INFORMATION SYSTEMS EDUCATION JOURNAL

Volume 20, No. 1
February 2022
ISSN: 1545-679X

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ISEDJ is published online (https://isedj.org). Our sister publication, the Proceedings of EDSIGCON (https://proc.iscap.info) features all papers, panels, workshops, and presentations from the conference.

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INFORMATION SYSTEMS EDUCATION JOURNAL

Editors

Implementing Service-Learning in an IT Strategy Course

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Abstract

Students studying technical fields like IS/IT (Information Systems/Information Technology) face the challenge of showing potential employers that they have done work for real clients, not just course projects that are never used. At the same time, instructors face the challenge of actively engaging students in learning course content and understanding how to apply course content in different situations. Previous work shows that service-learning can be a valuable tool to improve student engagement while offering an opportunity for a real-world learning experience. However, the existing literature provides examples of using service-learning in various IS/IT courses but with little discussion of service-learning in IS/IT strategy courses. This work discusses implementing a service-learning project with a local non-profit organization in an IS/IT strategy class. Details of the design and implementation of the service-learning project and assessment from the student, instructor, and client perspectives are provided.

Keywords: Service-learning, IT Strategy, Pedagogy

1. INTRODUCTION

As students move through a program of study, different types of course activities and assignments are needed as students advance to upper-level courses. From the view of Bloom's taxonomy, students need to progress from remembering and understanding ideas to analyzing and connecting ideas and ultimately creating new work (Armstrong, n.d.).

A different way to view the process of IS/IT education is that individuals enter as students and leave as workforce ready IT professionals. The concept of engaged learning argues that during a course of study, students should evolve from being given knowledge to a state where they can actively discover new knowledge (Hodge, Baxter Magolda, & Haynes, 2009).

A common way of achieving this in IS/IT courses is active learning. While active learning can be done individually, group projects increase the size and complexity of the problems that students can be asked to solve. Working in groups is also a better match for what students will experience once they become working IT professionals. However, group projects introduce new challenges, including communication, participation, and accountability (Bakir, Humpherys, & Dana, 2020).

While many techniques can be used to improve the operation of student teams, an additional challenge of course projects can be the artificial nature of the project. Class projects rarely produce something that is used once the course is over. Service-learning, where a course project develops a solution to a problem faced by a community partner, offers a way to address this concern.

Implementing service-learning in an IS/IT course presents some challenges, but previous work has documented many successful examples and suggested methodologies (Lee, 2012; Leidig &

Lange, 2012; Wilcox & Zigurs, 2003). Several of the documented examples involve system analysis and design. However, the use of service-learning in an IS/IT strategy course, where the focus is on the organizational strategy and decision making efforts that occur before detailed system analysis and design, is scarce. This work documents how a service-learning project was implemented in an IS/IT strategy course, along with an assessment of the project from the perspective of the students, instructor, and community partner.

2. BACKGROUND

Service-learning is a pedagogy that combines learning with community service. Service-learning is one of the high impact practices that "have been widely tested and have been shown to be beneficial for college students from many backgrounds" (Kuh, 2008, p. 9).

In addition to the concept of learning by doing, service-learning adds the concepts of working on a real-world project and providing a civic service to the local community (Heffernan, 2011). In addition, as Zlotkowski discusses, service-learning can help "students develop on a variety of levels – technical, interpersonal, and ethical (Zlotkowski, 1996, p. 15)."

Many articles review the observed benefits of service-learning in general and in the IS/IT curriculum. Service-learning is found to improve students' engagement in learning and understanding of course content and allow students to demonstrate their experience (Wei, Siow, & Burley, 2007). Wei also notes, "that service-learning is well established in fields with a strong human component," which aligns well with Agile methodologies and topics like data analytics that require more human interaction from IT professionals. Service-learning can also be more "comprehensible to students than simple passive learning in the classroom (Tan & Phillips, 2005, p.58)."

Other observed benefits of service-learning include improved learning, improved communication skills, and a better understanding of the issues their community partners were working to solve (Preiser-Houy and Navarete, 2006). Service-learning also provides reciprocal benefits. By interacting with a community partner, students enhance communication and collaboration skills.

Saulnier (2005) identifies service-learning as a source of "significant learning" where students apply their knowledge, explore careers, develop civic literacy, and develop occupational skills. Several key characteristics of service-learning courses are identified. These include time for reflection, effort to foster the development of intangibles like empathy, a reciprocal relationship with the service-learning partner, work that has value to both the student and the partner, and work dictated by the needs of the community.

A systematic method for service-learning projects was proposed by Wilcox and Zigurs (2003). In this method, the instructor identifies and initiates a project before the start of the class. Students then use an interactive process to complete the project. An essential part of the service-learning project is communication between students, instructors, and the client. Wei et al. (2007) provide a helpful discussion on communication and information flows.

The literature contains many examples discussing the use of service-learning in a variety of IS/IT courses. Petkova (2017) provides a valuable overview and discussion of theoretical models. Leidig and Lange (2012) offer a valuable retrospective from a capstone course that does service-learning projects for non-profit organizations. Among the lessons learned are the work needed to build relationships and find projects, the need to prepare students to work with the clients, the demands on the instructor's time to manage the projects and student teams, and details of working with non-profit organizations.

A school's community engagement office can be a valuable source of information and support for service-learning efforts. Discussions with the university's service-learning coordinator identified two main requirements for service-learning projects. First, they must provide value to both the class and the partner, as discussed in much of the literature on service-learning. Secondly, the projects must be sustainable – they need to continue to deliver value once the class is over. Sustainability is a significant concern for IT projects since troubleshooting, enhancements, training, and other ongoing support are needed to ensure that technology continues to provide value. Concerns about support get little discussion in the literature.

3. PLANNING

Implementing service-learning in an IS/IT strategy course requires an understanding of the goals and learning objectives of both service-

learning and IT strategy education, so that course activities and assignments achieve both sets of objectives.

IS/IT organizations are always part of a larger organization and provide a service to the larger organization. A critical factor in successfully serving the larger organization is understanding the parent organization's goals and the plans and activities undertaken to achieve these goals. IS/IT strategy is the effort to ensure that an organization's use of technology is aligned with the parent organization's goals, plans, and activities. The IS 2020 model curriculum express this as "implementing and using organizational information systems to achieve strategic organizational goals and objective." (Leidig & Salmela, 2021, p. 58)

The IS 2020 curriculum documents an IS Management & Strategy competency area that includes the capability to develop, maintain, and consistently improve the systems to deliver the information necessary for an organization." (Leidig & Salmela, 2021, p. 58).

The literature on the use of service-learning in the IS/IT curriculum provides examples from various courses, but these do not include the use of service-learning in an IT strategy course. However, examples from system analysis and design and capstone courses provide some ideas that can be applied to an IS/IT strategy course.

The IT strategy course discussed in this work is an upper-level course that all students working towards a bachelors degree in Information Technology or Health Information Technology are required to complete in their junior or senior year. Prior to this course, students will have completed courses covering several technical topics along with a project management/systems analysis course to understand how to design and implement a solution to a specific problem. The IT strategy course covers many topics focused on how an IT organization must design, implement, and support the IT infrastructure needed for a company or organization to achieve its strategic goals

A service-learning project to help an organization make a strategic decision about their technology infrastructure would clearly connect to the content of the IT strategy course. Additionally, while the project should consider the resources and support needed to implement the decision, it allows a clear delineation between the decision and any following activity, addressing concerns about the sustainability of the work.

This project concept also allows the instructor to work with non-profit organizations to develop potential project ideas. A good project idea will be one where the organization has a clear idea of what they are trying to achieve and a clear idea of what resources, including time and money, are available.

4. IMPLEMENTATION

After considering the overall learning objectives of the course and the goals for using service-learning in the course, a problem-based service-learning approach was selected. In this approach, "students work with community members to understand a particular community problem or need (Heffernan, 2011, p. 3).

Several sources provide helpful guidance on implementing service-learning projects in IS/IT courses (Wilcox & Zigurs, 2003; Lee, 2012; Wei, Snow, & Burley, 2007). Following the suggestions of Lee (2012), the service-learning activities were designed to include both written reflection and discussion reflection. The course also had a weekly journaling activity that provided students an opportunity for additional reflection. For this activity, students were asked to write at least one paragraph with a prompt to "Discuss what you learned, found interesting, and/or didn't understand. The discussion should not be a summary of the class meeting, but should be your reaction to what we did in class." The weekly journal assignment also required students to pose two questions for discussion in class.

Activities for the service-learning project involved three main areas. First, the students worked to develop a clear understanding of the problem. To understand the problem, students needed to learn about the client, the context of the problem, and constraints on potential solutions. Then students worked to identify possible solutions. Finally, students assessed the costs and potential benefits of different solutions and prepared a business case for the client. In total, the assignments for the service-learning project were 10% of the total course grade.

The problem-based approach to service-learning meant that service-learning project activities were blended with other course activities. This approach allowed students to learn about IT strategy concepts and tools through class discussions, case studies, and text readings (Austin, Nolan & O'Donnell., 2016) and then apply these to service-learning project activities.

The course used several team-based activities, including student-constructed learning and debates, so work on the service-learning project was also designed to be team-based. Students maintained the same teams throughout the course.

For the session of the course described in this paper, the client for the service-learning project was a local senior citizens center. The project involved reviewing the central technology system used to run the center's activities. The instructor had previously worked with the center to migrate their e-mail system from a local internet service provider (ISP) to Microsoft Office 365. This previous experience gave the instructor confidence that this client and the specific project would be an interesting way for students to get real-world experience with the concepts introduced in the course.

Before the start of the semester, the instructor developed a clear understanding of the client's project and needs. The client was looking to answer three related questions:

- What alternatives existed to replace their current software?
- Should several paper-based processes be automated (using either their existing system or a new system)?
- What would be the costs and benefits of moving to a new system?

Competition for the center's limited resources, both financial and staff time, meant that the center could not commit to acting on any recommendations developed by the students. Still, the center had been considering these questions for an extended period and was eager to have help in developing a better understanding of the situation.

Once a project had been identified, the instructor met with the campus community engagement office to gain their assistance. In addition to providing valuable references on service-learning, the office helped the instructor gain a service-learning designation for the course. This designation meant that any student who completed the course would satisfy the service-learning portion of the university's general education requirements.

Initial discussions of the service-learning project took place on the first day of class. These made students aware of the client, project details, and how they were integrated into the course structure.

The next project activity took place during the fifth week of the class. The goal was to prepare students for an initial meeting with the client the following week. The instructor provided a brief introduction to the client and the project. Small group discussions were used to have students generate ideas about the value that a senior center provides to the local community.

During this class, the student teams were also introduced to their specific area of responsibility for understanding the client's requirements. Students were split into six groups of four. The focus areas included both functionality of the current system and the paper-based processes that would potentially be automated. The specific areas were:

1. Current system functionality from the user's (i.e., the senior citizen's) perspective.
2. Current system functionality from the staff/administrative perspective
3. Donor management functionality.
4. Transportation (potential functionality)
5. Meals-on-Wheels (potential functionality)
6. Adult Daycare (potential functionality).

Student teams completed an assignment to generate initial requirement ideas for their designated area and notes on the users associated with the specific activity assigned to the team.

The following week the team met with the senior center's executive director and administrative director. The executive director provided an overview of the center's mission and basic information about the center. Having students realize that 40% of the center's paid staff was present in the classroom provided a good idea of the center's limited resources.

The senior center staff members and the instructor then met with each student team to provide detailed information about the team's assigned area and answer questions. After the class, teams worked to document requirements for their area. Requirements were expressed as Agile user stories.

Following this class meeting, students also completed a research assignment. This assignment was an individual rather than a team assignment and used an online group discussion. Students were prompted to do online research in two areas:

- Potential software solutions to support a senior center.

- Research on other senior centers and how they use technology.

Students were required to make two posts discussing what they had found in each area and offering additional user stories. The instructor seeded the discussion by providing two example posts. Teams were expected to review the research discussion and add relevant user stories to the team's documented requirements.

Three weeks after the initial client visit (week 8), teams submitted a condensed, prioritized set of user stories to document the requirements for their assigned area. User stories were prioritized using the MoSCoW method (MoSCoW, n.d.), which was covered in class. The submitted user stories were posted to a content page in the course site in the university's LMS (Learning Management System) and were also discussed in class.

Following an assigned reading and class discussion of a sample request for proposals (RFP), students used the shared user stories to write an RFP for the project. This work was an individual assignment where the students provided background on the senior center, discussed the current state of the technology used to manage the center, and requested proposals to update this technology.

The instructor was able to arrange for a vendor to demonstrate one of the potential solutions. To prepare for this, each group identified a scenario relevant to their assigned area that they would like to see presented. In addition to letting students see one potential solution in action, the vendor demo also introduced students to the marketing and sales activities that are part of the technology selection process.

After the vendor demo, students completed a reflection on the demo. In their reflections, students posed several questions. The majority of the questions were not about the product but rather about the sales process, offering an opportunity for an impromptu class discussion about organizational purchasing and decision-making processes that can significantly impact the evolution of an organization's technology infrastructure.

After the vendor demo, the remaining project activities focused on preparing to meet with the client and make a recommendation. This work was broken down into three parts:

- Costs, especially non-financial costs.
- Potential benefits and how they might be measured.
- Non-functional requirements.

Students completed an assignment where they identified and discussed three items from each of these categories. To generate a broader range of ideas, this assignment was an individual rather than a team assignment.

The project concluded during the last week of the class with presentations to the client. Each of the six teams was asked to prepare a presentation discussing what the team thought were the two most essential items from each of the three categories (cost, benefit, and non-functional requirement). The teams presented two of these items, with the condition that they could not repeat an item that another team had already discussed. An additional constraint was that the client had to hear about items from all three categories. In addition to presenting, teams were also expected to respond to questions from the client.

At this point, the project was complete, although what action the senior center would take was unknown. The senior center staff enjoyed the presentations and felt that the information provided by the students would be very useful in conferring with the center's board of directors to decide how to proceed.

5. ASSESSMENT

The service-learning experience was assessed from several perspectives. Students were asked to complete an end-of-semester survey about course activities, including the service-learning project. The weekly student journals were also reviewed to identify observations and discussions about the project. The instructor also completed a project retrospective with the client and a personal retrospective on all aspects of the course.

Of the twenty-four (24) students enrolled in the course, sixteen (16) completed the survey (67 % response rate). The survey included Likert scale questions in several areas, including how the service-learning project aided learning, the value of the project, the effort required for the project, and whether students enjoyed the project. Full details of the questions and responses can be found in Appendix 1.

The first four questions used a 5-point Likert scale asking students to agree or disagree with the statements:

- I found the senior center project helpful in learning how IT organizations develop requests for changes to technology services.
- I found the senior center project helpful in learning how IT organizations work to document the costs of proposed changes to technology services.
- I found the senior center project helpful in learning how IT organizations work to document the value of proposed changes to technology services.
- I found the senior center project helpful in seeing how vendors demonstrate their technology solutions.

For all four questions, the average response was at least 4.4. Except for one neutral response to the second question, all responses agreed or strongly agreed. The question about the vendor demonstration received the highest average response at 4.8.

The next set of questions covered the value of the project to the student, both for their learning and the value of helping the community:

- I saw the value of the senior center project for learning the processes an IT organization might use to respond to requests for changes to technology services.
- I liked that the senior center project provided an opportunity to help a local non-profit organization.
- I feel that my participation in the senior center project will improve the center's use of technology.

