of a wireless network, and configuration of network devices were specifically searched. These terms are seen in the CompTIA objectives, and the frequency of their use was used to determine the participant's confidence level with their knowledge, skills, and abilities for the topics. An automated word-frequency analysis was performed looking for the top 20 words appearing in the responses written by each group. Comparing the word-usage results showed that in each instance the frequency was higher in the competency group than it was seen in the control group. The top word in both groups was network, referenced 58 times within 24 responses from competency group and 54 references in 22 control group responses. Configure, representing a skill, produced 54 references from 24 competency group responses and 44 references within 19 control group responses. Appendix E shows the word occurrences for the competency-based group, and appendix F shows word occurrences for the control group. A majority of the students used many of the key words in their responses, and a few included the job role. One student wrote "As a junior network engineer, I have the skills of troubleshooting, configuring IP addressing, and connecting and securing wired and wireless networks. Using all of these skills I will be able to provide adequate services on configuring networks, including DHCP and DNS servers." These results indicated that the competency group used technical terms at a higher rate than the control group, and within a higher number of student responses. This is evidence that the competency group demonstrates a higher level of proficiency and confidence with regards to their knowledge, skills, and abilities.

5. CONCLUSION

Competency-based statements provide students with a better understanding of what they need to know and be able to do. This study demonstrates their effectiveness in assessing students' knowledge, skills, and abilities of students through performance assessments, as well as measuring their opinions and attitudes through written responses. Statically significant evidence from the study showed increases in the three data points. First, the overall average score on the Packet Tracer assessment was higher for the competency group than for the control group. Second, the students in the competency-based group rated themselves higher on the Likert scale questions than the control group. And third, the competency group displayed higher skills and proficiency when writing about their abilities, as seen in the word-frequency analysis. These gains in knowledge, skills, and abilities help produce individuals better prepared for the workforce. While educators may need to invest time into updating current objectives or writing such statements, the results show that using competency-based statements positively affects students and employers.

6. FUTURE RESEARCH

The sample size was relatively small with 54 students, which can be a limitation and influence the results. All students completed the same pre-requisites; however, those grades were not evaluated for this study. Student prior knowledge can influence performance, as well as the control group having a class time later in the evening. Future studies will be implemented with a larger population to measure the effectiveness of competency-based statements on a larger scale and a longer time period. In addition, groups will be flipped with the competency group having the later time. Conducting the study with a similar course at other institutions would provide valuable data. These future studies could also evaluate the effectiveness of providing students with competency-based statements before the learning process, then administer an assessment afterwards. A future longitudinal analysis study could be designed to measure student opinions on competency-based education after a year of employment. In future studies, the word 'or' will be replaced with the word 'nor' on the Likert scale for clarity.

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APPENDIX A

40-point checklist for the Packet Tracer assessment

Group: Competency Objectives

Total score: _____ / 40

	Yes	No
1. Applied a private class C network:	☐	☐
2. Borrowed 2 bits for subnetting:	☐	☐
3. Configured acceptable static IP address on Internet port on WAP:	☐	☐
4. Configured correct subnet mask on Internet port on WAP:	☐	☐
5. Configured correct default gateway on Internet port on WAP:	☐	☐
6. Configured correct DNS address on Internet port on WAP:	☐	☐
7. Configured correct static IP address on local port on WAP:	☐	☐
8. Configured correct subnet mask on local port on WAP:	☐	☐
9. Configured correct DNS address on local port on WAP:	☐	☐
10. Configured a DHCP pool on the wireless access point:	☐	☐
11. Set the maximum number of users to less than 50:	☐	☐
12. Configured the SSID for a WLAN:	☐	☐
13. All other Wireless LANs are off:	☐	☐
14. Turned off broadcasting of the SSID:	☐	☐
15. Configured WPA2 Personal security:	☐	☐
16. WPA2 password meets complexity requirements:	☐	☐
17. All Guest wireless networks are disabled:	☐	☐
18. Configured a wireless mac address filter for the PC:	☐	☐
19. Configured a wireless mac address filter for the laptop:	☐	☐
20. Configured a wireless mac address filter for the smartphone:	☐	☐
21. Changed the admin password on the WAP:	☐	☐
22. Remote management of the WAP is disabled:	☐	☐
23. Configured acceptable IP settings on www.sports.com:	☐	☐
24. Configured acceptable IP settings on www.lacrosse.com:	☐	☐
25. Configured acceptable IP settings on www.basketball.com:	☐	☐
26. Configured acceptable IP settings on www.football.com:	☐	☐
27. Configured acceptable IP settings on DNS server:	☐	☐
28. Configured correct A record for sports.com om the DNS server:	☐	☐
29. Configured correct A record for lacrosse.com om the DNS server:	☐	☐
30. Configured correct A record for basketball.com om the DNS server:	☐	☐
31. Configured correct A record for football.com om the DNS server:	☐	☐
32. PC is a DHCP client:	☐	☐
33. PC is configured properly for wireless connection to the WAP:	☐	☐
34. Tablet is a DHCP client:	☐	☐
35. Tablet is configured properly for wireless connection to the WAP:	☐	☐