For all questions, the average response was over 4.0. One student was neutral on the value question, with the rest agreeing or strongly agreeing. The students clearly appreciated the opportunity to help the local community, with an average response of 4.7 for the second question. The last question had a lower response with three neutral responses, possibly reflecting the fact that the center was still considering the students' recommendations when students completed the survey.

The final set of questions on the survey used a 7-point Likert scale to learn about the effort required for the project, student enjoyment of the project, and whether they would like to do service-learning projects in future courses:

- How effortful was it for you to participate in the senior center project?
- How much did the senior center project help you understand how IT professionals strategically manage technology services?
- How much did you enjoy the senior center project?
- How much would you like to do similar activities that engage you with proposed changes to technology services in a real organization in a future course?

The average response for the effort question was 5.1, with responses ranging from 3 – 6. This response was similar to responses seen in surveys about other activities in the course. For the second question, the average response was 5.9, with all responses in the 5 – 7 range showing clear value in helping students learn about IT strategy. The average response for whether students liked the project was 6.4, with the majority (56 %) of students selecting 7. For the final question about doing similar activities in other courses, the average response was 6.7, with a large majority (75 %) selecting 7.

Overall, the survey responses show that students found that the service-learning project helped them learn course concepts and did not feel that the project required any more effort than other activities in the course. In addition, students clearly appreciated the opportunity to help an organization in the local community. And the students greatly enjoyed the project, which always makes a class more pleasant.

The client retrospective was part of a follow up discussion with the client. The conversation collected feedback on the work done by the students and included a discussion of the client's future plans and how the instructor could continue to assist the senior center. The retrospective showed that the senior center director and staff saw significant value from the work done by the students. Shortly after the project started, the center had an issue with its current system and found it challenging to contact the vendor for support. The students' work throughout the project provided reassurance in knowing that there were several good options for replacing the current system.

Additionally, the senior center staff appreciated the knowledge that the students' shared in the final presentations. While most of the costs and potential benefits discussed in the presentations were not new to the senior center staff, they did appreciate the discussion of measuring the benefits of a new system. The concept of non-functional requirements was new to the center staff. They greatly appreciated the education they received from the students on topics including

support, security, availability, and user experience.

The center staff also appreciated other knowledge shared by the students in the discussions after the presentations. All of the potential replacement systems were cloud-based software-as-a-service (SaaS) solutions. Earlier in the semester, the class had engaged in a debate about the adoption of cloud and shared information about the pros and cons of cloud computing with the senior center staff.

From the instructor's perspective, the service-learning project was a success. The quality of work submitted by students for the service-learning project assignments met or exceeded expectations. It showed that students could apply what they were learning in the course in a new situation.

There were some initial concerns that a group of mostly traditionally aged college students would have trouble understanding what the senior center did and how it provided value to the community. This concern was not the case, and many students shared stories about how grandparents or other relatives were or could benefit from similar services.

The students' interest and engagement in the project were a pleasant surprise. Students regularly discussed the project in their weekly journals and made connections between new course content and the ongoing project activities. Students were also invested in the senior center, regularly asking when the center staff would be back to meet with the class. At the end of the course, several students asked to be updated on what the senior center decided to do and were pleased to hear that the center implemented the solution that had been demonstrated to the class.

Adding a service-learning project to the class did require additional work. Still, by carefully connecting the project activities to content and other activities in the class, there was little extra work required to teach the class. Building a relationship with the senior center and developing the initial project idea did take some time. However, this work counts as part of the service work faculty are expected to perform, so it has value outside the course. In addition, this project received some extra attention from colleagues and the school administration because of the engagement with the local community and the novelty of service-learning in IT relative to service-learning in other disciplines at the university.

6. CONCLUSIONS AND FUTURE PLANS

This project shows that service-learning can be successfully incorporated into an IS/IT strategy course. The project met the goals of providing sustainable value to the client while also providing support for student learning in the course.

Planning for other potential non-profit client projects has shown that the approach discussed in this work can be applied to other projects that would be appropriate for this class. There have been some challenges in continuing to use a service-learning project in the course. The main challenge is that the IS/IT strategy course is now taught in an online format that does not allow any synchronous class meetings, making it hard to have students engage with a client. As a consequence of recent experiences with synchronous online classes in response to the COVID-19 pandemic, there is some potential that this constraint may be relaxed.

The impact of COVID on non-profit organizations also presents another challenge. Non-profits have been impacted in several ways, from stress on fundraising to significantly increased demand for their services. Technology has the potential to help with all of these but is likely to be a lower priority while non-profit leaders and staff respond to more immediate concerns.

Overall, while this effort required significant time to develop a relationship with the client and plan the project, the rewards of the benefits to the client, the value to student learning, and the level of engagement students showed made this a very worthwhile and rewarding effort.

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Editor's Note:

This paper was selected for inclusion in the journal as an EDSIGCON 2021 Distinguished Paper. The acceptance rate is typically 7% for this category of paper based on blind reviews from six or more peers including three or more former best papers authors who did not submit a paper in 2021.

Appendix 1

Survey questions and response data

Question	Likert Scale Max	Average	Standard Deviation
I found the Senior Center project helpful in learning how IT organizations develop requests for changes to technology services.	5	4.63	0.48
I found the Senior Center project helpful in learning how IT organizations work to document the costs of proposed changes to technology services.	5	4.44	0.61
I found the Senior Center project helpful in learning how IT organizations work to document the value of proposed changes to technology services.	5	4.63	0.48
I found the Senior Center project helpful in seeing how vendors demonstrate their technology solutions.	5	4.81	0.39
I saw the value of the Senior Center project for learning the processes an IT organization might use to respond to requests for changes to technology services	5	4.44	0.61
I liked that the Senior Center project provided an opportunity to help a local non-profit organization.	5	4.69	0.46
I feel that my participation in the Senior Center scheduling project will improve the center's use of technology.	5	4.19	0.63
How effortful was it for you to participate in the Senior Center project?	7	5.06	0.66
How much did the Senior Center project help you understand how IT professionals strategically manage technology services?	7	5.94	0.66
How much did you enjoy the Senior Center project?	7	6.38	0.78
How much would you like to do similar activities that engage you with proposed changes to technology services in a real organization in a future class?	7	6.69	0.58

Using Machine Learning Sentiment Analysis to Evaluate Learning Impact

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Abstract

Can sentiment analysis be used in an educational context to help teachers and researchers evaluate students' learning experiences? Are sentiment analyzing algorithms accurate enough to replace multiple human raters in educational research? A dataset of 333 students evaluating a learning experience was acquired with positive, negative, and neutral sentiments. Nine machine learning algorithms were used in five experimental configurations. Two non-learning algorithms were used in two experimental configurations. Each experiment compared the results of the algorithm's classification of sentiment (positive, neutral, or negative) with the judgment of sentiment by three human raters. When excluding neutral sentiment, 98% accuracy was achieved using naive Bayes. We demonstrate that current algorithms do not yet accurately classify neutral sentiments in an educational context. An algorithm using a word-sentiment association strategy was able to achieve 87% accuracy and did not require pretraining the model, which increases generalizability and applicability of the model. More educational datasets with sentiment are needed to improve sentiment analysis algorithms.

Keywords: sentiment analysis, educational research, machine learning, learner experience.

1. INTRODUCTION

Sentiment analysis is the identification of attitude, opinions, and emotions in a statement (Tang et al., 2015). Pang and Lee (2004) used sentiment analysis to classify opinions of movies in statements written online by movie viewers. Other uses of sentiment analysis have been to understand the opinions of customers regarding products, sentiments of airline travelers expressing their opinions online, and identifying positive and negative attitudes in tweets. Sentiment analysis has many subfields that solve personality recognition, sarcasm detection, metaphor understanding, aspect extraction, and polarity detection (Cambria et al., 2017). Sentiment analysis has been successfully used in marketing, product development, politics, etc.
Machine learning (ML) is one approach to sentiment analysis that involves a pretraining phase to learn from labeled data. Examples of ML algorithms include naive Bayes, support vector machines, logistic regressions, random forests, etc. Pang and Lee achieved 86% classification of sentiment accuracy in movie reviews with naive Bayes and support vector machine. Neural networks have been applied to sentiment analysis and resolve many of the lower-level NLP tasks, such as tokenization, part of speech recognition, etc. (Zhang et al., 2018).

In contrast to ML, rule-based models are expert systems that use a set of rules to achieve a conclusion or classification (Grosan & Abraham, 2011). Valence Aware Dictionary and Sentiment Reasoner (VADER) is a lexicon- and rule-based sentiment analysis model used to detect sentiments in social media posts from word-emotion associations. VADER is available in the Natural Language Toolkit package (NLTK;

http://nltk.org). NRC Word-Emotion Association Lexicon (EmoLex) uses a list of English emotion lexicon labeled by eight basic emotions (anger, fear, anticipation, trust, surprise, sadness, joy, and disgust) and two sentiments, negative and positive (Saif, 2021). The labeling was originally performed by crowdsourcing.

Similar to the needs of organizations to understand the opinions of their patrons, educators need to understand the opinions and sentiments of their learners. Sentiment analysis may be able to help in an educational context.

2. LITERATURE REVIEW

Rani and Kumar (2017) propose using natural language processing and ML as tools to help university administrators process student feedback. They used NCR EmoLex to classify emotions and infer students' satisfaction and dissatisfaction with Coursera courses (coursera.org). They observed that class performance (course grade) highly correlates with student course survey results.

Munezero et al. (2013) used sentiment analysis to extract emotions from learning diaries, which are written reflections regarding students' learning experiences. Munezero et al. propose using sentiment analysis to help instructors identify emotions and track changes over time, which can be a labor-intensive task without computational aid.

One avenue of research is the investigation of which sentiment algorithms provide the highest classification accuracies in an educational context: Do the sentiment algorithms achieve the same results as human raters? Can one be a substitute for the other?

One challenge is that sentiment analysis via machine learning requires large quantities of data (Cambria et al., 2017). Existing sentiment analysis algorithms have been trained from data in non-educational domains, often from numerous online product reviews, Twitter feeds, or political forums (Yue et al., 2019). Educational research does not have the large datasets necessary to train machine learning. Different domain data means potentially different patterns and lexicons. Therefore, can existing algorithms trained in non-educational domains perform as well as or better than an ML algorithm trained only on smaller educational datasets?

Transfer learning may help resolve these challenges. Transfer learning takes an algorithm designed in one domain on an unrelated, large dataset and applies it to another domain. The algorithm learns quickly to adapt as the researcher feeds new, smaller but domain-relevant data into the pretrained algorithm for model refinement (Yang et al., 2020; Zhuang et al., 2021). The pretrained algorithm may have been trained on millions of data points and the smaller dataset only on a few hundred. The premise is that the pretrained algorithm may share many of the foundational NLP learning that still apply to the smaller dataset. The smaller dataset offers the algorithm-specific context in which to learn new patterns.

Research Questions— We propose that sentiment analysis be used to investigate the learner's experience of a learning treatment. Instead of using multiple human raters to evaluate the student's opinion about the learning experience, a sentiment analysis algorithm could be used. Specifically, we investigate algorithms to identify the positive/negative sentiments in an experimental treatment on student learning in computer information system (CIS) courses. Our aim is to use algorithms to automate the identification of students' sentiments toward a taught subject from their reviews. We tested a set of machine learning algorithms to answer the following research questions:

- Can sentiment analysis be used in an educational context to possibly help instructors and researchers evaluate students' learning experiences?
- Are sentiment analyzing algorithms currently accurate enough to replace multiple human raters in educational research?
- Can other domain datasets with sentiments be used to train sentiment analysis algorithms to detect sentiments in educational datasets?

3. METHODOLOGY

Participants and Design

Graduate and undergraduate students in three CIS courses (eight sections) were taught and practiced time management as a professional development skill. Quantitative measures of grade performance were analyzed. The main finding in regard to the impact of learning time management skills on grades is reported by Humpherys and Lazrig (2021). In that study, a survey was administered regarding students' perceptions of the learning exercise with the question "Each week you were asked to preplan your study schedule and identify your deliverable. Did this activity help you improve your time management skills? Why or why not? You get points for participation, not for any predefined

answer." 180 student reviews were collected, with judgement of sentiment (positive, negative, and neutral) from three human raters. The current study uses machine learning sentiment analysis to compare the performance of algorithms to human raters.

Variables

Sentiment is the construct in question. Sentiment was derived by human raters and algorithms, then compared for *accuracy* as follows:

Human rater-derived sentiment— the sentiment assigned by three human raters regarding the participant's review of the learning experience was encoded as -1 for negative, 0 for neutral, and 1 for positive sentiment. The average of the human rater-derived sentiment is calculated and rounded to the nearest integer. *Positive* indicates a sentiment of improvement in time management, positive results, or valuable learning experience. *Neutral* indicates the participant expressed no improvement in time management or indifference to the learning experience. *Negative* expresses a decrease in time management, negative results, or dissatisfaction with the learning experience.

ML-derived sentiment— encoded as -1 for negative, 0 for neutral, and 1 for positive sentiment derived from an ML sentiment analyzing algorithm. Various algorithms are used and explained later.

Accuracy— how well the ML algorithm predicted the same sentiment score (positive, neutral, negative) as the human raters. The human rater-derived sentiment was considered to be ground truth. Accuracy is a percentage representing the number of sentiments correctly classified by the algorithm divided by the total number of sentiments (Hossin & Sulainman, 2015).

$$\text{accuracy} = \frac{TP + TN + TNu}{TP + TN + TNu + FP + FN + FNu}$$

Accuracy Term	Matching Results:	
	Algorithm	Human
TP (True Positive)	Positive	Positive
TN (True Negative)	Negative	Negative
TNu (True Neutral)	Neutral	Neutral
FP (False Positive)	Positive	Negative or Neutral
FN (False Negative)	Negative	Positive or Neutral
FNu (False Neutral)	Neutral	Positive or Negative

Table 1. Meanings of accuracy terms

Table 1 shows the definition of terms used when calculating accuracy. Each term is a count (integer). For example, if the algorithm classified a student's comment as negative sentiment but the human rater-derived sentiment was either positive or neutral for the same student's comment, the count of false negatives was incremented. This process was repeated for every data point in the datasets.

Data Collection Procedures

Five datasets were acquired or generated for use in this research (Table 2).

Dataset	Dataset Description	Sample Size
Learning Sentiment	Dataset of students' perceptions of a learning exercise in CIS courses (positive, negative, neutral) augmented with additional negative and neutral ratings of instructors/courses.	333
Learning Sentiment w/o Neutral	Learning Sentiment dataset without neutral sentiments	285
Movies	Pretrain on reviews of movies (positive and negative)	2,000
Airline	Pretrain on tweets about airline service (positive, negative, neutral)	14,640
Airline w/o Neutral	Airline dataset without the neutral sentiments	11,541

Table 2. Datasets.

Learning Sentiment dataset— The dataset has a total of 333 student reviews. 180 students reviewed a time management learning exercise in three CIS courses of which 154 reviews were positive. To increase the number of negative and neutral sentiments, 153 student reviews regarding instructors and courses were collected from rateMyProfessor.com. RateMyProfessor.com lets students write evaluations and comments about courses. In addition to the text-based comments, students select a quality score of 1–5. A quality score of 4 or 5 is labeled "awesome," 3 is considered "average," and 2 or 1 is

considered "awful." Furthermore, green, yellow, and red icons are associated with the respective quality scores/labels, which can be equated to positive, neutral, or negative sentiment respectively.

First, the ratings were filtered with the name of the university to match the original data's student population. Next, a random course was selected, but not one of the three CIS courses in the original 180 student review dataset. "Awesome" quality scores (4 and 5) were ignored, given the desire to collect more neutral and negatives comments. If the quality score was a 1, 2, or 3, a human rater read the student's comment. If the human rater agreed that the student's comment was classifiable as a quality score of 1, 2, or 3, the comment and quality score were included in the Learning Sentiment dataset. The quality score was recoded to match the sentiment score in the original dataset. A 1 or 2 quality score was recoded as negative sentiment (i.e., a -1 value in the Learning Sentiment dataset). If the quality score was 3, the sentiment was recoded as neutral (0 value).

These extra reviews were collected to more closely balance the positive and negative reviews and increase the neutral reviews in the dataset. The limitation of the extra review data is that the learning experience reviewed by the students was not just the time management exercise, as originally planned. But since the research questions are about the accuracy of the sentiment algorithms, not about the learning exercise, this limitation should not impact the validity of the sentiment accuracy results. In addition, the threat to validity by an unbalanced dataset where the ML algorithm learns to predict all data as positive sentiments is a greater threat than the limitation of adding extra reviews from different courses. The final sentiment counts in the Learning Sentiment dataset were 154 positive, 48 neutral, and 131 negative. An IRB review process authorized the analysis but did not explicitly permit the dataset to be made public.

Learning Sentiment without Neutral dataset— Neutral sentiments were removed from the Learning Sentiment dataset to compare with publicly available datasets that do not include neutral sentiment and because in past research, neutral sentiments have demonstrated difficulty to evaluate. This resulted in 154 positive and 131 negative data points. The accuracy calculation therefore removed TNu and FNu as terms.

Movie Review dataset— The Movie Review dataset is included in the Natural Language Toolkit (NLTK) package publicly available at https://github.com/nltk/nltk. The dataset was originally collected by Pang and Lee (2004) and has 2,000 reviews with 50% negative sentiment, 50% positive, and no neutral. The movie reviews were written before 2002 on www.rottentomatoes.com by 312 authors with a maximum of 20 reviews per author.

Airline Review dataset— The Airline Review dataset contains 14,640 tweets made about a US Airline in February 2015 with 2,363 classified as positive, 9,178 as negative, and 3,099 as neutral (Crowdflower, 2019). The dataset is publicly available at https://www.kaggle.com /crowdflower/twitter-airline-sentiment.

Airline Review without Neutral dataset— Neutral sentiments were removed from the Airline Review dataset to pretrain some ML models for transfer learning.

Data preprocessing— The preprocessing stage prepares the five datasets for sentiment analysis by cleaning and vectorizing the data. Cleaning the data pertains to removing irrelevant terms, names, and symbols (# and @), and converting all words into lowercase to simplify word matching procedure. In addition, some high frequency words are filtered out, such as stopwords.

A stopword is a commonly used word (such as "the", "a", "an", "in") that adds little value to classification. The NLTK corpus package used has a predefined list of stopwords stored in many different languages, and we used the English stopwords from that list.

Vectorization— We converted the cleaned text into numerical vectors to be used as features in the algorithm. A tokenizer split the text into words, or tokens (known as bag-of-words), then converted them into a feature vector based on word count or term frequency-inverse document frequency (TF-IDF), which is a statistical measure that evaluates how relevant a word is to a document in a collection of documents.

Experimental Configurations

To answer the research questions, we ran seven sets of experiments. In experiments 1–5, we used the NLTK for natural language processing and we used the scikit-learn library in Python (https://scikit-learn.org/) for the machine learning algorithms. *Local-training* means we used the Learning Sentiment data for training and testing the algorithms. Local-training gives a baseline to compare against transfer learning

using external-training models. *External-training* means the ML models are pretrained (transfer learning) using the Airline Review dataset or Movie Reviews dataset. Then, the model is tested for accuracy with the entire Learning Sentiment dataset. It is anticipated that external-training can overcome the relatively small sample size of the Learning Sentiment dataset and simulate the desired outcome of being able to replace human raters in educational research.

Experiment #1 used the Learning Sentiment dataset for both training and testing. Nine classification algorithms were used (see Appendix A). We employed a 10-fold cross-validation method to calculate the average accuracy: In each fold, the dataset was randomly shuffled and divided into training and testing subsets with the ratio 80:20, then the 10 accuracies were averaged. This process was repeated for each of the nine classification algorithms. Cross-fold validation reduces overfitting and increases generalizability.

Experiment #2 used the Learning Sentiment without Neutral dataset and repeated the procedures of Experiment #1. Since most of the false positives and false negatives in Experiment #1 were due to the misclassification of the neutral sentiments, we decided to investigate the accuracies without neutral reviews. Even human raters can display low inter-rater consistency when classifying neutral sentiments.

Experiment #3 used the Movie Review dataset to pretrain the ML model. All 285 records in the Learning Sentiment without Neutral dataset were used for testing the accuracy of the ML model, since the Movie Review dataset does not have neutral sentiments.

Experiment #4 used the Airline Review dataset for pretraining the ML model. All 333 records in the Learning Sentiment dataset were used for testing accuracy as the Airline Review dataset includes neutral sentiments.

Experiment #5 used the Airline Review without Neutral dataset for pretraining the ML model. All 285 records in the Learning Sentiment without Neutral dataset were used for testing the accuracy of the ML model. This allows for comparison to Experiment #3 regarding transfer learning.

We included two more experiments (Exp#6 and Exp#7) that used rule-based modeling rather than ML, namely VADER and EmoLex. VADER returns a composite real score value ranging between -1 and 1 for the sentiment of a given text with -1 for most negative, +1 for most positive, and around zero for neutral. We set a threshold for the neutral sentiments to be between -0.05 to +0.05. The EmoLex algorithm returned integer scores for positive and negative words in the text. We compared the two scores to determine the overall sentiment of the text. If the positive score is greater than the negative, then the final sentiment will be positive and vice versa. If both are similar or both are zero, the sentiment will be neutral.

Experiment #6 used the rule-based VADER and EmoLex models to test the accuracy of sentiment detection on the Learning Sentiment dataset. Experiment #7 used the rule-based VADER and EmoLex models to test the accuracy of sentiment detection on the Learning Sentiment without Neutral dataset.

The link to the code used in this study is available using the following link:
https://github.com/iLazrig/Sentiment-Analysis-Experiment.git

4. RESULTS

Experiment #	Highest Accuracy %	Highest Performing Algorithm
#1 Learning Sentiment	85.1	Naive Bayes, Random Forest, Logistic Regression
#2 Learning Sentiment w/o Neutral	98.3	Naive Bayes
#3 Movies pretraining	77.2	Naive Bayes & AdaBoost
#4 Airline pretraining	55.6	Naive Bayes
#5 Airline pretraining w/o Neutral	61.4	Naive Bayes
#6 Learning Sentiment	72.3	VADER
#7 Learning Sentiment w/o Neutral	86.7	VADER

Table 3. Highest accuracies and algorithms

Table 3 summarizes the highest accuracies of sentiment classification achieved in each experiment (#1–7) and the algorithm that performed the best.

Algorithm	Accuracy %				
	Local Training		External Training		
	Exp#1 Learning Sentiment	Exp#2 Learning Sentiment w/o Neutral	Exp#3 Movies	Exp#4 Airline	Exp#5 Airline w/o Neutral
Bernoulli-NB	85.1	94.0	54.4	55.6	57.9
Complement NB	85.1	98.3	77.2	52.9	57.9
Multinomial NB	82.1	98.3	77.2	54.7	61.4
K-Neighbors	47.8	57.4	43.9	48.7	61.4
Decision Tree	71.6	89.2	68.4	52.9	50.9
Random Forest	85.1	96.3	61.4	52.0	54.4
Logistic Regression	85.1	94.3	63.2	40.8	52.6
MLP	82.1	96.0	73.7	40.8	54.4
AdaBoost	73.1	93.7	77.2	42.3	56.1

Table 4. Accuracies from experiments #1–5 using sentiment ML algorithms.

The nine ML algorithms and their classification accuracies from experiments #1–5 are shown in Table 4. The highest accuracies in experiments #1–5 are as follows: The naive Bayes, random forest, and logistic regression ML algorithms had accuracies of 85% in experiment #1 and up to 98% when neutral sentiments were removed in experiment #2.

Pretraining the ML model from the Movie Review dataset and validating the accuracy on the Learning Sentiment without Neutral dataset (experiment #3) saw classification accuracies up to 77%. Pretraining the ML model using the Airline Review dataset (with and without neutrals) performed worse. External training did not improve classification algorithms over the local training.

Experiments #6 and #7 used rule-based modeling, specifically VADER and EmoLex (see Table 5). VADER achieved 72.3% accuracy in experiment #6 and 86.7% in experiment #7. EmoLex achieved 55.0% accuracy in experiment #6 and 73.8% in experiment #7. Experiment #6 used the full Learning Sentiment dataset while experiment #7 used the Learning Sentiment without Neutral dataset.

Algorithm	Accuracy % in Exp#6 Learning Sentiment	Accuracy % Exp#7 Learning Sentiment w/o Neutral
VADER	72.3	86.7
EmoLex	55.0	73.8

Table 5. Accuracy of the rule-based models for sentiment

5. DISCUSSION

Sentiment can be positive, negative, or neutral. Sentiment analysis has largely been used in product/service reviews, movie reviews, and politics. This study proposes using sentiment analyzing algorithms to evaluate sentiment in an educational context. Teachers could use sentiment analysis to quickly evaluate sentiment from student reviews after administering a learning exercise or from course evaluations. Researchers could save time and resources when evaluating an educational treatment for sentiment by replacing multiple human raters with a sentiment analyzing algorithm.

Can sentiment analysis perform accurately in an educational context? The experiment with the highest sentiment classification accuracy was

Experiment #2, which used the Learning Sentiment without Neutral dataset for both training and testing. Accuracy of predicting positive and negative sentiment reached 98% using naive Bayes. For predicting positive, negative, and neutral, the highest performing algorithms were in Experiment #1, which used the Learning Sentiment dataset for both training and testing. In Experiment #1, naive Bayes, random forest, and logistic regression produced accuracies of 85%. These results show the potential of using sentiment analysis in education.

From these results we deduce that neutral sentiment is hard to detect. The observed lower accuracies in some experimental configurations was due to misclassification of the neutral sentiments. Our recommendation is that if a teacher or researcher wishes to apply sentiment analysis to an educational context, they are currently limited to only positive and negative sentiment, not neutral, at least until the neutral-detecting algorithms improve.

Another research question is whether or not sentiment analyzing algorithms perform accurately enough to replace human raters. Here, the scenario is a researcher evaluating an educational treatment regarding the sentiment of the learner. The Learner Sentiment dataset originally used three human raters to assess sentiment. Can an algorithm be used to replace the human raters? The requirement for this proposal to succeed is that the researcher should not have to use the target dataset to train the ML model, as in Experiments #1 and #2, since doing so would defeat the purpose of performing a sentiment analysis on unlabeled data and without human involvement. Experiments #3 through #7 tested this scenario. Experiments #3, #4, and #5 used ML models pretrained from movie reviews and airline reviews. Pretraining with those datasets offered tens of thousands of records to refine a sentiment model before applying the model to a target educational dataset. However, accuracy rates were only 77%. The sentiment models trained on the Movie Review dataset and tested on the Learning Sentiment without Neutral dataset (Experiment #3) performed better than the models trained on the Airline Review dataset (Experiment #4 and #5).

We conclude that the Movie Review data is possibly closer in characteristics to the educational dataset than the Airline Review dataset. The pretrained models became domain-dependent. The Airline Review dataset entries are short tweets while the Movie Review dataset entries were longer reviews. The vocabulary distribution across the opinions is different between the two datasets. Neither dataset is sufficient to offer a viable replacement to human raters. Data domain is very important for supervised ML sentiment analysis. Because sentiment domain-specific datasets are sparse in educational research, we opine that if ML algorithms are to be improved, more educational datasets need to be collected and made publicly available, following ethical guidelines for privacy. When a model was trained on educational data, the ML algorithms performed as well as human raters in identifying positive and negative sentiment with the advantage of speed and automation.

Unsupervised algorithms, like VADER, are promising. In Experiments #6 and #7, pretraining the sentiment model was not required. One could take the VADER rule-based algorithm as is and evaluate a target dataset for sentiment. The VADER algorithm performed better than many of the supervised ML algorithms with 72% accuracy for the Learning Sentiment dataset with neutral sentiments included and 87% with neutral sentiments removed. Arguably, 87% approaches an adequate level of accuracy to be useful in an educational context. The VADER algorithm is useful for getting a quick and general (summarized) view or trend of students' opinions about a topic without the need for human intervention, which could save resources and the instructors' time. One application of using VADER in the classroom is to have students digitally text opinions about a lecture topic, e.g., business case, scenario, or argument position, and the VADER algorithm can instantly quantify how many students expressed a positive or negative opinion about it. The summary can be presented back to the students as part of the same lecture. Sentiment analysis can also be applied to short essay assignments or to analyze exam responses. Another application can be for administrators to identify struggling teachers and offer assistance after using an automated sentiment analysis for course reviews. With thousands of students' comments, reading all the comments may be fatiguing and ineffective, but an algorithm can identify positive and negative comments to better focus an administrator's care and attention.

In conclusion, instructors desire to evaluate if learning activities (e.g., individual project, group project, service-learning activity, presentation, student research, etc.) have positive impacts on students. Grades are only one measure of learning impact. The sentiment of the student is another measure. After conducting a learning

activity, instructors can collect reflective experiences via a short essay or open-ended response from the students. Sentiment analysis can then be used to categorize the students' reflections as positive or negative. Having a count of how many students had a positive or negative experience may guide the instructor in making adjustments to future learning activities and can quantitatively track the impact of adjustments over time. Educational researchers have similar opportunities using sentiment analysis.

Based on the results of this study, we have two recommendations. If the instructor has enough data or prior data from an educational context, they can vectorize the words and train a naive Bayes to detect positive and negative sentiment. Then, they can use that model on the remaining student reflection data. We do not recommend detecting neutral sentiment at this time because the current algorithms and datasets are not sufficiently accurate for neutral sentiment analysis. Future research is needed to accurately identify neutral sentiments. Nor do we recommend augmenting the machine learning training process with data from publicly available sentiment datasets that are outside the educational context (e.g., movie reviews, airline reviews, product reviews, etc.). If the instructor does not have enough student data to pretrain a model, we recommend using the VADER algorithm as is. VADER achieved 87% accuracy in this study and may be sufficient for the instructor's analytical needs. VADER has the advantage of speed and ease as it does not require pretraining a model.

Positive and negative sentiment labels derived from VADER or a naive Bayes algorithm could also be used as input, along with student demographic variables, for clustering algorithms. The clustering algorithm may categorize which subgroups of students had positive or negative experiences from a learning activity. This insight may inform the instructor if certain student populations are disproportionately impacted so that corrective action can be taken. More educational datasets with sentiment are needed to improve future sentiment analysis algorithms.

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Reflections on the Creation of a Business Analytics Minor

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Abstract

This article presents the details of a business analytics minor that we created at our institution in the fall of 2019. In the two years since, our program has successfully met our enrollment goals. Out of over 50 minors offered at our institution, our business analytics minor is currently ranked fourth in enrollment. In this article we will present the process that we followed to create our minor, cover our curriculum (including course descriptions), the staffing of the courses, program enrollment, enrollment by course/semester, and enrollment by major/semester. Finally, we will conclude with some reflections on our experience. The hope is that this paper can help others who are contemplating, or in the process of, introducing a business analytics minor.