36. Smartphone is a DHCP client:	☐	☐
37. Smartphone is configured properly for wireless connection to the WAP:	☐	☐
38. R1 port to LAN with web servers is correctly configured:	☐	☐
39. R1 port to LAN with DNS server is correctly configured:	☐	☐
40. R1 port to WLAN is correctly configured:	☐	☐

APPENDIX B

Objectives and Questions given to the control group

Lab Activity: Use the topology provided in Packet Tracer to configure the network so it fully functions, including the wireless network, the DNS server, the DHCP server on the wireless access point, and the web servers. The html files are already configured on each of the four webservers. Use a private class C network. All needed devices are provided in the topology.

Objectives:

1. Apply subnetting to a network scenario
2. Configure network devices with IP addresses
3. Configure DNS services
4. Configure a wireless access point with appropriate standards and technologies
5. Configure DHCP services
6. Apply network hardening techniques for wireless security

Questions:

1. Once you have completed the lab activity, answer the following questions by circling your selection.

	Strongly Disagree	Disagree	Neither Agree or Disagree	Agree	Strongly Agree
When the objectives were presented at the start of the lab activity, I knew exactly what I was expected to be able to do	1	2	3	4	5
When I was completing the lab activity, I felt that the objectives were fully assessed	1	2	3	4	5
After completing the lab activity, I feel that I am prepared to complete the same skills with a physical network	1	2	3	4	5

2. You are applying for a job as a junior network engineer with a local company that provides IT services. On the application you are asked to explain what skills you have when it comes to configuring and securing a wireless network and connecting to a wired network, and configuration of both DHCP and DNS servers. Provide a written statement to the question in the space below.

APPENDIX C

Competencies and Questions given to the competency group

Lab Activity: Use the topology provided in Packet Tracer to configure the network so it fully functions, including the wireless network, the DNS server, the DHCP server on the wireless access point, and the web servers. The html files are already configured on each of the four webservers. Use a private class C network. All needed devices are provided in the topology.

Competencies:

In this lab activity you will be performing the following tasks in a Packet Tracer network demonstrating skills required by a Network Operations Specialist.

Subnet a class C private network address to meet the requirements for the full topology, (number of networks and hosts needed), and configure all devices with appropriate addressing.

Configure the wireless access point as a DHCP server for the wireless clients and connect the access point to the local area network (LAN).

Apply sufficient wireless protection that includes SSID configuration, non-broadcasting, MAC address filtering, encryption, and password configuration.

Configure the DNS server for name resolution for the existing webservers on the network.

Verify full network connectivity for all devices.

Questions

1. Once you have completed the lab activity, answer the following questions by circling your selection.

	Strongly Disagree	Disagree	Neither Agree or Disagree	Agree	Strongly Agree
When the competencies were presented at the start of the lab activity, I knew exactly what I was expected to be able to do	1	2	3	4	5
When I was completing the lab activity, I felt that the competencies were fully assessed	1	2	3	4	5
After completing the lab activity, I feel that I am prepared to complete the same skills with a physical network	1	2	3	4	5

2. You are applying for a job as a junior network engineer with a local company that provides IT services. On the application you are asked to explain what skills you have when it comes to configuring and securing a wireless network and connecting to a wired network, and configuration of both DHCP and DNS servers. Provide a written statement to the question in the space below.