Keywords: Business Analytics Minor, Business Analytics Minor Curriculum, Education in Data Analytics

1. INTRODUCTION

This article is a follow-up to an article written by the authors in 2019 (Burns, T. J., Sherman, C. (2019)**.** In that previous article our research was focused on determining the optimum curriculum for a minor in business analytics. In order to determine that curriculum, we gathered data from sixty business analytics minor programs. Later in this paper we include a synopsis of the results of that original paper. In the years since that paper was published, we have successfully created a business analytics minor at our institution with a curriculum based on the results.

The purpose of this article is to present the details of the minor that we created. We introduced our business analytics minor in the fall of 2019. In the two years since, our program has successfully met our enrollment goal. Out of over 50 minors offered at our institution, our business analytics minor is currently ranked fourth in enrollment. In this article we will present the process we followed to create our minor, our curriculum (including course descriptions), the staffing of the courses, program enrollment, enrollment by course/semester, and enrollment by major/semester. Finally, we will conclude with some reflections on our experience. The hope is that this paper can help others who are contemplating, or in the process of, introducing a business analytics minor.

In recent years, there has been an explosion in the demand for personnel in the field of analytics. An understanding of analytics has the potential to add value to almost any career path as analytics spans across all disciplines and industry sectors. Students with these skills are in high demand in a variety of industries and sectors. Ranked second in a *Computerworld* survey on the most difficult skills to find, analytics expertise is scarce (Computerworld, 2018). McKinsey Global Institute reports that the United States could face a shortage of between 140,000 and 190,000 individuals who possess business analytics skills

and an additional 1.5 million managers with the skills to implement the results (McKinsey Global Institute, 2018).

Given that the demand for this skill set cuts across so many disciplines, it is a useful addition to any major and an ideal candidate for an academic minor. In fact, 16% of job offers for those with bachelor's degrees in information technology are in data analytics and the average salary is approximately $63,000. For graduates with master's degrees, data analytics job offers constitute 42% and the average salary is approximately $20,000 more (AIS and Temple University, 2019).

Furthermore, as the underlying analytics tools and techniques emerge from disciplines such as management science, operations research, statistics, business intelligence, information systems, and traditional business fields, the school of business makes an ideal place to house an analytics minor.

A proposed undergraduate information systems curriculum, under development by the IS Task Force of the AACSB MaCuDe project, may offer more guidance as to the components of the minor (Lyytinen, K, Topi, H. & Tang, J., 2020).

2. LITERATURE REVIEW

The starting point for creating a business analytics minor was to research existing curricula models and programs. However, this proved somewhat problematic. The literature related to data analytics education is not abundant and it remains scattered and difficult to retrieve by a keyword search. This is in part due to an imprecision in nomenclature which is a natural outgrowth of an evolving discipline. For example, terms such as "business analytics," "data analytics," or "decision science" are often used as substitute terms (Zheng, 2018). To add to the confusion, a business analytics program can be offered through a computer science department or be interdisciplinary, making it difficult to identify programs which could be used as models (Phelps & Szabat, 2015).

Also, according to a survey by Phelps and Szabat (2015), most schools were not yet even offering an undergraduate major in business analytics or decision sciences and 59% did not offer a minor. However, 30% of the respondents were considering creating such a major and 26% were considering a minor, a strong demonstration of interest and of future direction for the field.

Wymbs (2016) echoed the findings of Phelps and Szabat (2015) noting that as of 2016, there were 517 data science/data analytics programs of which 374 were Master's programs, 88 Certificate programs, 36 Bachelor's programs, and 10 PhD programs. A query of the AACSB database of 1,500 institutions indicated only 11 undergraduate programs in data analytics and data science but 56 programs in business analytics.

Utilizing an outcomes-based approach to curriculum development, Wymbs (2016) discussed insights provided by the 2015 Business Higher Education Forum Conference which was attended by organizations in a number of business and public sectors including investment banks, accounting firms, tech companies, and the Federal Reserve. Attendees identified "R" and Python as programming languages of choice and also made specific reference to the needs of the accounting profession. They indicated new accounting graduates would need to demonstrate data analytics proficiency in order to be hired. In fact, this recent focus on business analytics in the accountancy field is reflected in upcoming changes to the CPA exam (Dorata, 2021). And, given that accounting is a robust major at most business schools, a new emphasis on data analytics within accountancy should affect every aspect of a business analytics minor, including enrollment, staffing, double-counting of courses, resource sharing, and the like.

As with many new undertakings, it can prove difficult to find the correct focus for a program. Wilder and Ozgur (2015) provided a model for addressing this conundrum by 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.

To connect their observations to curricula development, Wilder and Ozgur (2015) identified 49 pertinent graduate programs and suggested using their curricula as a starting point. 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).

The market demand for students with an analytics skill set was also a driving force behind the Business Intelligence Congress sponsored by the AIS Special Interest Group on Decision Support, Knowledge and Data Management Systems (SIGDSS) and the Teradata University Network (TUN) (Wixom (2014). Utilizing surveys and insights from industry representatives, they investigated academia's response to this demand and noted the dramatic increase in Business Analytics and Business Intelligence programs and the increased access to teaching resources. They also noted the continuing need for students to have foundations skills and practical experience and that demand for analytics graduates was continuing to outpace supply. While communications skills remained a top demand of employers, SQL and basic analytics, such as descriptive statistics, regression and ANOVA were in second and third place.

They also noted that major questions about curricula remained unanswered and that there was very little in the way of guidelines or model curricula. Decisions about the number and type of courses, prerequisites, and integration with other majors were yet to be answered in a systematic manner. However, one survey revealed that 296 out of 313 professors were participating in business analytics academic alliance programs to offer software to students. Interestingly, another survey revealed that students were now taking analytics courses because they wanted to do so, rather than because it was a requirement for a degree.

Conceptually, there is therefore some agreement as to what a business analytics minor might include but on a more granular basis there continues to be disagreement. 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.

In fact, the Association for Computing Machinery (ACM) and the Association for Information Systems (AIS) have recognized the afore-mentioned diversity of curricula in the IT field. Rather than specifying courses, they articulated the competencies that graduates should attain upon completing a graduate program in information systems (Topi, 2016). They describe a telescoping model which consists of competency areas that contain competency categories with individual foundational competencies.

In keeping with the discovery that more research was needed before developing a business analytics minor, the authors (Burns & Sherman, 2019) reviewed the curricula of sixty colleges and universities, in the United States, offering a business analytics minor. Most commonly, the subject universities required courses in statistics and IT. Accordingly, Management Statistics and Principles of Information Technology became the prerequisites for our minor. Principles of Information Technology covers, at least cursorily, traditional IT subjects such as database, spreadsheets, programming, and networking. The required courses of our minor, Business Analytics I and II cover the basic statistical, analytical, and visualization tools comprising business analytics as well as the role of business analytics in an organization. Two electives, selected from a list of eight, encourage specialization in functional business areas or deeper study of specific mathematical and software tools. Our minor is open to students of any major, which reflects the interdisciplinary nature of the college.

3. THE PROCESS TO CREATE THE MINOR

In this section we will explain the process that we went through to introduce the new business analytics minor at our institution. Listed below are the general steps that we followed. As each institution is unique, this process is not intended to be a "cookie cutter" approach, but rather a general guide that can be used by other institutions that are interested in developing a business analytics minor program.

We included the following steps in developing our business analytics minor:

1. Reviewed business analytics minors offered at other institutions.
2. Defined the curriculum for the minor.
3. Developed the program description, mission, learning goals/outcomes, and assessment process.

4. Developed new courses needed including course description, materials, and syllabus.
5. Followed the institution's administrative process to introduce a new minor.
6. Scheduled new courses.
7. Hired needed faculty.
8. Marketed the new program

Review of business analytics minors offered at other institutions.
For this first step, sixty colleges/universities that offer a business analytics minor were randomly selected (see Burns & Sherman 2019 for an in-depth discussion of this process). The curriculum for each of the programs was then reviewed, analyzed, and tabulated. For each program, it was determined the number and nature of the prerequisite courses, required courses, and elective courses. A list of the courses was then recorded. Once the courses were identified, the researchers then reviewed the catalog descriptions of the courses. Based on the catalog descriptions a list of the topics covered was compiled. The end result was three lists; 1) a list of the most common prerequisite topics, 2) a list of the most common required topics, and 3) a list of the most common elective topics offered. The analysis of the sixty programs showed that, on average, business analytics minor programs have two prerequisite courses, three required courses, and two electives.

Definition of the Curriculum.
Table 1 lists the curriculum of the minor that was developed based on the results of the review of other programs. The course descriptions from our college catalog are shown in Appendix A.

Our curriculum has two required prerequisites, (Management Statistics and Principles of IT). The role of the prerequisite courses is to prepare the student for the material covered in the minor (particularly students from non-technical majors) The Management Statistics course covers 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 Principles of IT course topics include the following: computer hardware and software architecture, organizing data, telecommunications and networks, types of systems and their development, and the role of information technology in business and society.

The prerequisite courses listed in table one are those offered in our school of business (which is the home school for our minor). We designed our minor so that it could be added to any major in the college. Minors are open to students regardless of school affiliation. Therefore, non-business students enrolled in the minor are able to fulfill the prerequisite courses with similar courses offered in their home school (or with courses taken at other institutions).

Prerequisites:
Management Statistics
Principles Of Information Technology
Required:
Business Analytics I
Business Analytics Ii
Electives: Select Two
Econometrics
Introduction To Programming
Introduction To SAS
Database Management Systems
Data Visualization
Decision Support Systems
Management Science
Marketing Research

Table 1 Business Analytics Minor Curriculum (See Appendix A for course descriptions)

Our curriculum has two required courses: Business Analytics I and Business Analytics II. The Business Analytics I course provides students with the fundamental concepts and tools needed to understand the emerging role of business analytics in organizations. The course covers managerial statistical tools in descriptive analytics and predictive analytics, including probability distributions, sampling and estimation, statistical inference, and regression analysis. Students develop an understanding of basic visualization techniques and how to apply them which enables them to effectively communicate with analytics professionals and make better business decisions.

The second required course, Business Analytics II, provides students with advanced concepts and tools needed to understand the role of data analytics in organizations. Topics 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.

The elective courses in the curriculum help the students develop skills that increase their knowledge of a specialized area within their field. Our curriculum requires two electives. The electives offered are shaped by the goals of the program and, at least to start, the available course offerings at our institution.

Developed the program description, mission, learning goals/outcomes, and assessment process.

Once we had defined the curriculum for the program we moved on to the overall definition of the program. This included developing a program description, mission, learning goals/outcomes, and an assessment process.

Our program description is:

"Business Analytics studies data in order to identify patterns or trends that can then be used to predict future patterns or trends, allowing businesses to make better decisions. We live in a time when large amounts of data are being collected, in almost every aspect of society—and there is a tremendous demand for people with analytics skills. The U.S. Bureau of Labor Statistics predicts a strong demand for people with business analytics skills well into the next decade. The Business Analytics minor is available to students in any major to add to their marketable skills and knowledge."

Our mission statement is:

"The Business Analytics Minor prepares students to have the knowledge, skills, tools, and competencies required for the methodical exploration and investigation of data. Using descriptive, predictive, and prescriptive statistical tools, students will support decision-making and gain insight into business performance."

Our program has two learning goals and outcomes:

Goal 1: Foundation - Our students will have a broad-based knowledge in the functional areas of business analytics.

Outcome 1: Students will comprehend principles and practices in key business analytics disciplines.

Goal 2: Communication - Our students will demonstrate effective visualization of data skills.

Outcome 2: Students will effectively present the results of business analytics cases visually using graphics.

Learning Goal and Related Outcomes:	Direct Measure(s)	Indirect Measure(s)
Goal 1: Foundation: Students will have a broad-based knowledge in the functional areas of business analytics. Outcome 1: Students will comprehend principles and practices in key business analytics disciplines.	Rubric-based evaluation of students' analysis of business cases. The rubric will evaluate how well students comprehend principles and practices in key business analytics disciplines.	Syllabi Review and Student Perception of Learning Survey
Goal 2: Communication: Students will demonstrate effective visualization of data skills. Outcome 2: Students will effectively present the results of business analytics visually using graphics.	Rubric-based evaluation of the presentation of business analysis results. The rubric will evaluate the visualization skills of the students. Evaluation will take place in Business Analytics II	Syllabi Review and Student Perception of Learning Survey

Table 2 Direct/Indirect Measures of Assessment

Our initial assessment measures and process:

"The assessment process will take place over a five-year cycle with the Business Analytics faculty assessing the program bi-annually, evaluating each outcome twice in five years. The outcomes will be assessed in courses taken in the final semester of the program utilizing both direct and indirect measures. The BA faculty in conjunction with the School Assessment Committee will develop rubrics. The ITM faculty will discuss results and closing the loop suggestions will be

implemented as needed to close identified gaps in achievement of learning outcomes."

Table 2 lists the direct and indirect measures of assessment that were developed.

Developed new courses needed including course description, materials, schedule, and syllabus.
The prerequisite courses and most of the electives already existed in our college catalog. So, for the new program, we were required to create four new courses. Those courses included the two required courses (Business Analytics I and Business Analytics II) and two new electives (Data Visualization and Introduction to SAS).

The two required courses were developed based on a graduate introductory analytics course that was already being offered in the MBA program. We were able to identify a textbook (*Business Analytics* by James Evans) that covered the topics we had identified through our prior research and based on the coverage of the MBA course. Given the broad spectrum of topics covered by the textbook we were able to use the same book for both courses. Also, using the textbook we were able to develop a schedule of topics covered.

For the elective, Data Visualization, we relied on the expertise of a current faculty member. He had previously developed a similar course and had extensive experience in the subject matter. He was able to draw upon his expertise to develop the course. The elective "Introduction to SAS" was developed by a new faculty member who had certification and expertise in the topic. Both faculty selected the textbook and materials for their respective courses.

Followed the institution's administrative process to introduce a new minor.
The process to introduce a new program at our institution took about a year. After preliminary approval by the convening group (department) and Dean of the school, a new program proposal was prepared for the Provost. This proposal included a feasibility study that summarized the program, the program's impact on the college and other programs within the college, the need for the program, a comparison to other programs in our state, and the program's anticipated enrollment from launch to optimal level. In addition, the proposal included a curriculum section that listed the program's mission and learning goals, the program assessment measures, the program's relationship to the college mission and strategic plan, degree requirements, and details of the curriculum.

Once the Provost approved the program proposal, a series of documents were prepared for the college's Academic Review Committee (ARC). These documents included a form that described the new program and a form for each new course in the minor. Each of these forms had to be approved by the convener (department chair), the chair of the school curriculum committee, and the Dean before they were sent to ARC. ARC then reviewed the documents, provided feedback, and then eventually approved the program.

The ARC documents were then sent to the Provost for approval. Once the Provost approved the program it was presented to the entire college faculty for approval. The program then went to the college's board of trustees and ultimately to the state for final approval.

Scheduled new courses.
We decided to offer the Business Analytics I course in the fall and winter semesters and Business Analytics II in the spring semester. The prerequisites are offered every semester (they were already required courses for the business students) and the electives are offered in different combinations every semester. By offering Business Analytics I in the winter semester it allowed students who wanted to start the program in the spring to complete Business Analytics I before the spring semester (as Business Analytics I is a prerequisite to Business Analytics II).

Hired needed faculty.
As most of the courses were already part of the business curriculum and currently staffed by existing faculty, our need for new faculty was limited. An existing faculty member was able to develop and teach the new course, Data Visualization. We ended up needing one new faculty member to teach three courses (Business Analytics I, Business Analytics II, and Introduction to SAS). We convened a search committee (consisting of IT management faculty and faculty with analytics experience) and conducted a search in academic year 2018/2019. We had over 100 applicants for the position. Eventually we were able to narrow the list to three candidates, and after visits to campus, we were able to make an offer to our top candidate (who accepted the position). The ideal candidate had the experience and education to teach the new analytics courses as well as other courses in the IT Management curriculum.

Marketed the new program.
Once all the pieces were in place, we were ready to launch our program in the fall semester of

2019. We were able to market the program to the college community through several vehicles. First, we added a blurb about the new program to the college's "Daily Digest" email that is delivered daily to the entire college community. We ran the blurb for a week or two. We then sent a specific targeted email to all students in the school of business. This email introduced and explained the new minor to the students. We also added a slide about the new minor that became part of the display on hall monitors that are posted throughout the school of business building. Finally, we asked all business faculty to announce the new minor in their classes.

4. ENROLLMENT

This section will discuss the enrollment numbers in our program. Table 3 shows the total enrollment in our minor by semester. Our original projected goal was to have 20 students in the program. As Table 3 shows we were able to surpass that goal in the spring 2021 semester and attain a total of 34 students by the fall 2021 semester. Table 3 also shows how the program has grown over the last two years. It should be noted that the total undergraduate enrollment at our institution is 4,981 students.

Fall 2021	34
Spring 2021	27
Fall 2020	15
Spring 2020	19
Fall 2019	2

Table 3 Business Analytics Minor Enrollment by Semester

The largest major is biology with 435 students. The Information Technology major has 86 students enrolled.

Psychology	79
Crime and Justice	51
Marketing	39
Business Analytics	**34**
Spanish	27

Table 4 Enrollment by Minor Fall 2021

Table 4 is included to show where the business analytics minor ranks in enrollment in comparison to other minors at our institution. There are approximately 50 minors offered at our institution and business analytics ranks fourth with a total of 34 students. This is especially notable, *and highly significant*, given that the business analytics minor is only two years old and psychology (the most popular minor) and the other popular minors have been established for many years.

Table 5 shows, by semester, which major programs our students are pairing with the business analytics minor. These numbers vary by semester, but it appears that most students minoring in business analytics, major in marketing, finance, or international business.

Enrollment By Major	F19	S20	F20	S21	F21
Accounting		1	1	2	3
Business Admin	1	5	4	4	
Communication Arts			1	1	
Economics		1			2
Finance		3	2	3	7
ITM	1	5	1	4	3
International Business				1	4
Management		2	2	2	3
Mathematics				1	1
Marketing		1	3	8	10
Theater		1	1	1	1
Total	2	19	15	27	34

Table 5 Business Analytics Minor Enrollment by Major/Semester

Tables 6, 7, 8, and 9 are included to show the enrollment in the new courses that were created for the new business analytics minor. It should be noted that the new courses offered also were added to the pool of elective courses available to students majoring in IT management and that's why the numbers don't coincide exactly with the minor enrollment numbers.

Fall 2021	20
Winter 2021	6
Fall 2020	22
Winter 2020	10
Fall 2019	15

Table 6 Enrollment in Business Analytics I Course by Semester

Spring 2021	22
Spring 2020	11

Table 7 Enrollment in Business Analytics II Course by Semester

Spring 2021	24
Spring 2020	14

Table 8 Enrollment in Data Visualization Course by Semester

Fall 2021	6
Fall 2020	4

Table 9 Enrollment in Introduction to SAS Course by Semester

5. Other Measures of Success

	1	2	3	4	5	Mean
BA1						
F19		4	2	5	2	3.38
W20				3	4	4.57
F20			4	3	12	4.42
W21			1	0	5	4.67
F21	1	0	6	0	7	4.15
W22		1	1		6	4.38
BA2						
S21		1	5	1	13	4.30
DV						
S21			3	1	15	4.63
SAS						
F21					6	5.00
Total	**2**	**8**	**25**	**17**	**75**	**4.29**

Table 10 Student Rating of Learning

Even though the enrollment numbers are excellent, enrollment alone may not be sufficient to show the success or failure of the curriculum design. Tables 10 and 11 show data from student opinion surveys collected from several of the courses. The left column lists the course and the semester. Table 10 shows student responses when asked to rank how well they learned the subject on a scale from 1 to 5. Table 11 shows student responses when asked to rank how excellent the course was on a scale from 1 to 5. Both tables show an overall mean greater than 4.2 which indicates that students rate both measures very high.

	1	2	3	4	5	Mean
BA1						
F19	1	4	4	2	2	3.25
W20			2	1	4	4.29
F20			4	2	13	4.47
W21				2	4	4.67
F21	1	0	4	3	7	4.29
W22			2	1	5	4.38
BA2						
S21	2		4	4	10	4.44
DV						
S21		2	4	1	12	4.21
SAS						
F21					6	5.00
Total	**5**	**8**	**27**	**20**	**68**	**4.24**

Table 11 Student Rating of Excellence

We also chose our institution's program learning assessment process that is used for accreditation and internal measurement as a metric for the business analytics minor. Our institution implements a bi-annual assessment process with each program (majors, minors, and certificates) being assessed every two years. The results of the assessment of student learning for the business analytics minor will be reported in future research as the first scheduled assessment and subsequent report will be completed at the end of the spring 2022 semester. The assessment process consists of preparing an assessment plan that is approved by committees both within the school of business and college wide, and then implementing the plan and analyzing the assessment results. Appendix B is a copy of the assessment plan that was prepared for the business analytics minor (and will be implemented later year).

The plan details the learning goals and desired outcomes for the program (also shown in table 2). The two goals include foundational business analytics knowledge demonstrated by the comprehension of the principles and practices in key business analytics disciplines and

communication demonstrated by effectively presenting the results of business analytics cases visually using graphics. The goal will be assessed using a business case involving business analytics completed by the students in a required second level course. The students' responses will be evaluated using a Business Analytics Rubric (shown in appendix C). The outcome will be assessed by business analytics faculty using a blind review after an inter-rater reliability session. The achievement target is that 75% or more of students will be rated "Very Good to Excellent".

6. REFLECTIONS/CONCLUSION

The overall reflection/conclusion of the effort that we undertook to create a business analytics minor is that it was a worthwhile and successful initiative. For us, the most labor-intensive parts of the project were the administrative process to have the minor approved at our institution and the hiring of new faculty. The administrative process involved a lot of "red tape," bureaucratic tasks that slowed the process. Hiring a new faculty member was labor-intensive because at the time there was a lot of competition for candidates with analytics and IS education/experience.

It should be noted that one thing, fortunately, that we had in our favor was that our school, dean, and institution supported the minor. Our institution had recently decided to undertake a major data science effort in conjunction with the computer science and math departments. We were able to introduce the business analytics minor as a program that fit the business niche of the data science program.

The primary limitation of this research is that the program is only two years old and we have not yet had enough time to collect enough data to properly assess the program. Future research on this topic will report on assessment data and results. However the strong initial enrollment in the program serves as a promising indicator of future success.

Our hope is that we can use the same process again to introduce a graduate degree in business analytics. If you are contemplating, or in the process of, introducing a business analytics minor, we hope that the information contained in this article has been helpful.

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Appendix A – Course Descriptions

MANAGEMENT STATISTICS: A study of statistical theories and techniques commonly used in the analysis of business data. Special emphasis will be placed on descriptive measures, probability theory, estimation techniques and forecasting methods, hypothesis testing, and time series analysis.

PRINCIPLES OF INFORMATION TECHNOLOGY: The course focuses on why and how information technology should be used to meet organizational goals. Topics include the following: computer hardware and software architecture; organizing data; telecommunications and networks; types of systems and their development; and the role of information technology in business and society. Students will solve selected business problems using the Microsoft Office Professional for Windows suite of software and acquire the background to serve as internal systems consultants to all the functional areas of an organization. Prerequisite: Knowledge of MS Office and facility with the Internet.

BUSINESS ANALYTICS I: The course provides students with the fundamental concepts and tools needed to understand the emerging role of business analytics in organizations. Through lectures, hands on analyses, and various assignments, students learn how to apply basic business analytics tools in a spreadsheet environment. Students will become familiar with advanced Microsoft Excel functions and the use of Excel in solving analytical problems. Students also learn how to communicate with analytics professionals to effectively use and interpret analytic models and results for making better business decisions. The course covers managerial statistical tools in descriptive analytics and predictive analytics, including regression. Emphasis is on applications, concepts and interpretation of results as well as conducting statistical analyses. Students form groups to collect and analyze data, and to write and present a final report.

BUSINESS ANALYTICS II: The course provides students with advanced concepts and tools needed to understand the emerging role of business analytics in organizations. Through lectures, hands on analyses, and various assignments, students learn how to apply business analytics tools in a spreadsheet environment. Students also learn how to communicate with analytics professionals to effectively use and interpret analytic models and results for making better business decisions. The course covers managerial statistical tools in predictive and prescriptive analytics. Topics 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. Students form groups to collect and analyze data, and to write and present a final report.

ECONOMETRICS: Econometrics is the application of mathematical and statistical methods and techniques in order to: 1) help understand, analyze, and interpret economic and financial data, 2) test economic and financial hypotheses/theories, and 3) generate predictions about particular economic and financial variables. Econometrics is fundamentally a regression-based correlation methodology used to measure the overall strength, direction, and statistical significance between a "dependent" variable - the variable whose movement or change is to be explained - and one or more "independent" variables that will explain the movement or change in the dependent variable. Students are expected to have a solid grounding in algebra and Management Statistics.

INTRODUCTION TO PROGRAMMING: Introduces students to the basics of computer programming using a modern computer programming language. Emphasis will be on designing structured, event-driven programs to solve business problems. Topics include programming constructs, object-oriented programming, algorithms and problem-solving and event-driven programming.

INTRODUCTION TO SAS: This course introduces students to the latest SAS platform and basic knowledge in data management and exploratory data analysis using SAS software. Students are provided the opportunity to learn a comprehensive set of SAS data-related techniques through lessons, demonstrations, and ab/homework assignments. Students will learn how to import data, structure data, prepare data for analysis, explore data, and create reports. Students will work in teams and learn how to communicate with analytics professionals by creating and presenting effective data-driven reports. The material covered in this course is designed to prepare students for starting their SAS certification journey.

DATABASE MANAGEMENT SYSTEMS: A study of theoretical and practical aspects of database management systems, with emphasis on relational systems, the SQL language, and database

design. Applications will be designed using Microsoft Access and/or other relational database software.

DATA VISUALIZATION: Business processes in the current times are data driven which makes it important for managers to consume the data correctly. Data mining, processing and analysis prepares the data to provide business analytics. However a visual of the analytics is what makes the data consumption process seamless and more impactful. This course is focuses on understanding the underpinnings of data visualization process. The course will leverage the power of visualization tools to facilitate the visualization process.

DECISION SUPPORT SYSTEMS: A study of ways in which computers can clarify complex data needed for making strategic business decisions. Students will acquire introductory knowledge of decision theory and methods of making best decision in complex situations. Topics will include optimization and linear programming, network modeling, regression analysis, time-series analysis, simulation, and decision analysis. Problems will be analyzed using advanced spreadsheet tools, especially those in the Microsoft Excel software.

MANAGEMENT SCIENCE: Planning and control are among the essential functions performed by a manager. This 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.

MARKETING RESEARCH: An examination of the concepts and practical methodology used in market research. Emphasis will be given to research methods and techniques, including market analysis, questionnaire formulation, sampling, interviewing, and panels.

Appendix B – Assessment Plan

Program Name: Business Analytics Minor

Discipline Goal:

1. Foundation: Our students will have a broad-based knowledge in the functional areas of business analytics.

Outcome 1: Students will comprehend principles and practices in key business analytics disciplines.

2. Communication - Our students will demonstrate effective visualization of data skills.

Outcome 2: Students will effectively present the results of business analytics cases visually using graphics.

Measure:

Who will assess the outcome (e.g., faculty who are not teaching the course? Note: if necessary, faculty can assess their own courses provided there are at least two readers and an interrater reliability session)?

The students' work will be reviewed by the BA faculty.

What is the instrument or method (e.g., rubric, survey, multiple-choice questions…)? Note that rubrics and other instruments can be attached to the template. The students' responses will be evaluated using a Business Analytics Rubric.

The Business Analytics Rubric provides five categories or "traits" which are appraised on a scale of 1 to 6 with: 1-2 being "poor / below average," 3-4 being "average / good," and 5-6 being "very good / excellent".

What is the student product (e.g., paper, final exam question)?

The goal will be assessed using a business case involving business analytics. The entire class will be assessed.

What is the assessment process (e.g., blind review after an inter-rater reliability session and number of readers)?

Blind review after an inter-rater reliability session

When will it be measured (e.g., fall 2018)?

Spring 2022

What courses or which student populations will be measured (e.g., CA 456)?

The assessment will be performed using student work in the course INFO 311 Business Analytics II. INFO 311 is a required course for all Business Analytics students.

How many student products will the program assess (e.g., 25% of the total)?

100%

Achievement Target

75% or more of students will be rated "Very Good to Excellent".

Appendix C – Assessment Rubric

TRAIT	Unacceptable (0-1)	Acceptable (2-3)	Excellent (4-5)	Score
Problem Definition	Does not identify and summarize the problem, is confused or identifies a different or inappropriate problem.	Identifies the main problem and subsidiary, embedded, or implicit aspects of the problem.	Identifies not only the basics of the issue, but recognizes constraints and nuances of the issue.	
Data Collection	Did not collect meaningful data.	Collected most of the needed data, but data cleaning and prepration was not done.	Collected the appropriate data and the data was properly cleaned and prepared.	
Methods	Statistical methods were completely misapplied, were applied but with significant errors or omissions, or were absent.	One or two statistical methods were correctly applied, but the it was not justified why it is a proper method to answer the problem.	At least two statistical methods were fully and correctly applied. Use of the methods were justified.	
Presentation of Results	Results presented in an unclear manner. Little use of charts or tables.	Approriate tables and charts used to clearly convey the results.	Advanced charts and tables used to present the results in an aesthetically pleasing manner.	
Discussion	Entirely missed the point of the experiment.	Analyzed only the most basic points.	Results and discussion well focused and included all important points.	

A Framework to Implement Academic Digital Badges when Reskilling the IT Workforce

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Abstract

Information technology (IT) plays an increasingly significant role in today's world. The COVID-19 pandemic has increased that reliance. Employers in all industries are struggling with considerable shortages of skilled IT workers and are seeking innovative alternatives to meet these needs. Digital badging and micro-credentials have emerged as an alternative system to validate skills. The issuing of digital badges has spanned across a wide spectrum of settings and purposes. However, there is currently less application of digital badges in graduate-level programs to link to important academic or subject-matter related achievements and higher-level competencies. Reskilling and upskilling existing employees need a more practical and sustainable approach and often do not require completion of an entire IT master's degree. To align with such demand, this study aims to demonstrate how a digital badging system can be used to validate stackable certificates for micro-credentials in a graduate-level program. The paper starts with a background introduction of the current IT employment landscape. The next two sections provide an overview of micro-credentials in workforce development and higher education today. This is followed by a section on our conceptual framework used to determine the potential value of digital badging to our graduate programs. The next section focuses on the case study. The last sections conclude with the lessons learned and the future research directions.