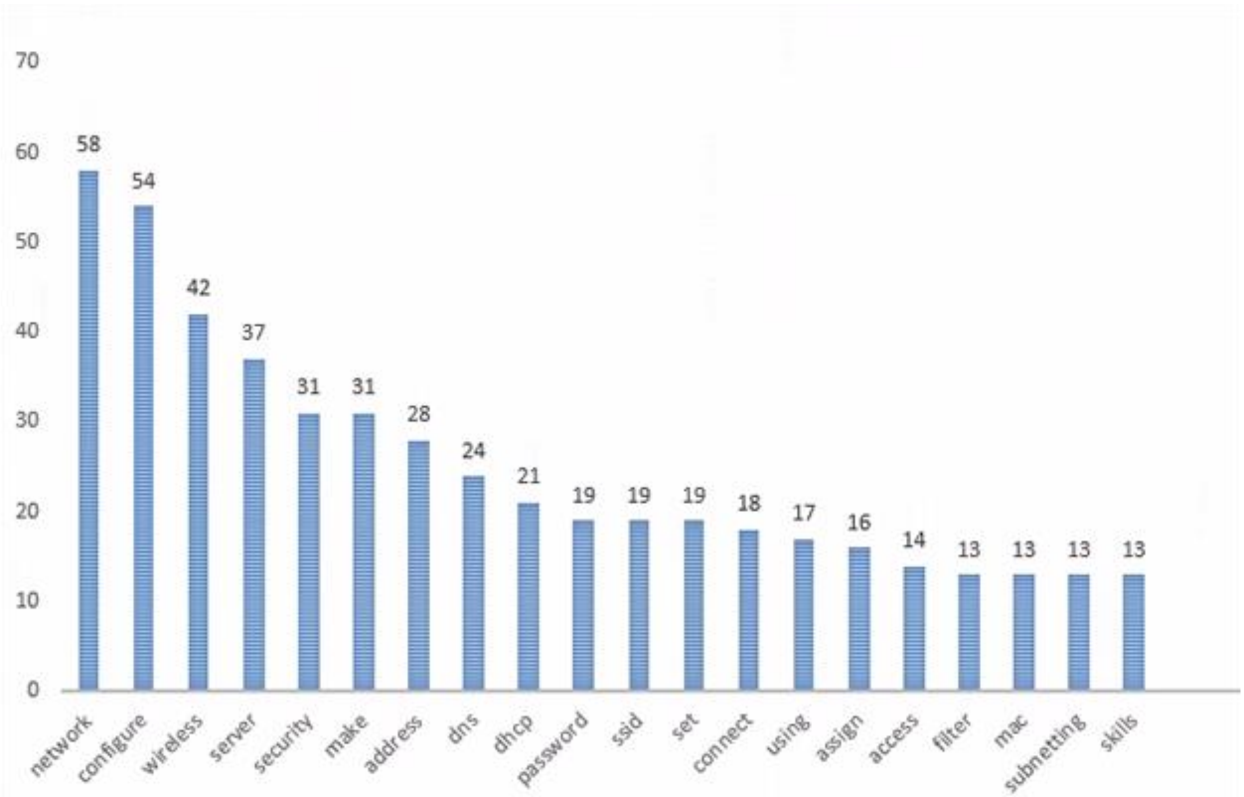
APPENDIX D

Likert scale calculations of the mean, median, and standard deviation for both groups

	Mean	Median	Standard Deviation
Competency group: *When the competencies were presented at the start of the lab activity, I knew exactly what I was expected to be able to do*	3.93	4	.917
Control group: *When the objectives were presented at the start of the lab activity, I knew exactly what I was expected to be able to do*	3.04	3	.940
Competency group: *When I was completing the lab activity, I felt that the competencies were fully assessed*	3.89	4	.892
Control group: *When I was completing the lab activity, I felt that the objectives were fully assessed*	3.07	3	1.174
Competency group: *After completing the lab activity, I feel that I am prepared to complete the same skills with a physical network*	3.33	3	.920
Control group: *After completing the lab activity, I feel that I am prepared to complete the same skills with a physical network*	2.59	3	1.047

APPENDIX E

Word occurrence data for the competency group



APPENDIX F

Word occurrence data for the control group