Keywords: Digital badge, Micro-credential, IT Workforce, Reskill, Upskill, Graduate program

1. INTRODUCTION

Today's competitive and volatile employment environment poses significant challenges to both employers and educators in higher education institutions, a situation exacerbated by the COVID-19 pandemic. While underemployment has prevailed for many college majors, employers from industries such as healthcare and information technology (IT) are struggling with considerable shortages of appropriately skilled employees (Restuccia, Taska, & Bittle, 2018). The annual Cybersecurity Workforce Study suggests that employment in the cybersecurity field, for example, needs to grow by approximately 41% in the U.S. and 89% worldwide in order to fill the talent gap ($(ISC)^2$, 2020). Increasingly, organizations that have primarily relied upon

colleges and universities to supply job-ready graduates are looking at other sources to find employees with the skills that they seek (Welch, 2021). To stay relevant, educational institutions preparing students for the ever-changing technology world need to keep updating their programs and curricular to address the discrepancies between employer expectations and perceived students' employability. Both the supply and demand sides of the employment landscape are seeking innovative alternatives to close these gaps. Digital badging and micro-credentials have emerged as alternative credentialing systems to validate skills and competencies with the ultimate goal being to build a highly-skilled and constantly reskilled and upskilled workforce (Erickson, 2015).

Micro-credentials are certifications that demonstrate competency in a particular skill, verified by a central authority, such as an academic institution (Fanfarelli & McDaniel, 2019). For micro-credentialing, digital badges are more than just an image showing a skill, they should also be verifiable through a set of metadata (Gibson et al., 2015). Clicking on the badge should enable any employer to independently verify, in more detail, the individual's skills.

Digital badges now serve as a part of an individual's branding when displayed on social media outlets like LinkedIn, Facebook, and Twitter. To-date most of the digital badges have come from non-traditional training providers such as Coursera (www.coursera.com), credentialing organizations such as CompTIA (www.comptia.org) or professional organizations such as the Greater Washington Partnership Capital CoLAB (capitalcolab.com). An example of a digital badge issued by Coursera and authorized by IBM is shown in Figure 1.

Several factors are, however, now suggesting the need for more higher education institutions to consider the implementation and adoption of their own digital badging in traditional education settings. Employer hiring practices are increasingly dependent on digital searches, including an applicant's social media presence. Accrediting agencies and governments are focusing more on program outcomes and what students are able to achieve after graduation. Young adults are demanding shorter and more workplace relevant learning. A large number of non-traditional training providers are issuing digital credentials (International Council for Open and Distance Education, 2019). In addition, employers are saying that they cannot simply hire a brand-new workforce because of the cost and the perceived deficit of qualified recruits (Marion, Fixson, & Brown, 2020).

Figure 1: Example of digital badge issued by Coursera

The issuing of digital badges has spanned across a wide spectrum of settings and purposes. They can be used in informal learning setting as well as government settings, and in all levels of education from K-12 to higher education (Stefaniak & Carey, 2019). However, in graduate-level programs there is currently less use of digital badges to link to academic or subject-matter related achievements and higher-level competencies. The main purpose of this paper is to conduct a case study to explore and gain a better understanding of digital badging systems and how they can be integrated with stackable certificates in a graduate-level program. The intent being to better position our graduating students in the cybersecurity and technology job marketplace given the increasing trend by employers towards skill-based hiring practices (Ark, 2021)

2. MICRO-CREDENTIALS IN WORKFORCE DEVELOPMENT

A micro-credential is defined as a certification that attests proven competency in a particular skill (Ryerse, 2017). Micro-credentials are also described as "on-demand, shareable, and personalized" and are have traditionally been used to update existing skills or provide alternatives for people that do not hold traditional degrees (Jones-Schenk, 2018). According to Lemoine & Richardson (2015), micro-credentials are associated with competency-based learning and acknowledge proficiency in particular skills. A 2018 study surveyed 750 Human Resource (HR) leaders at U.S. organizations on their best practices in hiring appropriately skilled employees

(Resei et al., 2019). The survey results highlighted that hiring managers often referenced micro-credentials for job applicants' skills and competencies instead of only relying on applicants' academic transcripts and on-site interview performance. Further evidence shows that micro-credentials are an excellent tool for employers to identify a candidate's "authentic skills" and clearly evaluate and align the candidate's skill level in relationship to the position skills (Gauthier, 2020). The evolution of micro-credentials awareness has influenced hiring in the IT industry in which more and more emphasis is directed on verifiable skills (Welch, 2021). Skills-based hiring has become an increasing trend during the COVID-19 pandemic (Roslansky, June 08, 2021).

As micro-credentials that reflect specific skill attainment have gradually gained significance in workforce development, competency-based hiring is becoming widespread. Employers demand an articulate and verifiable understanding of a candidate's capabilities prior to extending a job offer. Consequently, the micro-credentialing system can be perceived as a double directional mechanism: (1) for the employers to easily match the required skills for the position with the candidate's abilities, and (2) for the applicant to highlight and verify their competency, proving their adequacy for the job (Gauthier, 2020).

There is also another trend where some large employers are developing in-house micro-credential programs for current and future employees. In-house micro-credentials are used to train new employees and to re-train the current employees. In addition, such micro-credential programs may also be offered to the employees of other organizations. For example, Google created a group of private companies including Bank of America, Walmart, Sprint, GE Digital and PNC Bank who are willing to hire candidates who complete Google certificates (Oliver, 2019). Another example is the Greater Washington Partnership CoLAB, a consortium of major employers and academic institutions in the region between Baltimore, Washington DC, and Richmond. CoLab has created digital badging in data science and cybersecurity based on the needs of these employers and undergraduate courses in these fields taught at member universities (Blumenstyk, 2019).

Along with this trend in industry, more and more higher education institutions are beginning to offer micro-credentials to allow their graduates to be better identified by potential employers for their specific employable skills (Oliver, 2019). The next section provides a brief overview of micro-credentialing in higher education realm, from community colleges to graduate schools.

3. MICRO-CREDENTIALS IN HIGHER EDUCATION

There is an increased demand for traditional degree programs to also create programs that are aligned with industry needs and that can be validated by employers (Resei et al., 2019). Micro-credentials are not intended to replace traditional degrees, but to supplement the knowledge and skills acquired through traditional learning or to better identify knowledge, skills and abilities at a more granular level. In higher IT education, micro-credentialing can have several advantages as students look to incrementally deepen their knowledge and skills either through updating their current knowledge (upskilling) or re-training and gaining new abilities (reskilling). They do not want to wait two or four years until they graduate to get the recognition for those new skills.

College students are showing a distinct preference towards work-integrated learning and curriculum that incorporates these industry requirements, hoping to obtain a better employment opportunity (Oliver, 2019). Additionally, students are looking for institutions that are providing micro-credentials that hold "value" when presented in the industry (Gauthier, 2020). Therefore, institutions are expected to develop micro-credentials that are "endorsed by leading employers" (Resei et al., 2019) and prepare candidates for industry requirements.

According to Fond et al. (2016), three in every four higher education institutions regard micro-credentials as important to their future. Hanafy (2020) suggests that higher education institutions consider transforming their curriculum systems to include micro-credentials as stackable certificates. Such practice allows potential employers to have direct access to candidates' specific skills. The importance of the micro-credential implementations in educational institutions has been widely explored both in academia and in the industry. Moreover, the micro-credentials system has been adopted at various formal education levels – from community colleges all the way up to some graduate levels.

Community colleges are an important part of the U.S. educational profile and the National Student Clearinghouse for Education Statistics (NCES) estimates that at least 38% of undergraduate

students in 2018-19 attended community college. These institutions are well positioned to become leaders in providing digital badging as they offer many shorter programs as micro-credentials that focus on developing the competencies sought by employers (Gallagher & Maxwell, 2019). Using digital badging for these micro-credentials allows a visual indicator of the skill developed to be displayed, accessed, and verified online. An example institution that has successfully developed digital badges in technical areas is the Colorado Community College System (Perea, Chieppo, & Woodmanee, 2018).

Several higher education institutions have also implemented digital badging, mainly in undergraduate programs. In addition to helping improve workforce readiness, the micro-credentials have been shown to increase student engagement. Moreover, the implementation of digital badging has demonstrated a positive impact on student retention in their first-year experience (Mah, 2016). Digital badges have also been adopted by a number of colleges and universities to reward students for accomplishments such as achieving undergraduate academic milestones in the Illinois State University Honors Program, co-curricular activities including projects and workshops at the University of California, Davis, and competencies in support disciplinary work at Portland State University (Wienhausen & Elias, 2017). Rimland & Raish (2019) explained that Penn State uses digital badges within undergraduate general education courses to recognize information literacy skills. Additionally, other universities use badging programs to track student progress.

Implementation of digital badging at the graduate level is not as common but some higher education institutions have embraced the concept, mainly in professional development programs. For example, Stony Brook University School of Professional Development uses digital badges to denote skills and knowledge mastered in graduate coursework (Wienhausen & Elias, 2017).

Digital badging provides the verifiable evidence of achieving a micro-credential, in much the same way that universities use the transcript for validated evidence of a degree. These digital badges can be used to denote particular technical skills or for other workplace skills such as teamwork, critical thinking or entrepreneurship. For students, they can denote skills acquired to meet specific workplace needs, in demand by potential employers, and they may earn badges as they incrementally work towards a degree. Students can display these digital badges on their social media throughout their university program, illustrating their growing skills. Social media has increased the focus on digital-badging as an appealing image of the individual's credentials such as a certificate or certification. It enables the individual to update their profile and increase their likelihood of being identified when employers search sites such as LinkedIn for potential candidates for specific positions with defined skill requirements.

Another benefit of a digital badging system is that it offers a clear understanding of the learning outcomes to both the student earning the badge and any potential employer (Pangaribuan & Febriyanto, 2019). Additionally, the system can contribute to a higher engagement level of the badge earners. A survey that evaluated the IBM Digital Badge Program found out that 87% of the employees that received IBM badges stated that "were more engaged" because of the badging system (IBM, 2019). The same survey showed that the digital badging programs are helping leaders and managers to reward and recognize employees' efforts. This is also an important concept and mechanism for academic degree programs to reward the students' efforts incrementally, which potentially increase the student retention rate.

In summary, digital badges are used by companies and higher education institutions in two main ways:

- Looking for new talents: while micro-credentials refer to the acquired skills, the digital badges are perceived as "a visual representation and evidence" as well as an "icon" that can specify a candidate's abilities (Bowen & Thomas, 2014). The badging system can be seen as a bridge between formal education and employment readiness.
- The re-training of existing employees: employers offer digital badges as a proof of completion of continuing learning requirements and as evidence of the updated skills (Hurst, 2015). The implementation of digital badging at the organization level illustrates employers' commitment in employees' professional development (Pakstis, 2019).

4. CONCEPTUAL FRAMEWORK FOR IMPLEMENTING DIGITAL BADGES

When faced with implementing micro-credentials and digital badges in their graduate programs, the authors visited a strategic model for when to incorporate new materials into the IT curriculum (Liu & Murphy, 2012) and adapted it to the task at hand.

Liu and Murphy (2012) depicted an educator's dilemma as a challenge to find the balance between accommodating new materials emerging from the discipline and maintaining a viable curriculum without overload. The model provides a conceptual framework to help dissect the challenge discussed in the previous sections. We adapted six forces from the original framework to help us make a valid "when and if to implement digital badge" decision, as illustrated in the figure below.

Figure 2: Conceptual Framework of Six Forces (see appendix)

The first force driving our decision is based on the widely recognized "*Diffusion of Innovation*" theory which asserts that the adoption of technological innovation usually follows an S-shaped curve (Rogers, 1983). Five categories of adopters are involved in this curve over periods of time. It starts with a small group of "innovators", gradually leveled up by the "early adopters" and "early majority", and lastly followed (saturated) by the "late majority" and "laggards". This theory provides a macroscopic angle to examine how digital badging is growing to address the gap between education achievement and employment preparedness (Welch, 2021). Even though digital badging credential initiatives have been implemented and promoted by some employers, some non-traditional training organizations, and some education institutions, more opportunities are yet to be created in universities, particularly at the graduate level, to connect students' skills and capabilities with workforce needs (International Council for Open and Distance Education, 2019). In reviewing digital badges in the higher education space, little focus seems to center on graduate students including adult learners and career changers during the movement to digital badging. Following the process outlined in The Innovator's Solution (Christensen & Raynor, 2003), we felt the need to start early and assume the role of an early adopter of digital badge programs targeting graduate-level or post-bachelor students.

The second force in the framework is *the current status of digital badging in industry*. More and more industry leaders have launched their own digital credential programs or have partnered with educational institutions to offer job-oriented courses coming with digital badges. For example, IBM's digital badge program had garnered more than an estimated 200 million social media impressions through early 2018 (Credly, 2020).

The third force in the decision-making process is *the impetus for digital badges*. Both faculty and student interest are important. Faculty members wanted to develop a digital badge program to provide stackable credentials in a modular manner and respond to workplace needs. On the other hand, students are more likely to obtain micro-credentials that they believe would add value to their employability, including employer acceptance and recognition. One study showed that when transcripts were juxtaposed with digital badges, 86 percent of knowledgeable employers preferred a digital badge over an academic transcript when verifying a student's specific skills (Finkelstein et al., 2018). Most of these skills are included in the curriculum but may not be readily discernable by a potential employer when looking at transcripts. Course names and their content vary across institutions. Digital badging will make actual content more obvious.

The fourth force factor is *the adoption status of digital badges in other institutions*. Adoption by another institution is often a consideration in university approval processes and needed to be thoroughly investigated. As discussed above, several higher education institutions are now offering digital badges and many of these are appearing on social media.

The fifth factor in the model is a consideration of *avoiding curriculum "bloating".* Due to its modular and stackable nature, digital badging should not cause curriculum bloating. Students can achieve a badge after competing smaller units of an existing degree program, for example Python Coding included in a computer science program. Students can have some freedom to select different digital badges offering them a degree of personalization.

The sixth factor is *the level of risk*. Risks for adding a new alternative pathway program vary from one institution to another and often relate to its risk posture. Due to the intensively competitive and dynamic higher education environment today, time is of the essence to prepare students for the workplace. Hence, the agility of converting or mapping existing curriculum to suitable skill-based and workforce-related micro-credentials turns out to be a significant critical success factor. Another risk factor is the additional costs for awarding digital badges and ensuring their verification when clicked. This has been made much easier now that several vendors provide badging service. There is also the concept of open badging which allows verifiable badges to be shared across organizations. The Open Badges organization reports that 475,000 open badges were issued in 2020, and over 43 million open badges have been issued in total (IMS Global Learning Consortium and Credential Engine, 2020).

5. CASE STUDY: MICRO-CREDENTIALS AND DIGITAL BADGING AT THE GRADUATE LEVEL

Our analysis based on the above conceptual framework led us to decide that now was the time to implement a digital badging program at the graduate level provided that we did not incur any major costs, given current budget limitations.

The faculty in our school ascertained two years ago that our existing approach of master's degrees in IT and Cybersecurity, with specialties offered, worked well for new entrants in the field, but not for existing workers looking for a quick sprint of additional knowledge and skills for the "new" economy (Liu & Murphy, 2021). At that time, we examined our existing master's level curriculum in IT and cybersecurity and recognized that our existing 12-credit specialties covered most of the content needed for some of these quick sprints. We decided, therefore, to separate them out into new certificates, including:

- Cybersecurity
- Data Science
- Digital Health
- Digital Transformation
- Project Management

Each of the certificates was created from courses in the specialty tracks of the master's level programs which were already approved by the university. Under the micro-credential approach, students can enroll in the certificates individually and get the master's level certificate in as little as two semesters. Due to many recent revisions in the university's curriculum process to maintain the university's agility in today's environment, the certificate program was created and approved in less than one year and began in Fall 2020.

We believe we now have the curriculum structure for our micro-credentials. Our next step is to add digital badging to indicate the significant achievement of each of these certificates and to tie them to employer stated skill requirements.

We gained some experience over the last six months at the undergraduate level as a result of being added as a higher education institution to the area's Capital CoLAB initiative. To meet the stringent requirements for their existing five digital badges in cybersecurity and data science, we had to map our undergraduate courses against their major employer-generated knowledge, skills, and abilities (KSA) list. This provided us with valuable insights into the employer-requirements and the perceived relevance on what we were teaching.

Based on this background, we mapped our graduate cybersecurity and data science certificates to similar, but higher level, KSAs to determine the first two graduate badges in our university.

Having established the KSAs for the graduate certificates, our next step was to invest in a badging system. Through the Capital CoLAB, we have been working with Credly and decided to continue with them, so that we used the same platform for undergraduate and graduate badging programs. We felt this would minimize the training requirements of our faculty and staff. As the badging costs are primarily based on the number of badges issued, we were able to start small given the size of our program. Credly staff were also helpful in the design of our badges, both in terms of visuals and in terms of metadata for verification purposes.

Having designed and developed the first two badges, we then turned to developing the KSAs for the other three existing certificates. We first looked at industry certifications in the fields. This

was easier for Project Management but Digital Health and Digital Transformation were a little harder as they are newer entrants in the field. For these, we used the learning outcomes from each of the courses in the program as the major drivers for the KSAs, taking advantage of the research we had conducted in the industry when developing these courses. This is still a work in progress and we expect badging for all the certificates to be in place in a 90-day timeframe.

While researching the value of micro-credentials, we also identified the need for early recognition of skills in the program for career-changers in our M.S. in IT program. We began by creating a new certificate, Business Information Technology, which covered the first four courses in the M.S. in IT program with a focus on skills such as requirements analysis, computer infrastructure, cybersecurity, and data management. Following the university's approval for the new certificate, we also developed the accompanying badge, both to be introduced in the fall of 2021. We believe this will facilitate early recognition for career changers as they further pursue their master's program and look for entry-level jobs.

6. LESSONS LEARNED AND FUTURE RESEARCH

As higher education institutions, large and small, we need to remain agile in today's fast changing world. We are, in part, being increasingly measured by our ability to place our graduates in excellent jobs in the workforce. Therefore, we must listen to the expressed needs of the employers who are recruiting our IT students, both undergraduate and graduate. One of these requirements is more detailed documentation of the skills of our graduates' technical skills and soft skills. A transcript is no longer enough. Badging provides this visibility into the knowledge, skills, and abilities that we are teaching, and enables our students to take it to the social media realm where more and more hiring professionals are looking for IT talent.

Micro-credentialing is the precursor to badging and this allows us to re-evaluate our curriculum to ensure we are meeting both employer and student needs for incremental learning. Making education available in smaller units does not distract us from our overall educational mission and instead, is largely a repackaging of content we already deliver. Badging these micro-credentials allows students to display their increasing skill level to their peers and to potential employers. Micro-credentials also provide vehicles for students to personalize their education.

The infrastructure for badging can be obtained through the Open Badge initiative under which many of the traditional problems of vendor-specific approaches can be easily avoided. Mapping the curriculum to an external badge can be time consuming but if approved, will provide for additional status for the badge. Internally developed badges can be mapped against course and program outcomes and require less effort.

As we begin to award badges for our undergraduate (through the Capital COLAB project) and for our graduate students (through the university), we will launch the assessment process of the effectiveness of the alternate credentialling systems. We will follow students who are awarded badges in both programs, assess their social media presence based on their demographics, examine the effect the badges have on their job acquisition process, and determine their retention and completion rate in the degree program. This further research should inform us, and others, of the value of external and internal digital badging for graduate-level educational programs.

The authors acknowledge that the current study provides limited empirical evidence on the effectiveness for digital badging due to the early stage of implementation in the program. The research next in line will provide further insights on how the digital badges impact the student retention rate in the degree program and change the visibility of graduates in the job market.

7. CONCLUSION

In summary, the present paper contributes to a relevant and recent topic on the emerging, alternative systems of digital-badging and micro-credentials. A case study is carried out to demonstrate how a digital badging system can be used to validate stackable certificates for micro-credentials in a graduate-level program. The paper provides new findings on how to implement digital badging systems and how to tackle some problems and challenges.

Digital badging based on micro-credentials are becoming an increasingly disruptive part of education and job acquisition, particularly in the social-media world of the day. They document and allow for verification of specific skills and professional development. They also increase transparency into the quality of our educational programs, better communicating what has been

learned than is commonly available on a university transcript. Given the need for reskilling and upskilling in the fast-moving IT field, digital badging of micro-credentials in the academic community is a must.

To end with a quote:

"While the traditional college degree will hold sway in 2026, more employers may accept alternate credentialing systems as self-directed learning options and their measures evolve" (Pew Research Center, 2017).

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Editor's Note:

This paper was selected for inclusion in the journal as an EDSIGCON 2021 Distinguished Paper. The acceptance rate is typically 7% for this category of paper based on blind reviews from six or more peers including three or more former best papers authors who did not submit a paper in 2021.

Appendices and Annexures

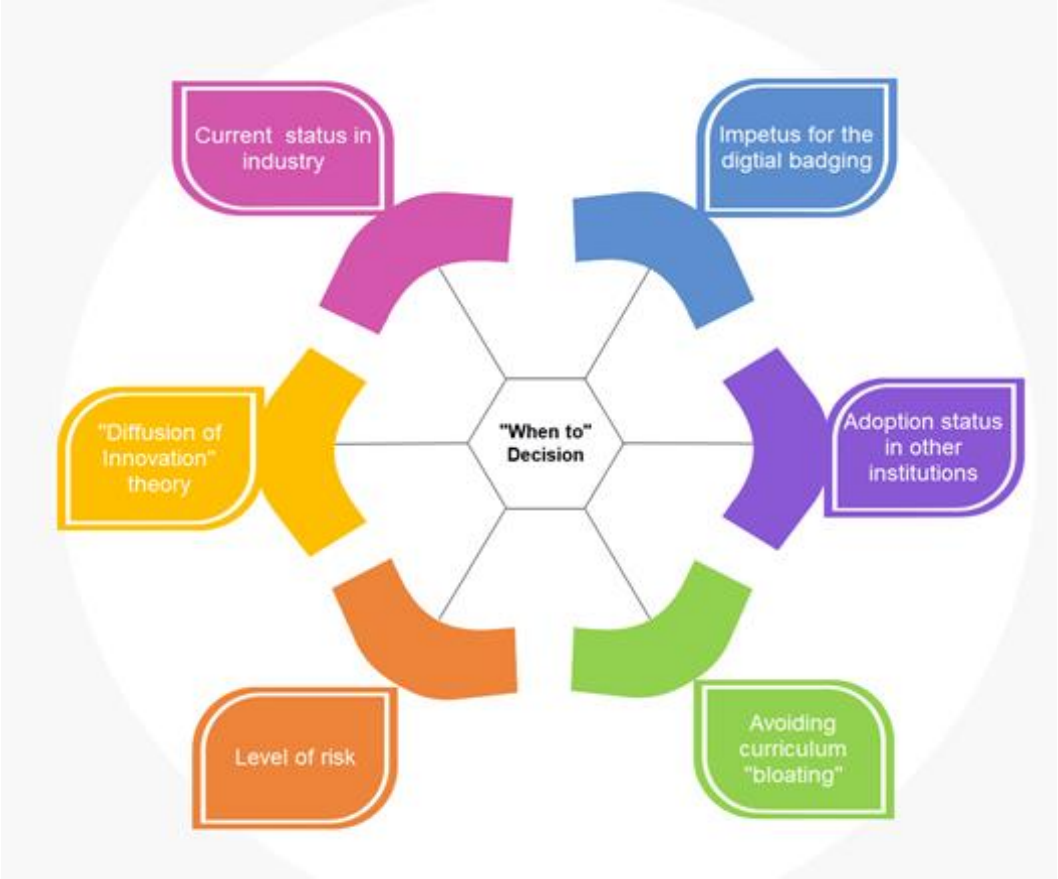

Figure 2: Conceptual Framework of Six Forces

IS Model Curriculum: Adoption Rate of IS 2010 Model Curriculum in AACSB Schools and Impacts of the Proposed 2020 Model Curriculum

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Abstract

As the skills and competencies needed by Information Systems (IS) undergraduates continues to grow, various IS professional societies have developed recommendations which are updated on a periodic basis. These recommendations known as 'model curricula' are a guide for faculty and institutions to consider when developing or evaluating the effectiveness of their program. This research is based on the IS2010 Model Curriculum to determine their adoption rates by schools that currently offer a major or concentration in IS. Based on the evaluation of over 300 schools and using the IS2010 model as a benchmark, the key findings include that of the six recommended upper-level core courses, four had above a 50% adoption rate, while the remaining two were adopted by less than 30% of the schools surveyed. It is interesting to note that the IS2020 Model (in draft at the time of this research) reflects the rapid change to the needs of employers and includes concepts from the software development, security, and analytics courses as core competencies. These were missing from the IS2010 Model core competencies. Our findings suggest that, in a technology field like Information Systems, a 10 year refresh rate to model curriculum is too long a period to wait as employer demands change more frequently.

Keywords: IS2010 Model Curriculum, Computing Curricula 2020, AACSB, Information Systems, Curriculum

1. INTRODUCTION

Curriculum for a rapidly changing field such as Information Systems (IS) can be a challenging area for academicians to manage. This challenge comes from ensuring that the courses offered by a MIS/CIS (Management Information Systems / Computer Information Systems) department for the major/concentration remain current and relevant while adapting to employer's changing needs.

To assist in this endeavor, professional societies in the information systems and computing fields have gathered input from a wide variety of colleagues around the world to issue guidelines for potential model curriculum. These guidelines are issued roughly every ten years. However, the

question remains: "How helpful are these guidelines and are they implemented?".

There has been a variety of research that examines the use of the IS2010 model curriculum (ACM, 2010). A study by Apigian and Gambill (2010) provided initial insights into the model curriculum as it was being developed in 2009. Later studies have also evaluated IS2010 in the context of ABET accreditation (Feinstein, D., Longenecker, B. and Shresthat, D., 2014). For this research, we build on prior studies that detailed the adoption patterns of AACSB (Association to Advance Collegiate Schools of Business) schools and their implementation of the IS2010 model curriculum (Bell, Mills and Fadel, 2013 & Mills, Velasquez, Fadel and Bell, 2012).

The current research summarizes the results from investigating the adoption rate of core and elective courses from the IS2010 Model Curriculum guidelines. Over 300 AACSB accredited schools were evaluated to determine which courses within the model curriculum were implemented as either core or elective courses across various IS programs. ACM (Association for Computing Machinery), AIS (Association for Information Systems) and others have updated the model curriculum (i.e., IS2020) with an initial draft in December of 2020 (ACM/AIS, 2020). Given the recent release of this draft, it would not be practical to measure their level of implementation. Thus, this paper is intended as an overview of current curriculum based on the previous model with the intent to serve as a guide moving forward. Additionally, it will also provide several recommendations on matching courses in the IS2020 model curriculum to employer needs projected for the next ten years as reported by the United States Bureau of Labor Statistics.

2. INFORMATION SYSTEMS (IS) MODEL CURRICULUM

Periodically, IS professional societies update the model IS discipline curriculum. The first model curricula were developed in the 1970s and have been updated regularly. In 2010, the Association for Information Systems (AIS) and the Association for Computing Machinery (ACM) provided guidance as far as courses and resources needed for Information Systems programs (ACM, 2010).

Per IS2010, the use of the report is "to provide a local academic unit with rationale to obtain proper resources to support its program. Often, the administration at a local institution is not aware of the resources, course offerings, computing hardware, software and laboratory resources needed for a viable program" (ACM 2010, p. v). These guidelines were built to provide a set of core courses as well as electives centered around specific careers in the IS field. The "core" courses were designed to provide a high-level of IS knowledge for business school students and non-business school students in the IS field. In addition to the core courses, all programs should have some elective courses prescribed to meet the institution's stakeholders' needs for specific career tracks.

IS 2010 Recommended Core Courses

This section will describe the high level IS conceptual courses that are recommended by the study as well as a brief description of the concepts included in that course or module. The number after the course title (e.g., 2010.1) reflects the model's coding for courses.

1. **Foundations of Information Systems (2010.1)**
   This course is a basic introduction to Information systems for all students within the major as well as non-IS majors. Topics include:
   - Digital World Characteristics
   - IS Components (Hardware / Software / Networks / Data)
   - IS in Organizations (Value/Strategic)
   - Globalization
   - Valuing Information Systems
   - Infrastructure
   - Security
   - Business Intelligence
   - Ethics
   - Development and Acquisition
   - Enterprise Wide

2. **Data and Information Management (2010.2)**
   Introduce the core concepts in data and information management. Topics include:
   - Database approaches
   - Basic file processing
   - Physical and logical models
   - Languages
   - Data Security
   - Data Quality
   - Use in Business Intelligence

3. **Enterprise Architecture (2010.3)**
   The design, selection and implementation of enterprise-wide IT solutions. Topics include:
   - Service oriented architecture
   - Integration
   - Role of Open Source software
   - System Administration

- IT Controls
- Risk Management

4. Infrastructure Architecture (2010.4)
Topics pertinent to systems architecture and communication networks. Topics include:
- Operating Systems
- Computing systems architecture and organizing structures
- Data Centers
- Security infrastructure
- Cloud, grid, "as service"
- Performance analysis

5. Project Management (2010.5)
Introduction to the methods, tools, controls to manage IS projects. Topics include:
- Project Management (PM) Lifecycle
- Managing IS Teams
- Communications
- Scope
- Scheduling
- Quality
- Risk

6. Systems Analysis and Design (2010.6)
Discuss the approaches to solve business problems or opportunities. Topics include:
- Identify opportunities
- Understand business requirements
- Analysis of project feasibility
- Different approaches to analysis and design
- Approaches to implementing systems

7. IS Strategy, Management and Acquisition (2010.7)
How the IS function integrates and supports the overall organizational strategies and operations. Topics include:
- IS strategic alignment
- Strategic use of information
- Managing the IS function
- Financing and evaluation
- IS/IT governance frameworks

Elective Courses as described in the IS2010 model.
As mentioned earlier, the elective courses should be chosen to meet the institution's stakeholders' need to support specific career tracks. This list of electives follows.

E1. Application Development
Introduce the concepts of building applications. Topics include:
- Design
- Modular design
- Program Structures
- Variables/Procedures
- Coding
- Testing
- Development Approaches

E2. Business Process Management
Understanding and designing business processes. Topics include:
- Organizational Processes
- Process assessment/improvement
- Using IT for mgt and improvement
- Understanding the customer
- Outsourcing

E3. Enterprise Systems
Discussion of the theoretic and practical issues related to enterprise systems in organizations. Topics include:
- Business Processes
- Justification of enterprise systems
- Strategic alignment
- User commitment
- Job redesign
- Governance of processes

E4. Introduction to Human Computer Interaction (HCI)
Overview of the interdisciplinary field that integrates psychology, design and computer science. Topics include:
- Principles of HCI
- User Centered Design
- HCI issues related to age/disabilities
- individuals
- Development techniques
- Evaluation Methods

E5. IT Audit and Controls
Understanding information controls and the management. Topics include:
- Need for audit and controls
- Definition of risks
- Ethics, guidelines and standards in the profession
- Controls
- Assessment techniques

E6. IT Innovation and Technologies
Impact of new innovations related to technologies on organizations. Topics include:
- Globalization
- Technologies shaping the electronic world
- Process of IS innovation
- Strategic importance of the Web as a platform

E7. IT Security and Risk Management

Learn the concepts of security principles and the developing and monitoring of security tasks. Topics include:

- Inspection
- Protection / Detection / Reaction
- Risk Assessment Frameworks
- Physical Aspects
- Connected system security concepts
- Security engineering

3. METHODOLOGY

To evaluate the implementation of the 2010 model curriculum in current MIS/CIS programs, a list of all AACSB accredited schools within the United States was utilized. AACSB International provides accreditation for both business schools and accounting programs that meet specific standards (more information may be found at https://www.aacsb.edu/). AACSB schools were chosen because the accreditation requires participating schools to consider model curriculum in their programs.

This list of AACSB schools was further divided into three categories. Based on the Carnegie Classification of Institutions of Higher Education (https://carnegieclassifications.iu.edu/), two of the categories were based on Doctoral Universities classified as either Very High Research Activity (i.e., R1) or High Research Activity (i.e., R2). All universities within these 2 categories that had an AACSB accredited business program were evaluated. For the last category, 100 of the remaining 300 universities (not classified as R1 or R2) were randomly selected to evaluate. This number (i.e., 100) was chosen in order to make an equivalent comparison to the R1 and R2 categories. The final number evaluated was 329 universities.

Procedures

Once the list of universities was compiled, the authors then evaluated each one to determine if it contained an information system major or concentration within the business school. Minors, certificates, and programs outside of the business school were not included.

The most common program names included Management Information Systems (35%), Information Systems (27%) and Computer Information Systems (11%) (a complete list of program names can be found in Appendix A). For this paper, we will be referring to all programs as Information Systems (IS). Additionally, universities provided a variety of bachelor's programs but were primarily either a Bachelor of Science (64% of universities analyzed) or a Bachelor of Business Administration (34% of universities).

Classification	IS Major	No Major	Total
R1	75 (63%)	45 (38%)	120
R2	76 (70%)	33 (30%)	109
Other	58 (58%)	42 (42%)	100
Total	209 (64%)	120 (36%)	329

Table 1. Universities with/without IS Majors

The final number of universities which included either a major or concentration in IS was 209 (64%) universities while 120 (36%) universities did not have one. A complete view based on classification categories can be found in Table 1.

If the university had a major/concentration, we then collected all the required and elective courses that were included as part of the program. Only the courses specifically concerning information systems were included in the final list. For example, a small number of schools listed all business courses as required for the IS major but only the courses related specifically to IS were included in the total number of hours. This was to be consistent with the majority of universities and how they list the IS major.

The list of required and elective courses was then evaluated based on the IS2010 Model Curriculum. This included matching the course title to the model curriculum and when needed, further evaluating the course description to ensure it matched the model curriculum description. To ensure interrater reliability, each author took a random sample of the other author's evaluated schools to ensure the ratings were similar. The observations from this analysis are discussed in the next section.

4. OBSERVATIONS

Overall, the schools studied were very similar in the number of credits required for the major or concentration (see Table 2). The average total number of courses across all categories was 8 (24 hours) with an average of 21 hours for R1 institutions, 24 hours for R2, and 25 hours for the other institutions. The average number of required courses was approximately 6 courses with an additional 2 courses as electives.

	Avg. # of Program Hours	Avg. # of Required Courses	Avg. # of Elective Courses
R1	20.95	5.49	1.60
R2	24.43	5.92	2.05
Other	25.91	6.17	2.16
Total	24.04	5.98	1.93

Table 2: Number of credits required for the IS major

The IS2010 model recommends seven core courses, one of which is the Introduction to Management Information Systems course. As this course is generally required of all business majors in AACSB schools, it was excluded from the analysis because most universities do not list this as a required course specifically under the major or concentration. A list of the remaining core courses can be found in Table 3.

The top three required courses adopted across AACSB schools as part of their core classes include: Data and Information Management (90%), System Analysis and Design (85%) and Infrastructure Architecture (52%). The least adopted required courses were Project Management (37%), IS Strategy (18%) and Enterprise Architecture (17%). These percentages only include programs that have core courses as required for major/concentration.

Model Curriculum Core	Data and Info Mgt		System Analysis and Design		Infra-structure Architec-ture		Project Mgt		IS Strategy Mgt and Acquisition		Enterprise Architec-ture	
R1												
Required	67	89%	61	81%	35	47%	27	36%	14	19%	11	15%
Elective	1	1%	3	4%	11	15%	13	17%	8	11%	2	3%
R2												
Required	70	92%	66	87%	35	46%	30	39%	12	16%	15	20%
Elective	2	3%	3	4%	11	14%	16	21%	4	5%	5	7%
Other												
Required	53	91%	52	90%	39	67%	21	36%	11	19%	9	16%
Elective	1	2%	1	2%	7	12%	11	19%	6	10%	5	9%
Total of All Universities Adopting Core Courses												
Required	190	90%	179	85%	109	52%	78	37%	37	18%	35	17%
Elective	4	2%	7	3%	29	14%	40	19%	18	9%	12	6%
Total	194	92%	186	88%	138	66%	118	56%	55	27%	47	23%

Table 3 – Adoption of IS 2010 Model Curriculum Recommended Core Courses by AASCB Schools in order of the total percentage of adoption

Note: the first column is the raw number of schools adopting that course into the curriculum and the second column is the % of schools adopting a particular course divided by all AACSB schools in that category (R1/R2/Other).

Model Curriculum Electives	Software Develop-ment		Security / Risk Mgt		10E Enterprise System		Business Process Mgt		Innovation / New Technology		HCI		Audit / Controls	
R1														
Required	57	76%	13	17%	4	5%	5	7%	3	4%	0	0%	0	0%
Elective	6	8%	24	32%	8	11%	7	9%	8	11%	0	0%	4	5%
R2														
Core	69	91%	19	25%	12	16%	6	8%	2	3%	1	1%	1	1%
Elective	4	5%	22	29%	14	18%	4	5%	8	11%	3	4%	0	0%
Other														
Core	44	76%	13	22%	4	7%	3	5%	2	3%	1	2%	0	0%
Elective	4	7%	18	31%	2	3%	3	5%	4	7%	2	3%	1	2%
Total of All Universities Adopting Elective Courses														
Core	170	81%	45	21%	20	9%	14	7%	7	3%	2	1%	1	0.5%
Elective	14	7%	64	30%	24	11%	14	7%	20	9%	5	2%	5	2%
Total	184	88%	109	51%	44	20%	28	14%	27	12%	7	3%	6	2.5%

Table 4 – Adoption of IS 2010 Model Curriculum Recommended Elective Courses by AASCB Schools

Model Curriculum	Capstone		Data Analytics	
R1				
Core	10	13%	12	16%
Elective	0	0%	31	41%
R2				
Core	18	24%	17	22%
Elective	0	0%	25	33%
Other				
Core	19	33%	15	26%
Elective	6	10%	18	31%
All Schools				
Core	47	22%	44	21%
Elective	6	3%	74	35%

Table 5 – Adoption of new courses not detailed in the model curriculum

Table 4 details the adoption of the elective courses from the elective list of courses found in the model curriculum. It details the adoption of these courses into the school's major/concentration as part of their required or elective list of courses.

Interestingly, one of the recommended elective courses has a higher adoption rate than four of the model curriculum core courses. This course is Software Development Concepts which is a required course in over 80% of the schools analyzed. Additionally, Security and Risk Management has a high adoption as a required course (21%). The recommended elective courses of HCI and Audit and Controls have been adopted by only 3 to 4% of AACSB schools.

The researchers found two other courses that had a higher implementation rate compared to other required or elective courses (see Table 5). Data Analytics, which is an emerging field, has worked its way into over 20% of the AACSB schools as a required course and over 30% as an elective course. We noticed that a "Capstone" course that was adopted by over 20% of the schools as a required course. We should mention it was difficult to determine what the learning concepts were in the Capstone courses and these learning concepts may overlap with other required or elective courses.

5. DISCUSSION

Observations from the curriculum analysis showed mixed results. Some courses such as Data Management and Systems Analysis/Design have become standard in many programs while others such as Strategy and Enterprise are still not widely included in IS programs at AACSB schools. To understand these differences and where the field may be moving, the following sections provide an attempt to address these

concerns. First, a discussion concerning how programs may be shifting their curriculum to meet employer demands is presented. This is followed by a discussion of the implications from the recent curriculum report (i.e., Computing Curriculum 2020). Finally, the findings are compared to the release of the IS2020 Model Curriculum draft released.

Aligning Curriculum with Industry Demands

A goal of any education program should be to have a high placement rate for its graduates. This may be one reason our results show elective courses such as software development, security and data analytics are being adopted at higher rates compared to some of the 2010 suggested core courses.

According to the United States Bureau of Labor Statistics (BLS), there is significant demand for computer and computer related professionals (Bureau of Labor Statistics, Computer and Information Technology Occupations, 2021). As mentioned in the overview of the model curriculum guidelines, its elective options have been suggested to assist in developing career tracks for graduates. This may be the reason we are seeing increases in programs offering a software development class as a required course. As can be seen in Table 6, software developers are not only the second fastest growing occupation by percentage, but also highest in terms of new positions (316,000).

In fact, Information Technology occupations are projected to grow 11% by 2029, which is higher than the projected growth of 4% for all occupations in the United States. Demand for these workers will grow from the greater emphasis on cloud computing, collection and storage of data and information security. Table 6 summarizes the US Bureau of Labor Statistics findings for technology occupations requiring a bachelor's degree.

As seen in Table 6, the top 3 highest growing occupations include security analysts, software developers and database administrators. Skills in the occupations are included in the top core course (Data Management) and the top elective courses (Development and Security). Overall, the demand for software developers, security analysts and system analysts are suggested to yield at least 400,000 new jobs in these three specific occupations in the next 10 years.

CC2020 and the Current IS Curriculum

The updated Computing Curriculum 2020 was released in the first quarter of 2021 (ACM, 2020). The previous edition was issued in 2005 (ACM, 2005) which provided a foundation for computing curriculum across various fields and was followed by specific curriculum reports for each field (e.g., IS2010). The draft of the IS2020 model curriculum was released in December of 2020.

Occupation	Description	# Jobs (as of 2019)	Projected new jobs (by 2029)	Growth Rate
Security Analysts	Plan and carry out security measures to protect networks and systems	131K	41K	31%
Software Developers	Create applications / systems that run on a computer or other device	1.5M	316K	22%
Database Administrators	Use specialized software to store and organize data	133K	13K	19%
Web Developers	Digital designers develop, create, test a website or other devices	174K	14K	8%
System Analyst	Study an organization's current system and find a solution that is more efficient and effective	632K	47K	7%
Network Architects	Design and build data communication networks	160K	8K	5%
Network Administrators	Responsible for day to day operation of networks	374K	16K	4%
Programmers	Write and test code	214K	-20K	-9%

Table 6: US Bureau of Labor Statistics, Computer and Information Technology Occupations (BLS, 2021)

The CC2020 focuses on competencies for various computing fields. This has been a shift from the previous report which focused on knowledge-based learning (ACM, 2005). These competencies focus on the qualities graduates should possess in order to be effective in their future role or function. The goal is to encompass knowledge ("know-what"), skills ("know-how") and dispositions ("know-why") instead of specific courses (ACM 2020).

The draft for key competencies in Information Systems (IS) include 9 broad categories followed by more specific competencies (for a total of 88) within each of these broad categories. These categories have been identified as the following (note: the number of specific competencies in each category is in parentheses):

1) Identifying and designing opportunities for IT enable organization improvement (14)
2) Analyzing trade-offs (5)
3) Designing and implementing IS solutions (10)
4) Managing ongoing IT operations (10)
5) Leadership and collaboration (16)
6) Communication (7)
7) Negotiation (5)
8) Analytic and critical thinking (17)
9) Mathematic foundations (4)

In addition to the CC2020, a draft of the IS2020 model curriculum was also released outlining potential competency areas that are needed within programs. This initial report appears to be closer to industry needs and reflects the changes that AACSB schools have implemented in their programs. Specifically, the areas of software development, security and data/business analysis have become part of the 'core competencies' recommended. Additionally, based on our analysis of over 200 IS programs, there were 2 courses referenced in Table 3 (the Strategy and the Enterprise Architecture courses) that are not being widely required in IS programs. These two courses have been removed from the core requirements as part of the IS2020 recommendations.

Recommendations for Future IS Model Curriculum

After evaluating IS programs against the 2010 model, it may be that ten years between releases is too long a period for updates to the model. Current areas of importance such as cloud, cyber security and data / business analytics were not envisioned in 2010, but clearly schools have adopted them into their curriculum. What will be the topics that evolve in the next few years and should be included? Perhaps an interim update to the model curriculum could be made on a 5-year cycle versus the current 10-year cycle.

6. LIMITATIONS

One of the limitations is that the authors were limited to the information available on public facing college websites. The data collected was based on reviewing both the course titles and descriptions. It is possible that some courses may have been miscategorized. Additionally, it is possible that a course might cover additional topics or different material we did not recognize. This is one reason we reviewed the course description as well to ensure we were capturing the correct courses listed in IS2010.

Additionally, this research only surveyed AACSB schools that offered either a major or concentration within IS. There are many schools that are not AACSB accredited with a major/concentration in IS. There are many academic units only offering minors that have not been included in this study. Additionally, some universities have moved these programs into schools specializing in technical fields (e.g., Schools of Informatics). Researchers that wish to expand our research should consider including non-AACSB accredited universities, because these may be seeking to follow the IS curriculum guidance but have not obtained AACSB accreditation or may not wish to apply for AACSB accreditation.

A final limitation of the current study concerns the model curriculum (i.e., 2010) used to evaluate programs. While these suggestions are over 10 years old, the researchers felt they provided good guidance to understand courses being offered in IS programs currently. Additional research is needed once the latest course curriculum suggestions are published.

7. CONCLUSIONS

This research has summarized the implementation of required and core courses. The research demonstrated those courses that are closest to the needs of employers appear to have the highest adoption rates. These courses and their matching potential occupations are shown in Table 8. Those courses in the core model curriculum that tend to be more conceptual (Enterprise Architecture, Strategy) and less skill based have the lowest adoption rates.

Finally, as with all programs, IS has limitations based upon university administration and AACSB requirements. While it would be valuable to

provide more courses, the average number of courses in IS programs is currently 8 (6 core and 2 electives). This may be why we see some recommended electives being included as required courses.

Course	Adopted Required/ Elective	Occupation Title
Security/Risk Management	52%	Security Analysts
Software Development	87%	Software Developers
		Web Developers
Data and Info Management	92%	Database Administrators
System Analysis and Design	88%	System Analyst
Infrastructure	65%	Network Architects

Table 8 – Matching Courses to Occupations in demand. Listed by Occupation Growth Rates

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Appendix A. Various IS Program Names

Business Analytics and Information Systems
Business and Information Technology
Business Computer Information Systems
Business Informatics
Business Information & Technology
Business Information Management
Business Information Systems
Business System Management
Computer Information Science
Computer Information Systems
Computer Information Technology
Computer Science and Information Systems
Information Management
Information System Management
Information Systems
Information Systems & Decision Sciences
Information Systems & Technology
Information Systems & Technology Management
Information Systems and Business Analytics
Information Systems Technology
Information Systems/Supply Chain
Information Technology
Information Technology and Systems
Information Technology Management
Information Technology and Management Information Systems
Management Information Systems
Management Information Systems & Technology
Management of Information and Technology
Operations and Information Systems
Technology
Technology and Management